WHAT DRIVES FIRM-LEVEL CONSENSUS GROWTH FORECASTS? CASH FLOW NEWS OR EXPECTED RETURN NEWS?

by

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This dissertation is dedicated to my parents:

My mother, Pham Thi Cuu

My father, Nguyen Xuan Quynh

and to my parents in-law:

My mother-in-law, Duong Thi Loan

My father-in-law, Vu Duc Van

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ABSTRACT

WHAT DRIVES FIRM-LEVEL CONSENSUS GROWTH FORECASTS? CASH FLOW NEWS OR EXPECTED RETURN NEWS?

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Recent findings in the finance literature document that analysts adjust their growth forecasts in response to major news, proxied by large changes in company stock price. However, Campbell and Shiller (1988) argue that stock prices, themselves, carry two sets of information: news about changes in cash-flow expectation (i.e. cash flow news) and changes in discount rate (i.e. expected return news). The former one directly relates to changes in expectation about the fundamentals of the company while the latter one to the changes in market expectation. Hence, are analysts more concerned about expectation of the permanent movement in the stock price (cash flow news) or the temporary movement in the stock price (expected return news)?

In this study, I use a firm-level vector autoregressive approach to examine the relative impact of cash flow news and expected return news on unexpected changes in analysts next fiscal year growth forecasts. My findings indicate that analysts do raise their forecasts on positive cash flow news. However, the magnitude of the response to cash flow news is significantly lower than the magnitude of the response to expected return news. This suggests that while analysts do react to changes in firm fundamentals, they respond more strongly to changes in future expected return.

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CHAPTER 1

BACKGROUND AND CONTRIBUTION

Brokerage houses and investments banks invest enormous amounts of capital to research, analyze and forecast firm performance. Most prior studies have documented that the analysts working for the brokerage houses have done their job fairly well. In particular, the information they produce helps investors better understand the risk and return trade-off of potential investments. This, in turn, promotes efficiency in the capital market.

However, security analysts' failure to foresee the meltdown of the Internet Bubble in the late 1990's has significantly affected their reputation as well as led to heightened scrutiny from policymakers. Analysts were criticized for maintaining unrealistically optimistic forecasts which resulted in billion dollar losses in shareholder wealth. As Lahart (2006), a Wall Street Journal columnist, said, "Wall Street stock analysts went from heroes to zeroes after the 1990s." On the academic side, researchers also mount aggressive empirical attacks on the way analysts generate forecasts. Analysts are blamed for generating overly optimistic forecasts that place heavier emphasis on personal incentives, such as maintaining relations with management, generating investment banking deals and climbing up the career ladder, than on

accuracy. In fact, Hong and Kubik (2003) document that during the high-tech peak, many brokerages valued optimism more than forecast accuracy.

In addition to economic incentives, analysts are also attacked on psychological grounds. In particular, many studies suggest that analyst misinterpret information and thereby produce biased forecasts. In a study of analyst overreaction, DeBondt and Thaler (1990, p. 57) conclude, "The conclusion we reach from our examination of analysts' forecasts is that they are decidedly human. The same pattern of overreaction observed in undergraduates is replicated in the predictions of stock market professionals. Forecasts changes are simply too extreme to be considered rational." Furthermore, Bradshaw (2004) suggests that analysts base their recommendations on heuristic valuation models which are also used by noise traders. Cornell (2001) implies that analysts simply adjust their recommendations and forecasts in reaction to the news associated with the firm.

From an investor's perspective, the thought that an analyst, a market professional and supposedly a rational decision maker, is misinterpreting and placing bias on available information is troubling. Nonetheless, the good news is that the answer to whether analysts misinterpret information or not is still inconclusive. The misinterpretation conclusion is based on the arrival of accounting earning news. However, analysts may provide or revise their forecasts and recommendations in reaction to news other than accounting earnings. Campbell (1991), Vuolteenaho (2002) and others suggest that it is more important to look at cash-flow news, defined as the shock to the predicted long-run log of price. Hence, cash flow news is the result of a

summary of information, including accounting news, which causes the stock price to deviate away from its long-run prediction.

Therefore, how do analysts react to cash-flow news? The answer to this question is the focus of this dissertation. The research contains three essays which, combined, attempt to find the answer to the question. In the first essay, I investigate the effect of efficiency score on equity returns. Fama and French (1992) document that size and book-to-market ratio (B/M) are sufficient in explaining the cross-section of returns. In particular, B/M captures the effect of most other accounting anomalies, namely earnings yield (Basu, 1977), size (Banz, 1981) and debt-equity (Bhandari, 1988). However, B/M is also criticized for not being able to capture effect of other firm characteristics such as growth opportunities and intangible assets. In this essay, I devise a new approach to defining firm efficiency levels based on firm specific characteristics. I use stochastic frontier analysis to compute an efficiency score for each firm with the efficiency score being derived from current market prices and from various firm-specific fundamental measures including book equity. I show that efficiency score not only produces results comparable to those of B/M but also captures the effect of factors that are not explained by B/M (e.g. growth opportunities and intangible assets). Further, I document that in a panel regression setting efficiency score subsumes the effect of B/M.

In the second essay, I investigate the relationship between analysts' forecasts and equity returns. Specifically, I directly examine the profitability of a contrarian strategy that is long in low consensus growth forecasts and short in high consensus growth forecasts. I find that the strategy yields significant abnormal returns for growth

forecasts of the next fiscal year. However, the strategy does not earn abnormal returns for growth forecasts of the current fiscal year. The findings are consistent with the notion that analysts gradually obtain more information as time approaches the earning announcement date. Most previous studies have implied that investors should follow a contrarian strategy based on analysts' forecasts. My study is a direct empirical examination of such as strategy.

The last chapter of this dissertation combines the findings and implications from the previous two essays and addresses the primary question of this study: How do analysts react to cash flow news? I use Campbell (1991) and Vuolteenaho (2002) vector autoregressive (VAR) approach to measure analysts' reaction to cash flow news. Specifically, the VAR approach allows for decomposition of stock returns into cash-flow news and discount rate news components. The cash-flow news is the capital gain that would have been realized if the discount rate had not changed. The decomposition can be thought of transitory and permanent shocks to shareholder wealth. This in turn enables me to investigate the relative impact of the two components on changes in analysts growth forecasts. In sum, analysts' reaction to a summary of all information, proxied by cash-flow news, should shed more light on how analysts generally react to new information in general.

CHAPTER 2

RELATED LITERATURE

This section provides an overview of the literature that is relevant to this study. The first part discusses studies surrounding analysts' forecasts. Specifically, I focus on empirical papers documenting the upward bias in analysts' forecasts. The second part of the section looks at the literature on return predictability. I emphasize papers that are most relevant to my study. In particular, I look at studies relating firm characteristics, analysts' forecasts and momentum to stock returns.

2.1 Evidence of Analysts Forecast Bias

2.1.1 Analysts Forecast Bias and Economic Incentives

The analysts' forecasts literature takes the view that analyst recommendations do add economic value to investors (Givoly and Lakonishok, 1979, 1984). More recent findings also suggest that analysts' forecasts appear to contain valuable non-public information (Stickel, 1990; Womack, 1996). Nevertheless, many studies also document that analysts tend to provide upwardly biased information.

Chan, Karceski and Lakonishok (2003) document that analysts' forecasts of earnings growth rates appreciably exceed realized growth rates. The difference in median growth rates between analysts' forecasts and five-year realized rates is approximately 3.5%. For firms with high past earnings growth rates, the difference is

close to 13%. Similarly, O'Brien (1988) provides evidence that analysts' forecast errors exhibit statistically significant negative bias which is attributable to overestimates of actual earnings. However, the magnitude of the optimistic bias decreases over the forecast horizon. Chopra (1998) indicates that calendarized earnings estimates overstate actual earnings by approximately 11% at the start of the year. These estimates are revised downward as the year goes by. The studies imply that analysts forecast bias is inversely related with the forecast horizon. The explanation for this relationship is simple. If analysts gradually obtain more precise information about the company over time then their mean forecast error for the company decreases over time. This is may be due to the fact that when the initial forecasts were made, analysts did not have enough information about the company. Lim (2001) finds that analysts' forecasts are generally higher for companies with high information uncertainty. Similarly, Duru and Reeb (2002) and Scherbina (2004) find evidence that if analysts have less than precise information about the firm's performance, they tend to issue more optimistic forecasts.

Another stream of literature on analysts' optimism suggests that analysts tend to issue optimistic forecasts because of various economic incentives. Brav, Lehavy and Michaely (2002) examine the difference in target prices issued by sell-side analysts to those issued by Value Line, an independent research provider. They document that stock prices issued by sell-side analysts exceed Value Line target prices by approximately 14%. The results indicate that the optimism is more severe for sell-side analysts than for independent researchers. Most of the sell-side analysts are employed by brokerages houses that also provide investment banking services. For these analysts,

generating underwriting business for the brokerage not only enhances their economic wealth but also their reputation which is a major determinant for future deals. Lin and McNichols (1997) document that recommendations provided by underwriters are more positive that the ones provided by non-affiliated analysts. Similarly, Dechow, Hutton and Sloan (2000) provide evidence that earning estimates by underwriter analysts are significantly higher than those of unaffiliated analysts. Moreover, stocks are most overpriced when they are covered by affiliated analysts. Michaely and Womack (1999) compare performance of stocks recommended by affiliated and non-affiliated analysts. Results show that the long-run post-recommendation performance of firms recommended by affiliated brokerages is significantly worse than the performance of firms recommended by other houses. In a comprehensive study, Jegadeesh et. al. (2004) document that the economic incentives analysts receive from underwriting deals also affects the types of stocks they recommend. In particular, the incentives may cause analysts to tilt their preference and forecasts in favor of growth and glamour stocks.

It is also possible that analysts issue optimistic forecasts because they want to maintain good relations with company management. Francis and Philbrick (1993) study analysts' earnings forecasts in a multi-task environment in which analysts forecast earnings while maintaining relations with the management. The findings suggest that the relation with company executives influences analysts' earnings forecasts. Moreover, analysts' forecasts, on average, are optimistic and the optimism is stronger for sell and hold stocks than for buy stocks. Das et. al. (1998) hypothesize that analysts have greater incentives to seek and acquire access to private information from management for low

predictability firms. Consistent with the hypothesis, they find that analysts tend to be more biased and to issue more favorable forecasts to firms with low performance predictability. Similarly, Lim (2001) suggests that management may limit or eliminate an analyst's flow of non-public information if the analyst issues unfavorable forecasts.

More recently, Hong and Kubik (2003) argue that career concerns also influence analysts' forecasts. Controlling for previous accuracy, analysts with more optimistic forecasts than the consensus are 90% more likely to move up to a better brokerage house. For analysts in the brokerage with an investment banking relation with the company they follow, the job movement sensitivity is more dependent on optimism than on accuracy. Hong and Kubik conclude that brokerage houses reward optimistic analysts who promote stocks.

Overall, the literature connecting analysts' forecasts and incentives suggest that while analysts are rational decision makers, their decision and forecasts are influenced by various economic and political forces. Regardless of the causes of the bias, the studies generally support the hypothesis that analysts' forecasts are overly optimistic.

2.1.2 Analysts Forecast Bias and Misinterpretation of Information

A behavioral link to analysts forecasts suggests that analysts make biased forecasts because they suffer from cognitive failures and misinterpret publicly available information. There are two different viewpoints on how analysts react to new information.

Barberis, Shleifer and Vishny (1998), Hirshleifer (2001) and Chan, Frankel and Kothari (2004) argue that individuals overreact to most recent information. DeBondt

and Thaler (1990) find evidence that analysts systematically overreact to past earnings and conclude that analysts form expectations that are too extreme.

An alternative view to overreaction is the underreaction or conservatism argument[1]. It is possible that analysts are slow in adjusting their prior beliefs in response to new information and hence, bias the forecasts. Abarbanell (1991) documents that analysts fail to incorporate prior price changes into their forecasts and Abarbanell and Bernard (1992) do not find any evidence of overreaction and extreme forecasts suggested by DeBondt and Thaler (1990). Similarly, Mendehall (1991) and Mikhail, Walther and Willis (2004) find positive serial correlation of forecasts errors in quarterly earnings which implies that analysts underreact to earnings information. Ali, Klein and Rosenfeld (1992) find the positive serial correlation in annual forecasts errors.

Easterwood and Nutt (1999) reconcile analysts' under- and overreaction by documenting that analysts underreact to negative information but overreact to positive information. The findings are supported by behavioral models that suggest that investors exhibit overreaction in one instance and underreaction in another (see Barberis, Shleifer and Vishny, 1998; Daniel et. al., 1998; and Hong and Stein, 1999).

In more recent findings, Bradshaw (2002, 2004) argues that analysts do not rely on any type of valuation models in making forecasts and recommendations. In particular, Bradshaw (2004) studies the relationship between analysts' recommendations and valuation models and finds that residual income valuation models

[1] See Chan, Frankel and Kothari (2004) for a more detailed discussion.

are either unrelated or negatively related to recommendations. Valuations estimates based on price-earnings-over-growth (PEG) and long-term growth ratios are highly correlated with recommendations. Moreover, residual income valuations are positively associated with excess returns while estimates based on long-term growth ratios are negatively related with excess returns. Results on PEG ratios indicate that while estimates are associated with future positive excess returns, these returns partially capture risk. In a similar study, Cornell (2001) documents that analysts do not base their recommendations on valuation models but simply adjust to news associated with the firm. Specifically, analysts revised their target price of Intel from $75 to $40 within one day in response to a 30% drop in Intel stock price. The price movement and analysts' revisions are the consequence of the announcement that expected revenue for the third quarter will be less than the previous forecasts by 4%. He found no economic justification for either the price movement or the revision because the release did not contain sufficient long-run valuation information to justify the new price. Cornell concludes that there may be a positive feedback between stock price movement and analysts' recommendations with price movement acting as a catalyst.

In summary the research on analysts' forecasts can be summarized with (1) analysts are overly optimistic and (2) analysts react to new information. In particular, the literature on analysts' forecasts and information processing generally conclude that analysts misinterpret (overreact or underreact) to new information. However, a caveat to the analysis is the usage of earnings releases as proxy for arrival of new information. Cohen, Gompers and Vuolteenaho (2002) argue that it is difficult to draw strong

conclusions about reaction from naïve approaches (i.e. using accounting earnings) because such conclusions implicitly assume that accounting return is a perfect proxy for all new information. Hence, the focus of this study is to look at analysts' forecasts in reaction to a set of information.

2.2 Return Predictability

This sub-section discusses the literature on return predictability. All empirical aspects of return predictability is beyond the scope of this study; therefore, I will focus on the most relevant studies. The remainder of the discussion is separated into three parts. The first part looks at firm specific characteristics in relation to stock returns. The second part discusses analysts' forecasts and stock returns. The last part reviews momentum studies.

2.2.1 Firm Characteristic and Stock Returns

Early studies by Sharpe (1964), Lintner (1965), and Black (1972) advocate the position that security returns are explained by the market. Consistent with this argument, the expected return is a linear function of beta, the covariance of the stock return and the market return. However, several papers document that in addition to beta there are other factors that can also explain returns. Basu (1977, 1983) documents that, controlling for beta, the expected return is positively related to earnings yield. Banz (1981) shows that market cap helps explain expected return. Bhandari (1988) finds that small firms include many highly levered firms which may possibly explain the relationship between size and return. Finally, Chan, Hamao and Lakonishok (1991) show that the book-to-market ratio has strong explanatory power on returns.

In a unified framework, Fama and French (1992) document that when size and B/M are included, beta has no predictive power on expected returns. Fama and French (1993, 1996, 1998) argue that size and B/M are risk factors within a risk-return framework. Specifically, the B/M ratio, a proxy for distress risk, is a distinct risk factor that can explain the cross-section of returns. Firms with weak earnings growth trends or in financial distress are likely to have higher B/M. These firms are especially sensitive to business cycles and economic conditions. Hence, the risk of holding these firms will increase thereby increasing the expected return. In support of this argument, Chen and Zheng (1998), Lettau and Ludvigson (2001) and Petkova and Zhang (2003) find that value firms (high B/M) are riskier than growth firms (low B/M) especially during negative business cycle shocks.

In a firm characteristics-based set up, Daniel and Titman (1997) do not find a strong relationship between risk factor sensitivities and expected return. However, their findings indicate a strong relationship between firm-level B/M and expected return. Consequently, they suggest that risk factors explain expected return only because the factor loadings are correlated with characteristics. Daniel and Titman conclude that firm-specific characteristics, in particular B/M and size and not covariances with risk factors, predict expected returns.

Regardless of factor-risk or characteristics, B/M is a strong and important determinant of expected return. Nevertheless, the variable is not without weaknesses. In particular, B/M may not be able to capture additional characteristics such as growth opportunities and intangible assets. Loughran (1997) and Brav, Gezcy and Gompers

(2000) indicate that the Fama-French 3-factor risk model may have difficulty explaining returns for NASDAQ stocks, which are predominantly high-tech firms with high expected growth. In a cross-sectional setting, Anderson and Garcia-Feijoo (2006) find significant explanatory power of firm-specific investment growth on monthly returns in addition to size and the B/M ratio. Specifically, the results imply that effects of size and B/M are conditioned by prior growth rates in firm-specific capital expenditures. Similarly, Nelson (2006) suggests that B/M may have difficulty capturing the value of intangible assets, and proposes a four-factor model with zero-investment portfolios of R&D and advertising expenses, instead of B/M, as risk factors. The model, designed to incorporate intangibles, provides results comparable to those of Fama-French's 3-factor model plus is capable of explaining returns for NASDAQ firms and for firms in different industries.

Although B/M is a strong proxy for firm characteristics and especially financial distress, it may not be a good measure for firms with high growth opportunities and with low capital intensity.

2.2.2 Analysts Forecasts and Stock Returns

As discussed in sub-section 2.1, most of the studies in analysts' forecasts document that analysts are overly optimistic. The findings also indicate that the forecasts are adjusted downwards as time approaches the earning announcement date. This implies that if prices overreact to analysts' initial forecasts, then they should approach the fundamental value as analysts acquire more information about the

company. However, empirical papers on forecasts and subsequent performance are still limited.

Bulkley and Harris (1997) and Frankel and Lee (1998) provide evidence that long-term growth forecasts and forecast errors are related to returns. La Porta (1996) argues that analysts' estimates are too extreme and finds that forecasts are negatively related to subsequent returns. Recently, Bradshaw (2004) finds that analysts' long-term forecasts are highly correlated with heuristics valuations ratios used by noise traders. Consequently, he documents that long-term growth is negatively related to subsequent excess returns. Further, Jegadeesh et. al. (2004) documents that within the subset of firms with unfavorable quantitative signals the stocks that analysts recommend favorably significantly underperform the stocks they recommend less favorably. The result is attributed to analysts' failure to quickly downgrade the stocks in line with unfavorable quantitative signals. However, Jegadeesh et. al. (2004) also provide evidence that upgraded stocks outperform downgraded stocks. The finding is consistent with the notion that analysts gradually incorporate more information into their revisions and subsequent forecasts.

Indirectly, the analysts' forecasts literature implies that investors should follow a contrarian strategy based on analysts' forecasts. Specifically, abnormal returns should be greater for a contrarian strategy that exploits either long horizon forecasts or initial forecasts that analysts provide.

2.2.3 Stock Return Momentum

Many studies document that lagged returns have predictive power on subsequent returns. In particular, DeBondt and Thaler (1985, 1987) find that a long-term contrarian strategy is capable of producing abnormal returns. The findings indicate that a portfolio consisting of previous loser stocks significantly outperforms the market over the three years after portfolio formation. Conversely, a portfolio consisting of previous winner stocks significantly underperforms the market over the three years after portfolio formation. On the other hand, Jegadeesh and Titman (1993) document significant abnormal returns from an intermediate-term momentum strategy. Specifically, they examine a variety of different strategies and find that a zero-cost strategy that is long winners and short losers based on previous 3- to 12-month returns yields approximately 1% per month profit for the following year. However, the academic community mounted aggressive attacks on Jegadeesh and Titman (1993) findings. Most notable criticisms are data snooping and time period specification.

Nevertheless, Rouwenhorst (1998) documents findings similar to those of Jegadeesh and Titman (1993) for European markets. Similarly, Chui, Titman and Wei (2000) provide evidence of momentum profits in some Asian markets. Finally, Jegadeesh and Titman (2001) find momentum profits in years subsequent to the sample period used by Jegadeesh and Titman (1993). They conclude that previous findings are not entirely due to data snooping.

In a firm-level VAR framework, Vuolteenaho (2002) and Cohen, Gompers and Vuolteenaho (2002) document significant predictive power of previous one-year return

on current year return. Using similar methodology, Callen and Segal (2004) find negative relationship between past one-year returns and current year returns. The difference may be due to sample and time-period specification.

CHAPTER 3

FIRM EFFICIENCY AND EQUITY RETURNS

3.1 Introduction

How efficiently a firm operates determines its cash flows, which in turn are priced in the financial markets. Yet the economic link between firm efficiency and asset prices remains relatively unexplored. This chapter studies the effect of firm efficiency on average equity returns.

There are a number of potential reasons why firm efficiency may affect stock returns. Firms make investment and financing decisions that may affect the riskiness of their cash flows. In an efficient market, these risky cash flows will be priced through the equilibrium rate of return. Take, for example, financial distress. According to Fama and French (1995), firms in financial distress have higher required rate of return because of higher distress risk. Hence, distress risk is one channel through which efficiency can be linked to equity return. Or consider market power. Firms that operate more efficiently may have relatively larger market shares and higher profits because of their low costs of production (Demsetz, 1973, 1974, and Peltzman, 1977). This, in turn, makes them less vulnerable to outside competition and to aggregate demand shocks. Hence, the required rate of return for efficiently operating firms will be lower than for inefficiently

operating firms[2]. Regardless of the underlying economic channel between efficiency and stock returns, my message is simple. The firm efficiency level should affect the riskiness of firm cash flows and cash flows should impact firm equity returns.

The first task in exploring the linkage between efficiency and equity returns is to estimate firm efficiency level based on some common standard. Two firms with similar characteristics facing the same conditions should have the same values. However, one firm being priced higher (lower) than another firm implies that one firm is more (less) efficient. One methodology for estimating firm efficiency is stochastic frontier analysis that provides a way to "benchmark" the relative value of each firm. This benchmark is a hypothetical value and represents the value a firm could obtain if it were to match the performance of its best-performing peer. The shortfall from the benchmark, measured by the difference between the hypothetical value and the actual value of the firm, is an estimate of the level of inefficiency of the firm. Firms with lower degrees of shortfall and hence lower inefficiencies are the more efficient firms.

While stochastic frontier analysis is a familiar technique to measure firm efficiency in production economics, its use is relatively new in finance[3]. In a recent study, Habib and Ljungqvist (2005) apply stochastic frontier analysis to measure firm efficiency in large publicly traded companies and study its relationship to corporate governance. I follow the same basic measurement technique to estimate firm level efficiency. Once the efficiency level for each firm is obtained, I form decile portfolios

[2] Hou and Robinson (2006) bridge the relationship between average stock returns and market concentration by documenting that firms in more concentrated industries earn lower risk-adjusted returns.
[3] Stochastic frontier analysis is widely used in banking efficiency studies. In addition, Hunt-McCool, Koh and Francis (1996) use the technique to study IPO underpricing.

based on firm shortfall from the frontier and evaluate the performance for each portfolio accordingly.

I find that firms that are most inefficient tend to outperform firms that are most efficient even after adjusting for size, book-to-market and momentum factors. While I find no difference in performance for value-weighted returns, the economic impact of equally-weighted returns is large. My findings indicate that firms in the most inefficient group earn monthly returns that are 0.76% higher than firms in the most efficient group, and the difference is statistically significant. Further, I test the results relative to characteristics benchmark portfolios proposed by Daniel, Grinblatt, Titman, and Wermers (1997). Even after controlling for both risk factors and characteristics benchmarks, the difference in performance is still economically and statistically significant.

