WHAT DECOMPOSING MARKET-TO-BOOK RATIOS CAN TELL US ABOUT FIRM PRICING AND SAFETY

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2012

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To all the people who have pushed and encouraged me

ACKNOWLEDGMENTS

There are countless people who have offered their encouragement and prodding to produce this dissertation. I suspect I'd never get this close without all their kindness. Thanks to Ani Manakyan and Atay Kizilaslan are especially in order. Ultimately, this paper would never have gotten anywhere without the unyielding patience of my dissertation advisors, Mark Flannery and Joel Houston.

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LIST OF ABBREVIATIONS

AIM	Amihud (2002) illiquidity measure
AMEX	American Stock Exchange
B	book value
b	natural log of book value
BA	book assets
BBBY	Bed, Bath & Beyond
CRSP	The Center for Research in Securities Prices
EBITDA	earnings before interest, taxes, depreciation, and amortization
ES	earnings before interest, taxes, depreciation, and amortization stability
FSE	firm-specific error
HML	high book-to-market returns minus low book-to-market returns
LEV	market leverage ratio
Ln	natural log
LRV	long-run intrinsic value
LRVTB	long-run intrinsic value-to-book ratio
M	market value
m	natural log of market value
NI	net income
M/B	market-to-book value ratio
M/V	market-to-true value ratio
MOM	momentum
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
Prob	probability

R	return
ROA	return on assets
ROE	return on equity
RKRV	Rhodes-Kropf, Robinson, and Viswanathan (2005)
S&P	Standard and Poor's
SEC	Securities and Exchange Commission
SEO	seasoned equity offering
SIC	Standard Industrial Classification System
SMB	small firm returns minus large firm returns
TNA	total net assets
TSSE	time-series sector error
V	true value
v	natural log of true value
V/B	true value-to-book value

Abstract of Dissertation Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy

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CAN TELL US ABOUT FIRM PRICING AND SAFETY

By

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December 2012

Chair: Mark Flannery
Cochair: Joel Houston
Major: Business Administration

I examine how market-to-book ratios can provide insight into firm valuation. My studies examine several uses of the Rhodes-Kropf, Robinson, and Viswanathan (2005) decomposition technique, from the external perspective of an investor, a mutual fund manager, and credit rating agencies. Much of the existing literature uses this technique to evaluate corporate behavior from the insider perspective; I extend its use to the perspective of outsiders. I conclude that the market-to-book decomposition technique yields only modest information for outsiders about misvaluation and growth options.

Through much of this work, I generally follow the established decomposition methodology, though I modify the technique to provide a more realistic application. By restricting the model to capture short-term historical and contemporaneous accounting information only, I examine a trading strategy that identifies over- and undervalued securities through this market-to-book decomposition and show only weak evidence of an abnormal return trading strategy.

This study further utilizes the market-to-book ratio to examine the influence of market valuations on prediction models of credit ratings. I show that market leverage

provides slightly more accurate predictions of rating than book leverage, in spite of institutional reliance on book leverage measures. I show that ratings of firms with large growth options, relative to assets-in-place, are better estimated by historical cost accounting measures, while ratings are better predicted with market measures when growth options are smaller relative to assets.

A third example illustrates how mutual fund managers could use the relative valuation technique to improve their liquidation decision process in portfolio rebalancing. I show there is little evidence that fund managers use this kind of valuation technique in deciding which holdings to liquidate.

CHAPTER 1
INTRODUCTION

The Literature of a Market-To-Book Decomposition Technique

Accurately measuring the true value of a firm is a holy grail for financial analysts, though if such a measure existed, analysts' jobs would likely be unnecessary. The Grossman and Stiglitz (1980) Paradox suggests that as markets get more efficient, i.e., as analysts get better at identifying the true value of the firm, their expertise becomes less and less valuable, while as firms remain misvalued, the analysts' work is more highly demanded. Fortunately for the analysts, the true value of a firm will likely remain unknowable, even as the academic and professional fields develop more sophisticated techniques for the analysis and understanding of valuation. A growing line of literature has examined a wide variety of corporate events, including merger activity, seasoned equity offerings, private placements, analyst coverage, and bankruptcy and noted that price-to-book ratios reflect misvaluation, growth options and information asymmetries (see, e.g., Baker and Wurgler (2002); Rhodes-Kropf, Robinson, Viswanathan (2005); Dong, Hirshleifer, Richardson, and Teoh (2006); Hertzel and Li (2010); Fu, Lin, and Officer (2010)).

Rhodes-Kropf, Robinson, and Viswanathan (2005), referred to as RKRV, develop an empirical methodology that estimates company misvaluation at a firm-level or at an industry-level. They suggest a firm's market valuation is a function of its true valuation and some market error, explicitly suggesting that market valuations can deviate from the true value. This empirical paper, building on the theoretical framework of Rhodes-Kropf and Viswanathan (2004), posits that firm management might correctly recognize the direction of their firm's misvaluation (i.e., over- or undervalued), and develops a

technique assessing how a firm's current market value relates to its accounting value and the historical valuation of its industry. In the context of these papers, merger waves may occur because firms are misvalued and management utilizes their inside information to analyze relative value between target and acquirer. Moreover, the type of financing—cash or stock—of the acquisition can be influenced by this relative valuation. If managers are acquiring firms using appropriate financing options, it is likely a value-enhancing action for shareholders.

The RKRV application of a market-to-book decomposition technique illustrates that if firm managers incorporate valuation errors in their acquisitions, the methodology might also have significant implications for investors. RKRV establish that although firm management might not be able to identify the source of their misvaluation (i.e., misvalued at the firm-level or as part of an industry-wide misvaluation), they are able to identify that there are errors in value. Chapter 2 builds on this idea to examine a potential investment strategy to be utilized by a sophisticated investor to earn positive abnormal returns. In part, RKRV offers a method to identify misvaluation direction and relative magnitude, yielding a possible trading strategy.

Recent literature uses the RKRV decomposition technique in a variety of examinations of internal corporate decisions. For example, Lin, Pantzalis, and Park (2010) utilize the decomposition technique as one of several measures of misvaluation to illustrate that better transparency results in more accurate valuation. In an investigation of private placement and spinoff attempts, Harris and Madura (2011) use the RKRV measure among others to highlight the effects of misvaluation at predicting management behavior in cash generating actions. While Hertzel and Li (2010) finds

evidence that firms initiating seasoned equity offerings (SEOs) underperform following their new issuances, they also find that the firms engaging in SEOs are overvalued as measured by a modified RKRV methodology.

Though the RKRV method has been used in recent literature examining internal corporate decisions, it appears unusable to make investment decisions external to the firm. My studies examine several uses of the valuation technique, testing whether it yields consistently useful predictions for an external investor, evaluating the decisions of a mutual fund manager, and illustrating how credit rating agencies might assess a firm's riskiness. If the decomposition results in consistently accurate identification of relative value, it would be useful in supporting corporate finance theories that hypothesize that managers have better instincts about the firm's true value than market participants, as well as demonstrating how a sophisticated investor might trade on misvaluation.

These essays serve to investigate the usefulness of the RKRV methodology across a range of applications. First, can sophisticated investors use the decomposition's misvaluation estimates to identify portfolios capable of generating abnormal returns over time? In short, the answer appears to be that generating abnormal returns using this methodology is unlikely, even over a brief holding period. Though the RKRV method has been used in recent literature evaluating internal corporate decisions, it appears ill equipped to make investment decisions external to the firm. The second essay tests whether the decomposition of market-to-book ratios indicate something tangible about how rating agencies value firms. Using the RKRV estimates of firms' long-run value, this study indicates that the traditional factors explaining credit rating are first-order determinants of firms' ratings, while rating

agencies also value a mix of tangible assets and growth opportunities by incorporating some private information directly from firm management. While tangible assets are important to establish collateral value, rating agencies also value having a pipeline of fresh cash flow. In a third study, I examine how mutual fund managers facing large outflows choose holdings to liquidate. While there are many reasons a fund manager may have to pick particular holdings to liquidate, the RKRV methodology may shed light on their proclivity to choose misvalued stocks. If the RKRV decomposition correctly identifies misvaluation, successful fund managers should lean towards liquidating holdings of overvalued securities and rebalance towards undervalued securities. Instead, I show exactly the opposite pattern, suggesting either the fund managers are choosing poorly, or the RKRV methodology results deviate from the valuations of professional fund managers.

While the literature has used the decomposition to explore firm management's assessments of contemporaneous misvaluation, I question whether the methodology yields useful misvaluation indicators to firm outsiders. I conclude that, in several instances, the methodology does not indicate useful, contemporaneous information for external parties. Through much of this work, I follow the RKRV methodology, though I modify the technique in the first study to provide a more realistic investment application. I will begin with a discussion of the original RKRV methodology upon which much of this work is based, and will describe my modifications in greater detail in the second chapter.

Decomposition Methodology

A schism exists in finance research between efficient market adherents and those who believe that markets are not always efficient. Efficient market adherents believe

that market valuations are the most accurate measure of a firm's intrinsic value, or its "true" valuation. Contrary to this belief is an array of theories that suggest that markets are imperfect estimators of true valuation. From a corporate perspective, Myers and Majluf (1984) illustrate how a firm's management, with private information, could issue equity when the firm's true value is less than the firm's market capitalization, capturing the misvaluation as a gain for existing shareholders. From an investor's vantage, a lengthy literature explores how markets might be imperfect, suffering from short-term myopia (Abaranell and Bernard (2000)), asset bubbles (Allen and Gale (2003)), and other behavioral or structural problems (for example, Shleifer (2000) surveys behavioral explanations for market inefficiency; Barber and Odean (2001) note how gender differences influence financial investment behavior; while Lamont and Thaler (2003) document how market structure can hinder efficiency).

Extending the literature of imperfect pricing, the model developed by RKRV separates a firm's current market valuation into estimates of intrinsic valuation and market error. They set out to establish a baseline estimate of the firm's intrinsic value while isolating potential sources of misvaluation, e.g. market excitement for particular firms or industries. The firm's value is split into three components—an estimate of true firm value based on long-term historical accounting valuation, an estimate of industry-wide misvaluation based on long-term average valuation, and a firm-specific misvaluation. The decomposition methodology assumes that a measurable relationship exists between a firm's long-term historical accounting valuation, its industry accounting valuation, and its market price.

At the model's core, RKRV assumes that, in the presence of asymmetric information, a firm's market value may not equal true, or intrinsic, value. Market values may deviate from the intrinsic value of the firm for a variety of reasons, including one as simple as private information being withheld from markets. Managers, who possess the private information about the firm, can act to exploit any discrepancy between market and intrinsic value. Myers and Majluf (1984) theorize that corporate equity issuance implies that equity market value, *M*, is probably greater than its true value, *V*, because managers capitalize on their informational advantage and issue equity only when the stock is overvalued. In an attempt to isolate and estimate a firm's true value, RKRV suppose a measure of fundamental value exists and create an identity from the market to book ratio, separating a simple fraction into two components: a measure of misvaluation referred to as market-to-true value, *M/V* and a measure of growth options referred to as true value-to-book, *V/B*, such that

$$\frac{M}{B} = \frac{M}{V} \times \frac{V}{B} \,. \tag{1-1}$$

If the market perfectly estimates the future growth opportunities, discount rates, and cash flows, i.e., perfectly estimates the intrinsic value of the firm, then M=V and Eq. 1-1 simplifies back to a simple fraction of M/B.

In motivating this decomposition of market-to-book ratios, RKRV suggest that some of a firm's misvaluation could be attributable to an industry or sector misvaluation shared by all firms in an industry, while another piece could be firm-specific. That is, a firm's market value could be distorted as a result of belonging to an overheated industry, while another firm could be temporarily misvalued due to momentary, idiosyncratic characteristics.

To illustrate this with a simple numerical example, suppose the firms in an industry are fairly valued between $100 and $200. The median firm, defined by a set of median fundamentals, has an intrinsic value of $150. Further suppose the median firm has a book value of $100, yielding a market-to-book ratio of 1.5. If all firms in the industry are fairly valued, M=V and M/B = M/V x V/B = 1 x 150/100 = 1.5. Now suppose that the market value for all firms in an industry overheats and doubles; the median firm's market value increases even though its fundamentals have not changed and its relative place within the industry is unchanged. Now the firms' prices range from $200 to $400 and our median firm is worth $300; its market-to-book ratio equals 3.0. Its long-run intrinsic value (LRV_i), based on its fundamentals, is still $150 and Eq. 1-1 indicates that the market-to-true value equals 2.0, while the true-to-book remains at 1.5. Given that all the firms in the industry have doubled in value, we would expect the median firm's value to double to $300. This increase in price is not firm-specific, but affects all firms in the industry.

Now suppose that our median firm, with its median fundamentals, suddenly increases in price to $350, independent of any further changes to other firms in its sector. The industry's market prices still range from $200 to $400, but our median firm no longer resides at the median price. Given its median fundamentals in an industry that doubled in price, we should expect the firm's market value ($E(V_i|V_j)$ to be 300, but we observe a market price of $350 (and M/B = 3.5). Thus, the firm's market value deviates from its fundamental value by $200 ($350 - $150 = $200). $150 of the misvaluation relates to the industry-wide doubling in value and $50 comes from a deviation unique to our median firm. This outlines that misvaluation can come from two sources—firm-

specific or sector-wide (or both)—expanding the decomposition from two components on the right side of Eq. 1-1 into three:

$$\frac{M_i}{B_i} = \frac{M_i}{(E(V_i)|V_j)} \times \frac{(E(V_i)|V_j)}{LRV_i} \times \frac{LRV_i}{B_i}, \tag{1-2}$$

which indicates that the firm's market-to-book ratio (M_i / B_i) is the product of three ratios:

- the observed market price of firm *i* (M_i) to the expected value of firm *i*, given its fundamentals and relative value within an industry *j* ($E(V_i|V_j)$);
- the expected value of the firm given its fundamentals and relative value within its industry ($E(V_i|V_j)$) to a long-run, firm-specific intrinsic value (LRV_i);
- the firm's long-run intrinsic value (LRV_i) to book value (B_i).

Returning to the simplified numerical example, the M/B ratio = 3.5 = (350 / 300) x (300 / 150) x (150 / 100). $\frac{M_i}{(E(V_i)|V_j)}$ = 1.167 is a measure of how much error is related to the market issues unique to the firm. The middle term, $\frac{(E(V_i)|V_j)}{LRV_i}$ = 2.0, captures misvaluation related to an overheated industry, while the last term, $\frac{LRV_i}{B_i}$, reports the long run intrinsic value-to-book; still at 1.5. This simplified example reveals how a firm's market value can be attributable to firm-specific issues, whole sector errors, or real fundamental value. Having demonstrated the basic concept of the misvaluation decomposition with a simplified numerical example, I'll turn attention to RKRV's formal methodology of estimating the long-run and expected firm values.

RKRV rewrite the basic decomposition of Eq. 1-1:

$$m - b \equiv (m - v) + (v - b), \tag{1-3}$$

where *m* is market value, *b* is book value, and *v* is a measure of fundamental, or true value, all expressed in logarithms. If the market value is an accurate estimate of the firm's true value, then *m – v* equals zero (i.e., no misvaluation). Therefore,

$$m - b = v - b, \tag{1-4}$$

and $v - b$ always equals $ln(M/B)$. However, if the market imperfectly estimates a firm's value, the market value will not equal the fundamental value such that $m - v \neq 0$. This implies that market errors due to misestimating discounted future cash flows or asymmetric information can be captured by a price-to-true value measure, $m - v$. When the firm is overvalued (undervalued) by the market, $m - v$ is positive (negative).

RKRV extends this decomposition to include an estimate of the firm's fundamental value, estimated as a function of its market value and contemporaneous accounting variables, the values and accounting values of all the firms in its industry, and an estimate of the firm's long-run industry valuations. In motivating their decomposition of market-to-book, RKRV suggest that some of a firm's misvaluation can be attributed to a sector misvaluation, shared by all firms in an industry, while another piece is firm-specific. This leads to separating $ln(M/B)$ into three components:

> (1) the difference between observed price and a valuation measure that reflects time-t fundamentals (firm-specific error); (2) the difference between valuation conditional on time-t fundamentals and a firm-specific valuation that reflects long-run value (time-series sector error); and (3) the difference between valuation based on long-run value and book value (long-run value to book) (p. 572).

The first component relates the market valuation and the firm- and time-specific accounting valuation by comparing the firm's market price to an estimate of the firm's true value. The second component compares the firm's true value to its industry's long-run value. The third term compares the estimated true value and the firm's book value. This expands Eq. 1-4 into these three components:

$$m - b = \begin{bmatrix} (\text{market value – firm accounting valuation measure}) + \\ (\text{firm accounting valuation measure – industry valuation measure}) \end{bmatrix}$$

$$+\left(\text{firm accounting valuation measure} - \text{book value}\right) \tag{1-5}$$

where the term in brackets represents a measure of market valuation to true value.

Estimating the firm's true value, *v*, is critical in establishing whether a firm is over- or undervalued. More specifically, RKRV estimate *v* for each firm *i* in industry *j* at time *t* as a linear function of firm-specific accounting information including book value, net income, and leverage, θ_{it}, and corresponding industry accounting multiples, α_{jt}. They decompose firm *i*'s market-to-book ratio at time *t* as

$$m_{it} - b_{it} = \underbrace{\left[\underbrace{m_{it} - v(\theta_{it};\alpha_{jt})}_{firm} + \underbrace{v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)}_{sector}\right]}_{total\ error} + \underbrace{v(\theta_{it};\alpha_j) - b_{it}}_{long-run\ value}. \tag{1-6}$$

The first term on the right-hand side of Eq. 1-6, $m_{it} - v(\theta_{it};\alpha_{jt})$, measures the difference between market value and fundamental value conditional on firm *i*'s accounting data, θ_{it}, and the contemporaneous sector *j* accounting multiples, α_{jt}. RKRV suggest that if the market or the firm's industry is misvalued at time *t*, it will be captured in the vector α_{jt}, so $v(\theta_{it};\alpha_{jt})$ represents all deviations common to a sector at time *t*. Therefore, misvaluation due to firm-specific deviations from fundamental value is measured by $m_{it} - v(\theta_{it};\alpha_{jt})$ and referred to as firm-specific error. The second term on the right-hand side of the equation, $v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)$, called time-series sector error, measures sector-specific deviations from long-run value at time *t*. The $v(\theta_{it};\alpha_j)$ component measures sector-specific valuation that does not vary over time, capturing the valuation of the firm using long-term industry multiples.

The third term, $v(\theta_{it};\alpha_j) - b_{it}$, referred to as long-run value-to-book, measures the difference between the long-run industry value and the firm's time *t* book value. If the first two terms—firm-specific and time-series sector errors—encapsulate all market

mispricing, then the third term captures the combined value of the firm's existing operations and future growth as a function of the book value of its assets in place. That is, it should be an implied market value of the firm, net of any mispricing, relative to book. Hertzel and Li (2010) interpret this term as the firm's investment opportunities, which can be viewed as a measure of the firm's growth options.

RKRV estimate $v(\theta_{it};\alpha_{jt})$ and $v(\theta_{it};\alpha_{j})$ using three different methods, which differ in the set of accounting variables included in the accounting information vector, θ_{it}. Following Hertzel and Li (2010), I focus on the third model, which includes log book value (*b*), log net income (*ni*), and market leverage ratio (*LEV*) in the accounting information vector, more information about the firm than in the other two models. Since net income can be negative, it is expressed as an absolute value (ni^{+}) and with an interaction dummy, $I_{(<0)}$=1, to indicate when net income is negative. Following the RKRV procedure utilized by Hertzel and Li (2010) and Harris and Madura (2010), among others, I sort each firm into the Fama-French twelve industry classifications (French (2012)) and run annual, cross-sectional regressions to estimate accounting multiples for each year *t* and industry α_{jt}.[1]

[1] Though RKRV do not explicitly state why the twelve industry classifications is chosen, greater precision in industry sorting would cost observations in per industry annual regression. For example, 16% of the industry-year regressions (39 of 240) over the 20-year period of 1970 to 1989 has fewer than 100 observations (12 industries times 20 years), with as few as 32, while the average over all 240 is 203 firms per industry-year. In 19 of 20 years from 1970 to 1989, Industry 7 (Telephone/Television) has fewer than 100 firms. In samples that include more recent years, the average number of observations increases, such that over the 1970 to 2007 sample period, there is an average of 370 firm-year observations per industry-year regressions.

The data comprise 168,661 firm-level observations between 1970 and 2007 from the Standard and Poor's Compustat database. I use this data to estimate a model of market values using the linear regression:

$$m_{it} = \alpha_{0jt} + a_{1jt}b_{it} + \alpha_{2jt}ni_{it}^{+} + \alpha_{3jt}I_{(<0)}(ni^{+})_{it} + \alpha_{4jt}LEV_{it} + \varepsilon_i \quad (1\text{-}7)$$

Using the results from these regressions, I estimate a firm's fundamental value given its industry's time-specific accounting multiples, $v(\theta_{it}; \alpha_{jt})$, for each firm *i* and year *t* as

$$v(b_{it}, ni_{it}, LEV_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}, \hat{\alpha}_{4jt}) =$$

$$= \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}b_{it} + \hat{\alpha}_{2jt}ni_{it}^{+}$$

$$+\hat{\alpha}_{3jt}I_{(<0)}(ni^{+})_{it} + \hat{\alpha}_{4jt}LEV_{it}. \quad (1\text{-}8)$$

Following RKRV, I estimate values for long-run sector multiples, $\bar{\alpha}_j$, by averaging $\hat{\alpha}_{jt}$ over all annual regressions for each of the k variables: $\bar{\alpha}_{kj} = 1/T \sum_t \alpha_{jt}$ for all α_k, where *k* = 0, 1, 2, 3, 4. RKRV note that by estimating separate equations for each industry, growth rates and discount rates embedded in the multiples are not required to be constant. The multiples can reflect the risk characteristics of the average firm in the industry. This yields a single value related to a firm's long-run industry average valuation. Table 1-1 presents the time-series averages of the coefficients for the regression equation for each Fama French industry classifications. The average adjusted-R^2 statistics for these regressions range from 85% to 92%, suggesting that the three accounting variables explain a significant portion of the cross-sectional variation in firm market values in a given year. The results are similar to those reported in Table 4 of RKRV and Table 2 of Hertzel and Li (2010), though more recent papers have not provided similar tables to confirm their consistency.

I estimate firm value given its industry's long-run accounting multiples, $v(\theta_{it};\alpha_j)$ for each firm by including the fitted values of $\bar{\alpha}_j$:

$$v(b_{it}, ni_{it}, LEV_{it}; \bar{\alpha}_{0jt}, \bar{\alpha}_{1jt}, \bar{\alpha}_{2jt}, \bar{\alpha}_{3jt}, \bar{\alpha}_{4jt}) =$$

$$= \bar{\alpha}_{0jt} + \bar{\alpha}_{1jt} b_{it} + \bar{\alpha}_{2jt} ni_{it}^{+}$$

$$+\bar{\alpha}_{3jt} I_{(<0)} (ni^{+})_{it} + \bar{\alpha}_{4jt} LEV_{it} \qquad (1\text{-}9)$$

This term captures a baseline for the long-run industry valuation. Comparing this value to a contemporaneous industry valuation, I can identify what part of the market-to-book ratio is driven by industry misvaluation (e.g., the industry may be relatively overheated at a point in time). Table 1-2 presents the mean firm-level decomposition of the market-to-book ratio by industry and over the entire sample. The results for sector-specific error are similar to those presented in Table 6 of RKRV and Table 3 of Hertzel and Li (2010).

Tying it all together, the decomposition specifies a long-run firm value estimate, which is independent from momentary valuation deviations. These valuation deviations, or misvaluations, can be firm-specific (e.g., the market is particularly keen or fearful towards a particular firm at a given moment) or industry-wide (e.g., the market is high on technology stocks or depressed on the banking industry). When these two valuation errors are combined, I consider them a "total firm misvaluation." A detailed discussion of this and other implications follow in each section.

The following chapters explore the significance of the misvaluation or long-run value and create applications to measure the impact of these components. Chapter 2 examines the trading returns of portfolios built with a modified version of the basic decomposition evaluates whether the model can reliably indicate misvaluation. Chapter 3 explores credit rating models and suggests that the long-run value measure of the

decomposition adds modest information about credit rating methods. Chapter 4 introduces the decomposition technique as a method to evaluate mutual fund manager decisions to strategically rebalance their portfolios away from overvalued stocks. Chapter 5 concludes.

Table 1-1. Conditional regression multiples

Model: $m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}ni+_{it} + a_{3jt}I_{(<0)}(ni+)_{it} + a_{4jt}Lev_{it} + e_i$

	Fama French Industry Classifications											
	1	2	3	4	5	6	7	8	9	10	11	12
Parameter	Consumer Non-durables	Consumer Durables	Manufacturing	Energy	Chemicals	Computers, Software, etc.	Telephone/ Television	Utilities	Wholesale	Medical	Finance	Miscellaneous
$E_t(a_0)$	1.46	1.50	1.42	1.53	1.83	1.76	1.83	1.81	1.50	2.15	1.95	1.67
	0.04	*0.09*	*0.07*	*0.08*	*0.08*	*0.12*	*0.12*	*0.11*	*0.07*	*0.05*	*0.05*	*0.06*
$E_t(a_1)$	0.72	0.73	0.80	0.78	0.70	0.72	0.63	0.74	0.78	0.68	0.60	0.74
	0.02	*0.02*	*0.01*	*0.01*	*0.02*	*0.02*	*0.03*	*0.02*	*0.04*	*0.02*	*0.02*	*0.01*
$E_t(a_2)$	0.37	0.31	0.23	0.21	0.34	0.30	0.27	0.19	0.27	0.33	0.36	0.27
	0.01	*0.02*	*0.02*	*0.02*	*0.01*	*0.02*	*0.01*	*0.01*	*0.02*	*0.01*	*0.03*	*0.03*
$E_t(a_3)$	-0.08	-0.05	-0.03	-0.03	-0.03	-0.09	0.29	0.10	-0.09	-0.08	-0.06	-0.07
	0.02	*0.02*	*0.01*	*0.01*	*0.03*	*0.02*	*0.22*	*0.09*	*0.03*	*0.02*	*0.01*	*0.02*
$E_t(a_4)$	-1.33	-1.34	-1.51	-1.14	-1.64	-1.60	-2.25	-2.43	-1.56	-2.00	-1.23	-1.43
	0.11	*0.12*	*0.08*	*0.09*	*0.10*	*0.13*	*0.08*	*0.19*	*0.09*	*0.08*	*0.06*	*0.08*
Adjusted-R^2	0.89	0.91	0.85	0.90	0.92	0.87	0.90	0.92	0.88	0.91	0.87	0.85

Note: Table reports the time-series average coefficients from regression equation (1-7). The dependent variable is the natural log of market value (m). The independent variables are the natural log of book value (b), natural log of absolute value of net income (ni+), an indicator interacted with log net income (ni+) to separately estimate net income for firms with negative net income and market leverage (Lev). Fama-French twelve industry classifications are reported across the top. Outputs from valuation regressions are reported in each row. Each model is estimated cross-sectionally at the industry-year level. The subscripts j and t denote industry and year, respectively. The variable $E_t(a_0)$ is the time-series average of the constant term for each regression. $E_t(a_k)$ is the time-series average multiple from the regression associated with the kth accounting variable. Regressions are run annually for each industry from 1970 to 2007. Standard errors are reported in italics below the average estimated coefficients. The reported Adjusted-R^2 is the average adjusted-R^2 for each industry.

Table 1-2. Firm-level decomposition of market-to-book ratios

		Fama-French Industry Classifications											
		1	2	3	4	5	6	7	8	9	10	11	12
Market-To-Book Component		Consumer non-durables	Consumer Durables	Manufacturing	Energy	Chemicals	Computers, Software, etc.	Telephone/ Television	Utilities	Wholesale	Medical	Finance	Miscellaneous
Ln(M/B)	m_{it}-b_{it}	0.6543	0.5423	0.5264	0.5943	0.8277	0.8567	0.6995	0.6495	0.4791	0.9962	0.8357	0.6946
Firm-specific	m_{it}-$v(\theta_{it};\alpha_{jt})$	0.0052	-0.0153	0.0017	0.0174	0.0033	0.0050	-0.0052	0.0075	-0.0015	0.0151	0.0084	0.0029
Sector-specific	$v(\theta_{it};\alpha_{jt})$-$v(\theta_{it};\alpha_{j})$	0.0337	0.0528	0.0633	-0.0330	0.0520	0.0558	0.0543	0.0275	-0.0167	-0.1913	-0.0340	0.1587
Long-run value-to-book	$v(\theta_{it};\alpha_{j})$-$b_{it}$	0.6155	0.5048	0.4613	0.6098	0.7723	0.7959	0.6504	0.6145	0.4973	1.1725	0.8613	0.5330
Firm-level observations		10,810	4,979	21,085	7,480	4,236	26,139	4,516	6,935	16,818	13,393	30,929	21,341

Note: The table reports the industry mean of the market-to-book ratio and of its three components at the firm level, based on the sample of 168,661 observations between 1970 and 2007. The market-to-book ratio is defined as the natural log of the ratio of market capitalization to book value of equity. The three components are firm-specific error, time-series sector error, and the long-run value-to-book.

CHAPTER 2
CAN A DECOMPOSITION OF THE MARKET-TO-BOOK RATIO INDICATE MISVALUATION?

Motivation

If the RKRV technique creates a useful measure of relative valuation, firms identified to be most overvalued in each industry should underperform firms that are least overvalued in the short term. If the methodology is successful at identifying this relative misvaluation, could a sophisticated investor use the market-to-book decomposition to capture abnormal returns? An investor capable of correctly identifying the relative magnitudes of mispricing could take a long position in the least undervalued firms and a short position in the most overvalued firms to capture returns. If a pattern of abnormal returns exists, over how long a buy-and-hold period might an investor capture these returns? Given an extensive literature on market efficiency, which indicates that markets quickly adjust to public information, I hypothesize that any abnormal returns would be achievable over only a relatively short holding period, if at all. Abnormal returns should evaporate as markets correct mispricing, leaving longer holding period abnormal returns relatively close to zero.

The results of this study indicate that a profitable trading strategy using the basic features of RKRV may exist, but it is a tenuous conclusion. The RKRV decomposition technique may generate a profitable, short-term investment strategy (prior to transactions costs), when measured against a market model or a Carhart (1997) four-factor model. Measured against a market model, the abnormal returns are realized only over a one-year holding period, evaporating over a two- or three-year window. One-year abnormal returns, as measured against the market model, appear greater than transactions cost estimates in the literature. However, robustness checks using returns

against a multiple factor model indicate that the trading strategy profitability depends on the size of the transactions costs, even at the one-year holding period. Finally, further analysis suggests that the abnormal returns may be driven by the arbitrary year the portfolios are constructed.

Nonetheless, even if these findings suggest that a profitable trading strategy is difficult to implement, these results may offer support to the literature utilizing the strategy in examination of corporate behavior. Firm management could issue overvalued equity to capture even fleeting misvaluation. Moreover, my findings support the results of Hertzel and Li (2010), who document that seasoned equity offering firms characterized by RKRV overvaluation have large future underperformance, while undervalued firms experience less underperformance.

One goal of the speculative investor is to reliably identify over- or underpriced securities and execute trades that capture the effects of mispricing, though in a world of efficient capital markets, this should be theoretically impossible. The empirical research on market efficiency indicates some mixed results: prices tend to reflect past return histories and adjust rapidly to new public information (Fama, 1991). Although Fama (1991) notes that the event study literature identifies some anomalies, the evidence remains largely supportive of market efficiency with regards to public information. There are few examples of public information-based trading strategies that exhibit potential for investment gains after including transactions costs, and those that do should evaporate in arbitrage. For example, Brock, Lakonishok, and LeBaron (1992) indicate that simple, technical trading rules could yield abnormal returns, but Bessembinder and Chan (1998) show that these returns generally did not adequately cover transactions costs to yield

net profits. Some persistent examples include the January effect and small company effect, though Keim (1983) suggests these persist because arbitrage of the small, most-affected companies is difficult to implement at scale.

Though the empirical research on market efficiency suggests that prices tend to reflect past return histories (see Fama (1970) and Fama (1991) for an extensive review of weak-form efficiency tests) and adjust rapidly to new public information, the literature is not uniformly aligned to this view. Specifically, Jegadeesh and Titman (1993) and Jegadeesh and Titman (2001) illustrate that momentum strategies, where strong prior performance indicates future outperformance, can yield positive abnormal returns over a one year investment horizon. The Carhart (1997) four-factor model incorporates momentum as a factor of market equilibrium pricing, though with an explicit omission relating to risk associated with momentum. In exploring the robustness of the momentum strategy to transactions costs, Grundy and Martin (2001) conclude that the momentum anomaly can produce profitable trading, while Korajczyk and Sadka (2004) note that mutual fund price impacts could affect large funds, while smaller funds could remain profitable on a momentum strategy. My research fits into the preceding literature in exploring potential returns anomalies and degrees of efficiency in capital markets.

Up until now, the RKRV methodology has been used mostly in the corporate finance literature to explore how valuation-related decisions impact corporate decisions. There is a long literature in this vein. For example, Myers and Majluf (1984) suggested corporate financing decisions relied on managerial (inside) estimation of “intrinsic” value and equity issuance occurs when market valuation exceeds this estimate. This offers a theoretical explanation to the findings of Asquith and Mullins (1986) that new stock

issues are followed by a decline in price. The attempt to benefit from misvaluation is not only internal to one company's management. Shleifer and Vishny (2003) propose a misvaluation hypothesis of takeovers, arguing that bidders try to profit by buying relatively undervalued targets. Using estimates of fundamental valuation, Dong, Hirschleifer, Richardson, and Teoh (2006) find evidence that bidder and target valuations are related to characteristics of acquisitions (means of payment, mode of acquisition, offer success, etc.) consistent with the misvaluation hypothesis.

The RKRV market-to-book decomposition is used in the context of this literature to establish that overvalued stock is linked to acquisitions financed with equity, while undervalued stock pushes managers to pay for acquisitions with cash (Rhodes-Kropf, Robinson, Viswanathan (2005)). Subsequent papers use the RKRV technique to confirm predictions of managerial behavior related to the valuation of a firm’s equity. For example, Hertzel and Li (2010) document evidence supporting the Myers and Majluf (1984) hypothesis that firms will issue equity if it is overvalued relative to a true estimate of firm value. Using the RKRV technique to set a pre-SEO misvaluation estimate, Hertzel and Li find that issuing firms are overvalued and note that greater mispricing is related to lower returns.

Lin, Pantzalis, and Park’s (2010) investigation of corporate hedging begins with the assumption that persistent mispricing is due to corporate opacity of information about the firm’s future cash flows. Using the RKRV decomposition as one of six components of a misvaluation estimate, they show that hedging policies improve transparency of firm cash flow information, resulting in less misvaluation. Similarly, Glegg, Harris, Madura, and Ngo (2011) and Harris and Madura (2011) use the RKRV

methodology as one of five components of a misvaluation estimate investigating private placements and withdrawn spinoffs. Where Harris and Madura's (2011) focus on a series of corporate decisions—to withdraw a proposed spinoff, the work of Glegg, Harris, Madura and Ngo (2011) provides more insight into the interaction of corporate decisions and investors. They note that the private placements of overvalued equity suffer larger price discounts with greater misvaluation, supporting a theory that price discounts provide restitution to informed investors (Hertzel, Lemmon, Linck, and Rees (2002)).

While all of these studies examine managerial behavior in relation to possible market misvaluation, Hertzel and Li (2010) and Glegg, Harris, Madura and Ngo (2011) also focus on the returns to investors resulting from the corporate actions of SEOs and private placements and are closer to the topic of this study. Both papers suggest that the RKRV technique yields measures of relative valuation that concurs with Myers and Majluf's (1984) signaling suggestion that overvalued firms issue equity. Specifically, SEO firms are overvalued by the RKRV measures (Hertzel and Li (2010)). Notably, only Hertzel and Li (2010) appear to acknowledge that the basic RKRV model includes forward-looking information, which would be unknowable to an investor in actual application. I use Hertzel and Li's deviation of RKRV's original specification to construct portfolios. Further discussion of this deviation follows in the Data and Modification section below. My research extends this literature in its focus on the returns to investors. Where the prior literature looks illustrates a correlation between RKRV misvaluation indicators, my efforts show how the RKRV composed portfolios in the context of an explicit trading strategy.

While the investment literature does not find much evidence supporting a reliable, executable valuation technique, the corporate finance literature suggests that firm behavior is linked to firm value. RKRV use the market-to-book decomposition methodology to identify relative mispricing at the firm level, which supports managers' choices of using overvalued stock in acquisitions to capitalize on market mispricing. Evidence linking the RKRV relative mispricing measures and future underperformance suggests that an investor could anticipate future performance by correctly identifying the RKRV misvaluation.

The remainder of this essay is as follows. I document the methodological shortcomings of the original RKRV specification and my adaptation to replicate an investor's portfolio construction process. The results section indicates the short-term nature of any abnormal returns and reports on tests against market and factor models.

Data and Modification to the Rhodes-Kropf, Robinson, Viswanathan (2005) Specification

In their SEO performance analysis, Hertzel and Li (2010) modify the original RKRV specification to address this look-ahead bias. Their paper explored behavioral and rational explanations of stock returns following seasoned equity offerings (SEOs). Modifying the RKRV decomposition technique to identify mispriced stock before an SEO, they show that firms are overvalued pre-SEO, consistent with behavioral explanations of post-SEO underperformance.

The original RKRV methodology employs a 24-year observation window to estimate a long-run industry valuation. As part of the decomposition, RKRV uses their full time-series to construct an estimate of the sector error. As Hertzel and Li (2010) footnote, this introduces a look-ahead bias in the original RKRV specification, because

the industry-average valuation specifications would include forward-looking accounting information not available to investors at time *t*. Though RKRV argue that this forward-looking information can reflect the private information of firm management, this presents a problem in developing a trading strategy implemented on public information. Where RKRV use a 24-year average of annual industry regressions to estimate long-run sector multiples (see the discussion following Eq. 1-8), Hertzel and Li (2010) average these annual regressions over varying lengths, as short as three years and capped at twenty years. They make this modification explicitly to avoid look-ahead bias by utilizing only information available to investors at the time.

Though Hertzel and Li (2010) address one issue with the original specification, their modification introduces a new one. In RKRV's original model, the long-run industry valuation is estimated over 24 years, where extreme valuation observations could be smoothed out. In using shorter periods to estimate a long-run sector value, Hertzel and Li's (2010) modification could affect the industry value because extreme observations do not get the same level of smoothing from averaging many years. That is, an extreme observation could have greater impact on the valuation error estimate if there are only two other years offsetting one outlier, and a smaller impact if there are twenty years averaged together. They note that this modification makes the industry valuation error term sensitive to the number of estimation periods, but consider that investors can only use information that is available to them at the time of an investment opportunity. The time-series sector error relies on an average of the prior years and with fewer observations in each average, the average is susceptible to swings caused by just a few outlying observations.

Similar to Hertzel and Li (2010), I also deviate from the original RKRV methodology by using shorter long-run periods in estimating the long-run sector multiples, which affects my analysis of the RKRV specification. First, as Hertzel and Li (2010) observe, the industry misvaluation should be less reliable, since there are fewer observations per estimation. It is not clear that this is necessarily biased; simply that this estimate could be more volatile than if there were twenty years of observations included in the averaging. Second, the firm-specific misvaluation is also less reliable, because it is a linear function of the sector error. The primary effect of increased noisiness should be to reduce the consistency of abnormal returns between long-short portfolios because there is less certainty that highly misvalued firms are included in the portfolios.