I also examine the persistency of the efficiency level in the years following portfolio formation. I find that a simple 5-year buy-and-hold strategy generates an average cumulative return difference of 44% in favor of inefficient firms. At the same time, the average efficiency level of the most inefficient firms is rising. This observation is in line with findings by Habib and Ljungqvist (2005) who document that firms with shortfalls from the benchmark take actions to improve their performance. Furthermore, Berger and Humphrey (1992), Cebenoyan, Cooperman and Register (1993), and Hermalin and Wallace (1994), among others, document low efficiency is correlated with high failure rate. Thus, my finding of improvement in efficiency levels

suggests that in order to stay competitive and survive in the market firms are forced to improve their efficiency levels.

Finally, I demonstrate that stock returns are related to firm efficiency level in cross-sectional analysis. In particular, I use the Fama and MacBeth (1973) approach to examine the relationship between average stock returns and firm efficiency level. I find that firm efficiency level helps explain monthly stock returns even after controlling for size and book-to-market. Interestingly, the results indicate that the firm efficiency level subsumes the information that is present in book-to-market.

The remainder of the chapter is organized as follows. Section 3.2 sets forth the empirical approach; the data is described in Section 3.3; Section 3.4 presents empirical findings. Section 3.5 provides supporting evidence for the efficiency score, and Section 3.6 concludes.

3.2 Empirical Approach

3.2.1 The Link between Firm Efficiency/Inefficiency and Stock Returns

I postulate a simple model to describe the relation between firm efficiency/inefficiency and expected stock returns. Consider firm value as follows

(3.1) $$V_t = V_t^* - I_t$$

where V_t is the observed firm value at time t, V_t^* is firm value at time t under minimum or no inefficiency and I_t are the inefficiencies or distresses incurred by the firm at time t.

I assume that I is non-negative. Therefore, $I > 0$ measures the net inefficiencies that the firm incurs as a result of any firm specific problems such as agency conflict, technical or managerial inefficiency or financial distress.

Define V_t' as the intrinsic value of the firm**,** where V_t' is simply the discounted value of future cash flows generated by firm assets and future growth opportunities. Hence,

$$V_t' = E_t\left[\sum_{n=1}^{\infty}\left(\frac{1}{1+r}\right)^n f(X_t,\beta)\right] \tag{3.2}$$

where E is the expected value operator, X is a *(1 x k)* set of firm inputs, β is a *(k x 1)* set of parameters and r is the discount rate.

In an efficient market with rational expectations, any firm inefficiency such as agency cost or financial distress should be incorporated in the market price and reflected through the required rate of return or the discount rate. This implies that

$$V_t = V_t' \qquad \text{or} \tag{3.3}$$

$$V_t^* - I_t = E_t\left[\sum_{n=1}^{\infty}\left(\frac{1}{1+r}\right)^n f(X_t,\beta)\right] \tag{3.4}$$

By rearranging equation (3.4), I have the following

$$I_t = V_t^* - E_t\left[\sum_{n=1}^{\infty}\left(\frac{1}{1+r}\right)^n f(X_t,\beta)\right] \tag{3.5}$$

This simple model predicts that firms with higher inefficiencies will have higher required rates of return. This is in keeping with well-established theory that greater returns are necessary for investors to undertake more risk. Inefficient firms face greater challenges as they attempt to attract better management, improve operational strategies, and raise necessary funding. Empirical evidence supporting this thesis include Barr,

Kilgo, Siems and Zimmel (2002), who, in a study of U.S. commercial banks, find that efficiency level is positively correlated with return on average assets. Further, Berger and Humphrey (1992), Cebenoyan, Cooperman and Register (1993), and Hermalin and Wallace (1994) document that banking and savings and loan institutions with low efficiency fail at greater rates than institutions with high efficiency. More importantly, Barr, Seiford and Siems (1994) show that the efficiency-failure relationship is evident a number of years ahead. Therefore, under the risk-based argument, firms with lower efficiency should require higher rates of return.

3.2.2 Firm Efficiency/Inefficiency: Efficiency Scores

To estimate firm efficiency, consider a set of firms where each firm faces the same opportunity set. Due to firm-specific characteristics such as managerial strengths, technical efficiency and investment choices, different firms may pursue the opportunity set in different ways, thereby creating different firm values. The logic implies that firms with higher valuations are the ones generating more value per dollar of assets. Consequently, the market perceives them to be the more efficient firms. Firms with lower valuations are the ones not making the best use of their assets. Hence, they are regarded as the less efficient firms. By varying the opportunity set and firm characteristics, I can estimate an optimal firm value function or the frontier function in a sample for any combination of firm characteristics and opportunities. Each firm's shortfall from the frontier is an approximate measure of the market perception of firm inefficiency.

A few important points must be noted before estimating the optimal value or the frontier. First, the assumption of a frontier function is that firms can only lie on the frontier or below it because it is the proxy for the "optimal" firm value. Second, the true "optimal" firm value is never known, and the frontier is only a benchmark consisting of the best performing companies facing a specific opportunity set. That benchmark is an econometric estimation. Third, a firm can be on the frontier simply because of random "luck" rather than superior management or foresight. For the same reason a firm can be below the frontier through no firm-specific reason. Therefore, it is important to be able to distinguish between actual inefficiency and random effects.

The determination of an efficiency score is based on the technique of stochastic frontier analysis, pioneered by Aigner, Lovell and Schmidt (1977), which enables us to capture both inefficiency and luck asymmetry. The intuition behind the stochastic frontier approach to firm value is that a point on the frontier represents the maximum value that a given firm can obtain given its fundamentals and no inefficiencies. The difference between the actual firm value and the maximum firm value is treated as an estimate for firm inefficiency. Nevertheless, the shortfall from the frontier can also be the result of white noise (comprised of random elements beyond the control of the firm's principals or agents) rather than systematic inefficiencies alone. To distinguish between the two, stochastic frontier analysis assumes a composed error model where inefficiencies follow an asymmetric distribution while random errors follow the standard normal distribution.

Unfortunately, standard ordinary least squares (OLS) cannot distinguish between systematic inefficiency and stochastic white noise. By assumption, systematic components in OLS are incorporated into the intercept and are therefore unidentifiable. In contrast, systematic inefficiency in stochastic frontier analysis will appear as skewness in residuals which can be computed for each firm and ranked accordingly.

Formally, the frontier or the optimal firm value, V_i, can be estimated as follows

(3.6) $$V_i = f(X_i,\beta)exp(\varepsilon_i)$$

where V_i is the value of firm i given input vector X and parameter estimate vector β. The composite error term is computed as $\varepsilon_i = v_i - u_i$; v_i is the standard two-sided white noise error and is distributed $N(0,\sigma_v^2)$; u_i, is proxy for systematic inefficiency and is the one-sided error half-normally distributed $N(0^+,\sigma_u^2)$; cov$(u_i;v_i)$ is assumed to be zero and $\sigma^2 = \sigma_v^2 + \sigma_u^2$. Note that the frontier only adds value if u_i is greater than zero which indicates a distinction between firms that maximize firm-value (these firms lie on the frontier) and firms that suffer from inefficiency (these lie below the frontier). In case $u_i = 0$ for all i, estimates from stochastic frontier analysis are indifferent from those obtained from OLS.

Once the parameters have been estimated and the location of the frontier is identified, computation of the efficiency score is straightforward. Specifically, for each firm I can measure the relative distance from the frontier as follows

(3.7) $$S_i = \frac{E\left(V_i \mid u_i, X_i\right)}{E\left(V_i^* \mid u_i = 0, X_i\right)}$$

where E is expected value operator and V^* is the frontier estimated firm value given no or minimum inefficiency. The efficiency score, S, is a normalized measure between 0 and 1. A score of 0.90 implies that the firm is valued at a 90 percent level in comparison to its best performing peers, ceteris paribus. Conversely, a firm with a score of 0.70 is only valued at a 70 percent level, ceteris paribus. Obviously, the market considers the first firm to be more efficient than the second firm.

It is possible that all firms operate at the optimal level (i.e. $u_i = 0$). If such is the case then there is no gain in using stochastic frontier analysis since $\sigma_u^2 = 0$. Similar to Habib and Ljungqvist (2005), I test the null hypothesis whether $u = 0$ for all i using the likelihood ratio test. If the null is rejected then the deviations from the frontier are attributed to systematic inefficiencies.

3.2.3 Frontier Construction

In order to estimate market valuation of firm efficiency, I need to construct a theoretical benchmark value for each firm while controlling for firm characteristics and opportunity sets. The frontier is dependent upon variables selected, and I base the choice of input variables (proxies for firm characteristics and fundamentals) on underlying theory and previous empirical research.

Tobin's Q or the market-to-book ratio is selected to proxy for firm value. Therefore, the stochastic frontier function is defined as[4]

[4] It is also possible to estimate the model using panel data which allows the frontier to shift over time (see Greene (2005)). This is valuable for observing the dynamics of an explanatory variable on firm value over time. For example, Habib and Ljungqvist (2005) use a panel stochastic frontier to study the dynamics of managerial incentives on firm value. However, in my study, I assume that investors make investment decisions based on the current efficiency level (current information) and that they have no knowledge of future firm characteristics. Thus, I compute the efficiency score for each cross-section

(3.8) $$Q_i = f(X_i, \beta)exp(v_i - u_i)$$

Employing a log transformation of equation (3.8) and adding dummy variables for the 49 Fama-French industries, I obtain the following estimating equation[5]

(3.9) $$ln(Market\ Equity_i) = \beta_0 + \phi_{ij} + \beta_1 ln(Book\ Equity_i) + \beta_2 ln(Sales_i) + \beta_3 ln(Total\ Assets_i) + \beta_4(Long\text{-}Term\ Debt_i\ /\ Total\ Assets_i) + \beta_5(CAPEX_i\ /\ Sales_i) + \beta_6(R\&D_i\ /\ Sales_i) + \beta_7(ADV_i\ /\ Sales_i) + \beta_8(Property\ Plant\ and\ Equipment_i\ /\ Total\ Assets_i) + \beta_9(EBITDA_i\ /\ Total\ Assets_i) + v_i - u_i$$

where ϕ_{ij} is a dummy variable that proxies for firm *i*'s industry *j* according to the Fama-French industry classification and u_i is the one-sided measure of inefficiency. The rationales, economic meaning and predicted signs of the remaining variables are as follows.

- β_1: The log of book equity is a control factor from the log transformation of Tobin's Q.
- β_2 and β_3: The log of sales measures firm size, and the expected relationship between size and value of the firm is positive. However, to control for a firm's asset base I also include the log of the firm's total assets which captures the diminishing

instead of for the whole panel. As a robustness test, I estimate firm level efficiency for the whole panel and create portfolios accordingly. The results are qualitatively the same and are available from the author.

[5] Log transformation, which converts the production function into a linear model, is commonly used in stochastic frontier analyses. Moreover, I use the log transformation to normalize the variables and to reduce skewness of the sample. For variables with many zero observations, I scale them either by sales or by total assets instead of log transform in order to avoid losing observations. The 49 Fama-French industry classifications are available with permission from Professor Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

nature of the relationship between size and firm value (Demsetz and Villalonga, 2001).

- β_4: Long-term debt scaled by total assets proxies for firm leverage. The expected sign is indeterminate because on one hand, high leverage implies higher interest expense and higher cost of equity, hence lower firm value. On the other hand, high leverage can also proxy for monitoring activities by creditors. Thus the relation between firm value and leverage is ambiguous.
- β_5: Capital expenditure *(CAPEX)* is a measure of "hard spending" and investment opportunities. Since many firms do not have capital expenditures, I scale *CAPEX* by sales instead of using log transformation. Similar to Habib and Ljungqvist (2005), I expect a positive relation between "hard spending" and firm value.
- β_6 and β_7: R&D expenses *(R&D/Sales)* and advertising expenses *(ADV/Sales)* scaled by sales proxy for intangible assets or "soft spending". Morck, Shleifer and Vishny (1988) and McConnell and Servaes (1990) found that Tobin's Q may not capture all growth opportunities and "soft spending" of the firm. Moreover, Grullon, Kanatas and Weston (2004) found that advertising is positively related to firm liquidity and visibility, which in turn reduces the cost of equity. I expect a positive relation between R&D and firm value and advertising and firm value.
- β_8: Property, plant and equipment scaled by total assets is used to measure the degree of capital intensity of the firm. While firms with more fixed assets should be worth more, they also incur higher operating leverage. Therefore, the relationship is ambiguous.

- β_9: Similar to Palia (2001), free cash flow, as measured by operating profits to total assets *(EBITDA/Total Assets*), serves as proxy for firm profitability. I expect market value to increase with profitability.

Multicollinearity tests for equation (3.9) reveal a high degree of correlation between *ln(Total Assets)*, *ln(Sales)* and *ln(Book Equity)* which is consistent with Fama and French (1992) who suggest that variables such as total assets and sales are being absorbed by book equity. Therefore, I remove the log of total assets and log of sales from equation (3.9) and estimate the following final model[6]

(3.10) $$ln(Market\ Equity_i) = \beta_0 + \phi_{ij} + \beta_1 ln(Book\ Equity_i) + \beta_4(Long\text{-}Term\ Debt_i / Total\ Assets_i) + \beta_5(CAPEX_i / Sales_i) + \beta_6(R\&D_i / Sales_i) + \beta_7(ADV_i / Sales_i) + \beta_8(Property\ Plant\ and\ Equipment_i / Total\ Assets_i) + \beta_9(EBITDA_i / Total\ Assets_i) + v_i - u_i$$

Once the frontier inputs have been determined, the frontier as of July of each year is constructed, and an efficiency score for each firm for each year is obtained.

3.2.4 Portfolio Construction

Portfolios are constructed based on a ranking of efficiency scores. In July of each year *t* from 1980 to 2002, I rank all the stocks in the sample by efficiency scores in descending order. I then split the sample into efficiency deciles which provides the ten portfolios which are the focus of the study. The top portfolio (top decile) contains firms closest to the frontier and with highest efficiency scores. I classify it as the portfolio of

[6] For verification purposes, I estimate both equations. The estimates and results on subsequent tests do not show any significant difference. This confirms the fact that total assets and sales are being captured by book equity. The correlation matrix and results using equation (3.9) are available upon request.

EFFICIENT firms. The bottom portfolio (bottom decile) contains firms farthest away from the frontier and with the lowest efficiency scores. I classify it as the portfolio of *INEFFICIENT* firms. The average number of firms per decile portfolio from 1980 to 2002 is 210 firms with the lowest of 98 firms (in 1980) and the highest of 368 firms (in 2002), pointing out the increasing number of firms in the sample over time.

Once the portfolios are formed, the monthly excess return for each stock is calculated by subtracting the risk-free rate from the return for that month. The excess return on individual stocks is then used to calculate excess monthly returns on the top and bottom decile portfolios based on sorting of the efficiency scores. Although I report results using both equally-weighted and value-weighted portfolio returns, I emphasize equally-weighted returns. The primary reason is because value-weighted returns place heavier emphasis on the size of the stock than on the efficiency level of the firm. If mispricing is common for both small and large firms then efficiency-driven performance for equally-weighted and value-weighted returns should be the same. Otherwise, value-weighted returns will not be able to capture the abnormal returns arising from the misvaluations. The results are mitigated by the size of the company[7].

3.2.5 Returns Comparison

Two different approaches for evaluating performance of the *EFFICIENT* and *INEFFICIENT* portfolios are examined. The first approach is the Carhart (1997) modification of the Fama-French (1993) three factor model. The second technique is the Daniel, Grinblatt, Titman, and Wermers (1997) approach which measures abnormal

[7] For more discussion on weighting, see Fama (1998) and Loughran and Ritter (2000).

returns relative to benchmarks that are designed and constructed to have similar firm characteristics.

1. The Fama-French and Carhart Four-Factor Model

The Fama-French and Carhart (1997) model, also known as the four-factor model, is an extension of the Fama and French (1993) three factor model. According to the model, in the absence of outperformance or underperformance (i.e. α is zero), the excess return of a portfolio is the sum of the risk-free rate and the products of the betas with the factor risk-premia. The model can be estimated as follows

$$ER_P = \alpha + \beta(RMRF) + s(SMB) + h(HML) + m(UMD) + \varepsilon_P \tag{3.11}$$

where ER_P is the excess return of portfolio p; *RMRF* is the market risk premium; *SMB* is the size-premium; *HML* is the value-premium; *UMD* is the momentum factor and is the difference between the return on a portfolio of high return stocks in the prior year and the return on a portfolio of low return stocks in the prior year. The four-factor model will generate Jensen's alpha while controlling for the covariance of portfolio returns with market return and size, book-to-market and momentum factors.

2. Characteristics-Based Benchmark Portfolios

Daniel and Titman (1997) argue that the Fama-French three factor model lacks explanatory power of stock returns when compared against the characteristics model. Specifically, the authors show that expected returns are directly related to firm specific characteristics rather than covarying with the aggregate level factor risk-premia. Moreover, Daniel, Grinblatt, Titman, and Wermers (1997) document that the characteristics model has more statistical power to detect abnormal performance than

risk factor models. Therefore, to control for firm characteristics in performance evaluation, I adopt the Daniel, Grinblatt, Titman, and Wermers (1997) characteristics benchmark approach.

The benchmark portfolios are designed such that each of the portfolios captures the size, value and momentum characteristics of its stocks[8]. The characteristics benchmark portfolios are created as follows. First, the NYSE stocks are sorted into size quintiles in order to obtain size breakpoints for the firms in the sample. The sort is based on each firm's market equity on the last day of the month prior to the formation date (beginning July). The market capitalization of each firm in the sample is then matched with the size portfolio to which it belongs. Firms in each size portfolio are further sorted into quintiles based on their book-to-market ratio for December of the preceding year when accounting data was reported. Finally, the firms in each of the 25 size and B/M portfolios (5 size by 5 B/M) are sorted into quintiles based on their prior year return. The 5 by 5 by 5 sorting of size, B/M and momentum results in 125 benchmark portfolios. The value-weighted returns for the benchmark portfolios are computed from July to June of the following year.

Once the yearly benchmark portfolios are formed, each stock is assigned to a portfolio according to its size, B/M and momentum rank. The benchmark-adjusted return for a stock is then the difference between the stock's raw return and the benchmark portfolio return. These benchmark-adjusted returns are used to calculate the value-weighted and equally-weighted returns for the *EFFICIENT* and *INEFFICIENT*

portfolios[9]. The time-series average of the returns for the *EFFICIENT* and *INEFFICIENT* portfolios yields the abnormal return adjusted for firm characteristics for that portfolio.

The intuition behind the adjustment for the benchmark return is to eliminate the characteristic factors that might have affected the performance of the stock. Moreover, the three factors, size, B/M and momentum, have been found to be the best ex-ante predictors of cross-section patterns in common stock returns (Daniel, Grinblatt, Titman, and Wermers, 1997) Thus, the returns of *EFFICIENT* and *INEFFICIENT* portfolios after the adjustment for benchmark characteristics are essentially the rate of return on the zero-cost portfolios. Theoretically, if benchmark returns already take into account size, B/M and momentum effects, then the benchmark-adjusted return on the decile portfolios should have zero-factor risk loadings. However, such may not be true in reality since investors may not have the ability to create portfolios with the same characteristics as the benchmark portfolios. Therefore, to test for robustness and to further eliminate the effect of factor risks, the *EFFICIENT* and *INEFFICIENT* portfolio benchmark-adjusted returns are regressed against the four-factor model and Jensen's alphas are compared.

3.3 Data Description

Firms included in the study are selected from the Daniel et. al. (1997) and Wermers (2004) databases which cover firms in the NYSE, AMEX and NASDAQ

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[8] The benchmark portfolios are available with permission from Professor Russ Wermers' website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[9] Note that the stock returns are benchmark adjusted prior to portfolio formation.

universe while excluding REITs, ADRs and non-US firms, close-end funds, primes and scores, and HOLDRs[10]. Monthly data on stock returns are obtained from CRSP. Shumway (1997) and Shumway and Warther (1999) find that there is a survivorship bias inherent in CRSP for performance-related delisted firms. To mitigate the problem, I follow Shumway and Warther (1999) and substitute -30% as the last month return for NYSE/AMEX firms and – 55% as the last month return for NASDAQ firms. The substitutions are only applied to firms that are delisted due to performance reasons. Company financial data such as sales, long-term debt and capital expenditures are gathered from COMPUSTAT, and 30-day Treasury bill rates serve as risk-free rates. While the Daniel et. al. (1997) and Wermers (2004) databases include data from 1975 – 2004, my sample period for stock returns is from July 1980 to June 2003[11].

To be included in the sample, a firm must meet the following criteria. First, it must have the CRSP stock prices for July of year t and June of year $t+1$ and the COMPUSTAT book equity for December of year $t - 1$. Second, the firm must not have negative book equity for the end of fiscal year $t - 1$. Third, the firm must have appeared in the COMPUSTAT database for two years to avoid potential survivorship bias problems.

Following Fama and French (1992), I match stock returns for the period of July of year t to June of year $t + 1$ to the accounting data of a firm for the fiscal year ending in year $t - 1$. This ensures that accounting information is known before it is used for

[10] The database is available with permission from Professor Russ Wermers' website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

testing. Firms with one or more missing monthly returns and firms that do not meet the accounting data requirement are excluded from the sample.

Table A.1 reports descriptive statistics for the final sample. There are 48,214 total firm-year observations in 49 industries over the period of 1980 to 2002. As the means and medians indicate, the sample suffers from left skewness. For example, firm market capitalization ranges from $0.17 million to $507,000 million with mean and median of $1,500 million and $118 million, respectively. The average long-term debt in the sample is approximately $520 million while the median is $15.76 million. Overall, the statistics suggest that the sample is diverse and consists of firms with different characteristics.

3.4 Empirical Results

3.4.1 Efficient Frontier and Efficiency Scores

To estimate the efficiency score I must determine the location of the frontier given selected firm characteristics and inputs. At the beginning of July of each year *t*, starting in 1980 and ending in 2002, I estimate equation (3.10) using the stochastic frontier approach. Panel A of Table A.2 reports the mean of parameter estimates for each independent variable over the period. For a robustness test, I also provide mean estimates using the standard ordinary least squares technique. The mean coefficients obtained from stochastic frontier analysis (SFA) are not appreciably different from the ones estimated by OLS. This supports the superiority of SFA because it not only

[11] I chose 1980 as the starting point for flexibility of going backward or forward in the analysis. Although Wermers database has returns available through 2004, the tested dataset covers returns only through June 2003 because other required firm specific financial data are only available through fiscal year 2002.

provides similar estimates to OLS but also provides a measure that helps distinguish between systematic inefficiencies and white noise.

In general, the signs of the coefficients from stochastic frontier analysis are consistent with previous expectations. In line with Habib and Ljungqvist (2005), firm value decreases significantly with leverage and increases with capital expenditure and R&D spending. Capital intensity has a negative relationship with firm value, suggesting investors perceive highly capital-intensive firms as having high operating leverage. Last but not least, firms with a larger amount of free cash flow tend to have higher market values.

In Panel B of Table A.2, I report the diagnostics for stochastic frontier analysis. The average p-value for the likelihood ratio test over the period is 0.0156 with a maximum of 0.1030 and a minimum of 0.0000. Thus, I reject the null that all firms operate at an optimal level. I also report λ, the ratio of σ_u to σ_v, which measures the relative influence of the asymmetric error to the symmetric error. The mean of λ is 0.9694 (p-value less than 1%) which confirms the existence of systematic inefficiencies. Hence, I conclude that the shortfalls from the frontier are attributed to systematic inefficiencies and there is a potential gain in statistical efficiency from the stochastic frontier specification[12].

Table A.3 presents the distribution of predicted efficiencies. The average efficiency for the entire sample is 70% with a maximum of 95% and a minimum of 8%. My estimate is in line with predicted efficiencies of other related studies. In a survey of

[12] Year-by-year diagnostics are available from the author upon request.