If the shortened estimation period results in less certainty, why not use longer periods? DeBondt and Thaler (1985) raise concerns about overlapping portfolio construction periods, suggesting that portfolios constructed with overlapping data may bias the portfolio composition as extreme variables might substitute for risk characteristics. Longer, non-overlapping estimation periods would yield fewer portfolios to examine. Following the example of DeBondt and Thaler (1985), who use three-year portfolio construction periods, I estimate valuation errors over three-year periods. Aware of the Hertzel and Li (2010) concern about the sensitivity of the valuation error to the estimation period, I also construct portfolios over a longer five-year period, with similar results. The issue of the estimation period length matters only to the extent that by modifying the original specification, I am not testing a pure form of the RKRV specification.

Another important issue to address is the timing of prices and the release of firm accounting information. In their investigation of SEO returns, Hertzel and Li's (2010) match Compustat accounting data with CRSP prices three months after the fiscal-year end to calculate and decompose the market-to-book ratio, so long as the SEO occurs at least four months after the fiscal year-end. If the SEO occurs prior to the four-month mark, they use the prior fiscal year information, as the most recent fiscal year accounting information would not yet be available to investors.

I address the timing of prices and information in the following way. Though firms can classify any date as the fiscal year-end, an investor constructing long-short portfolios must identify the portfolios as of an arbitrary date. As the majority of firms (approximately 70%) have fiscal year-ends on December 31, I've selected this date to capture the most current accounting data on the most firms. The investor could use a firm's year-end results disclosed in the firm's annual report, but in practice, this information is not legally required for three months following the end of the fiscal year.[2] I begin calculating returns each April, using CRSP monthly returns data for one to three years for each stock in the portfolio. For example, a portfolio is constructed as of March 31, 2004 using year-end financial data released between January and December 2003. One obvious concern is that the portfolio construction may utilize firm data that is up to 14 months out of date, exactly like Hertzel and Li (2010). This is because I require year-end data released at least three months and no more than fifteen months prior to March

[2] Historically, the Securities and Exchange Commission required all public companies to file an annual report, Form 10-K, within 90 days of the firm's year-end. In 2002, the SEC modified this rule to 75 days for larger public firms (firms greater than $75 million of public float). Three years later, the SEC again modified this rule, reducing the time to file form 10-K to 60 days, for the largest companies ($700 million of public float). Medium-sized companies must file within 75 days; small public companies (less than $75 million) are still subject to the 90-day reporting requirement (SEC 2009).

31 of a year. To illustrate this problem simply, consider the case of Bed, Bath & Beyond (BBBY), whose fiscal year end occurs in February. They are not required to disclose their financial data until May, which would occur after the buy-and-hold strategy is executed on March 31. The data used in evaluating BBBY for the March 31, 2004 portfolios would be the prior year's February (May disclosure), reported not three months previously, but eleven months earlier. Nonetheless, this method should mimic the approach of investors attempting to capitalize on misvaluation indicated by this market-to-book decomposition.

The accounting data sample includes firms in Standard & Poor's Compustat database from 1969-2007 that have non-missing values for common shares outstanding; net income; and fiscal year-end share price. Following the RKRV methodology, I exclude observations with a negative value for total assets or common equity. Firms are also excluded if their book-to-market ratio exceeds 100 or if the market value of equity is below $10 million, eliminating small market firms. I match this sample to stocks in the CRSP database (years 1970-2010) by PERMNO and YEAR, resulting in a sample is 161,587 firm years.

As outlined in general terms in Chapter 1, I estimate annual, cross-sectional regressions according to Eq. 1-7. To calculate the long-run sector multiples, $\bar{\alpha}_j$, I average the $\hat{\alpha}_{jt}$regression estimates over three- and five-year periods, rather than the twenty-year period of RKRV, or the varying three- to twenty-year periods in Hertzel and Li (2010) in each of the twelve Fama-French (French (2012)) industries. Fitting these values into Eq. 1-8 for each year and Eq. 1-9 over a three- or five-year period, and

comparing to the firm's market capitalization and book value, I estimate a firm-specific pricing error and industry misvaluation in each year.

Once the parameter values for firm-specific and time-series industry valuation errors are estimated, I begin the portfolio construction process. Though the decomposition takes place at an annual, industry-level, firms are recombined into a single pool and sorted into deciles of firm-specific error [FSE, for consistency with Hertzel and Li (2010) notation] for each observation year. Portfolios are constructed by replicating a value-weighted long position in the least overvalued FSE decile (Decile 1) and a short position in the most overvalued decile (Decile 10) for each observation year. As my tests investigate the ability of the RKRV model to properly identify over- or undervalued firms, I use value-weighted portfolios rather than equally weighted portfolios, which might conflate possible high returns related to a small firm effect with a portfolio constructed with the RKRV decomposition. Several papers, including Roll (1981), Grinblatt and Titman (1989), and Korajczyk and Sadka (2004), note that the expected returns of equal-weighted portfolios are higher than for value-weighted portfolios. Therefore, in an effort to limit a small-firm effect, and focus specifically on the success of the decomposition as a trading rule, I use value-weighted portfolios.

I calculate annualized returns using monthly CRSP holding period returns including dividends over one-, two-, and three-year holding periods. To reduce survivorship bias, firms that merged or were acquired during the appropriate holding period are assumed to realize the market return. Where appropriate, I use the value-weighted NYSE, AMEX, and NASDAQ market return from Dr. French's Data Library (2012). Firms which liquidate or disappear from the CRSP database are assumed to

have a -100% return from the month of the bankruptcy or removal. Firms that merge are assumed to have returns at the market return. I calculate an annualized risk-free rate, representing the baseline rate of return an investor would have over the holding period from a rolling one-month treasury bill rate, supplied on Dr. French's Data Library (2012), starting in April of each year. After estimating the position's value-weighted return, I subtract the risk-free rate from the portfolio to estimate the portfolio's excess return.

Results

Earlier, I hypothesized that if the RKRV decomposition technique correctly identified misvaluation, the most overvalued firms should underperform the least overvalued firms over relatively short periods of time. As noted above, I estimated firm-specific misvaluation with three- or five-year specifications and created portfolios beginning four months after the fiscal year ends of the final construction period. For example, using a three-year estimation period, the first portfolio is created in April 1973 using accounting data from 1970, 1971, and 1972 fiscal years ending in or prior to December 1972. The initial tables, Table 2-1 and Table 2-2, presents the average excess returns by FSE decile for both three- and five-year rolling construction periods, respectively, over one-, two-, and three-year holding periods. By rolling construction, I mean that data used in constructing the 1974 portfolio contains two years of overlapping information from the 1973 portfolio (specifically, fiscal years 1971 and 1972). It is possible that the FSE decile sorting nonetheless results in different portfolios compositions.

Cursory examination indicates a general pattern of underperformance by the most overvalued firms relative to the least overvalued firms for the first year of forward returns, though paired difference t-statistics (against the average annualized market

portfolio returns) are not significant for any decile portfolio at even the 80% level. I further investigate whether a long position in the most undervalued decile and short position in the most overvalued decile results in returns that consistently outperform the market. Table 2-3 notes that only the widest position, Decile 1 minus Decile 10 averaged higher annualized returns over a one-year holding period (6.74%) than the market risk premium (6.37%), although it was not significantly different from the mean annual return of the market portfolio. Moreover, across 3-year holding periods, positions including Decile 9 (second-most overvalued) have excess returns that significantly trail the market. Table 2-4 examines the portfolios' excess returns using a five-year construction period, indicating that all of these portfolios trailed the market portfolio; while several of the longest-term holding periods significantly trail the market.

Though many of the returns trail the market portfolio, all of the one-year long-short positions (using either three- or five-year constructions) experienced lower standard deviations in returns, regardless of the portfolio construction length. The lower standard deviations of the long-short portfolios suggest that investors might profit relative to the market in down years and trail in boom years. To compare against the annual market return, I regress the annual long-short position returns against the market portfolio and the results are reported in Table 2-5 and Table 2-6. Here, I note a brief one-year holding period positive alpha for the positions, along with a positive beta for 3- and 5-year construction periods (even though some of these are not statistically significant at a 90% level). These results suggest that over a short holding period, an investor might enjoy positive returns, before accounting for transactions costs. The story changes, however, as the holding period expands to two and three years. Though there are

positive alphas, negative betas suggest that for high market returns, the portfolio does not outperform. Instead, these portfolios are more likely to yield higher returns when the market yields poor returns, a potential valuable result for an investor looking to hedge against market declines.

It is worth commenting that strategies that imply abnormal returns may not actually yield positive returns to the investor, if the raw returns are not greater than the incurred transactions cost. Grundy and Martin (2001) suggest that trading costs on momentum strategies greater than 1.5 percent result in statistically insignificant returns, while costs greater than 1.77 percent drive abnormal profits to zero. Mitchell and Pulvino (2001) quantify transactions costs of merger risk arbitrage portfolios by netting returns between an unconstrained and more realistically constrained portfolios, which control for liquidity (in the case of stock-for-stock transactions) and direct and indirect transactions costs. They find that approximately 1.5 percent of the returns differences relate to direct transactions costs (i.e., commissions and taxes) and another nearly 1.5 percent is attributed to indirect costs (i.e., price impact). They report an additional 2.5 percent cost relating to imposing constraints of trading on illiquid stocks, which is relevant to this study, as I explicitly short overvalued securities, for a total of 5.41 percent in transactions costs. When compared to the one-year holding periods of this decomposition screen, indirect trading costs and commissions are smaller than the abnormal returns, suggesting that an investor following this trading strategy could earn abnormal returns even after expenses.

These results generally indicate that short-term abnormal returns may be achievable using a market-to-book decomposition relative to a simple, single factor

model benchmark. Yet Cochrane (2001) notes that asset-pricing theory has long observed the need for multiple factors to account for sources of risk in returns, noting the Fama and French (1992) 3-Factor model dominates empirical research. I extend my analysis to include this 3-Factor model, and following Hertzel and Li (2010), also include a fourth momentum factor to pick up whether the portfolio returns are driven by a mechanical construction of prior winners or losers as suggested by Carhart (1997).

Table 2-7 and Table 2-8 report the four-factor regression results of three- and five-year rolling portfolio constructions and indicate that though several alphas are positive, they are not significantly different from zero, particularly for the 1-10 and 2-10 positions. In the shorter construction period (Table 2-7), positions 1-9 and 2-9 have positive alphas at the 90% level and are large enough to cover transactions costs. This result is confusing. My proposed trading strategy dictates that the investor buys the undervalued (Portfolios 1 and 2) and sells the overvalued (Portfolios 9 and 10), yet the strategy including the most overvalued portfolio (Portfolio 10) does not yield statistically abnormal returns. Meanwhile, the strategy including a slightly less overvalued group does yield better returns for our investor. Though future returns depends on the action of the market, it seems a little strange that the less overvalued stock would have poorer returns than the more overvalued stock. This suggests that while the decomposition might indicate general clues of relative valuation, it does not reveal a precise indicator of how the market will act.

Though these results suggest short-term abnormal returns may be available, the returns are based on portfolios constructed on a rolling, or overlapping, basis. This rolling portfolio construction style is criticized in DeBondt and Thaler (1985), because

extreme variables used in the construction might actually proxy for risk and bias the portfolio composition. To address this concern, I create a series of non-overlapping time periods to avoid contaminating portfolios with repeated statistical outliers. Table 2-9 reports the single-factor regression results of non-rolling 3-year construction portfolio returns for extreme decile positions against the market over the same holding periods. Here, the 1973 portfolio regression returns represents portfolios built in 1973, 1976, 1979, etc., while the 1974 portfolio returns represent portfolios built in 1974, 1977, 1980, etc. For an investor, there is no discernable pattern of positive alphas; the one-year holding period of Portfolio 2-10 that was initially built in 1973 has positive abnormal returns, but the portfolios built each third year beginning with 1974 do not. This should be a troubling result for an investor interested in a trading strategy built on this market-to-book decomposition. These results suggest that the arbitrary moment chosen to implement the strategy impacts whether abnormal returns exist. The results of Table 2-10 do not indicate statistically significant alphas over 1-year holding periods, while longer term holding periods have no discernable pattern of significantly positive or negative signs.

Finally, I examine whether even a shorter time period results in a successful abnormal return. A one-year holding period may be too long to identify abnormal returns if markets adjust quickly. Fama's (1991) market efficiency review notes that event study literature typically finds stock price adjustment within a day to many company news announcements (e.g. tender offers), though Foster, Olsen, and Shevlin (1984) and Bernard and Thomas (1989) find that post-earnings announcement prices adjust somewhat more slowly. Bernard and Thomas's (1989) Figure 1 illustrates that much of

the adjustment occurs within the first few days, mostly the first month, and nearly all within two months. If prices adjust rapidly, I expect that a trading strategy buying undervalued securities while selling overvalued securities would have significant alpha over a reasonably short window.

As I constructed the four factors from Dr. French's monthly data, I use the shortest time period (one month) in my dataset of factor data to evaluate the strategy's returns. Table 2-11 presents a regression of annualized excess returns over a one-month holding period, April, the first trading month available to our investor after the construction period, using a 3-year rolling construction against the Carhart (1997) 4-factor model. I observe that only the 1-10 Portfolio has a statistically significant positive alpha, suggesting the potential for excess returns. However, the magnitude of this result (2.59%) is close to estimates of transactions costs in Grundy and Martin (2001) (1.77%) and Mitchell and Pulvino (2001) (3% - 5.41%), suggesting that tangible profits may be fleeting, if at all.

There are a virtually infinite number of periods I could test in search of consistently positive alphas from a trading strategy based on the RKRV decomposition technique. It is possible that longer holding periods than three years could reveal some successful implementation, but testing for this would substantially reduce the sample size of non-rolling construction periods. It is possible that there could be some intermediate holding periods, but I have no theoretical basis for why an intermediate period would show a reliable trading strategy, when shorter and longer periods do not show substantial evidence (e.g., why an 18-month holding period would yield statistically significant results when 12- and 24-months do not). There remains a question about whether the

shortest periods—less than one month—might yield better results, but technical issues are likely to make testing for this challenging. Because a high percentage of firms have fiscal year-ends in months other than December (approximately 30% in my study), it is unclear how to address the timing of price adjustment with a wide range of annual report releases. Relatedly, the required timing of reporting differs by size of company—larger firms are now required to release data more quickly than smaller companies (see Footnote 2 above for more information) and this could have an effect if the holding period is short.

Analysis

The results do not clearly indicate that the relative mispricing identified through the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book ratio decomposition yields a profitable trading strategy. Though several recent papers use the RKRV decomposition to proxy for levels of mispricing, the results of this study indicate that the methodology does not yield sufficiently accurate guesses of future performance to create a sustainable trading strategy. Though Hertzel and Li (2010) note future underperformance of SEO-issuing firms and Harris and Madura (2011) predict the successfulness of spinoffs, it remains unclear that the RKRV offers specific trading suggestions.

In assessing the implementation of a trading strategy using a market-to-book decomposition, it appears that abnormal returns may exist only for medium-term holding periods, and then perhaps dependent on an arbitrary implementation date, i.e., whether a 3-year portfolio was initially constructed in 2004 or 2005. One-month, short-term results do not provide much evidence of abnormal returns sufficient to yield a transaction cost-robust trading strategy. Long-term returns are not abnormal, either.

Moreover, successful implementation as outlined in this study suggests investors re-estimate the valuation errors and reallocate into new portfolios at the end of each fiscal period, obviously increasing transactions costs. Though the returns from some long-short portfolio appear to be large enough to outperform single market factor and multi-factor models, there are many dangers in implementing this strategy. I note that in several instances, the Portfolios 1-9 and 2-9 perform better than the 1-10 and 2-10 portfolios. However, there is no theoretical reason that this should occur: if the RKRV technique is accurately sorting on relative valuation and the market responds correctly to the relative misvaluation, then we should generally see the opposite pattern, yet this is not readily apparent. Finally, there is no reason that this pattern should continue in the presence of efficient markets—if a successful trading strategy exists, then arbitrageurs should capitalize until the pattern disappears.

It is possible that periods shorter than one month might exhibit a pattern of successful trades, though future research would have to address report-timing and data issues. Future research could utilize daily factor data (I use monthly factor data) and build portfolios with quarterly, unaudited corporate data (I use annual, audited accounting and market data consistent with prior literature). Research focusing on shorter holdings periods must address the timing differences of reporting, particularly as only 70% of year-ends occur in December, leaving nearly 30% spread across the remaining eleven months, and faster reporting required of larger companies.

Though Hertzel and Li (2010) find that overvalued firms, as characterized by the RKRV methodology, are more likely to issue seasoned equity and later underperform, this study finds that it is difficult to capitalize on the RKRV methodology to earn

abnormal returns. Perhaps there are additional characteristics that distinguish the firms that issue seasoned equity from the broader group of overvalued firms. Even though RKRV note that their metric, which includes look-ahead information, might proxy for some private information, perhaps the public signal of a seasoned equity offering delivers more impact to future returns than merely being characterized as overvalued by this technical indicator. Relatedly, since the long-short portfolio is designed to buy the undervalued equities, perhaps the undervalued firms do not outperform as we expect. Nonetheless, it is possible that the RKRV technique could still offer a general indicator of value. As my tests only examine how long-short portfolios compare to market risk factors and find limited evidence of a robust trading strategy, tests with different focus could show that RKRV characterizations of misvaluation are accurate, even if it is difficult to trade successfully on these identifications.

Table 2-1. Decile excess returns over 1- to 3-year holding periods using rolling 3-year portfolio construction periods

Decile	1-Year	2-Year	3-Year
1	9.97%	2.96%	0.49%
2	9.45%	3.73%	2.02%
3	9.63%	4.99%	3.83%
4	9.67%	5.25%	3.90%
5	10.07%	6.17%	4.76%
6	8.30%	4.71%	4.11%
7	6.69%	4.33%	3.62%
8	6.23%	3.10%	2.84%
9	4.19%	1.80%	1.90%
10	3.23%	-0.68%	-1.17%
MRP	6.37%	6.27%	6.35%
	18.53%	*11.11%*	*9.19%*

Notes: Table presents the mean excess returns by firm-specific error decile over the sample period, 1973-2010. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE and Decile 10 represents the most overvalued. Portfolios are constructed on a three-year rolling basis. Excess returns are defined as the difference between value-weighted annualized returns using monthly CRSP holding period returns including dividends over a one-, two-, or three-year holding period and the risk-free Treasury bill rate. Firms that merge or were acquired during the appropriate holding period are assumed to realize the market return. In those cases, I use the value-weighted NYSE, AMEX, and NASDAQ market return from Dr. French's Data Library (2012). Firms which liquidate or disappear from the CRSP database are assumed to have a -100% return from the month of the bankruptcy or removal. The market risk premium, defined as the value-weighted market return minus the risk-free rate, for the appropriate holding period is listed at the bottom, with the standard deviation of the market risk premium listed in italics.

Table 2-2. Decile excess returns over 1-to 3-year holdings periods using rolling 5-year portfolio construction periods

Decile	1-Year	2-Year	3-Year
1	11.09%	3.15%	0.22%
2	10.80%	4.17%	2.05%
3	10.89%	5.49%	3.95%
4	11.04%	5.57%	3.94%
5	11.47%	6.82%	4.99%
6	9.85%	5.41%	4.32%
7	8.10%	5.00%	3.86%
8	7.55%	3.88%	3.33%
9	5.69%	2.63%	2.46%
10	5.03%	0.41%	-0.33%
MRP	7.89%	5.97%	5.89%
	17.98%	*11.72%*	*9.91%*

Notes: Table presents the mean excess returns by firm-specific error decile over the sample period, 1973-2008. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE and Decile 10 represents the most overvalued. Portfolios are constructed on a five-year rolling construction basis. Excess returns are defined as the difference between value-weighted annualized returns using monthly CRSP holding period returns including dividends over a one-, two-, or three-year holding period and the risk-free Treasury bill rate. Firms that merge or were acquired during the appropriate holding period are assumed to realize the market return. In those cases, I use the value-weighted NYSE, AMEX, and NASDAQ market return from Dr. French's Data Library (2012). Firms which liquidate or disappear from the CRSP database are assumed to have a -100% return from the month of the bankruptcy or removal. The market risk premium, defined as the value-weighted market return minus the risk-free rate, for the appropriate holding period is listed at the bottom, with the standard deviation of the market risk premium listed in italics.