130 studies that use frontier analysis, Berger and Humphrey (1997) record mean predicted efficiencies to range between 61% and 95%.

3.4.2 Distribution of Portfolio Returns

To measure performance of the various categories of portfolios identified from efficiency scores, both equally-weighted and value-weighted portfolios are investigated, and abnormal returns are reported in Table A.4. Panels A and B present the excess returns while Panels C and D present the benchmark-adjusted returns. *SPREAD* is a zero-cost portfolio that has a long position in the *INEFFICIENT* portfolio and a short position in the *EFFICIENT* portfolio. I use the spread between the two portfolio returns to measure the premium associated with inefficient firms.

Panels A and B reveal that mean excess returns decrease as the level of efficiency increases which is consistent with my predicted relation between inefficiency and required rate of return. The statistics on the *SPREAD* show that the mean excess returns for the equally-weighted and value-weighted portfolios are 0.96% and 0.47% per month, respectively. Thus, on average, the equally-weighted (valued-weighted) *INEFFICIENT* portfolio outperforms the equally-weighted (value-weighted) *EFFICIENT* portfolio by approximately 12.15% (5.79%) on a compounded annual basis. This *INEFFICIENT/EFFICIENT* portfolio returns difference between equally-weighted and value-weighted results may be indicating the influence of small stocks.

The returns in Panels C and D are benchmark-adjusted rather than risk-free-adjusted; hence the effects of book-to-market, size and momentum are controlled. The adjusted returns for both types of portfolios are reduced dramatically, but again the

INEFFICIENT portfolio appreciably outperforms the *EFFICIENT* one. For the equally-weighted portfolios, the mean excess returns for the *INEFFICIENT* and the *EFFICIENT* portfolios are 0.72% and 0.43%, respectively, and both are significantly different from zero at the 1% level. For the value-weighted, the mean excess returns for the *INEFFICIENT* and the *EFFICIENT* portfolios are 0.26% and 0.08%, respectively. However, only the return for the *INEFFICIENT* portfolio is significant at 10%. Only the equally-weighted *SPREAD* return is significant at the 5% level while the value-weighted *SPREAD* return is indistinguishable from zero.

3.4.3 Measures of Performance Relative to Firm Efficiency

Results of the four-factor Jensen's alpha for equally-weighted and value-weighted portfolios are shown in Table A.5. For the equally-weighted portfolios the alphas decrease substantially in magnitude after adjusting for the four factors. The alpha for the *INEFFICIENT* portfolio is 0.87% per month and highly significant while the alpha for the *EFFICIENT* portfolio is statistically insignificant. It appears that efficient firms exhibit negative price momentum while inefficient firms do not reflect any specific momentum strategy. This finding is consistent with my assumption of efficient firms. By construction, efficient firms are the ones with the highest value per dollar unit of inputs and thereby are closer to the optimal frontier. Hence, the firm value appreciation potential for the more efficient firms is less than for the more inefficient ones.

The results for the value-weighted portfolios are presented in Panel B. The alphas for both the *INEFFICIENT* and *EFFICIENT* portfolios are statistically

insignificant, and the signs of the coefficients on the momentum factor are similar to those for the equally-weighted portfolios. The sensitivity parameters on *SMB* and *HML* indicate that the *INEFFICIENT* portfolio consists of small-value stocks and the *EFFICIENT* portfolio contains mostly large-growth stocks. The positive relationship between the *SPREAD* portfolio return with size and value premiums suggests that there is a relatively higher concentration of small value stocks in the *INEFFICIENT* portfolio. This implies that the most inefficient firms may be small cap firms possibly in financial distress and supports the choice of equally-weighted returns in assessing the impact of firm inefficiencies.

The preceding results for the four-factor model confirm the fact that the *INEFFICIENT* portfolio outperforms the *EFFICIENT* portfolio. As a robustness check, I adopt the Daniel, Grinblatt, Titman, and Wermers (1997) methodology where, instead of Jensen's alpha, the performance measure is the time-series mean of the benchmark-adjusted return.

Table A.6 presents benchmark-adjusted returns for the portfolios. The mean characteristics-adjusted return for the equally-weighted *SPREAD* portfolio is 0.29% per month. On an annualized basis, the *INEFFICIENT* portfolio outperforms the *EFFICIENT* one by approximately 3.54% after controlling for size, B/M and momentum effects. The standard t-test of the null hypothesis that the means of the *INEFFICIENT* and *EFFICIENT* portfolio are not statistically different from each other is 1.6827 with a one-tail p-value of 0.0465, rejecting the null at the 5% level. Hence, the

mean for the equally-weighted *INEFFICIENT* portfolio is statistically greater than the mean for the *EFFICIENT* portfolio.

The monthly time-series mean for the value-weighted *INEFFICIENT* portfolio is 0.46% smaller than for the equally-weighted portfolio and is significant at the 10% level. However, the differences in means for the value-weighted *EFFICIENT* and *SPREAD* portfolios are insignificant.

Although the benchmark-adjusted portfolio returns are zero-cost and zero-factor portfolios in theory, they are almost impossible to construct in reality. Therefore, the portfolio returns may still covary with factor risks. To control for factor risks, I regress the benchmark-adjusted returns against the Fama-French and Carhart factors. The results are also reported in Table A.6 (under FF-Carhart columns) for equally-weighted and value-weighted portfolios. The alphas for the equally-weighted *INEFFICIENT* and *EFFICIENT* portfolios are 0.78% per month and 0.48% per month, respectively. To measure the extent to which characteristics-adjusted returns capture factor risks, I compare the alphas against the means. If the abnormal performance is driven by factor risks then the alphas should be less than the means. A t-test of the null hypothesis that the alphas are not statistically different from the means yields test statistics of -0.4883 for the *INEFFICIENT* portfolio and -0.4666 for the *EFFICIENT* portfolio. The test results reject the null and the alphas are not statistically different from the means suggesting that benchmark-adjusted returns sufficiently control for the factor risks.

Overall, the means and the alphas indicate that after adjusting for characteristics and taking into account factor risks, the equally-weighted *INEFFICIENT* portfolio still

earns a higher return than the equally-weighted *EFFICIENT* portfolio. To check the robustness of the difference in alphas of the *INEFFICIENT* and *EFFICIENT* portfolios for equally-weighted benchmark-adjusted returns, I apply nonparametric tests on the medians of the alphas. Similar to Titman, Wei and Xie (2004), I obtain monthly alphas by adding back the residuals to the estimated alphas for the equally-weighted *INEFFICIENT* and *EFFICIENT* portfolios. The Wilcoxon nonparametric test on the medians yields a Z-score of 2.3961 and hence rejects the null hypothesis (at the 5% level) that the median alpha of the *INEFFICIENT* portfolio is the same as the median alpha of the *EFFICIENT* portfolio.

The alphas for the value-weighted benchmark-adjusted returns against the Fama-French and Carhart Factors are also reported in Table A.6 where the alphas for the equally-weighted *INEFFICIENT*, *EFFICIENT* and *SPREAD* portfolios are all significant. However, the alphas for the value-weighted portfolios are statistically insignificant. This suggests that when heavier emphasis is placed on the value of the company the abnormal returns from efficiency misvaluations disappear which confirms the assertion that misvaluations are larger and more common among smaller firms.

3.4.4 Performance of Buy-and-Hold Strategies

Persistence of the negative relation between firm efficiency and stock returns is examined with a 5-year buy-and-hold strategy for the *INEFFICIENT* and *EFFICIENT* portfolios. Table A.7 sets forth the 5-year cumulative performance of *INEFFICIENT* and *EFFICIENT* portfolios. Each firm's assignment to an efficiency decile is unchanged during the 5-year holding period. I adjust the weight for each firm in the portfolio after

each period to correct for firms dropping out of the sample. Annual performance is computed by compounding the 12 monthly returns from July of year *t* to June of year *t + 1*, and then annual returns are cumulated over the holding period.

Results of a buy-and-hold strategy in Table A.7 indicate that the equally-weighted *INEFFICIENT* portfolio outperforms the equally-weighted *EFFICIENT* portfolio after every formation year except for 1995. On average, buying and holding *INEFFICIENT* firms for 5 years should outperform buying and holding *EFFICIENT* firms for 5 years by approximately 44%. For the value-weighted returns, the *INEFFICIENT* portfolio outperforms the *EFFICIENT* portfolio for 15 out of 23 years. The average difference in cumulative performance between the two value-weighted portfolios is 8%.

Figure 3.1 illustrates the year-to-year persistence of efficiency levels and annual performance for the *INEFFICIENT* and *EFFICIENT* portfolios. During the 5-year holding period, inefficient firms slowly improve their efficiency level. Berger and Humphrey (1992), Cebenoyan, Cooperman and Register (1993) and Hermalin and Wallace (1994) find that low efficiency firms tend to have higher failure rates[13]. Hence, the upward trend in efficiency level for the *INEFFICIENT* portfolio suggests that the remaining firms are forced to improve their efficiency level in order to stay competitive. The improvement in efficiency level for inefficient firms is consistent with findings by Habib and Ljungqvist (2005) who find that board of directors do respond to shortfalls

[13] I also compute the number of firms dropping out of the market for the *INEFFICIENT* and *EFFICIENT* portfolios. Consistent with findings by Berger and Humphrey (1992), Cebenoyan, Cooperman and Register (1993), and Hermalin and Wallace (1994), the results indicate that the number of firms leaving the market for the *INEFFICIENT* portfolio is significantly higher than for the *EFFICIENT* portfolio.

from the frontier and firms that strengthen managerial incentive the most tend to improve their efficiency the most. At the same time, the efficiency level of the *EFFICIENT* portfolio is slowly decaying. However, the rate of decrease in efficiency level for the *EFFICIENT* portfolio is significantly lower than the rate of increase in efficiency level for the *INEFFICIENT* portfolio. Despite the difference in the trend for the two portfolios, at the end of 5-year holding period the efficiency level of the *INEFFICIENT* portfolio is still substantially lower than the efficiency level of *EFFICIENT* portfolio. Meanwhile, the return gap between *INEFFICIENT* portfolio and *EFFICIENT* portfolio is narrowing. Yet, at the end of the period, there is still no convergence in returns of the two portfolios.

3.5 Efficiency Scores and the Cross-Section of Returns

I investigate the relationship between firm level efficiency, B/M, size and average stock returns using cross-sectional regression analysis of monthly returns. Table A.8 contains the results for the Fama-MacBeth (1973) regressions. The parameter estimates are the time-series average of the cross-sectional slopes of monthly returns regressed against *size*, *B/M* and *efficiency score*[14]. Consistent with Fama and French (1992), I use log of size and log of book-to-market ratio.

Similar to the results obtained by Fama and French (1992) and Anderson and Garcia-Feijoo (2006), *size* and *B/M* have statistically significant predictive power for the cross-section of returns. When monthly returns are regressed on *ln(Size)*, the

[14] I do not include beta in the analysis since previous studies have shown that beta has no significant predictive power on returns when size and B/M are present (see Fama and French, 1992, and Anderson and Garcia-Feijoo, 2006).

parameter estimate is -0.17%, with a p-value of less than 1%. When monthly returns are regressed on *ln(B/M)*, the parameter estimate is 0.37%, again with a p-value of less than 1%. In the regression that includes both *size* and *B/M* (column (c)), the parameter estimates (p-value) are -0.15% (less than 1%) and 0.19% (less than 10%), respectively. Both of the coefficients have signs as expected and are consistent with previous findings.

When the *efficiency score* is included in the model, the parameter estimate is highly significant and has the expected negative sign. The regression of monthly returns on the *efficiency score* yields an estimate of -3.05%, with a p-value of less than 1% (column (d)). The result is consistent with equation (3.5) and implies that lower efficiency is associated with higher monthly returns. Furthermore, when *ln(Size)*, *ln(B/M)* and efficiency score are included in the regression (column (e)), *ln(B/M)* becomes statistically insignificant. The results suggest that the efficiency score absorbs part of the information that is present in B/M. Parameter estimates for *ln(Size)*, *ln(B/M)* and *efficiency score* are -0.15%, -0.13% and -3.07%, respectively[15].

3.6 Conclusions

Previous research on firm efficiency has focused primarily on the sources and determinants of efficiency levels. My study does not address what causes inefficiencies, but, instead, examines the linkage between the firm efficiency level and subsequent stock performance.

[15] For robustness, I also estimate the relationship between firm level efficiency, B/M, size and average stock returns using fixed effect panel regression. The results are consistent with those in column (e) of table 8.

The empirical analysis yields the following results. First, I document that the portfolio composed of highly inefficient firms significantly outperforms the portfolio composed of highly efficient firms even after adjusting for firm characteristics and risk factors. The difference is statistically and economically meaningful. Moreover, the firm efficiency level is robustly significant in explaining average stock returns in cross-sectional regression and appears to subsume the information that is present in the book-to-market measure.

Second, I observe that a simple 5-year buy-and-hold strategy generates an average cumulative return difference of 44% in favor of inefficient firms. The majority of this difference is generated in the first two years after portfolio formation. Over time, the average efficiency level of the most inefficient firms is rising while the average efficiency level of the most efficient firms is slowly decaying. This observation implies that the most inefficient firms are forced to improve their performance in order to stay competitive. Meanwhile, the return difference between the two portfolios is narrowing suggesting that as efficiency improves the required rate of return fall.

In summary, the findings strongly indicate that the level of firm efficiency is a significant determinant of stock returns and should be incorporated into asset pricing models.

CHAPTER 4

EARNINGS FORECAST HORIZON AND PERFORMANCE

4.1 Introduction

Analyst earnings forecasts serve a valuable economic role for investors (Givoly and Lakonishok, 1979, 1984). The forecasts are a vital component of the security selection decision providing information that is otherwise unavailable to the public [Stickel (1990), and Womack (1996)]. Analyst forecasts also function as the most widely utilized proxy for market expectations [Cragg and Malkiel (1968), Lopez and Rees (2001), Balsam, Krishnan and Yang (2003)]. Versus alternative sources, Brown, Hagerman, Griffin and Zmijewski (1987) attribute the superiority of analyst forecasts to more effective timing and utilization of contemporaneous information.[16]

Nonetheless, analysts have tended to overestimate earnings growth [O'Brien (1988), Stickel (1990), Dugar and Nathan (1995) and Brown (1997)]. Explanations for the forecast bias include systematic cognitive failures and misinterpretation of publicly available information. Abarbanell (1991), Mendenhall (1991), Abarbanell and Bernard (1992), and Teoh and Wong (2002) postulate analysts underreact to new information, while DeBondt and Thaler (1990) argue analysts overreact to new information.

[16] Analyst earnings forecasts are more accurate than predictions from univariate time-series models based on past earnings (Fried and Givoly, 1982).

Easterwood and Nutt (1999) reconcile the extremes by documenting analyst underreaction to negative information and overreaction to positive information.

The forecast growth bias is reflected in market valuation measures where high price-earnings multiples of glamour stocks are priced with high growth expectations that often cannot be sustained (Chan, Karceski and Lakonishok, 2003). As a result, contrarian investment strategies that select value firms with low growth expectations earn superior returns (LaPorta, 1996). This finding suggests the potential for style influences in analyst forecasts that may contribute to the widely acknowledged value premium.

Efficient market theorists postulate investment style returns should reflect changes in style risk or fundamentals (Fama and French, 1992, 1993). If so, better performing low forecast growth strategies should be inherently riskier under the risk proposition. In contrast, proponents of behavioral finance theory contend style returns accrue irrationally for reasons unrelated to risk or fundamentals [La Porta, Lakonishok, Shleifer, and Vishny, 1997; LaPorta, 1996; Lakonishok, Shleifer, and Vishny, 1994, hereafter LSV]. For example, LSV argue growth stocks become overvalued when analysts extrapolate past growth rates too far into the future. The superior returns to value stocks in their model are accrued by contrarians that recognize and exploit the relative misevaluation of growth and value stocks.

Barberis and Shleifer, (2004, hereafter B-S) provide a behavioral model to explain style trends. In their model, active "switcher" traders engage in momentum strategies that over (under) weight the better (worse) performing styles. The B-S model

also includes style value traders, contrarians expecting reversions, whose style allocations are inversely related to recent performance [Teo and Woo (2004); Asness, Liew and Stevens (1997)]. The potential influence of analyst forecasts in the style determination process has not, to my knowledge, been ascertained in the literature.

This section extends the literature on analysts forecasts by examining the investment value of analyst earnings growth forecasts over 1986-2005. I use a standard four-factor model that incorporates portfolio covariance with market, valuation, size, and momentum factors. I compare investment strategies using one-year (FY1) and two-year (FY2) fiscal earnings growth forecasts. I find support for a contrarian strategy purchasing low forecast stocks that provides superior returns relative to high forecast strategies. Portfolio strategies based on two-year fiscal forecasts performed better than the one-year estimates implying longer-term forecasts provide more informational content. Over the entire period, weak individual stock momentum is consistent with the issuance of lower forecasts but I find no evidence of any relationship between strong momentum and high earnings forecast.

The methodology is discussed in the next section. The empirical results are presented in section 4.3; section 4.4 provides supporting evidence and the conclusion is summarized in the last section.

4.2 Methodology

4.2.1 Sample

My initial sample consists of all stocks in the Daniel, Grinblatt, Titman, and Wermers (hereafter DGTW, 1997) and Wermers (2004) databases. The sample

includes data on firms traded in the NYSE, AMEX and NASDAQ markets over the sample period 1986-2004. The sample excludes REITs, ADRs and non-US firms, closed-end funds, primes and scores, and HOLDRs[17]. Monthly stock returns for sample firms are obtained from CRSP and data for the computation of firm book-market ratios are gathered from COMPUSTAT.[18] Analyst earnings forecasts are acquired from the Institutional Brokerage Estimate System (IBES) Daily Detailed Earnings Estimate History database. All other analyst data is acquired from the IBES Summary History (Consensus) database.[19]

Annual sample inclusion requires firms meet three criteria. First, each firm must have a complete time series of CRSP stock prices for both the first trading day of July (year t) through the last trading day of the subsequent June (year $t+1$). Second, firms must have non-negative COMPUSTAT book equity for the end of calendar year $t-1$. Third, each firm must have monthly returns for 12 consecutive months prior to the mid-year portfolio formation date. Firms that do not meet all three criteria are excluded from each annual sample.

I then merge the initial sample with the firms in the IBES Detail database. Each firm in the sample must have IBES earnings estimates issued by analysts whose identity is revealed. Firms must also survive two additional filtering criteria (Loh and Mian, 2006). One, to align the timing of accounting variables and synchronize the earnings

[17] The database is available with permission from professor Russ Wermers' website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[18] The book-market ratio is computed as book value of common equity (item #60) divided by the closing calendar year stock price (item #199) times number of shares outstanding (item #25).

[19] The Detail database provides estimates for companies at the individual analyst level for each firm covered. The Summary data is reported at the firm level.

forecast horizons across firms all sample firms must have a calendar fiscal-year end. And, two, each firm must have estimates from at least three analysts issuing earning forecasts for both the current fiscal year (FYR1) and for the subsequent fiscal year (FYR2) to assure breadth of coverage.[20] The sample observations range from 345 in 1986 to 767 in 2004.

4.2.2 Forecast Measures

Consensus firm forecast growth measures begin at the analyst level. Current year *t* (FYR1G) and subsequent year *t+1* (FYR2G) fiscal year growth analyst *i* forecasts for stock *j* are,

(4.1) $$FYR1G_{i,j,t} = (FYR1_{i,j,t} - EPS_{j,t-1})/P_j,$$

(4.2) $$FYR2G_{i,j,t} = (FYR2_{i,j,t} - EPS_{j,t-1})/P_j.$$

$EPS_{j,t-1}$ is the most recent fiscal year earnings per share reported for company *j* and P_j is the stock *j* calendar year *t-1* closing stock price (Doukas, Kim and Pantzalis, 2002). The individual analysts estimates for each firm are then averaged to create a firm level fiscal year growth forecast (CONStG),

(4.3) $$CONS1G_{j,t} = \frac{\sum_{i=1}^{N_{j,t}} FYR1G_{i,j,t}}{N_{j,t}}$$

(4.4) $$CONS2G_{j,t} = \frac{\sum_{i=1}^{N_{j,t}} FYR2G_{i,j,t}}{N_{j,t}}$$

[20] Similar to Loh and Mian (2006) criteria, we remove extreme observations by excluding absolute

where $N_{j,t}$ is the number of firm analyst estimates.

4.2.3 Portfolio Construction

For each mid-year *t* I initially rank sample stocks by consensus growth forecasts and divide the sample into growth quintiles. The first (fifth) quintile contains firms with (lowest) highest consensus growth forecasts. Equally weighted and value-weighted time series of returns in excess of the 30-day U.S. Treasury bill yield are then computed for each quintile over the subsequent 12 months. I also create a hedge portfolio that is long the first quintile portfolio and short the fifth quintile. The portfolio returns are the dependent time series in the tests of relationship between earnings forecast growth and stock performance.

I also create double sort portfolios to examine potential determinants of growth forecasts. For example, Diether, Malloy and Scherbina (2002) found stocks with high forecast dispersion performed poorly, particularly among smaller stocks. In these tests, the growth quintiles are sorted subsequent to primary tertile sorts on size and book-to-market ratio.

4.2.4 Portfolio Performance

The performance of the growth portfolios is evaluated with a `four-factor` model that combines the market, size, and valuation factors of Fama-French [1993] with the Carhart [1997] momentum factor,

$$R_{pt} = a_{p0} + b_{p1}\, RMRF_t + b_{p2}SMB_t + b_{p3}HML_t + b_{p4}UMD_t + \varepsilon_{pt}. \tag{4.5}$$

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growth forecasts and revisions that are greater than 25%.

The R_{pt} is the month *t* excess return on quintile portfolio i and the $RMRF_t$ is the time series excess return of the value-weighted CRSP market index. The SMB_t is the size factor, equal to the average monthly return difference between small stocks and large stocks, HML_t is the valuation factor, computed as the average monthly difference in returns between value and growth stocks, and UMD_t is the momentum factor, defined as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.[21] In addition to that of the market, the four-factor model also accounts for the portfolio covariance with size, valuation and momentum factors. A significant positive (negative) intercept (a_{p0}) indicates superior (inferior) systematic risk adjusted performance relative to the market proxy.

4.3 Empirical Results

Table A.9 presents summary statistics for the double-sorted portfolios sorted first by size, book-to-market ratio (BE/ME), analyst coverage, and analyst disagreement, respectively, and then by growth estimates. Statistics for the fiscal year 1 (FY1G), provided in Panel A, indicate the sample mean market capitalization during the 1985-2004 period was $5.449 billion. The size of the low FY1G forecast portfolio was $4.99 billion while that of the high forecast portfolio was only $2.475 billion. Thus, analysts, on average, forecasted higher growth for small companies. The mean 0.6527 BE/ME of the sample ranged between 0.7109 and 0.7846 for the low and high forecast portfolios, respectively. On average, there are five analysts per firm and this is

[21] More information on the construction of the four factors can be obtained from the website of Professor Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

consistent throughout the growth quintiles indicating no differentiation on analyst coverage. Forecast dispersion, a measure of analyst disagreement, averaged 0.52 percent with a range of 0.92 to 0.98 percent for the respective low and high forecast portfolios.

The fiscal year 2 (FY2G) portfolios, presented in Panel B, are more demarcated by size and disagreement than those for FY1G. The market capitalization of the low forecast portfolio averaged $7.551 billion against $2.196 billion for the high forecast stocks. This suggests analysts tend to assign higher (lower) longer-term forecasts to small (large) companies. Stocks with low disagreement and low forecasts averaged 0.72% while those with higher forecast growth with more dispersion earned 1.42%. Similar to FY1G, there is little separation by valuation with the FY2G portfolios: the mean BE/ME for the low (high) forecast portfolio was 0.7015 (0.7669). The analyst coverage summary for FY2G closely mirrors the numbers for FY1G.