Table 2-3. Mean excess returns by long-short position over 1- to 3-year holding periods using rolling 3-year portfolio construction periods

	1-Year		2-Year		3-Year		
Position	Mean Excess Returns	Mean Difference t-statistic	Mean Excess Returns	Mean Difference t-statistic	Mean Excess Returns	Mean Difference t-statistic	
Market - R_f	6.37%		6.27%		6.35%		
	18.53%		*11.11%*		*9.19%*		
Portfolio 1-10	6.74%	0.09	4.14%	-0.48	1.93%	-1.33	
	17.34%		*10.57%*		*10.05%*		
Portfolio 2-10	6.23%	-0.04	5.25%	-0.25	3.82%	-0.94	
	13.06%		*9.07%*		*8.74%*		
Portfolio 1-9	5.78%	-0.15	1.45%	-1.31	-1.29%	-2.38	*
	17.32%		*11.17%*		*10.82%*		
Portfolio 2-9	5.27%	-0.31	2.55%	-1.14	0.61%	-2.25	*
	12.86%		*9.72%*		*9.13%*		

Notes: Table presents the mean excess returns of long-short portfolios over the sample period, 1973-2008. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Portfolios are constructed on a three-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10). Excess returns are defined as the difference between value-weighted annualized returns using monthly CRSP holding period returns including dividends over a one-, two-, or three-year holding period and the risk-free Treasury bill rate. Firms that merge or were acquired during the appropriate holding period are assumed to realize the market return. In those cases, I use the value-weighted NYSE, AMEX, and NASDAQ market return from Dr. French's Data Library (2012). Firms which liquidate or disappear from the CRSP database are assumed to have a -100% return from the month of the bankruptcy or removal. The market risk premium, defined as the value-weighted market return minus the risk-free rate, for the appropriate holding period, is listed at the top. Standard deviations of returns are listed in italics. Difference of means test statistics, comparing position returns with the market risk premium, are listed to the right of the mean excess returns, while * indicates significance at the 95% level.

Table 2-4. Mean excess returns by long-short position over 1- to 3-year holding periods using rolling 5-year portfolio construction periods

	1-Year		2-Year		3-Year		
Position	Mean Excess Returns	Mean Difference t-statistic	Mean Excess Returns	Mean Difference t-statistic	Mean Excess Returns	Mean Difference t-statistic	
Market - Rf	7.89%		5.97%		5.89%		
	17.98%		*11.72%*		*9.91%*		
Portfolio 1-10	6.06%	-0.45	2.74%		0.55%	-1.97	*
	17.63%		*10.18%*	-1.06	*8.96%*		
Portfolio 2-10	5.77%	-0.56	3.76%		2.38%	-1.57	
	13.21%		*9.44%*	-0.78	*8.52%*		
Portfolio 1-9	5.40%	-0.63	0.53%		-2.24%	-2.85	**
	17.78%		*10.94%*	-1.79	*10.22%*		
Portfolio 2-9	5.11%	-0.77	1.54%		-0.42%	-2.69	**
	13.12%		*10.18%*	-1.57	*9.29%*		

Notes: Table presents the mean excess returns of long-short portfolios over the sample period, 1973-2008. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Portfolios are constructed on a five-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10). Excess returns are defined as the difference between value-weighted annualized returns using monthly CRSP holding period returns including dividends over a one-, two-, or three-year holding period and the risk-free Treasury bill rate. Firms that merge or were acquired during the appropriate holding period are assumed to realize the market return. In those cases, I use the value-weighted NYSE, AMEX, and NASDAQ market return from Dr. French's Data Library (2012). Firms which liquidate or disappear from the CRSP database are assumed to have a -100% return from the month of the bankruptcy or removal. The market risk premium, defined as the value-weighted market return minus the risk-free rate, for the appropriate holding period, is listed at the top. Standard deviations of returns are listed in italics. Difference of means test statistics, comparing position returns with the market risk premium, are listed to the right of the mean excess returns, while * and ** indicates significance at the 95% and 99% levels, respectively.

Table 2-5. Single factor regressions of excess returns for 1- to 3-year holding periods using rolling 3-year portfolio construction periods

Position	1-year			2-year			3-year		
	Intercept		Beta	Intercept		Beta	Intercept		Beta
Portfolio 1-10	6.34%	+	6.26%	5.10%	*	-28.38%	+	3.87%	+	-40.97%	*
	3.14%		*16.25%*	*1.86%*		*14.33%*		*1.76%*		*15.82%*	
Portfolio 2-10	6.17%	*	0.89%	5.38%	*	-18.66%		3.48%	+	-5.30%	
	2.37%		*12.27%*	*1.73%*		*13.33%*		*1.75%*		*15.71%*	
Portfolio 1-9	4.91%		13.72%	2.20%		-20.40%		0.69%		-39.01%	+
	3.11%		*16.10%*	*1.99%*		*15.28%*		*1.92%*		*17.24%*	
Portfolio 2-9	4.74%	+	8.34%	2.48%		-10.67%		0.30%		-3.34%	
	2.32%		*11.99%*	*1.85%*		*14.24%*		*1.82%*		*16.38%*	

Note: Table presents the coefficients of a single-factor regression of portfolio returns against the market risk premium. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a three-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10), held for one, two, or three years, purchased the April following the firms' latest fiscal year-end filing over the period 1973-2008. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. The independent variable is the market risk premium, defined as the value-weighted market return minus the risk-free rate. Standard errors are listed in italics. + and * report significance at the 90% and 95% levels.

Table 2-6. Single factor regressions of excess returns for 1- to 3-year holding periods using rolling 5-year portfolio construction periods

Position	1-year		2-year		3-year	
	Intercept	Beta	Intercept	Beta	Intercept	Beta
Portfolio 1-10	5.04%	12.87%	4.13% +	-23.31%	2.51%	-33.25% +
	3.38%	*17.46%*	*1.95%*	*15.02%*	*1.72%*	*15.12%*
Portfolio 2-10	5.36% +	5.16%	4.57% +	-13.64%	2.25%	2.25%
	2.55%	*13.16%*	*1.85%*	*14.25%*	*1.76%*	*15.44%*
Portfolio 1-9	3.92%	18.72%	1.56%	-17.28%	-0.26%	-33.68%
	3.38%	*17.45%*	*2.14%*	*16.47%*	*2.00%*	*17.51%*
Portfolio 2-9	4.25%	11.01%	2.00%	-7.60%	-0.52%	1.82%
	2.51%	*12.96%*	*2.02%*	*15.53%*	*1.92%*	*16.85%*

Note: Table presents the coefficients of a single-factor regression of portfolio returns against the market risk premium. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a five-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10), held for one, two, or three years, purchased the April following the firms' latest fiscal year-end filing over the period 1973-2008. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. The independent variable is the market risk premium, defined as the value-weighted market return minus the risk-free rate. Standard errors are listed in italics. + reports significance at the 90% level.

Table 2-7. Multiple factor regressions of excess returns for 1-year holding periods using rolling 3-year portfolio construction periods

Position	Intercept	MRP	SMB	HML	MOM
Portfolio 1-10	1.59%	-0.81% *	0.92% *	0.04%	0.09%
	5.86%	*0.22%*	*0.28%*	*0.27%*	*0.26%*
Portfolio 2-10	1.99%	-0.04%	0.72% *	0.11%	0.16%
	3.09%	*0.11%*	*0.15%*	*0.14%*	*0.14%*
Portfolio 1-9	7.07% +	-0.04%	0.82% *	-0.25%	-0.15%
	4.25%	*0.16%*	*0.20%*	*0.20%*	*0.19%*
Portfolio 2-9	5.09% +	-0.01%	0.62% *	-0.04%	-0.11%
	3.03%	*0.12%*	*0.15%*	*0.15%*	*0.14%*

Note: Table presents the coefficients of portfolio returns regressed against a multiple-factor model. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a three-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10), held for one year, purchased the April following the firms' latest fiscal year-end filing over the period 1973-2008. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. I use the Carhart (1997) 4-factor model as my factor model, including independent variables of market risk premium (MRP), defined as the value-weighted market return minus the risk-free rate, and factors for small-firm returns minus big-firm returns (SMB), high book-to-market firm returns minus low book-to-market firm returns (HML), and momentum (MOM) from Dr. French's Data Library (2012). Standard errors are listed in italics. + and * reports significance at the 90% and 95% levels, respectively.

Table 2-8. Multiple factor regressions of excess returns for 1-year holding periods using rolling 5-year portfolio construction periods

Position	Intercept	MRP		SMB		HML	MOM
Portfolio 1-10	-0.03%	-0.68%	*	1.08%	*	-0.02%	0.01%
	6.00%	*0.24%*		*0.28%*		*0.27%*	*0.26%*
Portfolio 2-10	0.80%	0.06%		0.86%	*	0.06%	0.09%
	2.78%	*0.11%*		*0.13%*		*0.13%*	*0.12%*
Portfolio 1-9	4.90%	0.11%		0.97%	*	-0.29%	-0.22%
	4.04%	*0.16%*		*0.19%*		*0.18%*	*0.17%*
Portfolio 2-9	4.47%	0.05%		0.75%	*	-0.10%	-0.18%
	2.88%	*0.11%*		*0.14%*		*0.13%*	*0.12%*

Note: Table presents the coefficients of portfolio returns regressed against a multiple-factor model. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a five-year rolling construction basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10), held for one year, purchased the April following the firms' latest fiscal year-end filing over the period 1973-2008. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. I use the Carhart (1997) 4-factor model as my factor model, including independent variables of market risk premium (MRP), defined as the value-weighted market return minus the risk-free rate, and factors for small-firm returns minus big-firm returns (SMB), high book-to-market firm returns minus low book-to-market firm returns (HML), and momentum (MOM) from Dr. French's Data Library (2012). Standard errors are listed in italics beneath the coefficients. * reports significance at the 95% level.

Table 2-9. Single factor regressions of excess returns for 1- to 3-year holding periods using non-rolling 3-year portfolio construction periods

Position	Construction Year	1-Year Intercept	1-Year Beta	2-Year Intercept	2-Year Beta	3-Year Intercept	3-Year Beta
Portfolio 1-10	1973	9.88%	-5.93%	7.46% +	-43.74% +	3.37%	-40.22%
		5.56%	*22.65%*	*3.54%*	*22.19%*	*3.42%*	*25.71%*
	1974	2.57%	-4.05%	1.89%	-8.59%	3.16%	-27.54%
		5.85%	*38.85%*	*3.22%*	*28.30%*	*3.09%*	*32.57%*
	1975	7.87%	37.19%	7.73% +	-41.12%	5.71%	-61.30%
		5.50%	*32.50%*	*3.29%*	*30.05%*	*3.46%*	*34.30%*
Portfolio 2-10	1973	11.38% *	-8.87%	7.18%	-33.50%	4.41%	-10.37%
		4.32%	*17.61%*	*3.71%*	*23.26%*	*3.08%*	*23.15%*
	1974	2.09%	-1.44%	2.98%	-1.61%	0.84%	35.46%
		4.73%	*31.44%*	*2.53%*	*22.25%*	*2.80%*	*29.51%*
	1975	5.81%	15.34%	7.17% +	-22.45%	5.03%	-33.70%
		3.46%	*20.45%*	*3.28%*	*29.90%*	*3.94%*	*39.13%*
Portfolio 1-9	1973	6.43%	18.17%	3.17%	-25.07%	-0.35%	-22.43%
		6.23%	*25.41%*	*4.30%*	*26.96%*	*4.01%*	*30.10%*
	1974	0.08%	-13.98%	-1.31%	-10.44%	1.06%	-61.48% +
		4.40%	*29.24%*	*3.01%*	*26.43%*	*2.81%*	*29.60%*

Table 2-9. Continued

Position	Construction Year	1-Year Intercept	1-Year Beta	2-Year Intercept	2-Year Beta	3-Year Intercept	3-Year Beta
Portfolio 1-9	1975	9.54%	29.02%	6.83% +	-46.67%	4.07%	-68.98%
		5.65%	*33.35%*	*3.37%*	*30.71%*	*3.55%*	*35.25%*
Portfolio 2-9	1973	7.93%	15.23%	2.89%	-14.83%	0.69%	7.42%
		4.98%	*20.30%*	*4.33%*	*27.19%*	*3.54%*	*26.55%*
	1974	-0.40%	-11.37%	-0.22%	-3.46%	-1.25%	1.52%
		3.50%	*23.23%*	*2.53%*	*22.23%*	*2.97%*	*31.27%*
	1975	7.48% +	7.17%	6.27% +	-28.00%	3.38%	-41.38%
		3.18%	*18.81%*	*3.12%*	*28.43%*	*3.63%*	*36.03%*

Note: Table presents the coefficients of a single-factor regression of portfolio excess returns against the market risk premium. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued), Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a three-year, non-rolling basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10). The positions, regardless of the holding period length, are initiated every third April, beginning with the listed year. For example, the 1973 row includes portfolios initiated in 1973, 1976, 1979, 1982, 1985, 1988, 1991, 1994, 1997, 2000, 2003, and 2006. Each position is held for up to three years, as listed, over the period 1973-2010. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. The independent variable is the market risk premium, defined as the value-weighted market return minus the risk-free rate. Standard errors are listed in italics below the coefficients. + and * report significance at the 90% and 95% levels respectively.

Table 2-10. Single factor regressions of excess returns for 1- to 3-year holding periods using non-rolling 5-year portfolio construction periods

	Construction	1-Year		2-Year		3-Year	
Position	Year	Intercept	Beta	Intercept	Beta	Intercept	Beta
Portfolio 1-10	1975	3.54%	17.88%	4.94%	-25.42%	1.44%	-32.58%
		6.59%	*26.55%*	*4.86%*	*34.99%*	*4.30%*	*31.26%*
	1976	9.66%	-10.68%	6.67%	-44.64%	4.09%	-25.90%
		5.12%	*37.76%*	*3.79%*	*32.82%*	*4.12%*	*41.88%*
	1977	2.01%	-18.12%	0.97%	-2.87%	2.90%	-73.71%
		5.45%	*22.37%*	*5.34%*	*36.39%*	*4.76%*	*45.71%*
	1978	-6.04%	92.47%	1.59%	0.73%	-6.31% *	73.25% *
		14.68%	*81.70%*	*8.72%*	*75.90%*	*2.31%*	*19.61%*
	1979	-6.74%	204.59% +	7.15% +	-54.52% +	4.81% *	-65.04% *
		9.15%	*84.40%*	*3.53%*	*27.38%*	*1.52%*	*14.15%*
Portfolio 2-10	1975	6.12%	4.07%	9.56% *	-35.60%	5.61%	-20.43%
		5.62%	*22.66%*	*3.38%*	*24.36%*	*3.90%*	*28.35%*
	1976	9.17%	-17.15%	3.06%	-17.87%	0.82%	7.76%
		4.86%	*35.82%*	*4.68%*	*40.55%*	*4.15%*	*42.18%*
	1977	3.28%	-12.99%	1.99%	-1.24%	1.91%	-2.30%
		5.63%	*23.11%*	*4.77%*	*32.55%*	*4.81%*	*46.14%*
	1978	-3.51%	80.60%	1.79%	20.62%	-11.00% *	130.39% *
		10.43%	*58.05%*	*7.94%*	*69.13%*	*3.25%*	*27.56%*
	1979	-1.00%	74.86% +	6.91%	-39.36%	5.31% *	-31.47%
		3.68%	*33.93%*	*3.83%*	*29.75%*	*2.00%*	*18.63%*

Table 2-10. Continued

Position	Construction Year	1-Year Intercept	1-Year Beta	2-Year Intercept	2-Year Beta	3-Year Intercept	3-Year Beta
Portfolio 1-9	1975	0.73%	24.95%	0.73%	-21.00%	-2.77%	-39.39%
		6.51%	*26.23%*	*5.56%*	*40.05%*	*5.12%*	*37.21%*
	1976	5.60%	-36.94%	2.60%	-31.36%	0.34%	-20.94%
		4.78%	*35.24%*	*3.43%*	*29.71%*	*4.19%*	*42.59%*
	1977	3.59%	-18.22%	1.85%	-19.21%	3.48%	-97.21% *
		3.07%	*12.61%*	*5.30%*	*36.16%*	*3.88%*	*37.25%*
	1978	-6.70%	134.78%	-8.74%	101.57%	-10.15%	101.31% +
		13.61%	*75.75%*	*9.26%*	*80.54%*	*6.02%*	*51.04%*
	1979	-10.44%	223.83% *	3.00%	-39.34%	1.07%	-63.08% +
		9.10%	*83.96%*	*5.78%*	*44.86%*	*2.72%*	*25.34%*
Portfolio 1-9	1975	3.31%	11.14%	5.36%	-31.19%	1.40%	-27.24%
		4.97%	*20.03%*	*3.52%*	*25.39%*	*3.94%*	*28.65%*
	1976	5.11%	-43.41%	-1.00%	-4.60%	-2.93%	12.72%
		3.89%	*28.70%*	*4.64%*	*40.16%*	*4.36%*	*44.27%*
	1977	4.87%	-13.09%	2.87%	-17.58%	2.48%	-25.80%
		3.16%	*12.96%*	*4.40%*	*30.03%*	*4.11%*	*39.47%*
	1978	-4.17%	122.92% +	-8.54%	121.46%	-14.84% *	158.45% *
		8.89%	*49.51%*	*7.55%*	*65.73%*	*4.86%*	*41.19%*
	1979	-4.70%	94.10%	2.76%	-24.17%	1.57%	-29.51%
		5.46%	*50.40%*	*6.40%*	*49.74%*	*3.43%*	*32.02%*

Note: Table presents the coefficients of a single-factor regression of portfolio excess returns against the market risk premium. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued), Decile 2 the

second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a three-year, non-rolling basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10). The positions, regardless of the holding period length, are initiated every fifth April, beginning with the listed year. For example, the 1975 row includes portfolios initiated in 1975, 1980, 1985, 1990, 1995, 2000, and 2005. Each position is held for up to three years, as listed, over the period 1975-2010. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. The independent variable is the market risk premium, defined as the value-weighted market return minus the risk-free rate. Standard errors are listed in italics below the coefficients. $^{+}$ and * report significance at the 90% and 95% levels respectively.