A summary of forecast growth portfolio returns is included in Table A.10. The table lists the mean excess monthly return, standard deviation of returns, maximum, median, and minimum returns, respectively, of each growth quintile portfolio. SPREAD is a zero-cost portfolio long a position in the low growth forecast portfolio and short the high growth forecast portfolio. SPREAD measures a risk premium for low growth forecast firms. All returns reported are monthly in excess of the 30-day U.S. Treasury bill return.

Table A.10 implies an inverse relationship between growth forecast and performance. A performance summary for the size-based portfolios is shown in Panels

A (FY1G) and B (FY2G). The FY1G low (high) forecast portfolio earned, on average, 0.67 (0.53) percent, as shown in Panel A. The returns for each quintile portfolio are significantly different from zero but the SPREAD (0.13 percent monthly, 1.56 percent annually) long-short hedge portfolio return is statistically insignificant. Results are more pronounced for the FY2G forecasts, provided in Panel B, where the low (high) forecast portfolios returned 0.98 (0.58) percent monthly. Each FY2G portfolio return is significant as is the SPREAD portfolio return (0.40 percent monthly, 4.80 percent annually).

In sum, the performance summaries of the quintile portfolio imply a contrarian forecast growth investment strategy produces higher returns (La Porta, 1996). Moreover, the strategy appears to perform better with the longer-term FY2G forecasts.

Table A.11 reports risk-adjusted performance that incorporates the size, valuation, and momentum factors for the size-based portfolios. The results provide support that growth forecast and portfolio performance is inversely related. For the FY1G forecasts (Panel A), the SPREAD range between the low forecast portfolio (a_{p0} =0.21 percent, t-statistic = 1.37) and the high forecast portfolio (a_{p0} = -0..26 percent, t-statistic = -1.66) is positive and significant (a_{p0} = 0.47 percent, t-statistic = 2.02). The spread reveals low growth forecast portfolios appreciably outperform those for the high growth rates by 5.64 percent annually. Again, the findings for the FY2G forecasts (Panel B) are even more pronounced with an expanded range between the low forecast (a_{p0} = 0.48 percent, t-statistic = 4.06) and high forecast (a_{p0} = -0.31 percent, t-statistic =

-2.01) portfolios. The FYR2 SPREAD (a_{p0} = 0.80 percent, t-statistic = 3.81) implies relative outperformance by the low forecast portfolio of 9.60 percent annually.

The coefficients on the momentum factor in Table A.11 are also of interest. In essence, there is a positive relationship between forecast and recent momentum for poor performing stocks. For example, momentum was detrimental to the performance of the lowest FY1G (b_{p4} = -0.2138, t-statistic = -5.20) and the FY2G (b_{p4} = -0.1691, t-statistic = -5.29) forecast portfolios. The UMD coefficients are negative and significant for the lowest two (three) FY1G (FY2G) portfolios. In no case does momentum contribute positively to performance. Thus, weak momentum may be a consideration in deriving low growth forecasts over the sample period.

The preceding results imply low growth forecast portfolios outperform high growth forecast portfolios, particularly for longer horizon forecasts. The results, however, do not necessarily support a risk-based argument since the performance difference may be driven either by analyst forecast errors or by specific characteristics of a stock rather than by factor risks. Hence, as both a robustness check and a control for firm-specific characteristics, I adopt the Daniel, Grinblatt, Titman, and Wermers (1997, hereafter DGTW) methodology where, instead of the Jensen intercept, the performance measure is the time-series mean of the benchmark-adjusted return regressed on the factors of the four-factor model. They suggest a benchmark-adjusted

method of evaluating performance that standardizes the size, value and momentum characteristics of the portfolios.[22]

DGTW benchmark portfolios are created as follows. Each mid-year, the NYSE sample stocks are sorted into size quintiles and size quintile breakpoints are computed for the sample firms. Every firm is then assigned to the respective size quintile. Firms in each size quintile are further sorted into quintiles based on December year *t-1* book-to-market ratios (BE/ME), creating 25 portfolios. Finally, firms in each portfolio are sorted once again into quintiles based on prior year return. In sum, the 5x5x5 sort creates 125 benchmark portfolios. Value-weighted returns for each characteristic benchmark portfolios are computed for the subsequent 12 months after portfolio formation.

Each sample stock is assigned to the DGTW portfolio consistent with size, valuation, and momentum characteristics. Subtracting the DGTW portfolio return from a stock's return produces a benchmark-adjusted return. The time series benchmark-adjusted returns are then regressed on those of the four-factor model to evaluate the quintile performance.

Table A.12 compares the performance of the DGTW and four-factor model intercepts. The characteristics-adjusted mean SPREAD returns for the FY1G and FY2G portfolios are 0.25 percent and 0.45 percent, respectively, per month. The intercepts for the SPREAD FYR1G (a_{p0} = 0.38 percent, t-statistic = 2.26) and FYR2G (a_{p0} = 0.65 percent, t-statistic = 4.10) are both positive and statistically significant. A

[22] The benchmark portfolios are available with permission from the website of Professor Russ Wermers

comparison of the SPREAD intercepts and means for each forecast group reveal the extent to which characteristics-adjusted returns capture factor risks: the intercepts should be less than the portfolio means if abnormal performance is driven by factor risks. The t-statistics for the null hypothesis that the intercepts are equal to the portfolio means are both negative (FYR1 t-statistic = -0.7625) (FYR2 t-statistic = -1.2135) but insignificant. Thus, portfolio means and intercepts are not statistically different, suggesting benchmark-adjusted returns sufficiently control for factor risks.[23]

In sum, it appears that even after adjusting for firm characteristics (DTGW) and risk factors, the portfolio of low growth forecast still statistically and economically outperforms the portfolio of high growth forecast. The results imply that there is indeed an upward bias in consensus growth forecasts.

4.4 Robustness Tests

4.4.1 Industry Momentum

Prior results indicate analysts tend to assign low forecasts to low momentum stocks. Moskowitz and Griblatt (1999) argue that price momentum is largely driven by industry. Hence, the momentum findings could simply reflect an industry effect. To address this possibility, I create an industry momentum factor that is added to the four-factor model.

Each mid-year I split the 49 Fama-French industries into three groups based on prior annual return from June year t-1 through May year t. The top (bottom) tertile

(http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm).

[23] Although not reported, four-factor benchmark adjusted performance coefficients and performance mirror those of the four-factor model. Results are available from the author upon request.

portfolio is comprised of industries with highest (lowest) prior annual. The industry momentum factor, IND, is the time series returns of the difference in the equally-weighted returns of the top and bottom tertile portfolios.

Panel A of Table A.13 provides results of the five-factor tests on the benchmark-adjusted FY1G sample. Findings indicate that although industry momentum has virtually no effect on the low growth portfolio (b_{p5} = -0.0303, t-statistic = -0.54) the UMD coefficient is still negative and statistically significant (b_{p4} = -0.2182, t-statistic = -5.20). In contrast, the IND coefficient for the high forecast for industry momentum (b_{p5} = -1096, t-statistic = -1.87) is negative and significant. The UMD coefficient for the high forecast portfolio is positive but insignificant (b_{p4} = 0.0146, t-statistic = 0.34). The FY2G industry momentum tests presented in Panel B of Table A.13 are consistent with the FY1G results.

Collectively, the momentum findings suggest that when controlling for industry momentum, analysts do rely on firm-level momentum. For example, analysts give out high FY2G forecasts for positive momentum stocks when industry momentum is negative. This implies that analysts pick the high momentum stocks within industries. The argument is consistent with Piotroski and Roulstone (2004) who suggest that analysts' value lies in their industry expertise and ability to filter stocks within an industry.

4.4.2 Double Sort Portfolios

So far the results indicate that a contrarian strategy of longing low forecast stocks and shorting high forecast stocks should earn abnormal return. As an additional

test of robustness, I examine the difference in returns of analysts growth forecasts portfolios while controlling for style effects. I create double-sort portfolios by first sorting the stocks into tertiles based on their style or firm characteristics and then into quintiles based on analysts growth forecasts. The 3 by 5 sorting results in 15 separate portfolios. The advantage of double-sorting is creating variation in growth forecasts while keeping style and characteristics relatively fixed.

Table A.14 reports results for double sort size tests. The first column indicates the size rank and the second column reports the growth rank. To conserve space, I only report the top and bottom size tertiles. SPREAD is the difference between the low forecast portfolio and the high forecast portfolio within each size tertile. Results in Panel A indicate that the intercept of the SPREAD portfolio for the small group (a_{p0} = 0.0063, t-statistic = 2.01) is higher than the intercept of the SPREAD portfolio for the large group (a_{p0} = 0.0053, t-statistic = 2.42) suggesting that there are larger forecast errors for small cap stocks. The same pattern is also observed in for FY2G portfolios in Panel B. Consistent with previous tests, the magnitude of SPREAD portfolios are more pronounced for FY2G portfolios.

Table A.15 presents findings for portfolios sorted by B/M and then by growth forecasts. The first column indicates the B/M rank and the second column reports the growth rank. SPREAD is the difference between the low forecast portfolio and the high forecast portfolio within each B/M tertile. Again, the results indicate that the abnormal returns for SPREAD portfolios are higher for FY2G portfolios than for FY1G portfolios. Moreover, the intercept for the SPREAD portfolios are positive and

significant for the growth group (low B/M) but are insignificant for the value group (high B/M). For the growth group, the parameter estimates for SPREAD portfolios are $a_{p0} = 0.0108$ with t-statistic = 3.29 and $a_{p0} = 0.0153$ with t-statistic = 4.79 for FY1G and FY2G, respectively.

Overall, the results of the double sort portfolios confirm the fact that the low growth forecast portfolio significantly outperforms the high growth forecast portfolio. Moreover, it appears that the results are stronger for small caps stocks and for growth stocks.

4.5 Concluding Remarks

This study employs size-based and benchmark-adjusted models to forecast growth portfolio strategies. The models assess both factor risks and firm-specific components of portfolio performance. I compare strategies using one-year and two-year fiscal earnings growth forecasts. I find support for a contrarian strategy purchasing low forecast stocks that provides superior returns relative to high forecast strategies. Portfolio strategies based on two-year forecasts performed better implying longer-term forecasts provide more informational content. Weak individual stock momentum does seem to contribute to the issuance of lower forecasts but I find no evidence of any relationship between strong momentum and high earnings forecast. Industry momentum does not appear a factor in forecasts at any level.

CHAPTER 5

WHAT DRIVES FIRM-LEVEL CONSENSUS GROWTH FORECASTS

5.1 Introduction

This chapter examines the relative impact of cash flow news and expected return news on changes in analysts growth forecasts. I focus on changes in the forecasts rather than on levels in order to understand the relative importance of the two news components in driving analysts forecasts.

A major part of an analyst's day-to-day job is to provide stock recommendations that are based on forecasts of growth potential of companies. As noted by Campbell (1991, p. 157): "To forecast the market means to predict changes in the near future". Hence, the forecasts and more importantly the changes in forecasts that analysts provide should be based on two basic components. First, the forecasts must envisage the future state of firm fundamentals (i.e. cash flows). This part relies heavily on foresights about changes that are directly related to the future cash flow stream of the firm. Second, the forecasts must incorporate expectations about future return. This component relies more on market-wide and systematic effects. Expectation about changes in the first component can be referred as "cash flow news" and expectation about changes in the second component can be referred as "expected return news". Intuitively, changes in analysts forecasts should weight more on cash flow news since it directly relates to firm

fundamentals. Piotroski and Roulstone (2004) argue that analysts are outsiders to the firm and hence do not have access to firm-level information. Therefore, analysts have to rely on both firm-level (whatever is available) and aggregate-level information in order to issue forecasts. Yet a direct comparison of the weight or measurement of the relative importance of the two news components on analysts forecasts remains unexplored.

This section uses the vector autoregressive (VAR) method proposed by Campbell (1991) and Vuolteenaho (2002) to decompose firm-level stock returns into cash flow and expected return news. The decomposition subsequently allows estimation of how important these two sources of stock return variation are to changes in analysts growth forecasts.

The findings can be summarized as follows. First, the estimates from the VAR reveal that last quarter firm fundamentals have almost no predictive power on consensus growth forecasts. Specifically, I find that only lagged stock return and lagged consensus growth forecast are strongly statistically significant in predicting current growth forecasts. The finding supports the hypothesis that analysts follow momentum and herding strategies.

Second, cash flow news is the primary driver of firm-level stock returns, consistent with previous results by Vuolteenaho (2002) and Callen and Segal (2004). Furthermore, the variance in cash flow news is substantially higher for small-cap stocks and for value stocks (high book-to-market ratio) in comparison to other types of stocks.

Finally, I document that analysts are more responsive to expected return news than to cash flow news. The result supports the findings by Boni and Womack (2006)

who find that analysts recommendations follow abnormal industry (aggregate) performance. Moreover, analysts tend to be particularly more responsive to news for firms with high uncertainty. This coincides with the notion there is a high demand for additional information for firms with highly unpredictable earnings (Diether, Malloy and Scherbina, 2002).

The remainder of the chapter is organized as follows. Section 5.2 sets the empirical approach; the data is described in Section 5.3; Section 5.4 discusses the empirical results and Section 5.5 concludes.

5.2 Empirical Approach

5.2.1 Decomposition Models

Theoretically, changes in stock prices and returns are driven by changes to dividends or a cash-flow component and changes to required rates of return or an expected return component. Campbell and Shiller (1988a, 1988b), Campbell (1991) and Vuolteenaho (2002) propose a model to decompose stock returns into these two separate components. Specifically, a stock return can be written as:

(5.1)
$$r_t = log(P_t + D_t) - log(P_{t-1})$$
$$= p_t - p_{t-1} + log(1 + exp(d_t - p_t))$$

where upper case letters P and D denote the actual value for stock price and dividends, and lower case letters denote the log of upper case letters. Note that the last term of the equation is a non-linear function.

Any non-linear function can be transformed into a linear function with the first-order Taylor expansion. Hence, Taylor approximation of equation (5.1) yields the following:

(5.2) $$r_t = k + \rho p_t + (1 - \rho)d_t - p_{t-1}$$

where k is a constant term and ρ is approximately the reciprocal of one plus the dividend yield. I follow Vuolteenaho (2002) and set ρ to equal to 0.967.

Deriving price and solving equation (5.2) forward yields the following valuation model:

(5.3) $$p_t = \frac{k}{(1-\rho)} + E_t\left[\sum_{j=0}^{\infty}\rho^j\{(1-\rho)d_{t+1+j} - r_{t+1+j}\}\right]$$

where E is the expectation operator. Equation (5.3) represents a dynamic valuation model where market value is a constant plus an infinite sum of the expected dividends less expected required returns. If dividends are expected to increase then there should be an increase in the market equity. Conversely, if the required rate of return increases then there should be a decrease in the stock price.

Substituting equation (5.3) into equation (5.2) yields the unexpected change in stock return:

(5.4) $$r_t - E_{t-1}r_t = \Delta E_t\sum_{j=0}^{\infty}\rho^j\Delta d_{t+j} - \Delta E_t\sum_{j=0}^{\infty}\rho^j r_{t+j} = N_{cf,t} - N_{r,t}$$

where *ΔE* denotes the change in expectation from period t – 1 to t, *Ncf* and *Nr* represent cash flow news and expected return news, respectively. Equation (5.4) says that an unexpected increase in stock return is either driven by an unexpected increase in dividends and/or by an unexpected decrease in required return.

However, the fact that many firms do not pay dividends along with stickiness of dividends may limit the potential application of the model. Vuolteenaho (2002) improved the model by replacing dividends with clean surplus return on equity. Callen and Segal (2004) also extend the model to include accrual news.

The Campbell (1991) and Vuolteenaho (2002) models are comparable to the Beveridge and Nelson (1981) decomposition that separates a series into a random walk component and a stationary component. Hence, shocks to stock returns in equation (5.4) correspond to shocks to the random walk component of log of stock price (cash flow news) and shocks to the stationary component of log of stock price (expected return news). Although equation (5.4) is only an approximation, it is being treated as an exact relationship between unexpected changes in stock return and unexpected changes in news components. Campbell and Shiller (1988) and Vuolteenaho (2002) show that an approximation error in the model has no significant effect on the results.

Ultimately, the model is superior to other models that solely rely on accounting variables because of its ability to use firm-level accounting data while incorporating time-varying expected future discount rates.

5.2.2 VAR Estimation

Return decomposition in equation (5.4) can be conveniently operationalized using a vector autoregressive process. Define $z_{i,t}$ to be a vector of firm-specific state variables. An individual firm's state vector is assumed to follow a multivariate log-linear dynamic:

(5.5) $$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t}$$

where Γ is a transition coefficient matrix assumed to be constant over time, $u_{i,t}$ is an error term assumed to have a variance-covariance matrix of Σ and to be independent of everything known at *t-1*. Firms with the same values in the state variables are assumed to behave similarly. However, since $u_{i,t}$ varies across firms, the behavior of similar firms can also vary across time periods. Note that equation (5.5) allows for VAR processes of order greater than 1.

Following Vuolteenaho (2002), I use a parsimonious one-lag model with log stock return, efficiency score, log return on equity, and log of analysts growth forecasts as variables to forecast next period returns. The variables are based on previous empirical work on return predictability. The lagged stock return is designed to capture mean-reversion and momentum effects in return series (DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993; Vuolteenaho, 2002). The lagged efficiency score, a composite measure of firm characteristics including book equity, proxies for the overall efficiency level of the firm. Nguyen and Swanson (2007) show that the efficiency score exhibits significant predictive power in cross-sectional analysis even after controlling for firm size and book-to-market (B/M). Moreover, the firm efficiency level (efficiency score) appears to contain more information than is present in B/M. The lagged return on equity measures the effect of profitability of future stock returns. Haugen and Baker (1996) and Vuolteenaho (2002) document that firms with higher profitability yield higher average returns. Finally, the lagged growth forecast captures the effect of the past-one quarter growth forecast on return. Studies on analysts forecasts document that

their forecasts are overly optimistic and hence there should be a negative relationship between the forecasts and future returns.

Campbell (1991) provides a simple method of computing cash-flow and expected return news from equation (5.5). Specifically, let e1' be a vector in which the first element is 1 and the rest are zeroes. Vector e1' is designed to pick out the first element from the state vector $z_{i,t}$. Hence, unexpected change in return is

(5.6) $$r_t - E_{t-1}[r_t] = e1'u_t$$

and cash flow news and expected return news are computed as follows:

(5.7) $$Ncf_t = (e1' + \lambda)u_{i,t} \quad \text{and} \quad Nr_t = \lambda\, u_t$$

where $\lambda' = e1'\rho\Gamma(I - \rho\Gamma)^{-1}$. Campbell's methodology (1991) first computes expected return news and then backs out the cash-flow news by summing unexpected change in return and expected return news. Note that if returns are purely driven by random shocks (i.e. unpredictable) then the first row of Γ is all zeroes and consequently expected return or expected return news is zero. This implies that the unexpected change in return is entirely due to cash flow news.

In order to estimate the variance-covariance matrix of the news, the estimate of the variance-covariance matrix of Σ is also required. By taking the variances of both sides of equations (5.6) and (5.7), I can estimate the elements of the news variance-covariance matrix as follows:

(5.8) $$Var(Nr) = \lambda'\Sigma\lambda$$

$$Var(Ncf) = (e' + \lambda')\,\Sigma(e + \lambda)$$

$$Cov(Nr, Ncf) = \lambda'\,\Sigma(e + \lambda)$$

Finally, by examining the relationship between analysts growth forecasts and news components, I can directly observe whether expectations in cash flow or expected return drive the forecasts, ceteris paribus.

5.3 Data and Variable Definitions

The data used in this chapter is the intersection of three databases: IBES, COMPUSTAT QUARTERLY and CRSP. Consensus growth forecast estimates are computed using data from Institutional Brokerage Estimate System (IBES), accounting data is from COMPUSTAT QUARTERLY and stock returns are from CRSP. I will discuss the filtering process for each database separately. The last sub-section provides discussion of the final sample.

5.3.1 IBES Requirements and Consensus Forecasts

For each firm in the sample, I require that its earnings forecasts be available in the IBES database which gathers earnings forecasts of companies from thousands of individual security analysts. In developing consensus forecasts estimates, I further specify the following filtering criteria.

1. I require that all firms must have a December fiscal-year end in order to avoid problems of nonoverlapping horizons and to align accounting variables across firms.
2. I exclude firms with earnings forecasts issued by analysts whose identity is not revealed in the IBES database.
3. I require that each firm in each quarter must have at least two analysts covering it, so that the consensus forecast is based on a reasonable number of analysts.

4. I require that each analyst must have earning forecasts for the next fiscal year (FYR2).
5. For each analyst, I only record the latest forecast made in that quarter. Further, I require that the forecast is made after the release of quarter $t-1$ earnings so that the analyst has incorporated the latest information into the estimates.

Once the IBES sample is "clean", I compute the consensus growth forecast variable for each firm as follows:

$$FYR2G_{i,t,q} = (FYR2MED_{i,t,q} - EPS_{i,t-1})/P_{i,t-1} \tag{5.9}$$

where $FYR2G_{i,t,q}$ is the consensus growth forecast for fiscal year $t+1$ made in quarter q of year t for firm i; $FYR2MED_{i,t,q}$ is the median of earnings forecasts for fiscal year $t+1$ made in quarter q of year t for firm i; $EPS_{i,t-1}$ is the $t-1$ fiscal year earnings for firm i and the scaling variable, $P_{i,t-1}$, is the closing stock price as of December year $t-1$[24]. I restrict consensus growth forecasts to be greater than -1. Furthermore, I eliminate extreme observations by removing forecasts in the top and bottom 1%.

5.3.2 COMPUSTAT Requirements

To be included in the sample, the firm must satisfy the following COMPUSTAT QUARTERLY data requirements. First, I require that the firm must have been in the database for at least eight quarters (or two years) in order to avoid survivorship bias. Second, I screen out firms with annual sales and market equity less than $10 million. In addition, I remove firms with total assets equal to zero and with negative R&D and

[24] IBES recommends using the median of the forecasts instead of the mean because the latter can be biased in the presence of extreme forecasts. I scale the difference between the median forecast and actual earnings by stock price to avoid problems associated with a negative and/or small denominator in case of scaling by previous year earnings.

capital expenditure (CAPEX). Third, following Vuolteenaho (2002), I exclude firms with negative book equity and book-to-market ratio more than 100 or less than 1/100.

For some firm-quarter observations, COMPUSTAT only reports annual data. To circumvent this, I equally divide the annual figure across four quarters. For example, COMPUSTAT QUARTERLY does not report data for advertising expenses. I resolve the problem by treating it as a missing firm-quarter issue and equally splitting the annual advertising expense (obtained from ANNUAL COMPUSTAT) across four quarters.

5.3.3 CRSP Requirements

I obtain monthly stock returns from CRSP database. Shumway (1997) and Shumway and Warther (1999) find that there is a survivorship bias inherent in CRSP for performance-related delisted firms. To mitigate the problem, I follow Shumway and Warther (1999) and substitute -30% as the last month return for NYSE/AMEX firms and – 55% as the last month return for NASDAQ firms. The substitutions are only applied to firms that are delisted due to performance reasons. Overall, the modifications do not qualitatively affect our final results.

Quarterly return for each stock is computed by compounding the returns for the three months within the quarter. Furthermore, I lag monthly returns for each quarter by four months to ensure that all accounting variables are reflected in the returns. For example, I define first quarter return as the compounded value of returns for April, May

and June instead of January, February and March[25]. I use the same method to compute quarterly returns for the market, proxied by the value-weighted CRSP index.