Table 2-11. Multiple factor regressions of excess returns for 1-month holding periods using rolling 3-year rolling portfolio construction period

Position	Alpha		MRP	HML	SMB		MOM	
Portfolio 1-10	2.59%	**	0.04%	-0.01%	-0.02%		-0.04%	
	0.94%		*0.04%*	*0.04%*	*0.05%*		*0.03%*	
Portfolio 2-10	0.75%		0.06%	-0.07%	-0.13%	*	-0.09%	**
	0.93%		*0.04%*	*0.04%*	*0.05%*		*0.03%*	
Portfolio 1-9	2.77%		0.08%	-0.06%	-0.02%		0.00%	
	1.60%		*0.07%*	*0.06%*	*0.08%*		*0.05%*	
Portfolio 2-9	-1.24%		0.04%	-0.06%	-0.11%	*	-0.10%	**
	0.97%		*0.04%*	*0.04%*	*0.05%*		*0.03%*	

Notes: Table presents the coefficients of portfolio returns regressed against a multiple-factor model. Firms are sorted into deciles by the firm-specific error (FSE), as calculated through a modification of the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition method. Decile 1 represents the least overvalued (i.e., undervalued) companies by FSE, Decile 2 the second-least overvalued, Decile 10 represents the most overvalued, and Decile 9 represents the second-most overvalued. Value-weighted portfolios of these deciles are constructed on a three-year rolling basis, beginning April 1973. Positions represent purchases of the least overvalued deciles (Deciles 1 or 2) and sales of the most overvalued deciles (Decile 9 or 10), held for one year, purchased the April following the firms' latest fiscal year-end filing over the period 1973-2008. Excess returns are defined as the difference between value-weighted annualized returns (using monthly CRSP holding period returns including dividends over the appropriate holding period) and the risk-free Treasury bill rate. The regressions' dependent variable is the excess return of the long-short portfolios. I use the Carhart (1997) 4-factor model, including independent variables of market risk premium (MRP), defined as the value-weighted market return minus the risk-free rate, and factors for small-firm returns minus big-firm returns (SMB), high book-to-market firm returns minus low book-to-market firm returns (HML), and momentum (MOM) from Dr. French's Data Library (2012). Standard errors are listed in italics beneath the coefficients. * and ** indicate significance at the 95% and 99% levels, respectively.

CHAPTER 3
DOES MARKET LEVERAGE ADD INFORMATION ABOUT CREDIT RATINGS?

Motivation

The implications of firm value on capital structure decisions have a long, divided history in finance literature. Understanding the factors that influence the choice of capital can have important consequences for the financial manager. Financial flexibility is the most important factor for CFOs in their capital structure decisions, followed closely by credit ratings, according to Graham and Harvey's (2001) survey of chief financial officers. Similarly, Kisgen (2006) argues that corporate managers target credit ratings in their capital structure decisions rather than targeting a particular optimal capital structure based on the traditional tradeoff argument (Frank and Goyal (2007)). Given ratings' importance to management, a complete understanding of the ratings factors should lead to better, more informed decisions by financial managers as they adjust their capital structure to maximize their firm's credit rating.

Unfortunately for the manager, the agencies' exact models are not transparent, though agencies' public comments and academic research suggests some key factors. The agencies assert that book value more accurately identifies a firm's true debt capacity. Moreover, agencies view market values skeptically because market volatility and investors' short-run focus can lead to periods of misvaluation and over- or underestimates of debt capacity (Pettit (2004)). Traditionally models in the finance literature include firm size, profitability, and book leverage ratios following the agencies' inclusion of book leverage (examples include Horrigan (1966); Pogue and Soldofsky (1969); and Ederington and Yawitz (1986)).

At the same time, finance textbooks and capital structure literature suggest that market values are more informative than book values about the value of a firm's future cash flow, future prospects, and residual value for debtholders and shareholders. Some credit rating research disregards the agencies' stated preference for book values and includes market values in modeling (Kaplan and Urwitz (1979); West (1970); and West (1973)), though the implications are nonetheless similar—higher leverage, measured with either book value or market value, is negatively related to rating. This study examines the informational differences between market and book leverage captured in credit rating models. My results indicate that corporate managers should use a market leverage measure if predicting credit ratings and evaluating how their portfolio of assets and growth options will affect ratings.

Even as rating agencies favor book leverage in their rating assignments, including market-based information might improve the predictions of a firm's rating. Specifically, while book leverage places substantial importance on the historical cost of assets-in-place, market leverage includes these historical costs and incorporates a forward cash flow valuation of those assets-in-place and the firm's future growth options. More generally, this study bridges a gap between a mature literature on credit rating determinants and more recent research in credit risk and capital structure. While earlier credit rating and capital structure literature largely focuses on publicly reported assets-in-place (book assets) and the market-to-book ratio as a proxy for growth options, I utilize the RKRV decomposition tool to strip away possible market misvaluation and focus on a firm's long-run value-to-book ratio, which Hertzel and Li (2010) characterize

as a measure of growth options. In particular, this study examines whether the RKRV growth option measure improves the rating prediction.

The crux of this analysis investigates the value of growth options to the firm and how their presence can affect credit ratings, and by extension, suggests how growth options can influence management decisions. Though Johnson (2003) confirms that growth options negatively affect leverage and Barclay, Smith, and Morellec (2006) indicate firms cannot borrow against them, perhaps these growth options serve a useful function as a safety net against default, perhaps by offering a backup source of revenue. My results indicate that firms with growth options are linked to better ratings, so long as the firms have sufficiently large existing assets.

I use the RKRV market-to-book decomposition methodology to separate a firm's misvaluation from its long-term value. Using this measure of long-term value, which Hertzel and Li (2010) refer to as growth options, I show how this long-term value can be economically important to a firm's credit rating. More specifically, I find that certain kinds of firms are better able to convert growth options into better ratings. My results imply that a firm whose market value is driven significantly by the value of its growth options is less likely to have a rating predicted by market values. Conversely, a firm heavy with assets-in-place can recognize ratings gains from adding growth options. In aggregate, models using market leverage modestly outperform book leverage, precisely because there are few firms whose growth options are large relative to assets-in-place. Moreover, the firms for which growth options are large are not themselves large firms, and therefore do not have substantial impact on aggregate results.

Though this study suggests that corporate managers can effectively use market valuations in their debt policy, this study also addresses a paradox facing financial researchers. If rating agencies do not use market information, why should academic literature investigating credit patterns? In practice, does it matter if researchers use market or book leverage when discussing credit ratings? In examining the impact of market valuations on prediction models of credit ratings, I show that the inclusion of market leverage provides small, aggregate improvement over pure book models, suggesting informational deficiencies in book-only models. The distribution between assets-in-place and growth options affects the difference in market and book models of credit ratings.

This chapter fits into my broader examination of the RKRV decomposition by exploring how an external party (albeit one with access to inside information), the rating agency, assigns ratings using historical accounting information, misvaluation, and growth options. Company investors might also use this decomposition to evaluate the management's strategic capital allocation decisions. I conclude that the use of the decomposition's estimate of growth options improves the prediction of a firm's rating.

Literature Review

A rating agency's evaluation of credit risk hinges on one or two basic questions: what is the probability of a firm's default and what is the bondholders' loss, given default.[3] The traditional focus of the credit rating determinant literature narrows to a select group of accounting variables measuring size, profitability, debt ratio, and stability

[3] The two major credit rating agencies differ on this point. Standard and Poors' ratings only focus on the first question: what is the probability of default. Moody's ratings address both issues—loss given default, and the probability of default. The dataset I use comprise S&P ratings; any conclusions drawn should therefore only address the probability of default and not residual value for bondholders.

to predict ratings. Horrigan (1966) utilizes a six-variable model (subordination, total assets, working capital/sales, net worth/total debt, sales/net worth, and net operating profit/sales) to predict 58% of Moody's ratings and 52% of S&P's ratings correctly. Pogue and Soldofsky (1969) use five variables (debt/total capital, net income/total assets, coefficient of variation of net income/total assets, net total assets and net income plus interest/interest) to identify whether bonds should be rated high (Aaa) or low (Baa). Ederington and Yawitz (1986) survey the research of informational content of credit ratings and show that two thirds of new issue ratings can be predicted using publicly available information, though they also concentrate on book, not market, value.

The early academic research followed the practitioner approach, using accounting variables in models of ratings. Hawkins, Brown, and Campbell (1983) and Belkaoui (1983) discuss the process, methodology, and analysis used by the rating agencies, complete with exhibits of financial ratios. "As the ability of most companies to raise equity on the right terms and at the right time has historically been sporadic, S&P seldom factors in equity as an alternative in the near term" (p. 77). To this end, rating agencies do not consider a firm's market valuation, calculate a firm's market leverage, or lend much weight to equity markets as a source of capital (Hawkins, Brown, and Campbell (1983)).

While the inclusion of accounting determinants – book value of assets-in-place, operational cash flow, earnings stability – should help assign and predict ratings, they are naturally backwards looking. These variables contain information about the firm's past performance, stability, and financial health. On the other hand, the assessment of a firm's future likelihood of default is, by definition, a forward-looking question. The

agencies, like other market participants, use basic, publicly available information as a primary resource for quantitative determinants of default. Concurrent with agency evaluations, investors set a valuation of the firm, as residual rights holders, which would include their related assessment of a firm's default probability (Kliger and Sarig (2000)). This does not necessarily imply that the rating agencies use market pricing information in their forward looking assessment; it is possible that the agencies independently assess a firm's prospects and verify their assessments by comparing them to market valuations.

In fact, rating agencies occasionally state that they use market valuations as one component of the assessment methodology, though it appears discreetly among a list of capital structure financial ratios.

> "Knowing the true values to assign a company's assets is key to the analysis. Leverage as reported in the financial statements is meaningless if the assets' book values are materially undervalued or overvalued relative to economic value. Market values of a company's assets or independent asset appraisals can offer additional insights. However, there are shortcomings in these methods of valuation (just as there are with historical cost accounting) that prevent reliance on any single measure. Similarly, ratios using the market value of a company's equity in calculations of leverage are given limited weight as analytical tools. The stock market emphasizes growth prospects and has a short time horizon; it is influenced by changes in alternative investment opportunities and can be very volatile. A company's ability to service its debt is not affected by such factors" (Standard & Poor's, 2006, p. 28).

While this statement indicates the agency's awareness of a firm's market value, it also suggests that this valuation method is not substantially used. Moreover, it implicitly acknowledges the importance of fundamental valuation and expected returns. Nonetheless, several papers (Kaplan and Urwitz (1979); West (1970); and West (1973)) have included market values in models with other traditional determinants and, consistent with this literature, this study reports market leverage negatively affects

ratings. Altman and Rijken (2004) investigate the reasons for credit rating stability by developing a credit-scoring model using market equity value, but decline to extend their analysis into an exploration of an optimal set of model variables.

One method of evaluating the usefulness of market or book values is to build a model of ratings and substitute book and market values as primary determinants of ratings. If book leverage outperforms market in predicting ratings, we may conclude that historical cost accounting is the preferred method. If market leverage outperforms book models, we might surmise that there are subtle, but useful, information differences between book information and market valuations. What type of information is conveyed to market participants and credit rating agencies through market information that book value cannot?

One distinguishing characteristic of the rating process is the agencies' private information from firm management, which provides the agencies with an opportunity to reconcile differences between reported book- and 'true'- estimates of debt capacity. Specifically, when evaluating companies, agencies receive private management estimates of the value of a firm's growth options and assets-in-place. This suggests that the agencies depend on their independent analysis, as well as critical discussion with management regarding the firm's future prospects to evaluate forward-looking credit risks. "[M]anagement's financial projections are a valuable tool in the rating process, because they indicate management's plans, how management assesses the company's challenges, and how it intends to deal with problems. Projections also depict the company's financial strategy in terms of anticipated reliance on internal cash flow or

outside funds, and they help articulate management's financial objectives and policies" (Standard & Poor's, 2006, p. 16).

Accurately estimating a firm's default probability requires that the rating agency supplement publicly available accounting information with private information from management (Ederington and Yawitz (1986)). If rating agencies do not use market valuations to assess the firm's future, they can use management's inside discussion for guidance. However, from the external perspective of an investor, this inside information is unavailable. Does it make sense for market participants (investors) to use market values to improve their outside estimate of the company's default risk?

One significant problem facing the investor's assessment is that market value may also include mispricing, masking the true value of the firm's assets-in-place and growth options. The rating agency's private information may enable it to distinguish true value from market mispricing. As a result, if the agencies use market valuations at all, they may be able to identify and exclude short-term mispricing in their ratings models, as the mispricing provides no long-term value. I expect that a model of ratings that distinguishes between market mispricing and growth options will yield more accurate predictions than a model without, for both book-leverage and market-leverage.

Several papers, including Johnson (2003), use market-to-book ratio as a proxy for growth options. However, market value could include mispricing. Following the RKRV decomposition of market-to-book methodology, I isolate components related to growth options from estimated misvaluation of the firm. As noted in Chapter 1, the technique distinguishes between different sources of valuation errors and long-run value to book. Hertzel and Li (2010) explicitly refer to the long-run value to book estimate as a

measure of growth options. Importantly, the RKRV methodology also separates the valuation errors into firm-specific and industry-specific errors as two sources of market mispricing. However, examining the sources of misvaluation and their individual contribution to the rating process is outside the scope of this study, as I focus more specifically at the role of growth options on rating. As a consequence, I consider the misvaluation as a single factor, a summation of the two RKRV-methodological variables, I refer to as Total Pricing Error. I expect that probit models that distinguish between variables for market misvaluation and growth options will have greater explanatory power and more accurate predictions of ratings.

This paper relates to the capital structure literature as well. Recent capital structure literature suggests that firms target credit ratings when setting optimal debt policy. The Graham and Harvey (2001) survey indicates significant concern about credit ratings among their sample, perhaps because they proxy for distress costs. Kisgen (2006) demonstrates that firms adjust their capital structure in response to credit ratings, showing that firms near ratings upgrades or downgrades are less likely to issue debt relative to equity than firms not near a ratings change. My paper relates to this literature by suggesting that firms might strategically direct investment allocations towards new growth opportunities or assets-in-place to affect their ratings. This study indicates that market measures can yield superior information about firms' growth options and their relationship to assets-in-place in the context of credit ratings.

Data and Methodology

The sample includes firms with six consecutive years of data in Standard & Poor's Compustat database from 1981-2006 that have non-missing values for common shares outstanding; net income; fiscal year end share price; and earnings before interest,

taxes, depreciation, and amortization (EBITDA). I exclude observations with a negative value for total assets or common equity. Following the RKRV methodology discussed in Chapter 1, firms are also excluded if their book-to-market ratio exceeds 100 or if the market value of equity is below $10 million, eliminating small market cap firms. EBITDA stability is measured over a five-year period prior to the year in which the rating is measured, so the firm must have six years of consecutive, non-missing EBITDA data to be included in the sample. Consistent with earlier capital structure literature, I exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4800-4949) from the sample because their capital structures are likely to be influenced by factors that differ from other industrial firms, such as capital adequacy requirements or utility regulation. This “full” sample is 51,893 firm-years.

Table 3-1 contains summary statistics of firm characteristics for the initial sample, while Table 3-2 summarizes the ratings subsample, used in the market-to-book decomposition regressions. The size measures reported in these tables are raw figures, and vary greatly across the sample, so I use the natural log of book or market equity to attenuate the effects of large values. For general consistency with the RKRV methodology, market value is defined as market equity (fiscal year end share price times shares outstanding) plus the book value of assets minus deferred taxes and the book value of equity. I winsorize the performance measures at the 1st and 99th percentiles to eliminate extreme values (e.g. values exceeding the 99th percentile are set equal to the 99th percentile). Return on assets (ROA) and return on equity (ROE) are defined as net income in year t divided by book assets (BA) or book equity in year t-1, respectively. EBITDA stability (ES) is defined as the co-efficient of variation (CV) of

earnings before interest, taxes, depreciation, and amortization (EBITDA) over book assets over the preceding five years. Earnings stability is calculated for each firm, *i*, for each year, *t*, with five preceding years of EBITDA data:

$$ES_{it} = \frac{\sum_{t=1}^{5} \frac{EBITDA_{it}}{BA_{it}}}{\sqrt{\frac{1}{5}\sum_{t=1}^{5}\left(\frac{EBITDA_{it}}{BA_{it}} - \overline{\left(\frac{EBITDA}{BA}\right)_i}\right)^2}} \tag{3-1}$$

Firms with low variation in cash flow (more stable cash flow) have high earnings stability figures. I report two measures of leverage: book leverage (1 – book equity/total book assets) and market leverage (1 – market equity/market value of assets). The book leverage definition implies that debt is total book liabilities. The market leverage definition implies that debt is total book liabilities net of deferred taxes.

Firms in both samples are sorted into the Fama French twelve industry categories (French 2012). Table 3-3 presents summary statistics of firm characteristics by industry. As mentioned above, Industries 7 (Telephone/Television), 8 (Utilities), and 11 (Finance) are excluded, yielding nine industries in the sample.[4] The data in this table suggests that firms vary widely both across and within industries.

The RKRV technique uses long-run estimates of industry accounting multiples to develop relative valuation and growth option measures. I develop the industry, time-series valuation metric within the RKRV methodology using the broadest sample of 51,893 firm-year observations, rather than with a restricted, ratings-only sample, in consideration of the number of observations for the annual industry regressions. Nearly

[4] Though Industry 7 (Telephone/Television) is separated in the Fama French industry classifications, many papers exclude them, as though Utilities, given high levels of long-term assets and typically higher debt ratios.

two-thirds of the full sample does not have ratings data, skewed towards smaller firms (measured by total assets). In utilizing the broadest dataset, I remove a potential selection bias (towards larger firms) in estimating the industry valuation errors with all the firms in an industry, regardless of the presence of a rating.

There are few firms rated AAA, so I group these observations with AA-rated firms. Similarly, I combine CCC firms with B-rated firms. The S&P ratings documentation indicates that firms with ratings less than CCC face grave risk of default. In addition, there are very few firms of lower rating that survive. I chose to eliminate these firms to focus the analysis on firms with more substantial viability. Table 3-4 presents summary statistics of firm characteristics by industry after restricting the sample to firms with long-term ratings. Table 3-5 presents summary statistics of firm characteristics by rating. Examining the mean summary statistics by rating yields few surprises—higher rated firms are monotonically larger than lower rated firms. Performance measures are also monotonically better for higher rated firms.

In the following two sections, I describe the basic ordered probit specifications I use and establish that market leverage has higher explanatory power than book leverage and decompose the market-to-book ratio to distinguish between growth options and market mispricing. This requires ordinary least squares regressions to establish firm- and industry- valuation measures. These regressions are conducted using the initial dataset of 51,893 firm-year observations. I chose to restrict the sample after these first-stage regressions to establish broad industry valuation multiples with observations that would be lost because Compustat does not have complete rating information. For the advanced ordered probit specifications, I require the rating

information and use the restricted ratings dataset, reducing the observations to 18,004 firm-years.

Probit Models

Prior academic literature suggests that several pieces of accounting data are used in ratings assignments: firm size, profitability, profit stability, interest coverage, and leverage. Earlier research shows that default risk is negatively correlated with these features (e.g., more stable cash flow reduces the likelihood of default), and safer firms receive stronger ratings. These accounting figures are historical, or backwards looking, and while the data may cast light on the probability of a future default, the rating agencies should also look forward to estimate the likelihood of a default. In addition to the accounting figures, the rating agencies also receive private, internal information directly from firm management about the firm's existing and future business operations. This information is not directly available from the firm's public disclosures or accounting information, so perfect predictions of ratings are impossible. However, some of this information may be impounded in current market prices.

Modeling the probability of a particular credit rating given a vector of determinants is not easily accomplished with a linear regression because bond ratings are discrete. An ordinary least squares regression assumes the dependent variable is continuous and a model of discrete bond ratings would violate this assumption. Though agencies have sub-ratings (+ and – subcategories, for example), a continuous dependent variable would imply even further sub-rating categories that do not exist. Moreover, an ordinary least squares model predicting the probability of a rating may yield estimates greater than 100% or less than 0%. For these reasons, ordinary least squares models are inappropriate to predict bond ratings.

Greene (2003) specifically notes that models of discrete choice, such as probit models, are more appropriate to model bond ratings, though the model imposes an assumption of a normal distribution. I use an ordered probit model, which is designed to limit the estimation between 0 and 1 and provide intuitive estimates for probabilities of ratings. As an additional benefit, the ordered probit takes advantage of the ordinal sequencing of bond ratings, the dependent variable. The dependent variable, rating (y), is sorted in descending order, from AAA/AA (1) to B/CCC-rated (5).

I construct two ordered probit models of bond ratings using traditional determinants. As hypothesized earlier, if book value is more informative about rating, I expect that this model earns a higher pseudo-R^2, performing better at in-sample prediction—fewer mis-estimations and estimated valued closer to the actual, observed values. Expressing rating as a probit model of the traditional accounting variables yields cumulative and marginal probabilities of a firm receiving a specific rating given its accounting data and multiples decomposed from the market-to-book ratio.

Greene (2003) offers a textbook description of the ordered probit model, which starts with a latent regression of the form: $y^* = x'\beta + \varepsilon$, where *y** is unobserved and *x* is a vector of traditional rating determinants, market misvaluation estimates, and growth option values. I observe that

$$\text{rating} = \begin{cases} 1, \text{ if } y^* \leq \alpha_1 \\ 2, \text{ if } \alpha_1 < y^* \leq \alpha_2 \\ 3, \text{ if } \alpha_2 < y^* \leq \alpha_3 \\ 4, \text{ if } \alpha_3 < y^* \leq \alpha_4 \\ 5, \text{ if } \alpha_4 < y^* \end{cases} \tag{3-2}$$

The α's are unknown parameters and estimated with β. As this estimation is an ordered probit, I implicitly assume that ε is normally distributed, with a mean of zero and a variance of one. The probit model yields the following probabilities:

$$\begin{aligned}
&\text{Prob}(y = 1|x) = \Phi(-x'\beta) \\
&\text{Prob}(y = 2|x) = \Phi(\alpha_1 - x'\beta) - \Phi(-x'\beta) \\
&\text{Prob}(y = 3|x) = \Phi(\alpha_2 - x'\beta) - \Phi(\alpha_1 - x'\beta) \\
&\text{Prob}(y = 4|x) = \Phi(\alpha_3 - x'\beta) - \Phi(\alpha_2 - x'\beta) \\
&\text{Prob}(y = 5|x) = 1 - \Phi(\alpha_4 - x'\beta)
\end{aligned} \tag{3-3}$$

Using these probabilities, I estimate the likelihood that a firm, *i*, receives a rating given traditional accounting determinants, the market valuation errors and the value of growth options I estimated in the previous section. As outlined in the Data section, I restrict the sample to firms with Compustat ratings data, reducing the sample to 18,004 firm-year observations. These results are outlined in Table 3-6. Greene (2003) notes that the marginal effects of the regressors, *x*, on the probabilities are not equal to the coefficients. The sign of the coefficients indicate the direction of shift in the probabilities—a positive (negative) coefficient unequivocally implies a lower (higher) rating. However, interpreting the magnitudes of the probit model coefficient requires additional calculations, as the shifts in probabilities are not linear. I will explore the marginal effects in greater detail in the next section.

Unsurprisingly, leverage, both book and market, have negative impact on ratings (low rating number indicates better rating, so positive coefficients indicate negative influence, i.e. a worse rating, and negative coefficients indicate positive influence, i.e. a better rating). The other determinants are also properly signed, indicating better cash flow stability and higher operational income and size improve rating. Interestingly, the book leverage model has similar, but lower pseudo-R^2 (0.2252) than the market

leverage model (0.2356), suggesting that market valuation offers useful information about ratings.

Though the pseudo-R^2 statistic describes the degree of fit similar to an ordinary least squares R^2, the prediction quality of the model can also be measured on at least two dimensions – accuracy (the frequency of correct predictions) and precision (how close the predictions are to the observed results). I examine the accuracy of the models' predictions in Table 3-7. I use the firm-year observation data and probit model coefficient estimates to predict the rating value, *y*. For example, the Model 1 prediction for a firm-year observation of rating is calculated as

$$y^* = \left(\beta_{BookLeverage} \times BookLeverage_{i,t}\right) + \left(\beta_{Ebitda/Assets} \times \frac{Ebitda}{Assets}_{i,t}\right)$$
$$+\left(\beta_{EbitdaStability} \times EbitdaStability_{i,t}\right) + \left(\beta_{Ln(Assets)} \times Ln(Assets)_{i,t}\right) \quad (3\text{-}4)$$

where *i* and *t* represent each firm and year, respectively. The value of *y* is compared against the partition parameters, α_1 through α_4. For example, to predict the 1993 Maytag Corporation rating using Model 1, I calculate:

$$y^* = \left(\beta_{BookLeverage} \times 0.501\right) + \left(\beta_{Ebitda/Assets} \times 0.1764\right)$$
$$+\left(\beta_{EbitdaStability} \times 9.160\right) + \left(\beta_{Ln(Assets)} \times 7.825\right)$$
$$= (1.775 \times 0.501) + (-3.434 \times 0.1764) + (-0.035 \times 9.160) + (-0.589 \times 7.825)$$
$$= -4.639 \quad (3\text{-}5)$$

$$\alpha_2 = -5.304 < y^* < -4.212 = \alpha_3, \quad (3\text{-}6)$$

which indicates that Model 1 predicts a rating of 3, or BBB. In fact, Maytag Corporation did have a BBB rating in 1993; the model correctly predicts the rating. Consistent with earlier research on ratings, these models correctly predict ratings in approximately 60% of in-sample cases; 55.6% for Model 1 and 56.5% for Model 2.

Counting the rate of correct predictions is just one measure of accuracy; I also report the degree of over- and underprediction, noting how often the prediction misses the observed rating and show that there is no consistent bias in direction. In addition, I examine the precision, or degree of error, in the model, penalizing large misses in either direction by averaging the squared distance of error between the predicted and observed ratings. Smaller values for the precision estimate indicate that the misses are smaller or fewer. For example, if the model predicts a BBB-rating (3), while the observed rating is an AA-rating (1), this is a miss of two rating categories. The squared distance used would be four, penalizing large misses more than small errors. This implies that the models with smaller total error offer closer misses. Table 3-7 indicates that Model 2, the market leverage model, has closer misses.

It is possible that a naïve grouping of all firms into a single model of rating insufficiently accounts for ratings differences across industries. I examine this by constructing a probit model with dummy variables for the nine remaining Fama-French industries. Table 3-8 presents book and market leverage models with industry dummy variables, with results consistent with the simpler model; market leverage continues to have greater explanatory power (0.246 to 0.2351), while the signs of the coefficients are in the properly directions. Table 3-9 indicates that the market leverage model continues to outperform the book leverage model on accuracy and precision, while the improvements in accuracy (i.e, frequency of correctly predicted ratings) and precision (measuring average squared size of misses) are better than the results without the industry dummies from Table 3-7. Further interested in ratings by industry, I estimate separate probit models of rating for each industry. To save space, the industry-specific

coefficients of these probit models are unreported, but Table 3-10 presents the prediction assessments for the book leverage (Model 1) and market leverage (Model 2) models. The “Correct Rate” column illustrates the 9 industry-specific probit models’ frequency of accurately predicting ratings, while the “Precision Estimate” reports the squared difference between predicted and observed rating. The right two columns report the difference between the market leverage (Model 2) and book leverage (Model 1) models. Here, the market leverage model generally produces more correct predictions and better precision, again suggesting that the market valuation yields some insight about ratings. To examine the effect of the market valuation in greater detail, I decompose the market-to-book ratio to identify the market information that is in fact useful for ratings predictions.

While the firm’s market valuation incorporates the market’s belief of the value of the firm’s growth options, an imperfect market may also include a misvaluation component that is related to the firm, industry, or market. Investor sentiment regarding a particular firm, or sector may impact a firm’s market valuation, masking the true value of growth options, as measured by market-to-book value. To extract the value of the growth options, separate from any misvaluation, I follow the RKRV methodology.

I estimate a model of market values through these variables in a linear regression, exactly the same as Eq. 1-7, yielding 189 regressions (9 industries and 21 years). As outlined in Chapter 1, I estimate values for long-run sector multiples, $\bar{\alpha}_j$, by averaging $\hat{\alpha}_{jt}$ over all annual regressions for each of the *k* variables. I use the broadest sample of 51,893 firm-year observations, rather than with a restricted, ratings-only sample, in consideration of the number of observations for the annual industry regressions. These

regression multiples are presented in Table 3-11 and appear quantitatively similar to Table 1-1. Table 3-12 presents the firm-level decomposition for the full sample, though I use the values from the ratings subsample, presented in Table 3-13. Specifically, Table 3-13 presents the mean firm-level decomposition by rating, following the additional sample restrictions detailed at the end of the Data Section. Although the RKRV decomposition identifies two sources of misvaluation, I sum the pair of misvaluation estimates into a single variable, Total Pricing Error (as Total Error in Equation 1.6), while considering the Long-run Value-to-book a measure of a firm's growth options, consistent with the analysis of Hertzel and Li (2010).

Results

While discussing the initial probit models, I outlined that market leverage models have higher explanatory power and greater prediction accuracy, as measured by frequency of correctly specified ratings and minimization of errors. This result should address the initial criticism of market leverage usage by showing that market valuation information offers prediction results that are at least as good book leverage models. Though Standard and Poor's notes that market valuations can be volatile and focus on short time horizons, leading them to a preference for book leverage (2006), these results imply that there is limited cost to outsiders using market leverage in evaluating credit ratings.

This finding is important because book value should contain little information about growth options or a firm's future prospects generating a follow-up question: if a model mimicking the rating agency's focus on book leverage yields poorer prediction than one explicitly minimized, why does a model with market leverage perform as well as it does? Since firm management can supply additional private information to the credit rating

agency about the firm's future, perhaps a model incorporating market valuation captures some of this information as well. Using market leverage could provide a reasonable link between the importance of book leverage and the supplementary private information, in line with the theoretical underpinning that market values are more informative about a firm's future financial situation than book values alone.

From this standpoint, it is also interesting to consider the type of information in market valuations that rating agencies find useful. Using the RKRV decomposition of market-to-book generated in the previous section, I test if market misvaluation or growth opportunities have a significant impact on ratings. A rating agency, with access to internal information, is positioned to establish whether a firm's existing assets and future growth opportunities are properly valued. The agencies could use this information when determining a firm's default probability and assigning a rating. Therefore, I am interested in modeling the probability a firm receives a particular rating, given its accounting variables, market valuation error, and growth options.

Table 3-14 presents ordered probit results of book and market leverage models with traditional ratings determinants (profitability (ebitda-to-assets), profit stability (ebitda stability), and size (natural log of assets)), as well as variables for market valuation error (Total Pricing Error) and growth options (Long-run Value-to-Book). In both models, signs for the traditional determinants are appropriate—increasing leverage lowers rating, while higher profitability, stability, and size result in better ratings (in these probits, high ratings are low numbers; AAA/AA = 1, BBB = 3, etc.). Further examination of the models' coefficients yields interesting results. Within the book leverage model, the coefficient for Total Pricing Error is negative (-0.017), but statistically insignificant. I

interpret this as indicating that market misvaluation is not significantly affecting a firm's rating. Meanwhile, a statistically significant, negative coefficient on the Long-run Value-to-Book indicates that having growth options also positively affects rating, supporting the hypothesis that growth options might serve as a safety net for firms.

Surprisingly, the signs on these two coefficients swap directions when the market leverage model is considered, suggesting exactly the opposite—that market overvaluation or growth options reduce your rating. The Long-run Value-to-Book variable is highly correlated with market leverage (-0.75), suggesting a multicollinearity problem, and I believe that the inclusion of these two variables together drives this strange result.

In spite of this issue, the pseudo-R^2 for the market-leverage model dominates the book leverage model. Moreover, these estimates of fit are better than their respective measures reported in Table 3-6, indicating more information about ratings from the components of market-to-book. I look to the model's in-sample performance and evaluate whether these models provide greater accuracy with more explanatory variables. Table 3-15 illustrates that the models including market-to-book components are more accurate (58.3% and 61.2% versus 55.6% and 56.5%) and precise (0.281 and 0.230 versus 0.397 and 0.303) than without the decomposition variables—there are more correctly predicted results and misses are closer, on average.

Table 3-16 presents the marginal probabilities of Model 3's probit regression. The top rows of the table establishes the mean values and standard deviations for the six independent variables within the book leverage framework. The Mean Marginal Probability column establishes the marginal probabilities of an average firm attaining

one of the ratings. This column indicates that the average firm is most likely to be BB-rated (39.83%), though a BBB-rating would occur approximately one third of the time. It would extremely unlikely for an average firm, based on the six variables, to be rated AA or higher (0.54%). These probabilities indicate an investment grade rating would occur 43% of the time (summing the mean marginal probabilities of the AAA/AA through BBB ratings). The six right columns for each rating present the marginal probabilities of ratings given a one standard deviation change in the column variable. For example, by increasing book leverage by one standard deviation (while keeping all the other variables at their mean value), the likelihood of an investment-grade rating falls to 32% from 43%. The specific marginal effect for a BBB rating fell to 26.33% from 33.32%, a change of -6.99%. These changes in marginal probabilities for a one standard deviation increase in the column variable are presented in Table 3-17.

The changes in the marginal probabilities indicate that the Long-run Value-to-Book variable has a small effect, increasing the likelihood of an investment grade rating approximately 4.6% with a one standard deviation increase (summing the changes in marginal probabilities of AAA/AA through BBB ratings). The Total Pricing Error variable also has an effect, albeit smaller; greater overvaluation leads to small increases in the probability of greater rating. It appears that the traditional determinants of rating have primary influence, as expected given the long line of research and focus on these factors, but growth options appear to have an impact on the ratings process as well. While assets may well serve as collateral against default, having growth options also has a positive impact on credit rating.

I further examine how rating agencies might evaluate firms on a case-by-case basis. Earlier, I hypothesized that firms, whose market value is driven primarily by assets-in-place, will see ratings predictions that are more accurate with market leverage, to account for the growth option safety net. Meanwhile, firms whose value is primarily driven by growth options will be better predicted by book value, because the effects of the safety net do not outweigh the primary, negative effects of leverage on default risk. To examine how rating agencies might account for these different types of firms, I sort the firms in the sample into quintiles based on growth opportunities relative to book assets (Long-run Value-to-Book to ln(assets)). Quintile 1 represents firms with low growth options to assets (value firms) while Quintile 5 represents firms with high growth options to assets (growth firms). I run pairs of probit regressions of the traditional determinants (leverage (book or market leverage), profitability (ebitda-to-assets), profit stability (ebitda stability), and size (natural log of assets)) for each of the five growth opportunity-to-asset quintiles. Table 3-18 presents the coefficient results for each of the five growth opportunity-to-asset quintiles. As expected, the firms that have large assets relative to growth opportunities, Quintile 1 (value firms), show the greatest difference in pseudo-R^2 between the two models (0.253 to 0.275), with market leverage providing greater explanatory power. At the other end of the spectrum, Quintile 5 (growth firms), exhibit better explanatory power in book leverage models (0.243 to 0.241). For firms with large growth options relative to assets-in-place, ratings can be predicted slightly better with book leverage than market leverage, while the smaller growth options-to asset firms are better predicted with market leverage. Further details of the accuracy and precision of these models is presented in Table 3-19. The market leverage model

(Model 2) appears more accurate (correctly predicting ratings 49.3% versus 47.1% of the time) for the value firms, as well as offering greater precision (0.801 to 0.819, where lower values are better), i.e, the size of the misses is smaller. The story changes some as I move towards the growth firms, where the book leverage model (Model 1) offers greater accuracy (56.2% versus 51.9%) for the growth firms, though the market leverage model remains more precise (0.625 versus 0.650). These findings generally support my contention that value firms (low growth options to assets) are better predicted by market models, capturing some details of the value of growth options for rating, while the growth firms (high growth options to assets) are better predicted by book models.

Evaluation

This study examines the impact of market valuations on prediction models of credit ratings. Though the credit rating agencies explicitly state a preference for and greater weight on book value, market valuations appear to predict ratings more accurately. I hypothesize that the use of market leverage can improve models of default risk and demonstrate that replacing book leverage with market leverage in otherwise identical models gives results that are both more accurate and precise in predicting credit ratings. The results suggest that corporate managers and investors can use market leverage without sacrificing the accuracy of credit rating assignment prediction. This may be because market information proxies for the private information utilized in the rating agencies' process.

Additionally, I examine whether firms with growth options are treated differently by rating agencies. I develop several hypotheses about the impact of growth options and market valuations on ratings assignments. If growth options have long-term value for a

firm, they should lower the default probability for the firm, either through the firm's ability to issue new equity on the options' value or through operational cash flow these options generate in the future. This yields a prediction that a rating agency should award a higher rating to a firm with more growth options, given similar accounting valuations.

The combination of these results indicates three things of importance to corporate managers and investors. First, while credit rating agencies might traditionally shun market valuations when considering ratings, market leverage predicts ratings better than book leverage. The degree of fit is better, and the predictions are more accurate and more precise. To the extent that corporate managers use book leverage when establishing debt policy, market leverage may provide more accurate estimates of how a rating agency might actually assign a rating. Second, while the traditional determinants of credit rating are of first-order concern, growth options can have a material impact on credit rating. For a corporate manager considering how to improve ratings or the investor assessing default risk, the investment decision between assets-in-place and growth opportunities may depend on the relative size of each category. Third, the degree to which market valuation tools can provide additional information about ratings also depends on the ratio between assets-in-place and growth opportunities. The larger existing assets are relative to growth options, market leverage models outperform book leverage models.

A more detailed look at the marginal results indicates the economic impact of a firm near a ratings change. Kisgen (2006) demonstrates how credit rating changes drive management decisions to change firm leverage. My results confirm that decreasing leverage has a first-order effect on ratings and should be the primary concern for

managers trying to change their rating. At the same time, my results also indicate that low-growth firms can adjust their allocation of assets-in-place and growth options to affect their rating at the margin. For example, a firm could sell existing assets for cash and use the proceeds to develop new products. I demonstrate that a positive marginal effect of adding growth options exists. Finally, I break down the distribution of firms into low and high growth firms and show that market leverage has better predictive power for firms with low-growth, which further indicates that firms with large collateralizable assets relative to growth options may have ratings which are positively affected by the presence of additional growth options.

To distinguish growth options from market misvaluation, I employ a market-to-book ratio decomposition developed by Rhodes-Kropf and Viswanathan (2004), isolating the value of growth options and quantifying the size of market misvaluation. Along with these components, I apply traditional book determinants to an ordered probit ratings prediction model to test how rating agencies might use estimates of growth options in their analysis. The results indicate that rating agencies consider growth options and the size of assets-in-place in assessing default risk. This study suggests that market valuations can yield better predictive results about a firm's rating than book leverage. I conclude that for an external market participant, there are subtle, useful information differences between book accounting and market valuations regarding ratings assignment.

Table 3-1. Full sample summary statistics

Variable		Mean	Standard Deviation	Min	Max
Observations	51,893				
Size Measures					
Market Value (assets)		4,564	23,197	10.3	1,825,103
Book Value (assets)		2,751	14,116	0.9	750,507
Market Equity		2,891	16,004	10.0	1,819,782
Book Equity		970	3,819	0.0	113,844
Net Income		120	806	-56,121.9	39,500
Performance Measures					
Return on Assets		0.022	0.143	-0.694	0.309
Return on Equity		0.053	0.273	-1.191	0.753
Market to Book		3.152	30.082	0.014	5603.07
Ebitda Stability		5.104	5.666	-2.994	30.299
Leverage Measures					
Book Leverage		0.487	0.209	0.001	1.000
Market Leverage		0.355	0.226	0.000	0.998

Note: Summary statistics for size, performance, and leverage taken from Compustat annual data between 1980 and 2006. Size measures are in millions of dollars; performance and leverage measures are ratios. Observations are required to have book-to-market ratios below 100 and market equity greater than $10 million. For consistency with RKRV, market value of assets is market value of equity + book assets - book equity - deferred taxes. Leverage is debt to total assets: market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. (These definitions imply that the market value of debt is the book value of total liabilities net of deferred taxes; the book leverage definition implies debt equals total book liabilities.) Ebitda stability is (five-year mean of ebitda/book value)/(five year standard deviation of ebitda/book value). Utilities (SIC codes 4800-4949; Fama French industry codes 7 and 8) and financial firms (SIC codes 6000-6999; Fama French industry code 11) are excluded from the sample. Performance measures are winsorized at the 1st and 99th percentiles.