5.3.4 Variable Definitions

In order to implement the VAR, I need to define the data items used to construct the state variables in the model. First I obtain the efficiency score using the following variables: sales as DATA2, total assets as DATA44, CAPEX as DATA90, R&D as DATA4 and EBITDA as DATA21[26]. Since, COMPUSTAT QUARTERLY does not report advertising expenses, I substitute DATA45 in COMPUSTAT ANNUAL for it.

Once the efficiency score for each firm is computed, I estimate equation (5.5). For returns, I follow Vuolteenaho (2002) and compute the log of return (denoted by *r*) as the log of one plus raw return. Similarly, I define the log of return on equity (denoted by *roe*) as the log of one plus return on equity. I construct return on equity as net income (DATA69) in quarter *t* divided by book equity in quarter *t-1*. Similar to Vuolteenaho (2002), I use common equity (DATA59) to proxy for book equity. If deferred taxes are available, I add them to book equity. If common equity for the quarter is missing, I assume that it is the same as in the previous quarter. I exclude observations with zero or negative book equity. Once book equity is obtained and return on equity is computed, I restrict the latter variable to be greater than -1. I do not log transform the efficiency score (denoted by *s*) since it is positive and less than one by

[25] Most companies will release their first quarter performance in mid-March or early April. Thus, the return in January, February and March will not reflect these firm characteristics.

[26] Estimation of efficiency score is discussed in detail in the Appendix. The estimation is based on stochastic frontier analysis method (discussed in detail in chapter 3). For this study, I use different variables from the method in chapter 3 and the dataset is for quarterly basis.

construction. Finally, I compute the log of analyst growth rates (denoted by *fyg*) as the log of one plus FYR2G (obtained from equation (5.9)).

5.3.5 Final Sample

The intersection of the "cleaned" and "transformed" samples from IBES, COMPUSTAT QUARTERLY and CRSP yields a firm-quarter panel of 46,759 observations which is the focus of this study.

Panel A of Table A.16 shows descriptive statistics for the final sample. There are 46,759 total firm-quarter observations in 49 industries over the period of 1989 to 2004. As the means and medians indicate, the sample suffers from left skewness, a common characteristics for cross-sectional firm data. For example, firm market capitalization ranges from $10 million to $484,000 million with mean and median of $4,100 million and $800 million, respectively. Overall, the statistics suggest that the sample is diverse and consists of firms with different characteristics.

Panel B of Table A.16 presents descriptive statistics for the four state variables in the VAR. The mean predicted firm efficiency is 73% which is in line with the estimate obtained by Nguyen and Swanson (2007). The mean and the median on the consensus growth forecast implies that, on average, there are more positive growth forecasts than negative ones.

5.4 Empirical Results

5.4.1 Results for Firm-Level VAR

To decompose firm-level return into cash flow and expected return news components, I operationalize equation (5.5) by estimating the following VAR model:

$$\begin{pmatrix} r_{i,t} \\ roe_{i,t} \\ s_{i,t} \\ fyg_{i,t} \end{pmatrix} = \Gamma \begin{pmatrix} r_{i,t-1} \\ roe_{i,t-1} \\ s_{i,t-1} \\ fyg_{i,t-1} \end{pmatrix} + \begin{pmatrix} u_{i,1t} \\ u_{i,2t} \\ u_{i,3t} \\ u_{i,4t} \end{pmatrix} \tag{5.10}$$

where r is the log of stock return, roe is the log of return on equity, s is the efficiency score, fyg is the next fiscal year consensus earnings growth forecast, Γ is the *(4 x 4)* transition coefficient matrix and u is the vector of error term.

Similar to Vuolteenaho (2002), I trade off efficiency for robustness and simplicity in estimating the transition coefficient matrix in the VAR. Specifically, I estimate the VAR using the weighted least squares approach on the panel data with one pooled prediction per state variable. First, each observation in a quarterly cross-section is deflated by multiplying it with the reciprocal of the number of firms in the cross-section of that quarter. The procedure ensures that the results are not driven by higher concentration of growth firms in the latter years of the panel. Second, each state variable is demeaned by subtracting the cross-sectional average of that variable. For return, I subtract the market return, instead of the cross-sectional average, from the stock return. Finally, I regress each state variable against its own lag and the lag of the other three state variables. I repeat the process for every quarterly cross-section. The time-series average of the parameter estimates for each state variable is used as elements in the transition matrix. The procedure is similar to the methodology used by Fama and Macbeth (1973). For computation of the level of significance for the coefficients, I use the Shao and Rao (1993) jackknife method to obtain consistent and robust standard errors. In addition, the jackknife approach corrects the standard errors

for cross-sectional correlations inherent in panel data. The methodology involves estimating the model over and over while dropping one cross-section at a time. The process yields a time series of estimates for each parameter. The time-series standard error for a parameter is used as the standard error for that particular parameter in inference computation. The jackknife method results in consistent standard errors even in the presence of cross-sectional correlation.

Panel A of Table A.17 reports parameter estimates for the firm-level VAR. I find that lagged one-quarter stock return is positively (but insignificantly) related to current quarterly return. Consistent with Nguyen and Swanson (2007), the parameter estimate on lagged *s* is -0.20 and highly significant suggesting a negative relation between firm efficiency level and stock return. In line with Haugen and Baker (1996) and Vuolteenaho (2002), the estimates from the VAR imply that firms with higher profitability earn higher return. Finally, the results also indicate that past one-quarter growth forecast for next fiscal year has a negative relationship with subsequent quarter return indicating that higher analysts growth forecasts are followed by lower return which is consistent with previous studies.

The second and third row of the VAR in Panel A also document that efficiency score and return on equity are high when past one-quarter efficiency score and return on equity are high. Past one-quarter analysts growth forecast for next fiscal year has no predictive power on firm efficiency level. A finding of interest is the fact that analysts growth forecast is negatively and significantly related to subsequent quarter return on

equity. The result is consistent with the hypothesis that, on average, analysts forecasts are overly optimistic about the future performance of the firm.

The last row in the transition matrix shows the relationship of analysts growth forecast and past one-quarter state variables. Results indicate that analysts growth forecast is positively related with past one-quarter growth forecast. In fact, growth forecast is approximately an AR(1) process with an autoregressive coefficient of 0.78, but the lagged stock return also has significant predictive power. The positive correlation between growth forecast and the lagged growth forecast may reflect the fact that analysts exhibit herding behavior. The result confirms prior findings on analysts forecast herding documenting that analysts prefer to release forecasts that are close to prior forecasts (Scharfstein and Stein, 1990; Trueman, 1994; Hong, Kubik and Solomon, 2000). Analysts growth forecast for next fiscal year is high when past one-quarter return is high which implies that analysts give higher forecasts for positive momentum stocks. Jegadeesh, Kim, Krische and Lee (2004) document that analysts prefer "glamour" stocks that have positive momentum and high trading volume.

Overall, with respect to analysts growth forecasts, the findings from the VAR provide unpleasant news to investors. It appears that firm characteristics and valuation do not play major roles in determining growth forecasts. Momentum and, more importantly, prior estimates seem to be the primary determinants of analysts growth forecasts.

Panel B of Table A.17 shows the variance-decomposition for the VAR. Consistent with previous findings using monthly and annual data, the results indicate

that cash flow news is the main driver of firm-level stock returns. The standard deviation for the expected return news is 5.1% (variance is 0.26% with 0.02% standard error) while the standard deviation for the cash flow news is 19.2% (variance is 3.7% with 0.31% standard error).

5.4.2 Responses of Analysts Growth Forecasts to News Components

In this section, I examine the response of analysts growth forecast to cash flow news and expected return news. Specifically, I estimate the following fixed effects panel regression[27]

(5.11) $$ufyg_{i,t} = a + \mu_i + c(Ncf_{i,t}) + d(Nr_{i,t}) + e_{i,t}$$

where *ufyg* is the growth forecast shock and is the difference between the actual growth forecast and the growth forecast predicted by equation (5.10); *Ncf* is the cash flow news; *Nr* is the expected return news and μ_i is the fixed effect dummy for firm *i*. Equation (5.11) estimates the relation between analysts growth forecast shock and news components while controlling for heterogeneity of each firm.

Panel A of Table A.18 reports regression results for all firms in the sample. The parameter estimate for *Nr* is 15% (p-value of less than 1%) while the parameter estimate for *Ncf* is 0.78% (p-value less than 1%). The estimates suggest that while analysts do respond positively to positive cash flow news, they prefer to upgrade to higher expected return. The finding coincides with Bradshaw (2004) who finds that growth expectation

[27] I also estimate equation (5.11) using the Fama and MacBeth (1973) approach as per previous studies. The results are qualitatively the same. I report the fixed effects model for consistency with latter tests in the section. I chose the fixed effects model over the pooled OLS and random effects model because the latter ones are rejected by the F-test and the Hausman test, respectively. The results are available from the author upon request.

is the dominant factor in changes in stock recommendations which in turn are based on long term growth forecasts. Cornell (2001) provides similar results by suggesting that analysts price targets are more sensitive to temporary shocks rather than to changes in fundamental value.

Panels B, C, D and E of Table A.18 provide variance-decomposition and regression outputs for firms ranked by size, B/M, analysts disagreement and coverage, respectively. Firm allocation to each size quintile is based on the NYSE breakpoints. The B/M (analysts disagreement) quintiles are created by sorting firms based on their book-to-market ratio (standard deviation of growth forecasts). The transition matrix Γ and the variance-covariance matrix Σ are assumed to remain constant across all quintiles.

Results in panel B reveal that all news variances are statistically significant at the 1% level and decline monotonically with firm size. This implies that small firms tend to have more volatile cash flow and return expectations. The finding is consistent with previous expectations because larger firms tend to have less volatile performance. The responses of analysts growth forecast shock on news components again suggest that analysts respond more to expected return news. The parameter estimates of *Nr* for the smallest and largest quintiles are 17% and 11%, respectively. In the meantime, the parameter estimates of *Ncf* for the smallest and largest quintiles are 0.93% and 0.73%, respectively. Together, the results suggest that analysts respond more strongly to a change in cash flow expectation or expected return for small stocks than for large stocks.

Panel C presents results for firms ranked by B/M. The news variances are uniformly significant at the 1% and are increasing with B/M. In particular, the magnitudes of the news variances for value firms (high B/M) are higher than the magnitudes of the news variances for growth firms (low B/M). The finding is consistent with implications by Fama and French (1995) who argue that value firms tend to a have more volatile and poorer earnings growth trend. The coefficients of *Nr* for the growth and value stocks are 10% (p-value less than 1%) and 23% (p-value less than 1%), respectively. Again, the results indicate that analysts are more responsive to expected return news for firms with high uncertainty. The parameter estimate of *Ncf* for growth stocks is 0.61% (p-value less than 1%). Interestingly, analysts are much more responsive with cash flow news for value stocks. The coefficient estimate of *Ncf* for value stocks is 1.21% (p-value less than 1%) and almost twice as large as the estimate for growth stocks. The result implies that a unit of positive cash flow news for value stocks results in higher growth forecasts from analysts than a change in the same magnitude for growth stocks. Doukas, Kim and Pantzalis (2002) find that analysts are significantly more optimistic about value stocks than growth stocks. Our finding supports this argument.

Diether, Malloy and Scherbina (2002) interpret dispersion in earnings forecasts as differences in opinion and argue that there is a high demand for additional information where earnings are difficult to forecast. The argument implies that analysts should react more strongly to new information for high dispersion stocks than for low dispersion stocks. To examine this possibility, I create quintiles based on earnings

forecast dispersions. Results in panel D indicate a monotonic increase in parameter estimates as the level of dispersion increases. The *Ncf* (*Nr*) coefficient is 0.41% (6.64%) for the low dispersion group and 1.26% (26.65%) for the high dispersion group. In addition, the variance-decompositions also indicate that the news variances are significantly higher for the high dispersion group than for the low dispersion group. This is consistent with Diether, Malloy and Scherbina (2002) who find that dispersion is positively correlated with earnings variability and standard deviation of past returns.

Hong, Lim and Stein (2000) suggest that information travels more slowly for stocks with low analyst coverage. I examine this by creating quintiles of residual of number of analysts, proxy for analysts coverage. I purge size effect from analysts coverage by regressing the log of number analysts against the log of size and the squared log of size. I obtain the following Fama-MacBeth (1973) type equation with Shao and Rao (1993) standard errors in parentheses

$$\text{(5.12)}\quad \underset{}{log(number\ of\ analysts)} = \underset{(0.0633)}{-0.0634} + \underset{(0.0176)}{0.3712}log(size) - \underset{(0.0012)}{0.0135}(log(size))^2 + e$$

Equation (5.12) indicates that the number of analysts increases with size but at a diminishing rate. The residual of number of analysts, obtained from equation (5.12), creates variations in the number of analysts while keeping size fixed.

Panel E of Table A.18 presents the results for quintiles sorted by residual of number of analysts. The *Ncf* (*Nr*) coefficient is 0.53% (12.49%) for the low coverage group and 1.02% (17.45%) for the high coverage group. Holding size fixed, it appears that for stocks with a low number of analysts following the reaction is lower than for stocks with a high number of analysts following. Moreover, the variance-

decompositions suggest that the news variances are higher for stocks with high coverage than for stocks with low coverage. This may indicate that analysts prefer stocks with a higher degree of uncertainty.

5.4.3 Robustness Tests with Aggregate News

Pitroski and Roulstone (2004) argue that analysts base their forecasts on gathering and analyzing information at both the firm and industry levels. Hence, it is possible that for firms where earnings are difficult to forecast, analysts must consider the performance of the market in addition to firm-level information. To examine this, I measure the response of growth forecast shock on firm-level news components while controlling for market-level news[28]. Specifically, I estimate the following fixed effects panel regression

(5.13) $$ufyg_{i,t} = a + \mu_i + c(Ncf_{i,t}) + d(Nr_{i,t}) + \gamma(ANcf_t) + \lambda(ANr_t) + e_{i,t}$$

where γ and λ are parameter estimates of analysts growth forecast shock on market cash flow and expected return news, respectively; $ANcf_t$ is the market cash flow news for quarter t and ANr_t is the market expected return news for quarter t. I follow the same technique and use the same variables as in Campbell and Vuolteenaho (2004) and compute market cash flow and expected return news for each quarter from 1989 to 2004.

Table A.19 provides the results for equation (5.13) for the entire sample and for characteristics quintiles. Compared with results in Table A.18, the results in Table A.19 uniformly indicate that the magnitude of the response of analysts growth forecast shock

[28] I thank Larry Lockwood for suggesting to include macro-level news.

to *Ncf* is significantly lower after controlling for market cash flow and expected return news. In the meantime, the response to *Nr* remains relatively unchanged. This suggests that analysts do incorporate market level information in generating growth forecasts.

It appears that the parameter estimates for *ANcf* are higher for firms with high uncertainty (small cap stocks and value stocks). Furthermore, Campbell, Polk and Vuolteenaho (2005) document that the cash flows of growth stocks are more sensitive to temporary movements in aggregate stock prices while the cash flows of value stocks are more sensitive to permanent movements in aggregate stock prices. Results in panel C indicate that when aggregate news components are included, the parameter estimate for *Ncf* for low B/M stocks changes from 0.61% (Table A.18) to 0.32% (Table A.19) while only the parameter estimate for *ANr* is statistically significant. In the meantime, the parameter estimate for *Ncf* for high B/M stocks changes from 1.21% (Table A.18) to 0.46% (Table A.19) and the coefficient for *ANcf* is 7.69% and highly significant. The results indicate that for growth stocks analysts react more strongly to changes in temporary movements in aggregate stock prices while for value stocks analysts react to both temporary and permanent movements in aggregate stock prices. Results in panel D reveal an interesting pattern. For firms with low dispersion, analysts do not react to firm-level cash flow news in the presence of aggregate level information. However, for firms with high dispersion, analysts react stronger to all new firm-level and aggregate level information. This is consistent the argument by Diether, Malloy and Scherbina (2002) who argue that there is a higher demand for additional opinion when existing

information is difficult to interpret. This is further confirmed by results in panel E. It appears that the responses are stronger for stocks with high analysts coverage.

In summary, the robustness tests support the basic finding that analysts respond more strongly to expected return news rather than cash flow news. Moreover, for firms with high uncertainty, the aggregate-level news components appear to subsume the effect of firm-level cash flows. It is possible that in generating forecasts for these firms, analysts have to rely on expectation of how the market as a whole will perform. Hence, cash flow news will partially reflect the expected growth of the aggregate economy and the market.

5.5 Conclusions

I use the Campbell-Shiller and Vuolteenaho (2002) decompositions to examine the impact of cash flow news and expected return news on changes in analysts growth forecasts. The analysis yields the following results.

First, within the VAR framework, only the lagged stock return and lagged growth forecast have strong predictive power for current forecasts. This result supports the argument that analysts tend to issue forecasts that are close to the previous period forecast. Moreover, analysts appear to issue higher forecasts for stocks that have performed well in the last period.

Second, while analysts do react positively to cash flow news, they react much more strongly to expected return news. Specifically, analysts are more responsive to expected return news for firms with high uncertainty such as small-cap stocks and high

B/M stocks. The results hold even after inclusion of aggregate-level cash flow and expected return news.

5.6 Appendix: Firm Efficiency Estimation

Tobin's Q or the market-to-book ratio is selected to proxy for firm value. Therefore, the stochastic frontier function is defined as

(A.1) $Q_{it} = f(X_{it}, \beta)exp(v_{it} - w_{it})$

Employing a log transformation of equation (A.1) and adding fixed effects for the 49 Fama-French industries, I obtain the following estimating equation:

(A.2) $ln(Market\ Equity_{it}) = \beta_0 + \phi_{ij} + \gamma_1(RDDUM_{it}) + \gamma_2(ADVDUM_{it}) + \beta_1 ln(Book\ Equity_{it}) + \beta_2(CAPEX_{it}/Sales_{it}) + \beta_3(R\&D_{it}/Sales_{it}) + \beta_4(ADV_{it}/Sales_{it}) + \beta_5(EBITDA_{it}/Total\ Assets_{it}) + v_{it} - w_{it}$

where ϕ_{ij} is a dummy variable that proxies for firm i's industry j according to the Fama-French industry classification, v_{it} is the standard two-sided error term and w_{it} is the one-sided measure of inefficiency. Since COMPUSTAT does not report R&D and advertising expenses for many firms in many years, I follow Palia (2001) and create two dummy variables (RDDUM and ADVDUM) that are equal to one if respective variables are missing and zero otherwise. Many studies simply exclude observations with missing values. However, this filtering process reduces the sample size and potentially biases the estimates in favor of firms with reported R&D and advertising expenses. Therefore, to avoid losing observations, I replace missing values for R&D and advertising expenses with zeroes. I compute market equity as the closing stock price at the end of each quarter multiplied by the number of shares outstanding.

The rationales, economic meaning and predicted signs of the remaining variables are as follows.

- β_1: The log of book equity is a control factor from the log transformation of Tobin's Q.
- β_2: Capital expenditure (CAPEX) is a measure of "hard spending" and investment opportunities. Since many firms do not have capital expenditures, I scale CAPEX by sales instead of using log transformation. Similar to Habib and Ljungqvist (2005), I expect a positive relation between "hard spending" and firm value.
- β_3 and β_4: R&D expenses (R&D/Sales) and advertising expenses (ADV/Sales) scaled by sales proxy for intangible assets or "soft spending". Morck, Shleifer and Vishny (1988) and McConnell and Servaes (1990) found that Tobin's Q may not capture all growth opportunities and "soft spending" of the firm. Moreover, Grullon, Kanatas and Weston (2004) found that advertising is positively related to firm liquidity and visibility, which in turn reduces the cost of equity. I expect a positive relationship between R&D and firm value and advertising and firm value.
- β_5: Similar to Palia (2001), free cash flow, as measured by operating profits to total assets *(EBITDA/Total Assets*), serves as proxy for firm profitability. I expect market value to increase with profitability.

Once the frontier input variables have been determined, the frontier as of the end of each quarter is constructed, and an efficiency score for each firm for each quarter is obtained. At the end of each quarter *t*, starting in 1989 and ending in 2004, I estimate equation (A.2) using the stochastic frontier approach. Table A.20 reports the mean of

parameter estimates for each independent variable over the period. For a robustness test, I also provide mean estimates using the standard ordinary least squares technique. I use the Shao and Rao (1993) jackknife method to compute the standard errors.

The mean coefficients obtained from stochastic frontier analysis (SFA) are not appreciably different from the ones estimated by OLS. This supports the superiority of SFA because it not only provides similar estimates to OLS but also provides the ability to distinguish between systematic inefficiencies and white noise.

In sum, the results in Table A.20 indicate that the signs of the coefficients are consistent with previous expectations. Moreover, it appears that firms with larger amount of free cash flow tend to have higher market values.

CHAPTER 6

SUMMARY AND CONCLUSIONS

Previous research has documented that analysts do revise their recommendations and forecasts following large stock price changes, a proxy for new information. Moreover, it has also been shown that stock prices, themselves, carry information about future cash flow trend and information about future expected return trend. The former one is referred to as cash flow news and is the permanent component while the latter one is referred to as expected return news and is the temporary component. Yet, the relative impact of cash flow news and expected return news on analysts growth forecasts is relatively unexplored.

This study directly examines the impact of the two news components on changes in consensus growth forecasts. To estimate cash flow news and expected return news, I use the VAR approach proposed by Campbell (1991) and Vuolteenaho (2002). Essentially, the VAR first estimates predicted return and uses actual return to back out cash flow news. To operationalize the VAR for return prediction, I must address the following issues. First, I need to include state variables that are related to return (either empirically or theoretically) while maintaining a parsimonious model. Furthermore, the state variable must be able to reflect the effects of firm assets and growth opportunities. Second, I must consider how analysts forecasts, themselves, are related to return.

In my first essay, I use the stochastic frontier approach, proposed by Aigner, Lovell and Schmidt (1977) and Habib and Ljungqvist (2005) to develop an efficiency score that captures the effects of various firm characteristics including the effects of book-to-market ratio and other intangible assets. Further, I create a hedge portfolio which takes a long position in the most inefficient firms and a short position in the most efficient firms. I find that, on average, the hedge portfolio yields a return of 0.76% per month. The performance is statistically and economically significant even after adjusting for firm characteristics and risk factors. Hence, I conclude that firm efficiency level is negatively related to equity returns.

In my second essay, I examine the value of analysts forecasts by studying the performance of a hedge portfolio that is long in low consensus growth forecasts and short in high consensus growth forecasts. I find positive and statistically significant abnormal performance for a hedge portfolio formed on next fiscal year growth forecasts. However, a hedge portfolio formed on current fiscal year growth forecasts does not yield significant abnormal return. Further, I document that the results hold after additional robustness tests. Hence, I conclude that next fiscal year growth forecasts are negatively related to subsequent equity returns.

In my third and final essay, I use results obtained from the previous two essays to construct a VAR to forecast returns and to obtain the news components. Once the news components are obtained, I estimate the response of analysts growth forecast shock on cash flow news and expected return news. My analysis yields the following main results.

First, analysts do raise their forecasts on positive cash flow news. However, the magnitude of the response to cash flow news is significantly lower than the magnitude of the response to expected return news. This suggests that while analysts do react to changes in firm fundamentals, they respond more strongly to changes in future expected return. Cornell (2001) argues that growth is a dominant factor behind changes in analysts recommendations. My finding supports this argument since high growth should lead to high return. Hence, the stronger response to expected return news may reflect the fact that analysts focus more on the growth component of firm rather than on the fundamentals.

Second, I find that the magnitude of the responses is much stronger for firms with high variability in cash flow news (i.e. small cap stocks and value stocks). This coincides with the notion that analysts tend to react more strongly for firms with "bad" historical performance. My finding is consistent with the results by Eisdorfer (2007) who suggests that good cash flow news is particularly very important to firms in financial distress.

In sum, my study sheds light on and extends the literature on analysts forecasts by empirically documenting that expected growth component is the dominant driver behind analysts growth forecasts. While previous studies on the topic have indirectly implied this point, my thesis is the first empirical study on the direct relation between analysts growth forecasts and the breakdown of expected firm fundamentals and expected growth.