Table 3-2. Ratings subsample summary statistics

Variable		Mean	Standard Deviation	Min	Max
Observations	18,004				
Size Measures					
Market Value (assets)		11,481	37,835	15.2	1,825,103
Book Value (assets)		6,961	23,136	14.8	750,507
Market Equity		7,120	26,069	10.1	1,819,782
Book Equity		2,326	6,010	0.1	113,844
Net Income		309	1,232	-27,446.0	39,500
Performance Measures					
Return on Assets		0.047	0.084	-0.694	0.309
Return on Equity		0.112	0.217	-1.191	0.753
Market to Book		3.313	43.850	0.062	5,603.07
Ebitda Stability		6.954	6.135	-2.994	30.299
Leverage Measures					
Book Leverage		0.595	0.166	0.042	1.000
Market Leverage		0.427	0.214	0.003	0.998

Note: Summary statistics for size, performance, and leverage taken from Compustat annual data between 1980 and 2006. Size measures are in millions of dollars; performance and leverage measures are ratios. Observations are required to have book-to-market ratios below 100 and market equity greater than $10 million. For consistency with RKRV, market value of assets is market value of equity + book assets - book equity - deferred taxes. Leverage is debt to total assets: market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. (These definitions imply that the market value of debt is the book value of total liabilities net of deferred taxes; the book leverage definition implies debt equals total book liabilities.) Ebitda stability is (five-year mean of ebitda/book value)/(five year standard deviation of ebitda/book value). Utilities (SIC codes 4800-4949; Fama French industry codes 7 and 8) and financial firms (SIC codes 6000-6999; Fama French industry code 11) are excluded from the sample. Performance measures are winsorized at the 1st and 99th percentiles. The ratings subsample is restricted to firms with S&P long-term ratings in the Compustat database, reducing the sample to 18,004 firm-year observations.

Table 3-3. Full sample summary statistics of firm characteristics by industry

	Fama French Industry Classifications								
	1	2	3	4	5	6	9	10	12
	Consumer non-durables	Consumer Durables	Manufacturing	Energy	Chemicals	Computers, Software.	Wholesale	Medical	Miscellaneous
Size Measures									
Market Value (assets)	4,098	10,659	3,062	9,080	5,457	4,041	3,363	4,889	4,363
Book Value (assets)	2,140	9,368	2,202	6,085	3,171	1,839	1,847	1,607	3,127
Market Equity	2,804	3,358	1,727	6,117	3,560	3,051	2,229	4,092	2,330
Book Equity	736	1,906	800	2,605	1,136	823	673	766	930
Net Income (Loss)	142	183	80	403	179	64	84	137	103
Performance Measures									
Return on Assets	0.06	0.05	0.04	0.03	0.04	0.00	0.05	-0.07	0.02
Return on Equity	0.12	0.10	0.08	0.07	0.11	0.01	0.09	-0.09	0.06
Market to Book	2.79	2.32	2.86	2.95	3.01	3.42	2.51	5.72	2.62
Ebitda Stability	6.97	5.46	5.45	3.97	7.41	3.33	7.33	3.11	5.02
Leverage Measures									
Book Leverage	0.51	0.52	0.52	0.51	0.54	0.41	0.53	0.37	0.53
Market Leverage	0.37	0.41	0.41	0.36	0.37	0.26	0.42	0.19	0.42

Note: Summary statistics for size, performance, and leverage taken from Compustat annual data between 1980 and 2006. Size measures are in millions of dollars; performance and leverage measures are ratios. Observations are required to have book-to-market ratios below 100 and market equity greater than $10 million. For consistency with RKRV, market value of assets is market value of equity + book assets - book equity - deferred taxes. Leverage is debt to total assets: market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. (These definitions imply that the market value of debt is the book value of total liabilities net of deferred taxes; the book leverage definition implies debt equals total book liabilities.) Ebitda stability is (five-year mean of ebitda/book value)/(five year standard deviation of ebitda/book value). Utilities (SIC codes 4800-4949; Fama French industry codes 7 and 8) and financial firms (SIC codes 6000-6999; Fama French industry code 11) are excluded from the sample. Performance measures are winsorized at the 1st and 99th percentiles. The full sample has 51,893 firm-year observations.

Table 3-4. Ratings subsample summary statistics of firm characteristics by industry

	Fama French Industry Classifications								
	1	2	3	4	5	6	9	10	12
	Consumer non-durables	Consumer Durables	Manufacturing	Energy	Chemicals	Computers, Software.	Wholesale	Medical	Miscellaneous
Size Measures									
Market Value (assets)	9,448	26,147	6,755	16,526	9,226	15,108	7,916	17,471	10,374
Book Value (assets)	4,759	23,086	4,827	11,101	5,328	7,123	4,212	5,681	7,494
Market Equity	6,520	7,953	3,792	10,960	5,978	11,022	5,251	14,585	5,402
Book Equity	1,568	4,499	1,722	4,582	1,846	2,938	1,453	2,635	2,122
Net Income (Loss)	331	428	180	733	293	270	191	530	249
Performance Measures									
Return on Assets	0.07	0.04	0.04	0.04	0.05	0.04	0.05	0.07	0.03
Return on Equity	0.17	0.11	0.10	0.10	0.14	0.08	0.12	0.14	0.09
Market to Book	4.00	2.59	3.69	2.83	3.26	3.20	3.29	4.74	2.43
Ebitda Stability	9.03	6.58	6.34	4.72	8.39	5.56	8.80	8.16	6.13
Leverage Measures									
Book Leverage	0.61	0.64	0.60	0.60	0.62	0.53	0.59	0.50	0.64
Market Leverage	0.40	0.50	0.46	0.42	0.41	0.35	0.45	0.26	0.50

Note: Summary statistics for size, performance, and leverage taken from Compustat annual data between 1980 and 2006. Size measures are in millions of dollars; performance and leverage measures are ratios. Observations are required to have book-to-market ratios below 100 and market equity greater than $10 million. For consistency with RKRV, market value of assets is market value of equity + book assets - book equity - deferred taxes. Leverage is debt to total assets: market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. (These definitions imply that the market value of debt is the book value of total liabilities net of deferred taxes; the book leverage definition implies debt equals total book liabilities.) Ebitda stability is (five-year mean of ebitda/book value)/(five year standard deviation of ebitda/book value). Utilities (SIC codes 4800-4949; Fama French industry codes 7 and 8) and financial firms (SIC codes 6000-6999; Fama French industry code 11) are excluded from the sample. Performance measures are winsorized at the 1st and 99th percentiles. The ratings subsample has 18,004 firm-year observations.

Table 3-5. Mean firm characteristics by rating

	S&P Long-Term Ratings				
	AAA/AA	A	BBB	BB	B/CCC
Size Measures					
Market Value (assets)	50,034	17,802	9,002	3,213	1,425
Book Value (assets)	26,401	10,380	6,286	2,473	1,138
Market Equity	34,651	11,232	4,949	1,543	607
Book Equity	9,911	3,461	1,925	731	298
Net Income (Loss)	1,662	519	202	36	-22
Performance Measures					
Return on Assets	0.09	0.07	0.05	0.04	0.00
Return on Equity	0.20	0.17	0.13	0.09	0.00
Market to Book	4.33	3.52	2.76	2.23	5.01
Ebitda Stability	11.55	9.61	7.09	5.16	3.90
Leverage Measures					
Book Leverage	0.53	0.57	0.60	0.61	0.62
Market Leverage	0.27	0.35	0.42	0.49	0.52

Note: Summary statistics for size, performance, and leverage taken from Compustat annual data between 1980 and 2006. Size measures are in millions of dollars; performance and leverage measures are ratios. Observations are required to have book-to-market ratios below 100 and market equity greater than $10 million. For consistency with RKRV, market value of assets is market value of equity + book assets - book equity - deferred taxes. Leverage is debt to total assets: market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. (These definitions imply that the market value of debt is the book value of total liabilities net of deferred taxes; the book leverage definition implies debt equals total book liabilities.) Ebitda stability is (five-year mean of ebitda/book value)/(five year standard deviation of ebitda/book value). Utilities (SIC codes 4800-4949; Fama French industry codes 7 and 8) and financial firms (SIC codes 6000-6999; Fama French industry code 11) are excluded from the sample. Performance measures are winsorized at the 1st and 99th percentiles. The ratings subsample has 18,004 firm-year observations.

Table 3-6. Basic ordered probit regressions

	Model 1	Model 2
Book Leverage	1.775***	
	0.047	
Market Leverage		2.182***
		0.049
Ebitda Over Assets	-3.435***	-2.186***
	0.117	*0.123*
Ebitda Stability	-0.035***	-0.033***
	0.001	*0.001*
Ln(Assets)	-0.589***	-0.561***
	0.007	*0.006*
α_1	-6.542***	-6.366***
	0.061	*0.061*
α_2	-5.305***	-5.117***
	0.056	*0.056*
α_3	-4.212***	-3.996***
	0.053	*0.053*
α_4	-3.098***	-2.853***
	0.050	*0.050*
Observations	18,004	18,004
Pseudo-R^2	0.2252	0.2356

Note: Probit regressions of the ratings subsample use the long-term debt rating variable from Compustat annual data as the dependent variable. Firms rated AAA are categorized as AA and CCC as B for the probit model regressions. AAA/AA firms rating = 1, A = 2, …, B/CCC = 5. The regression coefficient variables are measured concurrently (i.e., same fiscal year) with rating. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively. Robust standard errors are listed in italics below the coefficients.

Table 3-7. Accuracy and precision of basic ordered probit regressions

	Model 1	Model 2
Percentage of Correctly Predicted Ratings	0.556	0.565
Percentage of High Error	0.223	0.219
Percentage of Low Error	0.221	0.216
Precision Estimate	0.397	0.303

Note: Accuracy and precision estimates of basic ordered probit regressions, which use long-term debt rating from Compustat as the dependent variable. There are 18,004 firm-year observations in these regressions. Model 1 includes book leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Model 2 includes market leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over

Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Percentage of high error indicates the fraction of in-sample predictions given higher than observed ratings; low error indicates fraction of in-sample predictions given lower than observed ratings. Precision estimate is the average of squared errors between predicted and observed ratings. For example, a predicted rating of 3 (BBB) when the firm was actually a 1 (AA), is a miss of 2 ratings levels and would have a value of 4 in the averaging. Low values indicate greater precision.

Table 3-8. Basic ordered probit regressions with industry dummies

	Book Leverage & Industry Dummy	Market Leverage & Industry Dummy
Book Leverage	1.922***	
	0.048	
Market Leverage		2.364***
		0.051
Ebitda Over Assets	-3.234***	-1.951***
	0.118	*0.124*
Ebitda Stability	-0.033***	-0.032***
	0.001	*0.001*
Ln(Assets)	-0.603***	-0.573***
	0.007	*0.006*
Consumer non-durables	-0.379***	-0.297***
	0.033	*0.033*
Consumer durables	-0.256***	-0.317***
	0.042	*0.042*
Manufacturing	-0.246***	-0.274***
	0.026	*0.027*
Energy	0.060	0.088*
	0.035	*0.035*
Chemicals	-2.781***	-0.169***
	0.039	*0.040*
Computers, Software, etc.	0.282***	0.341***
	0.032	*0.032*
Wholesale	0.003	-0.028
	0.029	*0.029*
Medical	-0.192***	-0.115**
	0.037	*0.037*
α_1	-6.680***	-6.480***
	0.064	*0.065*
α_2	-5.426***	-5.218***
	0.059	*0.060*
α_3	-4.310***	-4.071***
	0.056	*0.057*
α_4	-3.172***	-2.900***
	0.053	*0.054*
Obs	18,004	18,004
Pseudo-R^2	0.2351	0.246

Note: Probit regressions of the ratings subsample use the long-term debt rating variable from Compustat annual data as the dependent variable. Firms rated AAA are categorized as AA and CCC as B for the probit model regressions. AAA/AA firms rating = 1, A = 2, …, B/CCC = 5. The regression coefficient variables are measured concurrently (i.e., same fiscal year) with rating. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively. Robust standard errors are listed in italics below the coefficients.

Table 3-9. Accuracy and precision of basic ordered probit regressions with industry dummies

	Book Leverage & Industry Dummy	Market Leverage & Industry Dummy
Percentage of Correctly Predicted Ratings	0.564	0.575
Percentage of High Error	0.220	0.213
Percentage of Low Error	0.216	0.212
Precision Estimate	0.351	0.301

Note: Accuracy and precision estimates of basic ordered probit regressions, which use long-term debt rating from Compustat as the dependent variable. There are 18,004 firm-year observations in these regressions. Book leverage & Industry Dummy includes book leverage, ebitda/assets, ebitda stability, and ln(assets), and dummy variables for eight industries (the miscellaneous industry excluded) as independent variables. Model 2 includes market leverage, ebitda/assets, ebitda stability, and ln(assets) and eight industries as independent variables. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Percentage of high error indicates the fraction of in-sample predictions given higher than observed ratings; low error indicates fraction of in-sample predictions given lower than observed ratings. Precision estimate is the average of squared errors between predicted and observed ratings. For example, a predicted rating of 3 (BBB) when the firm was actually a 1 (AA), is a miss of 2 ratings levels and would have a value of 4 in the averaging. Low values indicate greater precision.

Table 3-10. Prediction accuracy by industry probit regressions

	Industry	Correct Rate	Precision Estimate	High Error Rate	Low Error Rate	Basic Market Leverage - Basic Book Leverage Correct Diff	Basic Market Leverage - Basic Book Leverage Precision Diff.
Book Leverage (Model 1)	1	0.569	0.461	0.214	0.217	0.016	-0.016
	2	0.628	0.431	0.169	0.203	0.002	-0.002
	3	0.525	0.522	0.239	0.237	0.021	-0.029
	4	0.613	0.424	0.190	0.197	-0.012	0.001
	5	0.641	0.386	0.178	0.180	0.008	-0.009
	6	0.565	0.485	0.234	0.201	0.005	-0.007
	7	0.553	0.495	0.233	0.213	0.018	-0.030
	8	0.556	0.512	0.218	0.226	0.028	-0.032
	9	0.537	0.516	0.235	0.229	0.011	-0.020
Market Leverage (Model 2)	1	0.585	0.445	0.210	0.206		
	2	0.630	0.429	0.178	0.191		
	3	0.546	0.492	0.228	0.226		
	4	0.601	0.426	0.197	0.202		
	5	0.649	0.377	0.160	0.191		
	6	0.571	0.478	0.230	0.199		
	7	0.571	0.466	0.223	0.205		
	8	0.585	0.480	0.197	0.218		
	9	0.548	0.496	0.234	0.218		

Note: Table presents measures of accuracy and precision for industry-specific probit regressions, which use long-term debt rating from Compustat annual data as the dependent variable. Model 1 includes book leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Model 2 includes market leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Correctly Predicted column indicates the frequency the industry-specific probit regressions correctly predict a rating. Precision Estimate is the average of squared errors between predicted and observed ratings. For example, a predicted rating of 3 (BBB) when the firm was actually a 1 (AA), is a miss of 2 ratings levels and would have a value of 4 in the averaging. Low values are better for the precision estimate. High Error Rate indicates the fraction of in-sample predictions given higher than observed ratings; Low Error Rate indicates fraction of in-sample predictions given lower than observed ratings. The differences in accuracy (i.e., correctly predicted) and the precision of the prediction (squared difference between predicted and observed) between the two models (Model 2 minus Model 1) are reported in the two right columns.

Table 3-11. Conditional regression multiples

	Fama French Industry Classifications								
	1	2	3	4	5	6	9	10	12
Parameter	Consumer non-durables	Consumer Durables	Manufacturing	Energy	Chemicals	Computers, Software	Wholesale	Medical	Miscellaneous
$E_t(a_0)$	1.4457	1.4901	1.4052	1.5158	1.8072	1.7416	1.4857	2.1299	1.6525
$E_t(a_1)$	0.7220	0.7323	0.8041	0.7904	0.7027	0.7262	0.7859	0.6849	0.7501
$E_t(a_2)$	0.3725	0.3157	0.2368	0.2091	0.3418	0.3081	0.2701	0.3337	0.2687
$E_t(a_3)$	-0.0816	-0.0504	-0.0302	-0.0294	-0.0298	-0.0868	-0.0845	-0.0788	-0.0696
$E_t(a_4)$	-1.2709	-1.2763	-1.4336	-1.0864	-1.5576	-1.5283	-1.4885	-1.9002	-1.3587
Adjusted-R^2	0.9203	0.9412	0.9238	0.9279	0.9401	0.9153	0.9222	0.9052	0.8903

Note: Table reports the time-series average coefficients from regression equation (1-7). The dependent variable is the natural log of market value (m). The independent variables are the natural log of book value (b), natural log of absolute value of net income (ni+), an indicator interacted with log net income (ni+) to separately estimate net income for firms with negative net income and market leverage (Lev). Fama-French twelve industry classifications are reported across the top. Outputs from valuation regressions are reported in each row. Each model is estimated cross-sectionally at the industry-year level. The variable $E_t(a_0)$ is the time-series average of the constant term for each regression. $E_t(a_k)$ is the time-series average multiple from the regression associated with the kth accounting variable. Regressions are run annually for each industry from 1985 to 2006. Standard errors are reported in italics below the average estimated coefficients. The reported Adjusted-R^2 is the average adjusted-R^2 for each industry.

Table 3-12. Firm-level decomposition of market-to-book ratios for the full sample

	Fama French Industry Classifications								
	1	2	3	4	5	6	9	10	12
	Consumer non-durables	Consumer durables	Manufacturing	Energy	Chemicals	Computers, Software	Wholesale	Medical	Miscellaneous
Ln(M/B)	0.6281	0.5151	0.4708	0.6224	0.7882	0.8122	0.5074	1.1965	0.5439
Firm-specific	0.0000	-0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000
Sector-specific	0.0028	0.0527	0.0053	-0.0027	0.0473	0.0507	-0.0014	-0.0159	0.0132
Long-run value-to-book	0.6281	0.5151	0.4707	0.6223	0.7881	0.8121	0.5074	1.1964	0.5439

Note: The data comprise 51,893 firm-level observations between 1986 and 2006. Regressions are run annually for each industry from 1986 to 2006. This regression uses natural logs of market (m) and book value (b), natural log of the absolute value of net income (ni), and an indicator interacted with log net income (ni+) to separately estimate net income for firms with negative net income and market leverage (Lev). The three components are firm-specific error, time-series sector error, and the long-run value-to-book. The table reports the mean fitted values from the coefficients generated in the annual industry regressions.

Table 3-13. Firm-level decomposition of market-to-book ratios for the ratings subsample

	Fama French Industry Classifications								
	1	2	3	4	5	6	9	10	12
	Consumer non-durables	Consumer durables	Manufacturing	Energy	Chemicals	Computers, software, etc.	Wholesale	Medical	Miscellaneous
Ln(M/B)	0.7537	0.6181	0.5649	0.7469	0.9458	0.9746	0.6089	1.4358	0.6527
Firm-specific	0.0000	-0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000
Sector-specific	0.0034	0.0633	0.0063	-0.0033	0.0567	0.0609	-0.0017	-0.0191	0.0159
Long-run value-to-book	0.7537	0.6182	0.5649	0.7468	0.9457	0.9746	0.6089	1.4357	0.6527

Note: The data comprise 18,004 firm-level observations between 1986 and 2006. Regressions are run annually for each industry from 1986 to 2006. This regression uses natural logs of market (m) and book value (b), natural log of the absolute value of net income (ni), and an indicator interacted with log net income (ni+) to separately estimate net income for firms with negative net income and market leverage (Lev). The three components are firm-specific error, time-series sector error, and the long-run value-to-book. The table reports the mean fitted values from the coefficients generated in the annual industry regressions.