APPENDIX A

TABLES

TABLE A.1

Sample Descriptive Statistics: from 1980 through 2002

Table A.1 presents sample descriptive statistics. The statistics include mean (Mean), standard deviation (St. Dev.), maximum value (Max), median (Med) and minimum value (Min). The data is gathered from the COMPUSTAT database. The units of measurement are in millions of dollars.

	Mean	St. Dev.	Max	Med	Min
Market Equity	1,509.71	8,934.27	507,216.70	118.37	0.17
Book Equity	678.98	2,891.15	142,468.00	76.87	0.11
Sales	1,402.84	6,137.20	218,529.00	149.50	0.00
Total Assets	2,774.47	17,830.61	799,791.10	186.52	0.05
Long-term Debt	519.85	4,957.47	419,975.00	15.76	0.00
Capital Expenditures	102.86	621.75	33,143.00	5.19	-0.18
R&D Expenditures	27.82	226.17	8,900.00	0.00	0.00
Adv. Expenditures	16.59	131.56	4,500.00	0.00	0.00
Dividends	30.55	172.39	6,555.00	0.00	0.00
Property, Plant & Equip.	587.17	2,840.34	128,063.00	29.78	0.00
EBITDA	239.45	1,252.33	49,708.00	17.45	-5,743.00

TABLE A.2

Mean Parameter Sensitivities from Stochastic Frontier Analysis (SFA) and Ordinary Least Squares (OLS) together with Summary Diagnostics for SFA

Panel A presents the average of parameter sensitivities for SFA and OLS. At the beginning of each year *t*, starting in 1980 and ending in 2002, we estimate the efficient frontier. We then take the average of the "betas". There are 23 total observations for each "beta". Panel A reports the average relationship between the independent variables and the dependent variable. For comparison purposes we also present the estimates using OLS. For both cases the dependent variable is the log of market value. Panel B contains the summary of diagnostics for SFA. Time-series standard errors are in parentheses and *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Average Parameter Sensitivities for SFA and OLS

Independent Variables	SFA		OLS		Expected sign
Log of Book Equity	**1.0172**	***	**1.0215**	***	+
	(0.0074)		(0.0071)		
Long-term Debt / Total Assets	**-0.2333**	***	**-0.2518**	***	Indeterminant
	(0.0427)		(0.0418)		
Capital Expenditure / Sales	**0.0664**	***	**0.0659**	***	+
	(0.0225)		(0.0224)		
R&D / Sales	**0.2923**	**	**0.2684**	**	+
	(0.1632)		(0.1508)		
Advertising Expenditure / Sales	**0.8649**	***	**0.8067**	***	+
	(0.1776)		(0.1739)		
Capital Intensity	**-0.2832**	***	**-0.2806**	***	Indeterminant
	(0.0196)		(0.0209)		
Free Cash Flow	**0.8770**	***	**0.8646**	***	+
	(0.1093)		(0.1089)		
Constant	0.8571	***	0.4563	***	
	(0.1122)		(0.1142)		

Panel B: Summary of Diagnostics for Stochastic Frontier Analysis

	Mean		Max	Med	Min
Likelihood ratio test of $u_i = 0$ (χ^2)	**7.4557**	***	28.3900	5.7000	1.6000
	(1.1608)				
P-value of likelihood ratio test	**0.0156**	***	0.1030	0.0080	0.0000
	(0.0047)				
Variance of v_i (σ^2_v)	**0.2850**	***	0.5442	0.2546	0.0809
	(0.0239)				
Variance of u_i (σ^2_u)	**0.2434**	***	0.4298	0.2349	0.1645
	(0.0143)				
$\lambda = \sigma_u / \sigma_v$	**0.9694**	***	1.7142	0.8889	0.6765
	(0.0472)				
No. of firms per year	2,096		3,680	1,815	985

TABLE A.3

Summary Statistics for Efficiency Scores: from 1980 through 2002

The statistics include mean (Mean), standard deviation (St. Dev.), maximum value (Max), median (Med) and minimum value (Min). The statistics include the mean, standard deviation, maximum, median and minimum values. At the beginning of each July of year *t*, all stocks are sorted into deciles based on their efficiency scores in descending order to form ten ES portfolios. The top decile portfolio is classified as the *EFFICIENT* portfolio and the bottom decile is classified as the *INEFFICIENT* portfolio. The efficiency levels are reported in decimals.

ES Portfolios	Mean	St. Dev.	Max	Med	Min
INEFFICIENT	0.52	0.08	0.67	0.54	0.08
2	0.62	0.04	0.70	0.62	0.50
3	0.66	0.04	0.72	0.66	0.56
4	0.68	0.04	0.74	0.68	0.60
5	0.70	0.03	0.75	0.71	0.63
6	0.72	0.03	0.77	0.73	0.65
7	0.74	0.03	0.79	0.75	0.67
8	0.76	0.03	0.82	0.77	0.70
9	0.79	0.03	0.85	0.79	0.71
EFFICIENT	0.83	0.03	0.95	0.83	0.75
Whole Sample	0.70	0.09	0.95	0.72	0.08

TABLE A.4

Monthly Excess Return and Benchmark Adjusted Return Characteristics of Equally-Weighted and Value-Weighted Portfolios formed on Efficiency Scores (ES): July 1980 to June 2003

Table A.4 presents the distribution of excess returns for all ten ES portfolios and the *SPREAD* portfolio. The statistics include the mean, standard deviation, maximum, median and minimum values. At the beginning of each July of year *t*, all stocks are sorted into deciles based on their efficiency scores in descending order to form ten ES portfolios. The top decile portfolio is classified as the *EFFICIENT* portfolio and the bottom decile is classified as the *INEFFICIENT* portfolio. Equally-weighted and value-weighted excess returns on a portfolio are calculated as compounded monthly returns from July of year *t* to June of year *t+1*. Panel A and panel B report the excess returns for the ten equally-weighted and value-weighted portfolios, respectively. Panel C and panel D present the characteristics benchmark-adjusted returns for the ten equally-weighted and value-weighted portfolios, respectively. The benchmark-adjusted return on each stock for the month is calculated by subtracting the characteristics benchmark portfolio return from the stock's return for that month. The *SPREAD* portfolio is a zero-cost portfolio that has a long position in the *INEFFICIENT* portfolio and short position in the *EFFICIENT* portfolio. The return series for the *SPREAD* portfolio is the difference between the *INEFFICIENT* portfolio return and the *EFFICIENT* portfolio return. All portfolios are rebalanced each year. Returns are reported in decimals. The *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Excess Returns for Equally-Weighted ES Portfolios

ES Portfolios	Mean		St. Dev.	Max	Med	Min
INEFFICIENT	0.0171	***	0.0545	0.2576	0.0139	-0.2862
2	0.0129	***	0.0520	0.1829	0.0132	-0.2706
3	0.0117	***	0.0495	0.1612	0.0138	-0.2963
4	0.0105	***	0.0478	0.1348	0.0127	-0.2823
5	0.0105	***	0.0474	0.1524	0.0135	-0.2834
6	0.0102	***	0.0465	0.1227	0.0119	-0.2575
7	0.0096	***	0.0482	0.1313	0.0120	-0.2758
8	0.0083	***	0.0518	0.1377	0.0125	-0.2789
9	0.0064	**	0.0569	0.1823	0.0086	-0.2922
EFFICIENT	0.0075	**	0.0664	0.2283	0.0111	-0.3104
SPREAD	0.0096	***	0.0335	0.1235	0.0093	-0.0807

Panel B: Excess Returns for Value-Weighted ES Portfolios

ES Portfolios	Mean		St. Dev.	Max	Med	Min
INEFFICIENT	0.0101	***	0.0626	0.2763	0.0124	-0.2821
2	0.0051	*	0.0519	0.1657	0.0038	-0.2096
3	0.0077	***	0.0487	0.1419	0.0086	-0.2681
4	0.0068	***	0.0479	0.1509	0.0053	-0.2088
5	0.0084	***	0.0467	0.1466	0.0109	-0.2312
6	0.0071	***	0.0471	0.1417	0.0102	-0.1789
7	0.0066	***	0.0439	0.1401	0.0080	-0.2049
8	0.0061	**	0.0528	0.1432	0.0067	-0.2411
9	0.0063	**	0.0484	0.1351	0.0060	-0.2277
EFFICIENT	0.0055	**	0.0545	0.1406	0.0074	-0.2163
SPREAD	0.0047	*	0.0483	0.2288	0.0069	-0.1344

TABLE A.4 - Continued

Panel C: Characteristics-Benchmark Adjusted Returns for Equally-Weighted ES Portfolios

ES Portfolios	Mean		St. Dev.	Max	Med	Min
INEFFICIENT	0.0072	***	0.0217	0.1160	0.0074	-0.1228
2	0.0029	***	0.0160	0.0654	0.0025	-0.0881
3	0.0020	**	0.0144	0.0836	0.0017	-0.0831
4	0.0013	*	0.0150	0.0632	0.0019	-0.1069
5	0.0016	**	0.0158	0.0849	0.0016	-0.1259
6	0.0027	***	0.0146	0.0781	0.0025	-0.1158
7	0.0032	***	0.0128	0.0583	0.0033	-0.0659
8	0.0028	***	0.0132	0.0589	0.0019	-0.0602
9	0.0021	***	0.0146	0.0990	0.0017	-0.0849
EFFICIENT	0.0043	***	0.0184	0.1244	0.0031	-0.0423
SPREAD	0.0029	**	0.0243	0.0638	0.0041	-0.1170

Panel D: Characteristics-Benchmark Adjusted Returns for Value-Weighted ES Portfolios

ES Portfolios	Mean		St. Dev.	Max	Med	Min
INEFFICIENT	0.0026	*	0.0316	0.1956	0.0022	-0.1109
2	-0.0017		0.0211	0.0722	-0.0031	-0.0829
3	-0.0001		0.0169	0.0687	-0.0016	-0.0427
4	0.0007		0.0159	0.0668	-0.0002	-0.0626
5	0.0013	*	0.0143	0.0641	0.0001	-0.0462
6	0.0007		0.0182	0.0650	-0.0003	-0.1062
7	0.0006		0.0115	0.0423	0.0002	-0.0347
8	0.0010		0.0158	0.0783	0.0006	-0.0998
9	0.0011	*	0.0128	0.0416	0.0007	-0.0337
EFFICIENT	0.0008		0.0144	0.0685	0.0005	-0.0361
SPREAD	0.0017		0.0338	0.1809	0.0028	-0.1156

TABLE A.5

Excess Returns on Fama-French and Carhart Factors: July 1980 to June 2003

Table A.5 presents Jensen's alphas and factor loading estimates from the following regression model:

$$ER = \alpha + \beta(RMRF) + s(SMB) + h(HML) + m(UMD) + \varepsilon$$

where *ER* is the portfolio return less the risk-free rate, *RMRF* is the market risk premium, *SMB* is the size premium, *HML* is the value premium, *UMD* is the momentum effect and α is the intercept. *RMRF* is calculated by subtracting the risk-free rate from the CRSP index return. *SMB* is the difference between the returns of small cap and large cap portfolios. *HML* is the difference between the returns of high book-to-market and low book-to-market portfolios and *UMD* is the difference between returns of last year's high return and low return portfolios. *SPREAD* is a zero-cost portfolio that takes a long position in the *INEFFICIENT* portfolio and short position in the *EFFICIENT* portfolio. Standard errors are in parentheses and *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A reports estimates for the equally-weighted portfolios and Panel B presents results for the value-weighted portfolios.

Panel A: Equally-Weighted Portfolios

	Independent Variables											
ES Portfolios	*Alpha*		*RMRF*		*SMB*		*HML*		*UMD*			
INEFFICIENT	**0.0087**	***	**0.8249**	***	**1.0879**	***	**0.4676**	***	**0.0682**			
	(0.0016)		(0.0379)		(0.0531)		(0.0589)		(0.0425)			
2	**0.0050**	***	**0.8375**	***	**1.0127**	***	**0.3638**	***	**0.0433**			
	(0.0012)		(0.0287)		(0.0401)		(0.0446)		(0.0321)			
3	**0.0036**	***	**0.8737**	***	**0.8775**	***	**0.3650**	***	**0.0479**	*		
	(0.0010)		(0.0237)		(0.0331)		(0.0368)		(0.0265)			
4	**0.0025**	**	**0.8772**	***	**0.8017**	***	**0.3821**	***	**0.0484**	*		
	(0.0009)		(0.0223)		(0.0312)		(0.0346)		(0.0249)			
5	**0.0026**	***	**0.9079**	***	**0.7081**	***	**0.3749**	***	**0.0276**			
	(0.0009)		(0.0209)		(0.0293)		(0.0326)		(0.0235)			
6	**0.0023**	***	**0.9088**	***	**0.6727**	***	**0.3738**	***	**0.0272**			
	(0.0008)		(0.0192)		(0.0269)		(0.0299)		(0.0215)			
7	**0.0017**	**	**0.9179**	***	**0.6995**	***	**0.2838**	***	**0.0513**	**		
	(0.0009)		(0.0201)		(0.0281)		(0.0312)		(0.0225)			
8	**0.0012**		**0.9479**	***	**0.7297**	***	**0.1926**	***	**-0.0342**			
	(0.0009)		(0.0212)		(0.0297)		(0.0329)		(0.0238)			
9	**0.0000**		**1.0422**	***	**0.6857**	***	**0.0939**	***	**-0.1345**	***		
	(0.0009)		(0.0214)		(0.0299)		(0.0333)		(0.0239)			
EFFICIENT	**0.0010**		**1.0893**	***	**0.9256**	***	**-0.0257**		**-0.1677**	***		
	(0.0013)		(0.0304)		(0.0425)		(0.0472)		(0.0340)			
SPREAD	**0.0076**	***	**-0.2644**	***	**0.1624**	***	**0.4933**	***	**0.2359**	***		
	(0.0016)		(0.0375)		(0.0524)		(0.0582)		(0.0419)			

TABLE A.5 - Continued

Panel B: Value-Weighted Portfolios

	Independent Variables									
ES Portfolios	*Alpha*		*RMRF*		*SMB*		*HML*		*UMD*	
INEFFICIENT	**0.0011**		**1.1389**	***	**0.3019**	***	**0.7086**	***	**-0.0439**	
	(0.0025)		(0.0575)		(0.0804)		(0.0893)		(0.0644)	
2	**-0.0010**		**1.0032**	***	**0.0297**		**0.3706**	***	**-0.1319**	***
	(0.0018)		(0.0411)		(0.0575)		(0.0639)		(0.0460)	
3	**-0.0006**		**1.0412**	***	**0.0575**		**0.4962**	***	**0.0410**	
	(0.0014)		(0.0335)		(0.0469)		(0.0521)		(0.0375)	
4	**0.0002**		**0.9918**	***	**0.0022**		**0.4287**	***	**-0.0821**	**
	(0.0014)		(0.0325)		(0.0454)		(0.0505)		(0.0364)	
5	**0.0009**		**1.0117**	***	**-0.0044**		**0.4437**	***	**0.0053**	
	(0.0012)		(0.0289)		(0.0406)		(0.0450)		(0.0325)	
6	**0.0009**		**0.9711**	***	**-0.0186**		**0.2923**	***	**-0.0758**	**
	(0.0014)		(0.0318)		(0.0445)		(0.0494)		(0.0356)	
7	**0.0008**		**0.9254**	***	**-0.0755**	**	**0.2124**	***	**-0.0546**	*
	(0.0012)		(0.0267)		(0.0374)		(0.0415)		(0.0299)	
8	**0.0009**		**1.0811**	***	**-0.1467**	***	**0.0652**		**-0.1834**	***
	(0.0012)		(0.0273)		(0.0382)		(0.0425)		(0.0306)	
9	**0.0023**	*	**0.9431**	***	**-0.2043**	***	**-0.1079**	**	**-0.1488**	***
	(0.0012)		(0.0279)		(0.0392)		(0.0435)		(0.0313)	
EFFICIENT	**0.0015**		**1.0377**	***	**-0.0728**	*	**-0.1739**	***	**-0.2175**	***
	(0.0013)		(0.0291)		(0.0407)		(0.0452)		(0.0326)	
SPREAD	**-0.0004**		**0.1012**		**0.3747**	***	**0.8824**	***	**0.1736**	**
	(0.0027)		(0.0627)		(0.0878)		(0.0975)		(0.0702)	

TABLE A.6

Benchmark-Adjusted Returns and Jensen's Alpha on the Fama-French and Carhart Factors: July 1980 through June 2003

Table A.6 reports mean excess returns (Mean) and the intercept (FF-Carhart) estimates. The mean excess returns are calculated as the time-series average of the portfolio excess returns. The benchmark-adjusted returns are calculated by subtracting the characteristics benchmark return from the stock's raw return. Jensen's alpha or the intercept is obtained from the following regression model:

$$BR = \alpha + \beta(RMRF) + s(SMB) + h(HML) + m(UMD) + \varepsilon$$

where *BR* is the weighted benchmark-adjusted return, *RMRF* is the market risk premium, *SMB* is the size premium, *HML* is the value premium, *UMD* is the momentum effect and α is the intercept. *RMRF* is calculated by subtracting the risk-free rate from the CRSP index return. *SMB* is the difference between the returns of small cap and large cap portfolios. *HML* is the difference between the returns of high book-to-market and low book-to-market portfolios and *UMD* is the difference between returns of last year's high return and low return portfolios. *SPREAD* is a zero-cost portfolio that takes a long position in the *INEFFICIENT* portfolio and short position in the *EFFICIENT* portfolio. Standard errors are in parentheses and *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Equally-Weighted				Value-Weighted			
ES Portfolios	Mean BR		FF-Carhart Alpha		Mean BR		FF-Carhart Alpha	
INEFFICIENT	**0.0072**	***	**0.0078**	***	**0.0026**	*	**0.0016**	
	(0.0013)		(0.0013)		(0.0019)		(0.0019)	
2	**0.0029**	***	**0.0038**	***	**-0.0017**		**-0.0014**	
	(0.0009)		(0.0009)		(0.0013)		(0.0013)	
3	**0.0020**	**	**0.0028**	***	**-0.0001**		**-0.0004**	
	(0.0009)		(0.0008)		(0.0010)		(0.0011)	
4	**0.0013**	*	**0.0020**	**	**0.0007**		**0.0009**	
	(0.0009)		(0.0008)		(0.0009)		(0.0009)	
5	**0.0016**	**	**0.0022**	***	**0.0013**	*	**0.0009**	
	(0.0010)		(0.0008)		(0.0008)		(0.0009)	
6	**0.0027**	***	**0.0031**	***	**0.0007**		**0.0011**	
	(0.0009)		(0.0007)		(0.0011)		(0.0011)	
7	**0.0032**	***	**0.0031**	***	**0.0006**		**0.0012**	
	(0.0008)		(0.0007)		(0.0007)		(0.0007)	
8	**0.0028**	***	**0.0033**	***	**0.0010**		**0.0012**	
	(0.0008)		(0.0008)		(0.0009)		(0.0010)	
9	**0.0021**	***	**0.0029**	***	**0.0011**	*	**0.0019**	**
	(0.0009)		(0.0008)		(0.0008)		(0.0008)	
EFFICIENT	**0.0043**	***	**0.0048**	***	**0.0008**		**0.0015**	
	(0.0011)		(0.0011)		(0.0009)		(0.0009)	
SPREAD	**0.0029**	***	**0.0031**	**	**0.0017**		**0.0001**	
	(0.0015)		(0.0015)		(0.0020)		(0.0021)	

TABLE A.7

The Raw Return Performance of Buy-and-Hold Strategies for Equally-Weighted *INEFFICIENT* and *EFFICIENT* Portfolios: 1980 through 2002

Table A.7 reports the cumulative returns of a 5-year buy-and-hold strategy of equally-weighted and value-weighted *INEFFICIENT* and *EFFICIENT* portfolios. At the beginning of each July of year *t*, all stocks are sorted into deciles based on their efficiency scores in descending order to form ten ES portfolios. The top decile portfolio is classified as the *EFFICIENT* portfolio and the bottom decile is classified as the *INEFFICIENT* portfolio. Firm assignment to each decile portfolio is unchanged for 5 years. The return in year t is calculated as the compounded return from July of year t to June of year *t+1*. The 5-year cumulative return is the sum of returns for year *t+1*, *t+2*, *t+3*, *t+4* and *t+5*. Returns are reported in decimals.

	Equally Weighted			Value Weighted		
Formation Year	(a) *INEFF.*	(b) *EFF.*	(a) > (b)	(c) *INEFF.*	(d) *EFF.*	(c) > (d)
1980	1.86	1.41	YES	1.12	0.85	YES
1981	2.09	1.21	YES	1.29	1.05	YES
1982	2.16	1.45	YES	1.75	1.43	YES
1983	0.83	0.36	YES	0.88	0.59	YES
1984	1.12	0.62	YES	1.01	0.95	YES
1985	0.90	0.37	YES	0.88	0.82	YES
1986	0.45	0.31	YES	0.65	0.37	YES
1987	0.37	0.35	YES	0.40	0.79	NO
1988	0.90	0.80	YES	0.89	0.74	YES
1989	1.02	0.80	YES	0.58	0.65	NO
1990	1.43	1.03	YES	0.88	0.49	YES
1991	1.92	1.15	YES	1.32	0.72	YES
1992	1.68	0.96	YES	1.01	1.08	NO
1993	1.55	1.01	YES	1.36	1.08	YES
1994	1.23	1.21	YES	1.20	1.46	NO
1995	1.19	1.29	NO	1.07	1.45	NO
1996	1.02	0.98	YES	0.89	1.04	NO
1997	1.16	0.79	YES	0.48	0.30	YES
1998	1.08	0.99	YES	0.03	0.20	NO
1999	1.59	1.10	YES	0.31	0.25	YES
2000	1.67	0.69	YES	0.19	0.02	YES
2001	1.57	0.50	YES	0.04	0.17	NO
2002	1.27	0.74	YES	0.42	0.23	YES
Average	1.31	0.87		0.81	0.73	

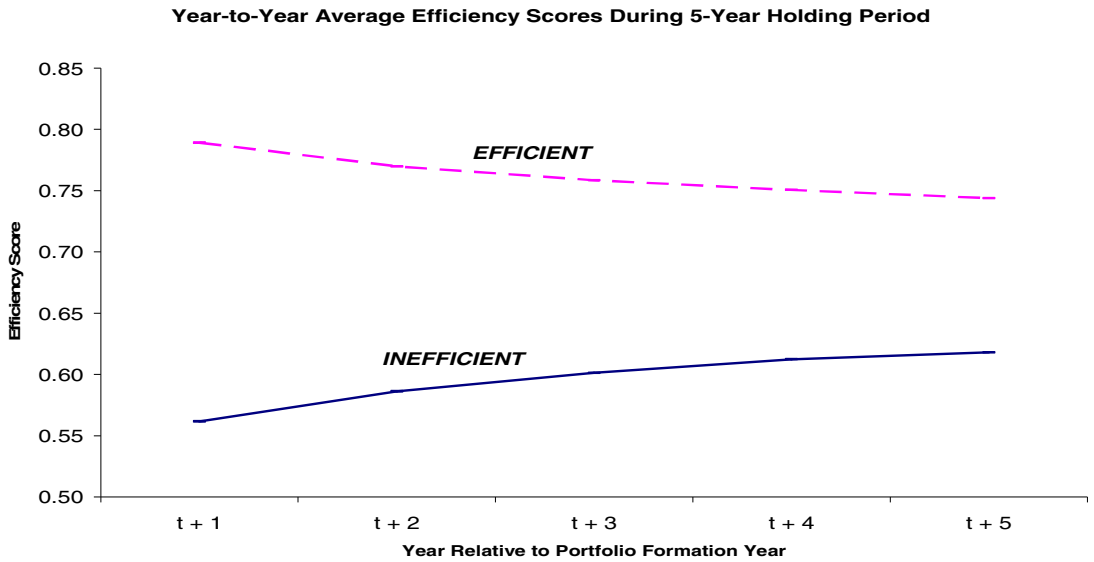
TABLE A.8

Average Parameter Values from Cross-Sectional Regressions of Monthly Returns on *Firm Size*, *Book-to-Market Ratio* and *Efficiency Score*

Table A.8 contains the results of Fama and MacBeth (1973) regressions. Monthly returns are regressed on *Size*, *Book-to-Market (B/M)* ratio and *Efficiency Score (ES*). Size is the market value of equity at the end of June of year *t*. Book-to-Market ratio is the ratio of book value of equity at the end of fiscal year *t-1* divided by the market value of equity at the end of December of calendar year *t-1*. Efficiency Score is computed as of July of year *t*. Average parameter values are time-series averages. Ln denotes natural logarithms. Time-series standard errors are in parentheses and *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Independent Variables	(a) *Size*		(b) *B/M*		(c)		(d) *ES*		(e)		Expected Sign
ln(Size)	**-0.0017**	***			**-0.0015**	***			**-0.0015**	***	-
	(0.0005)				(0.0006)				(0.0006)		
ln(B/M)			**0.0037**	***	**0.0019**	*			**-0.0013**		+
			(0.0011)		(0.0013)				(0.0029)		
Efficiency Score							**-0.0305**	***	**-0.0307**	**	-
							(0.0060)		(0.0184)		

Note: (c) = (a) + (b)
(e) = (c) + (d)



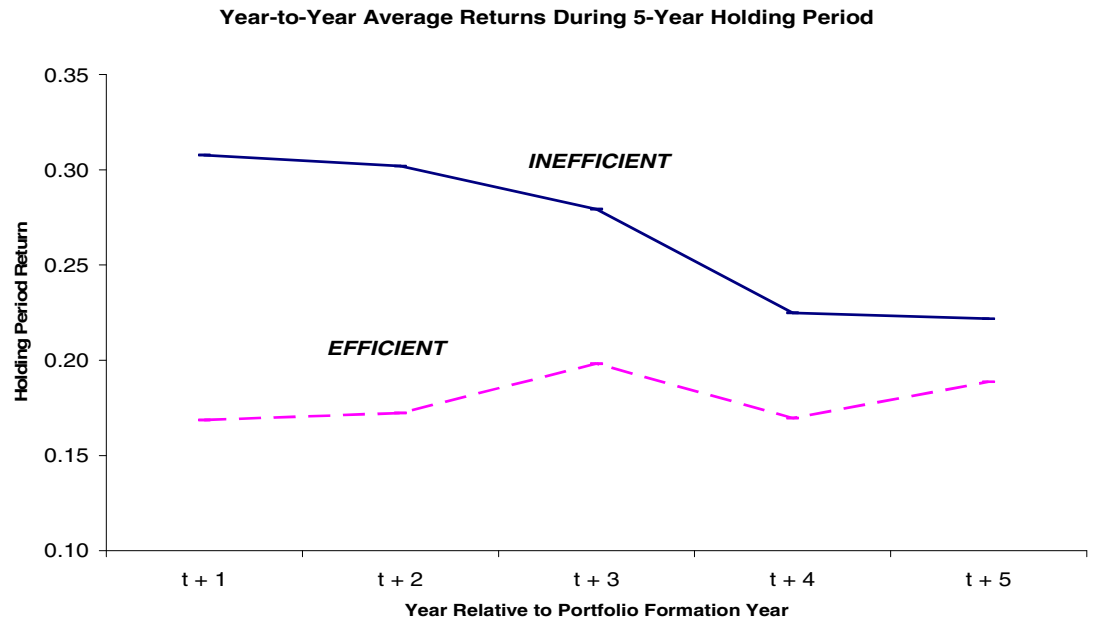


FIGURE A.1

The Average of Efficiency Score and Annual Return over a 5-year Holding Period for *INEFFICIENT* and *EFFICIENT* Portfolios

At the beginning of each July of year t, all stocks are sorted into deciles based on their efficiency scores in descending order to form ten ES portfolios. The top decile portfolio is classified as the *EFFICIENT* portfolio and the bottom decile is classified as the *INEFFICIENT* portfolio. Firm assignment to each decile portfolio is unchanged for 5 years. The portfolio efficiency scores and returns for years *t+1*, *t+2*, *t+3*, *t+4* and *t+5* are averaged across portfolio formation years. Efficiency scores and returns are expressed in decimals.

TABLE A.9

Sample Descriptive Statistics

This table presents characteristics of the forecast growth portfolios. Each mid-year, stocks are sorted first into tertiles on the basis of market capitalization (size), book-to-market ratio, analyst coverage (number of analysts reporting), and analyst disagreement (dispersion of forecasts), respectively, and then into quintiles of ascending growth forecasts. Portfolios are rebalanced annually. The mean, standard deviation, maximum, median and range of the double-sorted portfolios for the FY1G (FY2G) are contained in Panel A (B).

Panel A: FY1G Portfolios

	Size (in $ millions)				
FY1G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	4,990.31	16,957.23	334,237.20	1,316.68	4.91
2	7,768.81	21,008.27	398,104.80	2,128.61	22.68
3	7,359.79	22,883.74	475,003.20	1,784.31	19.69
4	4,644.41	17,706.92	507,216.70	1,157.81	5.57
High	2,475.50	7,661.15	207,430.80	707.26	5.76
All	5,449.00	18,130.27	507,216.70	1,305.45	4.91
	Book-to-Market				
FY1G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	0.7109	0.8351	21.1722	0.5714	0.0082
2	0.5553	0.5399	15.5327	0.4584	0.0007
3	0.5809	0.7530	20.6733	0.4734	0.0102
4	0.6318	0.6632	23.9322	0.5336	0.0016
High	0.7846	0.6360	11.4644	0.6644	0.0006
All	0.6527	0.6980	23.9322	0.5354	0.0006
	Analyst Coverage				
FY1G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	5	3	23	4	2
2	5	3	22	4	2
3	5	3	20	4	2
4	5	3	22	4	2
High	4	3	24	3	2
All	5	3	24	4	2
	Analyst Disagreement				
FY1G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	0.0092	0.0133	0.1580	0.0045	0.0000
2	0.0021	0.0045	0.0784	0.0008	0.0000
3	0.0018	0.0028	0.0446	0.0010	0.0000
4	0.0032	0.0056	0.1551	0.0018	0.0000
High	0.0098	0.0127	0.1603	0.0056	0.0000
All	0.0052	0.0096	0.1603	0.0019	0.0000

TABLE A.9 – Continued

Panel B: FY2G Portfolios

	Size (in $ millions)				
FY2G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	7,551.20	23,765.33	507,216.70	1,871.15	14.49
2	8,134.83	21,830.54	398,104.80	2,177.83	30.31
3	6,110.03	20,377.49	475,003.20	1,608.45	22.68
4	3,681.27	12,757.73	269,621.80	1,047.91	23.71
High	2,196.21	6,637.99	103,073.30	597.16	4.91
All	5,449.00	18,130.27	507,216.70	1,305.45	4.91

	Book-to-Market				
FY2G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	0.7015	0.8178	21.1722	0.5600	0.0080
2	0.5664	0.6784	16.2863	0.4565	0.0007
3	0.5808	0.6114	15.2369	0.4737	0.0102
4	0.6232	0.6654	20.6733	0.5265	0.0087
High	0.7669	0.7110	23.9322	0.6498	0.0006
All	0.6527	0.6980	23.9322	0.5354	0.0006

	Number of Analysts				
FY2G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	5	3	23	4	2
2	5	3	23	4	2
3	5	3	24	4	2
4	5	3	20	4	2
High	4	3	22	3	2
All	5	3	24	4	2

	Analyst Disagreement				
FY2G Portfolios	Mean	St. Dev.	Max.	Median	Min.
Low	0.0072	0.0130	0.1452	0.0022	0.0000
2	0.0023	0.0039	0.0648	0.0012	0.0000
3	0.0033	0.0043	0.0479	0.0019	0.0000
4	0.0051	0.0060	0.0770	0.0032	0.0000
High	0.0142	0.0162	0.1585	0.0093	0.0000
All	0.0064	0.0109	0.1585	0.0026	0.0000

TABLE A.10

Monthly Excess Return and Benchmark Adjusted Return Characteristics of FYR1G and FYR2G Portfolios formed on Analyst Growth Forecasts

Table A.10 presents the mean, standard deviation, maximum, median and minimum values of the forecast growth portfolios. Each mid-year, stocks are sorted into quintiles based on their consensus growth forecasts in descending order to form five growth portfolios. Portfolios are rebalanced annually. Value-weighted excess returns are computed for each quintile. Panel A and panel B report the excess returns for the five FYR1G and FYR2G portfolios, respectively. The spread portfolio is a zero-cost portfolio that has a long position in the lowest growth portfolio and a short position in the highest growth portfolio. The return series for the spread portfolio is the difference between the lowest growth portfolio return and the highest growth portfolio return. All returns are percent per month.

Panel A: Excess Returns for Fiscal Year 1 Growth Portfolios

Growth Portfolios	Mean		St. Dev.	Max	Med	Min
Lowest	0.0067	**	0.0507	0.1913	0.0087	-0.1981
2	0.0086	***	0.0457	0.1683	0.0118	-0.1811
3	0.0063	***	0.0424	0.1261	0.0087	-0.1900
4	0.0055	**	0.0455	0.1150	0.0095	-0.2193
Highest	0.0053	*	0.0541	0.1496	0.0057	-0.2472
SPREAD	0.0013		0.0342	0.1671	0.0008	-0.1493

Panel B: Excess Returns for Fiscal Year 2 Growth Portfolios

Growth Portfolios	Mean		St. Dev.	Max	Med	Min
Lowest	0.0098	***	0.0475	0.1489	0.0111	-0.1493
2	0.0077	***	0.0433	0.1234	0.0103	-0.2060
3	0.0056	**	0.0432	0.1275	0.0099	-0.1979
4	0.0043	*	0.0489	0.1535	0.0090	-0.2346
Highest	0.0058	**	0.0523	0.1216	0.0138	-0.2234
SPREAD	0.0040	**	0.0334	0.0895	0.0042	-0.1401

*, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

TABLE A.11

Excess Returns on Fama-French and Carhart Factors

Table A.11 presents Jensen's alphas and factor loading estimates from the following regression model:

$$ER = \alpha + b_{p1}(RMRF) + b_{p2}(SMB) + b_{p3}(HML) + b_{p4}(UMD) + e$$

where ER is the portfolio return less the risk-free rate, RMRF is the market risk premium, SMB is the size premium, HML is the value premium, RR1YR is the momentum effect and α is the intercept. RMRF is calculated by subtracting the risk-free rate from the CRSP index return. SMB is the difference between the returns of small cap and large cap portfolios. HML is the difference between the returns of high book-to-market and low book-to-market portfolios and UMD is the difference between returns of last year's high return and low return portfolios. Spread is a zero-cost portfolio that takes a long position in the low growth portfolio and short position in the high growth portfolio. Panel A reports estimates for the FYR1G portfolios and Panel B presents results for the FYR2G portfolios.

Panel A: FYR1G Portfolios

	Independent Variables									
Growth Portfolios	Alpha		RMRF		SMB		HML		UMD	
Lowest	**0.0021**		**0.9929**	***	**-0.0915**	*	**0.2061**	***	**-0.2138**	***
	(1.37)		(27.77)		(-1.92)		(3.68)		(-5.20)	
2	**0.0044**	***	**0.9293**	***	**-0.3325**	***	**0.0058**		**-0.1351**	***
	(3.69)		(32.83)		(-8.81)		(0.13)		(-4.15)	
3	**0.0014**		**0.8924**	***	**-0.3314**	***	**0.1152**	***	**-0.0484**	
	(1.33)		(33.92)		(-9.45)		(2.79)		(-1.60)	
4	**-0.0016**		**1.0031**	***	**-0.1521**	***	**0.3891**	***	**0.0528**	
	(-1.31)		(35.16)		(-4.00)		(8.70)		(1.61)	
Highest	**-0.0026**	*	**1.1376**	***	**0.0799**		**0.4762**	***	**-0.0010**	
	(-1.66)		(30.26)		(1.59)		(8.08)		(-0.02)	
SPREAD	**0.0047**	**	**-0.1446**	***	**-0.1714**	**	**-0.2700**	***	**-0.2127**	***
	(2.02)		(-2.62)		(-2.33)		(-3.12)		(-3.35)	

TABLE A.11 - Continued

Panel B: FYR2G Portfolios

	Independent Variables									
Growth Portfolios	Alpha		RMRF		SMB		HML		UMD	
Lowest	**0.0048**	***	**0.9774**	***	**-0.2496**	***	**0.0354**		**-0.1691**	***
	(4.06)		(35.19)		(-6.59)		(0.81)		(-5.29)	
2	**0.0026**	**	**0.9028**	***	**-0.3844**	***	**0.0404**		**-0.0903**	***
	(2.46)		(35.62)		(-11.12)		(1.01)		(-3.10)	
3	**-0.0000**		**0.9197**	***	**-0.2573**	***	**0.2224**	***	**-0.0850**	***
	(-0.01)		(36.13)		(-7.41)		(5.54)		(-2.90)	
4	**-0.0030**	**	**1.0324**	***	**-0.1179**	**	**0.3737**	***	**-0.0193**	
	(-2.08)		(29.93)		(-2.51)		(6.87)		(-0.49)	
Highest	**-0.0031**	***	**1.1044**	***	**0.1553**	***	**0.4967**	***	**0.0462**	
	(-2.01)		(30.01)		(3.10)		(8.56)		(1.09)	
SPREAD	**0.0080**	***	**-0.1270**	***	**-0.4050**	***	**-0.4613**	***	**-0.2154**	***
	(3.81)		(-2.59)		(-6.06)		(-5.97)		(-3.82)	

*, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

TABLE A.12

Benchmark-Adjusted Returns and Jensen's Alpha on the Fama-French and Carhart Factors

Table A.12 reports mean excess returns (Mean) and the intercept (FF-Carhart) estimates. The mean excess returns are calculated as the time-series average of the portfolio excess returns. The benchmark-adjusted returns are calculated by subtracting the characteristics benchmark return from the stock's raw return. Jensen's alpha or the intercept is obtained from the following regression model:

$$BR = a_{p0} + b_{p1}(RMRF) + b_{p2}(SMB) + b_{p3}(HML) + b_{p4}(UMD) + e$$

where BR is the weighted benchmark-adjusted return, RMRF is the market risk premium, SMB is the size premium, HML is the value premium, RR1YR is the momentum effect and α is the intercept. RMRF is calculated by subtracting the risk-free rate from the CRSP index return. SMB is the difference between the returns of small cap and large cap portfolios. HML is the difference between the returns of high book-to-market and low book-to-market portfolios and UMD is the difference between returns of last year's high return and low return portfolios. Spread is a zero-cost portfolio that takes a long position in the low growth portfolio and a short position in the high growth portfolio. T-stats are in parentheses.

	FYR1G				FYR2G			
Growth Portfolios	Mean BR		FF-Carhart Alpha		Mean BR		FF-Carhart Alpha	
Lowest	**0.0008**		**0.0014**		**0.0026**	***	**0.0036**	***
	(0.77)		(1.27)		(3.13)		(4.06)	
2	**0.0024**	***	**0.0033**	***	**0.0005**		**0.0014**	*
	(2.81)		(3.70)		(0.71)		(1.88)	
3	**-0.0004**		**0.0000**		**-0.0008**		**-0.0004**	
	(-0.54)		(0.08)		(-1.16)		(-0.57)	
4	**-0.0011**		**-0.0020**	**	**-0.0023**	**	**-0.0027**	***
	(-1.21)		(-2.17)		(2.28)		(-2.68)	
Highest	**-0.0017**		**-0.0023**	*	**-0.0019**	*	**-0.0029**	**
	(-1.35)		(-1.91)		(-1.58)		(-2.45)	
SPREAD	**0.0025**	*	**0.0038**	**	**0.0045**	***	**0.0065**	***
	(1.59)		(2.26)		(2.84)		(4.10)	

TABLE A.13

Excess Returns and Jensen's Alpha on the 4-Factors and Industry Momentum

Table A.13 reports Jensen's alphas after controlling for the 4-factors and industry momentum. Jensen's alpha or the intercept is obtained from the following regression model:

$$ER = a_{p0} + b_{p1}(RMRF) + b_{p2}(SMB) + b_{p3}(HML) + b_{p4}(UMD) + i(IND) + e$$

where ER is the weighted excess return, RMRF is the market risk premium, SMB is the size premium, HML is the value premium, RR1YR is the momentum effect and α is the intercept. RMRF is calculated by subtracting the risk-free rate from the CRSP index return. SMB is the difference between the returns of small cap and large cap portfolios. HML is the difference between the returns of high book-to-market and low book-to-market portfolios and UMD is the difference between returns of last year's high return and low return portfolios. IND is the industry momentum factor and is computed as the difference between the returns of last year's high return industries and low return industries. Spread is a zero-cost portfolio that takes a long position in the low growth portfolio and short position in the high growth portfolio. T-stats are in parentheses and *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: FYR1G Portfolios

	Independent Variables													
Growth Portfolios	Alpha		RMRF		SMB		HML		UMD		IND	
Lowest	**0.0020**		**0.9939**	***	**-0.0923**	*	**0.2116**	***	**-0.2182**	***	**0.0303**	
	(1.33)		(27.72)		(-1.93)		(3.71)		(-5.20)		(0.54)	
2	**0.0047**	***	**0.9240**	***	**-0.3279**	***	**-0.0237**		**-0.1115**	***	**-0.1641**	***
	(4.03)		(33.56)		(-8.94)		(-0.54)		(-3.46)		(-3.80)	
3	**0.0015**		**0.8908**	***	**-0.3307**	***	**0.1063**	***	**-0.0413**		**-0.0492**	
	(1.40)		(33.84)		(-9.41)		(2.54)		(-1.34)		(-1.19)	
4	**-0.0014**		**0.9997**	***	**-0.1491**	***	**0.3701**	***	**0.0679**	**	**-0.1055**	**
	(-1.18)		(35.36)		(-3.96)		(8.23)		(2.05)		(-2.38)	
Highest	**-0.0025**		**1.1340**	***	**0.0829**	*	**0.4564**	***	**0.0146**		**-0.1096**	*
	(-1.56)		(30.29)		(1.66)		(7.66)		(0.34)		(-1.87)	
Spread	**0.0045**	*	**-0.1400**	**	**-0.1753**	**	**-0.2448**	***	**-0.2328**	***	**0.1400**	
	(1.92)		(-2.55)		(-2.39)		(-2.79)		(-3.61)		(1.62)	

TABLE A.13 - Continued

Panel B: FYR2G Portfolios

	Independent Variables													
Growth Portfolios	Alpha		RMRF		SMB		HML		UMD		IND	
Lowest	**0.0047**	***	**0.9779**	***	**-0.2504**	***	**0.0429**		**-0.1766**	***	**0.0465**	
	(3.98)		(35.21)		(-6.61)		(0.97)		(-5.40)		(1.07)	
2	**0.0029**	***	**0.9012**	***	**-0.3820**	***	**0.0169**		**-0.0670**	**	**-0.1445**	***
	(2.78)		(36.51)		(-11.35)		(0.43)		(-2.30)		(-3.72)	
3	**0.0000**	*	**0.9191**	***	**-0.2564**	***	**0.2134**	***	**-0.0759**	**	**-0.0559**	
	(0.08)		(36.17)		(-7.40)		(5.26)		(-2.54)		(-1.10)	
4	**-0.0027**	*	**1.0305**	***	**-0.1150**	**	**0.3460**	***	**0.0082**		**-0.1707**	***
	(-1.90)		(30.45)		(-2.49)		(6.40)		(0.21)		(-3.21)	
Highest	**-0.0028**	*	**1.1022**	***	**0.1586**	***	**0.4644**	***	**0.0784**	*	**-0.1992**	***
	(-1.81)		(30.66)		(3.24)		(8.09)		(1.85)		(-3.52)	
Spread	**0.0075**	***	**-0.1243**	***	**-0.4091**	***	**-0.4214**	***	**-0.2551**	***	**0.2457**	***
	(3.66)		(-2.59)		(-6.25)		(-5.49)		(-4.51)		(3.25)	

TABLE A.14

Excess Returns on Fama-French and Carhart Factors for Size and Growth Forecast Double Sort Portfolios

Table A.14 presents Jensen's alphas and factor loading estimates from the following regression model:

$$ER = a_{p0} + b_{p1}(RMRF) + b_{p2}(SMB) + b_{p3}(HML) + b_{p4}(UMD) + e$$

where ER is the return of the double sort portfolio less the risk-free rate, RMRF is the market risk premium, SMB is the size premium, HML is the value premium, RR1YR is the momentum effect and α is the intercept. RMRF is calculated by subtracting the risk-free rate from the CRSP index return. SMB is the difference between the returns of small cap and large cap portfolios. HML is the difference between the returns of high book-to-market and low book-to-market portfolios and UMD is the difference between returns of last year's high return and low return portfolios. Spread is a zero-cost portfolio that takes a long position in the low growth portfolio and short position in the high growth portfolio. Panel A reports estimates for the FY1G portfolios and Panel B presents results for the FY2G portfolios.

Panel A: FY1G Portfolios

		FY1G									
Size	Growth	Alpha		RMRF		SMB		HML		UMD	
1(small)	1 (low)	**0.0043**	*	**0.9993**	***	**0.8176**	***	**0.2714**	***	**-0.0527**	
		(1.72)		(17.18)		(10.54)		(2.98)		(-0.79)	
	2	**0.0039**	*	**1.0560**	***	**0.5338**	***	**0.4062**	***	**-0.0289**	
		(1.93)		(22.71)		(8.61)		(5.57)		(-0.54)	
	3	**0.0018**		**0.9928**	***	**0.5069**	***	**0.2492**	***	**0.0375**	
		(1.11)		(26.69)		(10.22)		(4.27)		(0.88)	
	4	**-0.0021**		**1.0419**	***	**0.5854**	***	**0.3748**	***	**0.0101**	
		(-1.06)		(22.69)		(9.56)		(5.21)		(0.19)	
	5 (high)	**-0.0020**		**1.2713**	***	**0.7221**	***	**0.5222**	***	**0.0563**	
		(-0.81)		(22.42)		(9.55)		(5.87)		(0.86)	
	SPREAD	**0.0063**	**	**-0.2720**	***	**0.0956**		**-0.2508**	**	**-0.1090**	
		(2.01)		(-3.74)		(0.99)		(-2.20)		(-1.30)	
3(large)	1 (low)	**0.0031**	**	**0.9782**	***	**-0.1974**	***	**0.1688**	***	**-0.1832**	***
		(2.07)		(28.09)		(-4.25)		(3.09)		(-4.57)	
	2	**0.0047**	**	**0.9105**	***	**-0.4228**	***	**0.0178**		**-0.1150**	***
		(3.14)		(26.26)		(-9.15)		(0.33)		(-2.88)	
	3	**0.0022**		**0.8733**	***	**-0.4011**	***	**-0.0012**		**-0.0393**	
		(1.54)		(26.77)		(-9.22)		(-0.02)		(-1.05)	
	4	**-0.0006**		**0.9628**	***	**-0.2985**	***	**0.2373**	***	**-0.0734**	**
		(-0.43)		(32.60)		(-7.58)		(5.12)		(-2.16)	
	5 (high)	**-0.0022**		**1.0747**	***	**-0.0953**	**	**0.4483**	***	**0.0466**	
		(-1.56)		(32.91)		(-2.19)		(8.76)		(1.24)	
	SPREAD	**0.0053**	**	**-0.0964**	*	**-0.1022**		**-0.2795**	***	**-0.2297**	***
		(2.42)		(-1.90)		(-1.51)		(-3.51)		(-3.93)	

TABLE A.14 - Continued

Panel B: FY2G Portfolios

		FY2G										
Size	Growth	Alpha		RMRF		SMB		HML		UMD		
1(small)	1 (low)	**0.0081**	***	**0.8922**	***	**0.5990**	***	**0.1082**		**0.0240**		
		(3.38)		(16.14)		(7.95)		(1.24)		(0.38)		
	2	**0.0077**	***	**0.9128**	***	**0.5163**	***	**0.1176**	**	**0.0003**		
		(5.03)		(25.57)		(10.61)		(2.09)		(0.01)		
	3	**0.0002**		**1.0771**	***	**0.6301**	***	**0.1836**	***	**0.0127**		
		(0.13)		(26.24)		(11.26)		(2.84)		(0.27)		
	4	**-0.0047**	***	**1.1689**	***	**0.7139**	***	**0.4938**	***	**0.0144**		
		(-2.46)		(26.53)		(11.88)		(7.11)		(0.27)		
	5 (high)	**-0.0037**		**1.2256**	***	**0.7331**	***	**0.3534**	***	**0.0739**		
		(1.43)		(20.23)		(8.87)		(3.70)		(1.06)		
	SPREAD	**0.0118**	***	**-0.3334**	***	**-0.1342**		**-0.2453**	**	**-0.0499**		
		(3.73)		(-4.54)		(-1.34)		(-2.12)		(-0.59)		
3(large)	1 (low)	**0.0056**	***	**1.0123**	***	**-0.3098**	***	**-0.0110**		**-0.1967**	***	
		(3.84)		(30.09)		(-6.75)		(-0.21)		(-5.08)		
	2	**0.0042**	***	**0.8897**	***	**-0.4432**	***	**-0.0432**		**-0.1246**	***	
		(3.29)		(30.04)		(-10.97)		(-0.92)		(-3.65)		
	3	**0.0002**		**0.8296**	***	**-0.3677**	***	**0.1125**	**	**-0.0442**		
		(0.15)		(23.57)		(-7.66)		(2.03)		(-1.09)		
	4	**-0.0007**		**1.0062**	***	**-0.2989**	***	**0.2961**	***	**-0.0701**	**	
		(-0.62)		(35.93)		(-7.83)		(6.70)		(-2.17)		
	5 (high)	**-0.0031**	**	**1.0725**	***	**-0.0370**		**0.4626**	***	**-0.0223**		
		(-2.26)		(33.28)		(-0.84)		(9.10)		(-0.60)		
	SPREAD	**0.0087**	***	**-0.0602**		**-0.2728**	***	**-0.4736**	***	**-0.1744**	***	
		(3.97)		(-1.18)		(-3.93)		(-5.90)		(-2.97)		

TABLE A.15

Excess Returns on Fama-French and Carhart Factors for B/M and Growth Forecast Double Sort Portfolios

Table A.15 presents Jensen's alphas and factor loading estimates from the following regression model:

$$ER = a_{p0} + b_{p1}(RMRF) + b_{p2}(SMB) + b_{p3}(HML) + b_{p4}(UMD) + e$$

where ER is the return of the double sort portfolio less the risk-free rate, RMRF is the market risk premium, SMB is the size premium, HML is the value premium, RR1YR is the momentum effect and α is the intercept. RMRF is calculated by subtracting the risk-free rate from the CRSP index return. SMB is the difference between the returns of small cap and large cap portfolios. HML is the difference between the returns of high book-to-market and low book-to-market portfolios and UMD is the difference between returns of last year's high return and low return portfolios. Spread is a zero-cost portfolio that takes a long position in the low growth portfolio and short position in the high growth portfolio. Panel A reports estimates for the FY1G portfolios and Panel B presents results for the FY2G portfolios.

Panel A: FY1G Portfolios

		FY1G				
B/M	Growth	Alpha	RMRF	SMB	HML	UMD
1(low)	1 (low)	**0.0046** **	**1.0366***	**-0.2553** ***	**-0.2158** ***	**-0.4301** ***
		(2.35)	(22.82)	(-4.22)	(-3.03)	(-8.23)
	2	**0.0054** ***	**0.9355***	**-0.4452** ***	**-0.0911**	**-0.0473**
		(2.93)	(21.64)	(-7.72)	(-1.34)	(-0.95)
	3	**0.0020**	**0.9041***	**-0.4070** ***	**-0.2265** ***	**-0.1294** ***
		(1.15)	(22.18)	(-7.49)	(-3.54)	(-2.76)
	4	**-0.0021**	**0.9747***	**-0.1412** ***	**0.1356** **	**-0.1167** **
		(-1.21)	(23.91)	(-2.60)	(2.12)	(-2.49)
	5 (high)	**-0.0062** ***	**1.1666***	**0.0491**	**0.2967** ***	**-0.0357**
		(-2.51)	(20.20)	(0.64)	(3.28)	(-0.54)
	SPREAD	**0.0108** ***	**-0.1298***	**-0.3044** ***	**-0.5125** ***	**-0.3944** ***
		(3.29)	(-1.70)	(-2.98)	(-4.27)	(-4.48)
3(high)	1 (low)	**0.0011**	**1.0706***	**0.1500** **	**0.6906** ***	**-0.0478**
		(0.47)	(20.35)	(2.14)	(8.37)	(-0.79)
	2	**0.0009**	**0.8638***	**-0.1734** ***	**0.7456** ***	**0.2582** ***
		(0.55)	(21.52)	(-3.24)	(-11.85)	(5.59)
	3	**0.0019**	**0.8558***	**-0.2043** ***	**0.6512** ***	**0.2135** ***
		(1.19)	(23.28)	(-4.17)	(11.30)	(5.05)
	4	**0.0007**	**0.9261***	**-0.0233**	**0.7176** ***	**0.1836** ***
		(0.49)	(26.56)	(-0.50)	(13.13)	(4.58)
	5 (high)	**-0.0022**	**1.1445***	**0.1797** **	**0.6965** ***	**0.1281** **
		(-0.95)	(21.33)	(2.51)	(8.28)	(2.08)
	SPREAD	**0.0033**	**-0.073**	**-0.0297**	**-0.0059**	**-0.1759** *
		(0.97)	(-0.95)	(-0.29)	(-0.05)	(-1.96)

TABLE A.15 - Continued

Panel B: FY2G Portfolios

		FY2G									
B/M	Growth	Alpha		RMRF		SMB		HML		UMD	
1(low)	1 (low)	**0.0082**	***	**1.1161**	***	**-0.3727**	***	**-0.4639**	***	**-0.4014**	***
		(3.84)		(22.43)		(-5.49)		(-5.91)		(-7.01)	
	2	**0.0055**	***	**0.9091**	***	**-0.4188**	***	**-0.2391**	***	**-0.2290**	***
		(3.13)		(22.20)		(-7.49)		(-3.70)		(-4.85)	
	3	**-0.0004**		**0.8487**	***	**-0.2441**	***	**-0.0361**		**-0.0730**	
		(-0.17)		(17.02)		(-3.59)		(-0.46)		(-1.27)	
	4	**-0.0038**	***	**1.0304**	***	**-0.1756**	***	**0.1281**	**	**-0.1827**	***
		(-2.20)		(25.46)		(-3.18)		(2.01)		(-3.92)	
	5 (high)	**-0.0071**	***	**1.1869**	***	**0.2508**	***	**0.0055**		**-0.3073**	***
		(-2.75)		(19.82)		(3.07)		(0.06)		(-4.46)	
	SPREAD	**0.0153**	***	**-0.0708**		**-0.6236**	***	**-0.4694**	***	**-0.0942**	
		(4.79)		(-0.96)		(-6.17)		(-4.01)		(-1.10)	
3(high)	1 (low)	**0.0025**		**0.9622**	***	**-0.0887**		**0.6497**	***	**0.1266**	***
		(1.37)		(22.80)		(-1.54)		(9.76)		(2.61)	
	2	**-0.0006**		**0.8451**	***	**-0.2026**	***	**0.7202**	***	**0.2006**	***
		(-0.34)		(22.19)		(-3.90)		(11.99)		(4.58)	
	3	**-0.0007**		**0.9018**	***	**-0.1344**	***	**0.6912**	***	**0.1793**	***
		(-0.44)		(26.38)		(-2.88)		(12.82)		(4.55)	
	4	**-0.0002**		**0.9966**	***	**0.0249**		**0.5728**	***	**0.0099**	
		(-0.12)		(25.52)		(0.47)		(9.30)		(0.22)	
	5 (high)	**-0.0026**		**1.1130**	***	**0.2070**	***	**0.6850**	***	**0.1075**	*
		(-1.21)		(21.98)		(3.00)		(8.57)		(1.84)	
	SPREAD	**0.0051**	*	**-0.1509**	**	**-0.2956**	***	**-0.0353**		**0.0191**	
		(1.81)		(-2.29)		(-3.29)		(-0.34)		(0.25)	

TABLE A.16

Sample Descriptive Statistics: from quarter 1 of year 1989 to quarter 4 of year 2004

Table A.16 presents sample descriptive statistics. Panel A shows statistics for firm characteristics and panel B reports statistics for the state variables. The statistics include mean (Mean), standard deviation (St. Dev.), maximum value (Max), median (Med) and minimum value (Min). The data is gathered from the COMPUSTAT QUARTERLY database. The units of measurement are in millions of dollars. The statistics are obtained from pooled data of 46,759 firm-quarter observations.

Panel A: Descriptive Statistics for Firm Characteristics

	Mean	St. Dev.	Max	Med	Min
Market Equity	4,156.25	15,396.88	484,323.80	816.61	10.03
Book Equity	1,620.95	4,857.50	110,821.00	388.47	4.41
Sales	0.96	3.01	73.83	0.20	0.00
Total Assets	8.06	41.08	1,484.10	0.92	0.01
Capital Expenditures	0.17	0.81	33.14	0.02	0.00
R&D Expenditures	0.02	0.13	6.51	0.00	0.00
Adv. Expenditures	0.01	0.06	1.30	0.00	0.00
EBITDA	0.16	0.65	16.09	0.02	-2.73
Net Income	0.05	0.46	17.65	0.01	-54.24

Panel B: Descriptive Statistics for State Variables (Untransformed)

	Mean	St. Dev.	Max	Med	Min
Stock Return	0.0394	0.2511	6.6697	0.0281	-0.9473
Efficiency Score	0.7323	0.0830	0.9223	0.7456	0.1276
Return on Equity	0.0204	0.0715	1.7861	0.0297	-0.9891
Growth Forecast	0.0262	0.0659	1.5400	0.0128	-0.1936

TABLE A.17

Parameter Estimates and Variance-Covariance Matrix for the VAR

Table A.17 reports parameter estimates and variance-covariance matrix for the VAR. For each cross-section, we regress each of the state variables against the lag of the other variables and its own lag. The time series mean of parameter estimates for each variable is used as the estimate in the VAR. *r* is the log of stock return, *s* is the efficiency score, *roe* is the log of return on equity and *fyg* is the log of consensus growth forecasts. Panel A shows the estimates for the VAR along with the variance-covariance matrix of the residuals. Panel B reports the variance decomposition for the VAR. Robust jackknife standard errors are in parentheses and are computed using a jackknife method outlined by Shao and Rao (1993). *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Transition Matrix and Variance-Covariance Matrix

	r_{t-1}		s_{t-1}		roe_{t-1}		fyg_{t-1}	
r_t	**0.0095**		**-0.2008**	***	**0.3035**	***	**-0.1395**	***
	(0.0586)		(0.0441)		(0.0679)		(0.0542)	
s_t	**-0.0063**	***	**0.9001**	***	**0.0632**	***	**-0.0148**	
	(0.0024)		(0.0235)		(0.0078)		(0.0103)	
roe_t	**0.0247**	***	**0.1814**	***	**0.2912**	***	**-0.1113**	***
	(0.0041)		(0.0154)		(0.0335)		(0.0290)	
fyg_t	**0.0127**	***	**-0.0186**	*	**-0.0178**		**0.7837**	***
	(0.0018)		(0.0106)		(0.0158)		(0.0392)	

	r_t		s_t		roe_t		fyg_t	
r_t	**0.0415**	***						
	(0.0033)							
s_t	**0.0048**	***	**0.0015**	***				
	(0.0004)		(0.0001)					
roe_t	**0.0026**	***	**-0.0004**	***	**0.0064**	***		
	(0.0004)		(0.0001)		(0.0007)			
fyg_t	**0.0008**	***	**0.0001**	***	**0.0000**		**0.0008**	***
	(0.0001)		(0.0000)		(0.0001)		(0.0001)	

Panel B: Variance Decomposition

	Ncf		Nr	
Ncf	**0.0369**	***		
	(0.0031)			
Nr	**-0.0009**	***	**0.0026**	***
	(0.0002)		(0.0002)	

TABLE A.18

Regression of Consensus Growth Forecast Shock Against Firm-Level Cash Flow News and Expected Return News

Table A.18 presents variance decompositions by local groups and growth forecasts shock responses to cash flow news and expected return news. The variance decomposition assumes that all groups share the same transition matrix. The responses are based on the following regression

$$ufyg_{i,t} = b + c(Ncf_{i,t}) + d(Nr_{i,t}) + e_{i,t}$$

where *ufyg* is the difference between actual and predicted growth forecast, *Ncf* is the cash flow news and *Nr* is the expected return news. Parameter estimates *c* and *d* measure the relation between growth forecast shock and cash flow news and expected return news, respectively. Robust jackknife standard errors are in parentheses and are computed using a jackknife method outlined by Shao and Rao (1993). Standard errors from the panel regression are in brackets. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Responses to News for All Firms

					Coefficients			
	Var(Ncf)		Var(Nr)		c		d	
All Firms	**0.0369**	***	**0.0026**	***	**0.0078**	***	**0.1522**	***
	(0.0031)		(0.0002)		[0.0006]		[0.0028]	

Panel B: Responses to News By Size Quintile

					Coefficients			
Size	Var(Ncf)		Var(Nr)		c		d	
Small	**0.0619**	***	**0.0050**	***	**0.0093**	***	**0.1703**	***
	(0.0046)		(0.0004)		[0.0020]		[0.0093]	
2	**0.0457**	***	**0.0032**	***	**0.0078**	***	**0.1485**	***
	(0.0035)		(0.0003)		[0.0013]		[0.0064]	
3	**0.0357**	***	**0.0026**	***	**0.0080**	***	**0.1337**	***
	(0.0036)		(0.0002)		[0.0011]		[0.0060]	
4	**0.0256**	***	**0.0018**	***	**0.0068**	***	**0.1601**	***
	(0.0031)		(0.0002)		[0.0011]		[0.0062]	
Large	**0.0170**	***	**0.0014**	***	**0.0073**	***	**0.1077**	***
	(0.0016)		(0.0002)		[0.0009]		[0.0045]	

Panel C: Responses to News By B/M Quintile

					Coefficients			
B/M	Var(Ncf)		Var(Nr)		c		d	
Low	**0.0306**	***	**0.0021**	***	**0.0061**	***	**0.1042**	***
	(0.0024)		(0.0002)		[0.0009]		[0.0049]	
2	**0.0283**	***	**0.0019**	***	**0.0055**	***	**0.1074**	***
	(0.0019)		(0.0002)		[0.0012]		[0.0059]	
3	**0.0295**	***	**0.0019**	***	**0.0073**	***	**0.1184**	***
	(0.0021)		(0.0002)		[0.0013]		[0.0068]	
4	**0.0326**	***	**0.0024**	***	**0.0057**	***	**0.1496**	***
	(0.0034)		(0.0002)		[0.0015]		[0.0076]	
High	**0.0455**	***	**0.0040**	***	**0.0121**	***	**0.2308**	***
	(0.0054)		(0.0004)		[0.0019]		[0.0081]	

TABLE A.18 - Continued

Panel D: Responses to News By Dispersion Quintile

Dispersion	Var(Ncf)		Var(Nr)		Coefficients c		Coefficients d	
Low	**0.0288**	***	**0.0014**	***	**0.0041**	***	**0.0664**	***
	(0.0023)		(0.0001)		[0.0007]		[0.0048]	
2	**0.0333**	***	**0.0020**	***	**0.0042**	***	**0.0560**	***
	(0.0029)		(0.0002)		[0.0008]		[0.0046]	
3	**0.0345**	***	**0.0022**	***	**0.0053**	***	**0.1114**	***
	(0.0028)		(0.0002)		[0.0011]		[0.0057]	
4	**0.0388**	***	**0.0029**	***	**0.0107**	***	**0.1387**	***
	(0.0035)		(0.0003)		[0.0014]		[0.0067]	
High	**0.0440**	***	**0.0045**	***	**0.0126**	***	**0.2665**	***
	(0.0043)		(0.0004)		[0.0021]		[0.0083]	

Panel E: Responses to News By Coverage Quintile

Coverage	Var(Ncf)		Var(Nr)		Coefficients c		Coefficients d	
Low	**0.0247**	***	**0.0021**	***	**0.0053**	***	**0.1249**	***
	(0.0018)		(0.0002)		[0.0012]		[0.0059]	
2	**0.0325**	***	**0.0024**	***	**0.0087**	***	**0.1307**	***
	(0.0025)		(0.0002)		[0.0014]		[0.0071]	
3	**0.0322**	***	**0.0027**	***	**0.0052**	***	**0.1134**	***
	(0.0022)		(0.0003)		[0.0013]		[0.0063]	
4	**0.0372**	***	**0.0026**	***	**0.0058**	***	**0.1708**	***
	(0.0029)		(0.0002)		[0.0014]		[0.0072]	
High	**0.0514**	***	**0.0035**	***	**0.0102**	***	**0.1745**	***
	(0.0060)		(0.0004)		[0.0014]		[0.0070]	

TABLE A.19

Regression of Consensus Growth Forecast Shock Against Firm-Level and Aggregate Cash Flow News and Expected Return News

Table A.19 presents growth forecasts shock responses to firm level and aggregate cash flow and expected return news. The responses are based on the following regression

$$ufyg_{i,t} = b + c(Ncf_{i,t}) + d(Nr_{i,t}) + \gamma(ANcf_t) + \lambda(ANr_t) + e_{i,t}$$

where *ufyg* is the difference between actual and predicted growth forecast, *Ncf* is the firm level cash flow news, *Nr* is the firm level expected return news, *ANcf* is the aggregate cash flow news and *ANr* is the aggregate expected return news. Standard errors from the panel regression are in brackets. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Responses to News for All Firms

	c		d		γ		λ	
All Firms	**0.0048**	***	**0.1542**	***	**0.0267**	***	**0.0212**	***
	[0.0006]		[0.0028]		[0.0044]		[0.0019]	

Panel B: Responses to News By Size Quintile

Size	c		d		γ		λ	
Small	**0.0064**	***	**0.1728**	***	**0.0536**	***	**0.0203**	**
	[0.0023]		[0.0093]		[0.0198]		[0.0082]	
2	**0.0055**	***	**0.1502**	***	**0.0379**	***	**0.0167**	***
	[0.0014]		[0.0064]		[0.0115]		[0.0051]	
3	**0.0053**	***	**0.1352**	***	**0.0228**	***	**0.0183**	***
	[0.0013]		[0.0060]		[0.0089]		[0.0041]	
4	**0.0028**	**	**0.1625**	***	**0.0168**	**	**0.0234**	***
	[0.0013]		[0.0062]		[0.0077]		[0.0035]	
Large	**0.0027**	***	**0.1105**	***	**0.0125**	***	**0.0227**	***
	[0.0010]		[0.0045]		[0.0054]		[0.0025]	

Panel C: Responses to News By B/M Quintile

B/M	c		d		γ		λ	
Low	**0.0032**	***	**0.1038**	***	**0.0079**		**0.0185**	***
	[0.0011]		[0.0048]		[0.0062]		[0.0029]	
2	**0.0028**	**	**0.1080**	***	**0.0174**	**	**0.0164**	***
	[0.0013]		[0.0058]		[0.0076]		[0.0035]	
3	**0.0049**	***	**0.1204**	***	**0.0172**	**	**0.0151**	***
	[0.0014]		[0.0068]		[0.0081]		[0.0037]	
4	**0.0009**		**0.1542**	***	**0.0308**	***	**0.0283**	***
	[0.0016]		[0.0076]		[0.0102]		[0.0044]	
High	**0.0046**	**	**0.2387**	***	**0.0769**	***	**0.0445**	***
	[0.0022]		[0.0081]		[0.0161]		[0.0068]	

TABLE A.19 - Continued

Panel D: Responses to News By Dispersion Quintile

Dispersion	c		d		γ		λ	
Low	**0.0013**		**0.0714**	***	**0.0187**	***	**0.0166**	***
	[0.0008]		[0.0048]		[0.0052]		[0.0023]	
2	**0.0014**		**0.0588**	***	**0.0205**	***	**0.0178**	***
	[0.0009]		[0.0046]		[0.0058]		[0.0026]	
3	**0.0019**		**0.1144**	***	**0.0343**	***	**0.0211**	***
	[0.0012]		[0.0057]		[0.0079]		[0.0036]	
4	**0.0095**	***	**0.1395**	***	**0.0200**	*	**0.0084**	*
	[0.0015]		[0.0067]		[0.0105]		[0.0047]	
High	**0.0077**	***	**0.2665**	***	**0.0413**	**	**0.0351**	***
	[0.0023]		[0.0083]		[0.0166]		[0.0073]	

Panel E: Responses to News By Coverage Quintile

Coverage	c		d		γ		λ	
Low	**0.0004**		**0.1296**	***	**0.0297**	***	**0.0275**	***
	[0.0013]		[0.0059]		[0.0077]		[0.0034]	
2	**0.0057**	***	**0.1329**	***	**0.0282**	***	**0.0174**	***
	[0.0015]		[0.0072]		[0.0102]		[0.0045]	
3	**0.0015**		**0.1133**	***	**0.0208**	**	**0.0236**	***
	[0.0015]		[0.0063]		[0.0095]		[0.0042]	
4	**0.0014**		**0.1737**	***	**0.0305**	***	**0.0281**	***
	[0.0016]		[0.0072]		[0.0105]		[0.0047]	
High	**0.0086**	***	**0.1761**	***	**0.0379**	***	**0.0129**	**
	[0.0016]		[0.0071]		[0.0123]		[0.0056]	

TABLE A.20

Mean Parameter Sensitivities from Stochastic Frontier Analysis (SFA) and Ordinary Least Squares (OLS): from quarter 1 of year 1989 through quarter 4 of year 2004

Table A.20 presents the average of parameter sensitivities for SFA and OLS. At the end of each quarter t, starting in 1989 and ending in 2004, I estimate the efficient frontier. I then take the average of the "betas". There are 64 total observations for each "beta". The results in Table A.20 report the average relationship between the independent variables and the dependent variable. For comparison purposes we also present the estimates using OLS. For both cases the dependent variable is the log of market equity. Robust jackknife standard errors are in parentheses and are computed using a jackknife method outlined by Shao and Rao (1993). *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Independent Variables	SFA		OLS		Expected sign
Log of Book Equity	**1.0271**	***	**1.0304**	***	+
	(0.0026)		(0.0026)		
Capital Expenditure / Sales	**0.0151**	***	**0.0146**	***	+
	(0.0011)		(0.0009)		
R&D / Sales	**0.2464**	***	**0.2502**	***	+
	(0.0011)		(0.0009)		
Advertising Expenditure / Sales	**0.8159**	***	**0.7891**	***	+
	(0.1806)		(0.1746)		
Free Cash Flow	**4.6421**	***	**4.8682**	***	+
	(0.2003)		(0.2085)		
RDDUM	**-0.1186**	***	**-0.1205**	***	
	(0.0088)		(0.0091)		
ADVDUM	**-0.0353**	**	**-0.0341**	**	
	(0.0123)		(0.0124)		
Constant	**1.0219**	***	**0.6107**	***	
	(0.0425)		(0.0445)		
FF 49 Industries Control Dummies	YES		YES		

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