Table 3-14. Advanced ordered probit regressions

Parameters	Model 3	Model 4
Book Leverage	1.635***	
	0.053	
Market Leverage		2.642***
		0.067
Ebitda Over Assets	-2.752***	-2.564***
	0.128	*0.129*
Ebitda Stability	-0.034***	-0.034***
	0.001	*0.001*
Ln(Assets)	-0.578***	-0.582***
	0.007	*0.007*
Total Pricing Error	-0.017	0.104***
	0.013	*0.012*
Long-run Value-to-Book	-0.226***	0.254***
	0.019	*0.025*
α_1	-6.568***	-6.310***
	0.061	*0.063*
α_2	-5.322***	-5.059***
	0.057	*0.058*
α_3	-4.220***	-3.933***
	0.053	*0.055*
α_4	-3.102***	-2.779***
	0.050	*0.052*
Observations	18,004	18,004
Pseudo-R^2	0.2348	0.2434

Note: Probit regressions of the ratings subsample use the long-term debt rating variable from Compustat annual data as the dependent variable. Firms rated AAA are categorized as AA and CCC as B for the probit model regressions. AAA/AA firms rating = 1, A = 2, …, B/CCC = 5. The regression coefficient variables are measured concurrently (i.e., same fiscal year) with rating. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Total Pricing Error is the sum of the RKRV decomposition misvaluation components, firm-specific pricing error and time-series sector error. Long-run Value-to-Book represents a measure of a firm's growth options. *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively. Robust standard errors are listed in italics below the coefficients.

Table 3-15. Accuracy and precision of advanced ordered probit regressions prediction

	Model 3	Model 4
Percentage of Correctly Predicted Ratings	0.583	0.612
Percentage of High Error	0.210	0.197
Percentage of Low Error	0.206	0.193
Precision Estimate	0.281	0.230

Note: Accuracy and precision estimates of basic ordered probit regressions, which use long-term debt rating from Compustat as the dependent variable. There are 18,004 firm-year observations in these regressions. Model 3 includes book leverage, ebitda/assets, ebitda stability, ln(assets), and estimates of Total Pricing Error and Long-run Value-to-Book as independent variables. Model 4 includes market leverage, ebitda/assets, ebitda stability, ln(assets), and estimates of Total Pricing Error and Long-run Value-to-Book as independent variables. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Total Pricing Error is the sum of the RKRV decomposition misvaluation components, firm-specific pricing error and time-series sector error. Long-run Value-to-Book represents a measure of a firm's growth options. Percentage of high error indicates the fraction of in-sample predictions given higher than observed ratings; low error indicates fraction of in-sample predictions given lower than observed ratings. Precision estimate is the average of squared errors between predicted and observed ratings. For example, a predicted rating of 3 (BBB) when the firm was actually a 1 (AA), is a miss of 2 ratings levels and would have a value of 4 in the averaging. Low values indicate greater precision.

Table 3-16. Probit model 3 marginal probabilities

Rating	Mean Marg. Prob.	Book leverage	Return on Assets	Ebitda Stability	Ln(book assets)	Total Pricing Error	Long-run Value-to-book
		0.59	0.047	6.96	7.546	0.182	0.321
		0.17	*0.084*	*6.14*	*1.537*	*0.709*	*0.551*
AAA/AA	0.54%	0.22%	0.93%	1.22%	4.81%	0.67%	0.75%
A	9.28%	5.39%	12.72%	14.86%	29.47%	10.59%	11.23%
BBB	33.32%	26.33%	37.26%	39.01%	41.97%	35.01%	35.75%
BB	39.83%	42.49%	36.57%	34.42%	20.47%	38.63%	38.02%
B/CCC	17.02%	25.57%	12.54%	10.49%	3.29%	15.09%	14.25%

Note: Table presents the marginal probabilities of Probit Model 3, which uses long-term debt rating from annual Compustat data as the dependent variable. The probit includes book leverage, ebitda/assets, ebitda stability, ln(assets), and estimates of Total Pricing Error and Long-run Value-to-Book as independent variables. Book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Total Pricing Error is the sum of the RKRV decomposition misvaluation components, firm-specific pricing error and time-series sector error. Long-run Value-to-Book represents a measure of a firm's growth options. The top row presents the mean values of firms in the rating subsample for each of the six independent variables in the model. Standard deviations are listed in italics beneath their respective means. The Mean Marginal Probability column reports the marginal probabilities of receiving a rating for the mean firm. The six right columns for each rating report the marginal probabilities of receiving that rating by increasing the column variable one standard deviation, while keeping all other variables at their mean value.

Table 3-17. Probit model 3 changes in marginal probabilities

Rating	Mean Marg. Prob.	Book leverage	Return on Assets	Ebitda Stability	Ln(book assets)	Total Pricing Error	Long-run Value-to-book
		0.59	0.047	6.96	7.546	0.182	0.321
		0.17	*0.084*	*6.14*	*1.537*	*0.709*	*0.551*
AAA/AA	0.54%	-0.32%	0.39%	0.68%	4.27%	0.14%	0.21%
A	9.28%	-3.89%	3.43%	5.57%	20.18%	1.31%	1.95%
BBB	33.32%	-6.99%	3.93%	5.69%	8.65%	1.69%	2.43%
BB	39.83%	2.65%	-3.27%	-5.42%	-19.36%	-1.20%	-1.82%
B/CCC	17.02%	8.55%	-4.48%	-6.53%	-13.74%	-1.94%	-2.77%

Note: Table presents the changes in marginal probabilities of Probit Model 3, which uses long-term debt rating from annual Compustat data as the dependent variable. The probit includes book leverage, ebitda/assets, ebitda stability, ln(assets), and estimates of Total Pricing Error and Long-run Value-to-Book as independent variables. Book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Total Pricing Error is the sum of the RKRV decomposition misvaluation components, firm-specific pricing error and time-series sector error. Long-run Value-to-Book represents a measure of a firm's growth options. The top row presents the mean values of firms in the rating subsample for each of the six independent variables in the model. Standard deviations are listed in italics beneath their respective means. The Mean Marginal Probability column reports the marginal probabilities of receiving a rating for the mean firm. The six right columns for each rating report the changes in the marginal probabilities of receiving that rating by increasing the column variable one standard deviation, while keeping all other variables at their mean value.

Table 3-18. Ordered probit models by growth quintile

	Value Firms: Quintile 1		Quintile 2		Quintile 3		Quintile 4		Growth Firms: Quintile 5	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Book Leverage	0.304		1.659		1.904		2.613		2.308	
Market Leverage		2.092		3.797		3.237		3.189		2.363
Ebitda Over Assets	-2.117	-1.713	-3.734	-3.158	-4.358	-3.758	-4.157	-3.545	-3.376	-2.151
Ebitda Stability	-0.034	-0.034	-0.041	-0.039	-0.024	-0.023	-0.040	-0.037	-0.033	-0.031
Ln(Assets)	-0.674	-0.663	-0.599	-0.547	-0.515	-0.463	-0.606	-0.549	-0.593	-0.551
α_1	-7.242	-7.051	-6.758	-6.381	-5.904	-5.533	-6.549	-6.208	-6.550	-6.195
α_2	-5.971	-5.769	-5.406	-5.021	-4.654	-4.273	-5.295	-4.963	-5.381	-5.029
α_3	-5.026	-4.814	-4.314	-3.917	-3.543	-3.147	-3.954	-3.611	-4.234	-3.841
α_4	-4.053	-3.832	-3.156	-2.741	-2.451	-2.041	-2.807	-2.455	-2.911	-2.483
Pseudo-R^2	0.253	0.275	0.234	0.236	0.198	0.197	0.244	0.248	0.243	0.241
Observations	3600	3600	3601	3601	3601	3601	3601	3601	3601	3601

Note: Companies are sorted into quintile by Long-run Value-to-Book/Ln(Assets). Firms in Quintile 1 (value) have low growth options relative to assets; firms in Quintile 5 (growth) have high growth options relative to assets. Long-run Value-to-Book represents a measure of a firm's growth options, a component of the RKRV decomposition. Probit regressions of the ratings subsample use the long-term debt rating variable from Compustat annual data as the dependent variable. Firms rated AAA are categorized as AA and CCC as B for the probit model regressions. AAA/AA firms rating = 1, A = 2, …, B/CCC = 5. The regression coefficient variables are measured concurrently (i.e., same fiscal year) with rating. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions.

Table 3-19. Accuracy and precision of ordered probit model by growth quintile

	Value Firms: Quintile 1		Quintile 2		Quintile 3		Quintile 4		Growth Firms: Quintile 5	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Percentage of Correctly Predicted Ratings	0.471	0.493	0.481	0.477	0.460	0.452	0.489	0.494	0.526	0.519
Percentage of High Error	0.264	0.253	0.253	0.253	0.267	0.273	0.259	0.256	0.237	0.276
Percentage of Low Error	0.265	0.254	0.267	0.270	0.273	0.276	0.252	0.250	0.236	0.205
Precision Estimate	0.819	0.801	0.721	0.731	0.795	0.801	0.700	0.688	0.650	0.625

Note: Table presents accuracy and precision estimates of basic ordered probit regressions, which use long-term debt rating from Compustat as the dependent variable. Companies are sorted into quintile by Long-run Value-to-Book/Ln(Assets). Firms in Quintile 1 (value) have low growth options relative to assets; firms in Quintile 5 (growth) have high growth options relative to

assets. Long-run Value-to-Book represents a measure of a firm's growth options, a component of the RKRV decomposition. Firms rated AAA are categorized as AA and CCC as B for the probit model regressions. AAA/AA firms rating = 1, A = 2, …, B/CCC = 5. The regression coefficient variables are measured concurrently (i.e., same fiscal year) with rating. Model 1 includes book leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Model 2 includes market leverage, ebitda/assets, ebitda stability, and ln(assets) as independent variables. Market leverage is 1 - market equity/market value of assets; book leverage is 1 - book equity/book value. Ebitda stability is the coefficient of variation of ebitda-to-assets over the prior five years. Ebitda over Assets and Ebitda stability are winsorized at the 1st and 99th percentiles before the regressions. Percentage of high error indicates the fraction of in-sample predictions given higher than observed ratings; low error indicates fraction of in-sample predictions given lower than observed ratings. Precision estimate is the average of squared errors between predicted and observed ratings. For example, a predicted rating of 3 (BBB) when the firm was actually a 1 (AA), is a miss of 2 ratings levels and would have a value of 4 in the averaging. Low values indicate greater precision. Quintile 1 regressions have 3,600 observations; Quintiles 2-5 regressions have 3,601 observations.

CHAPTER 4
WHEN PUSH COMES TO SHOVE: WHAT DRIVES LIQUIDATION CHOICE?

Motivation

Malkiel (1995) notes that active management of mutual funds tends to underperform in the long-run, implying that investors could improve their returns by passively diversifying portfolios in broad-market index funds. This is consistent with market efficiency literature surveyed in Fama (1991) that argues that profitable trading strategies on equities using only publicly available information should be minimal. Yet actively managed mutual funds continue in popularity—as of 2011, nearly 83% of equity fund assets are under active management, rather than in index funds. Lubos Pastor, writing in Bloomberg News, notes that even active managers Peter Lynch and Warren Buffett advise most investors to hold index funds (Pastor (2012)).

Actively managed fund popularity is difficult to square with the suggestion that index funds perform better, though there is evidence that mutual fund managers are good at picking stocks, on average (for example, Daniel, Grinblatt, Titman, and Wermers (1997); Chen, Jegadeesh, and Wermers (2000); and Wermers (2000)). Yet research by Malkiel (1995) suggests that active management is not advantageous in the long run, as there is limited persistence in positive performance among fund managers. If positive performing funds have little persistence, Carhart (1997) illustrates that poorly performing funds do exhibit persistent underperformance. That is, while good funds struggle to maintain good performance, bad funds continue to be bad. What drives this persistent underperformance—are these poorly performing managers making identifiably bad choices in portfolio allocation?

Do the transactions of high-outflow managers differ from managers facing inflows? On the one hand, these managers are required to generate cash when other managers are not; to the extent that they may be forced to act differently is driven by the degree their hands are forced by redemption demands. At the same time, the work of Alexander, Cici, and Gibson (2007) indicates that both high inflow and outflow managers make valuation-based transaction decisions, while concurrently dealing with liquidity needs. Yet it is also possible that high-outflow fund managers trade differently, acceding to behavioral issues; Cici (2010) notes a disposition effect leads high-outflow funds to sell more winners than losers. This paper does not address the issue of whether the fund managers trade differently in response to their high outflows, which would require a comparison between high-outflow and other funds' behavior. Instead, I focus solely on the characteristics of the trading characteristics of the high-outflow funds.

I focus on this small subset of the universe of actively managed funds, because low outflow (or high inflow) funds may have the option to do nothing, i.e., make no reallocation decisions, while high-outflow funds must react to their changes in flows. Coval and Stafford (2007) show that funds do not generally hold enough cash to satisfy redemption demands, resulting in a forced sell-off of the portfolio components to address their immediate cash needs. Thus, fund managers facing redemptions actively decide what pieces of the portfolio to liquidate for cash to return to investors and provide an interesting study of decision making.

What motivates an active fund manager's choice of liquidation among his portfolio? While an infinite range of reasons exist, I might group them into several

identifiable categories: a preference regarding prior momentum (i.e., for prior winners or losers), liquidity, portfolio rebalancing in naïve or strategic forms, behavioral, or perhaps something else entirely. This study investigates several of these possibilities and surmises that at least some of the liquidation choice is non-random selection.

Several factors could drive the choice of liquidation for tactical or strategic reasons. Among tactical reasons, funds in need of quick cash may have a clear tactical preference for selling more liquid holdings, picking securities with less price impact (i.e., higher relative cash per sale) and faster execution (i.e., quicker cash following liquidation order). Funds may have a preference to liquidate stocks with positive (negative) momentum, perhaps expecting momentum reversal (continuation).

Alternatively, funds may use their selling as a strategic opportunity to reevaluate their portfolio. Funds might aim to reduce overvalued securities relative to undervalued securities. Funds may choose to reallocate their portfolio back to a previous allocation. If certain stocks have become overweighted (underweighted) within the portfolio due to a previous increase (decrease) in value, then the fund may want to sell the overweighted stocks and buy (or at least not sell) underweighted stocks. Obviously, measuring strategic rebalancing is fraught with problems, but this study represents a preliminary effort at evaluating the choices of active fund managers under pressure. By utilizing the Rhodes-Kropf, Robinson, and Viswanathan (2005) market-to-book decomposition to measure relative valuation, I examine whether fund managers are strategically rebalancing their portfolios.

This study examines the decisions of a subset of actively managed funds, those linked to high outflows, seeking to understand what factors drive the investment and

liquidation decisions of the active fund manager. This paper identifies some common characteristics of stocks sold by mutual funds with the highest outflows, examining four possible reasons underlying the liquidation decision. I illustrate that high outflow funds tend to sell recent (one-year) winners rather than losers, and prefer to sell more liquid stocks, but do not appear to use this opportunity to reevaluate or reallocate their portfolio choices. As the Rhodes-Kropf, Robinson, Viswanathan (2005) decomposition technique establishes measures for market misvaluation (i.e., over- or undervaluation relative to other securities in an industry) and a measure for a long-run average, 'intrinsic' value, I extend their application to characterizing the holdings and behavior of actively managed funds. This study extends the mutual fund performance literature by contributing evidence that high-outflow, actively managed funds make suboptimal decisions. In the following sections, I discuss the relevant literature, data used, methodology employed to identify the highest outflow funds, and techniques for evaluating liquidity and relative valuation. Results and conclusions follow.

Literature Review and Hypothesis Development

One way of assessing the decision process of the active manager is identifying moments when the manager must actively make a decision. In most situations, the fund manager may opt to do nothing, so it would be difficult to specify if the manager is making an active "do nothing" choice, or passively accepting the status quo. Even with net cash inflows, the fund manager can delay deployment of new resources. Only when the fund has net cash outflows might the manager be required to act, as cash holdings do not typically cover redemption demands of fleeing investors (Coval and Stafford (2007)). As a result, the catalyst for this study is the relative redemption demands of the fund, evidenced by high cash outflows.

One explanation of the fund manager's choice is the ease of liquidating his stock position. Fund managers under redemption pressure may be eager to sell holdings that suffer a smaller negative price impact from forced selling. Higher liquidity offers greater opportunity for the fund manager to liquidate at nearly full value for his holding. In other words, the impact of a fund manager's order flow on price could be a consideration. My investigation of this explanation utilizes Amihud's (2002) illiquidity measure (AIM) to examine the price impact of the sale of a particular security. Though this statistic does not come with a unit of measure, I can gauge a holding's liquidity in comparison to the universe of stocks or, more appropriately to this study, to the liquidity of other stocks in the fund's portfolio.

Tied to the liquidity of the holding is the past performance of the stock. Odean (1998) notes that firms may choose to sell past winners because they may be more liquid. Stocks with low prices are likely to be less liquid, and firms with prior negative returns are more likely to have a lower stock price. Alternatively, a fund manager's choice to liquidate a past winner could be related to a preference for negative momentum stocks because of the expectation of a reversal. Figelman (2007) notes the potential for intermediate term (within the subsequent four quarters) momentum reversal and implications for implementing a reversal strategy. Since funds with high outflows must act, in their effort to raise redemption cash, we can shed light on the fund managers' preference for liquidating prior winners or losers.

The next two explanations are both related to strategic decision making by management in choosing which securities to sell. I categorize the first of the two as strategic reevaluation. Active fund managers may reevaluate the strength of their

holdings and choose to retain or increase holdings perceived as undervalued while reducing holdings that are overvalued. Alexander, Cici, and Gibson (2007) consider a range of motivations for fund actions in relation to flows. For example, a fund with high inflows could buy stocks to alleviate extra liquidity without significant concern about valuation. More tellingly of funds with high inflows (i.e., lots of cash on hand) occurs if the fund sells stock, suggesting a motivation related to valuation. On the other hand, a fund facing high outflows could similarly trade for valuation by purchasing stocks at the moment that it faces redemptions. Moreover, Alexander, Cici, and Gibson (2007) find that the funds' performance varies with their motivation; if the trades appear valuation-related, future fund performance is greater, suggesting fund managers have the ability to value stocks. Meanwhile, they find that the performance of liquidity-related transactions (small buys concurrent with high inflows and small sells concurrent with high outflows) are more equivocal, though their results of outperformance of liquidity-based selling in the face of high outflows suggests that fund managers are valuing their liquidations. That is, the larger sales in the face of high outflows underperform smaller sales, consistent with a hypothesis that fund managers correctly value stocks and try to retain more of the stocks they expect to do well in the future. Their results suggest that fund managers are making transactions based on valuation, with some allowance for liquidity needs. While the valuation methodology of any stock picker is subject to criticism (if there was a perfect technique for valuation, there would be little need for the active fund manager), I nonetheless use the RKRV market-to-book decomposition technique to probe relative valuation among the holdings.

I call the second of these two strategic decision making tools ‘strategic rebalancing’. If funds have a target allocation of assets, then fund managers may wish to offset price movements that change the relative weightings of assets within the portfolio. It is possible that the choice of liquidating winners or losers is a simple recalibration of the funds’ holdings. Harjoto and Jones (2006) note that optimal rebalancing strategies depend on the path of the market movement and rebalancing holdings in response. Though they argue frequent rebalancing to a target weighting is unnecessary, it would be unsurprising if high outflow funds, forced into action, use the opportunity to rebalance their holdings because of prior movements. Dichtl, Drobetz, and Wambach (2011) note that several rebalancing strategies to a target holding weight outperforms a simple buy and hold strategy. In this case, I would expect to find that managers more readily sell stocks whose relative weight within the portfolio has increased, while buying or retaining stocks whose relative weight within the portfolio has fallen.

This study focuses on rational explanations for the selling decisions of constrained mutual funds. It is also possible that there is a behavioral explanation. In examining the disposition effect in mutual fund managers, Cici (2010) finds that funds that experience outflows are likely to sell disproportionately more winners than losers. Ritter and Chopra (1989) and Haugen and Lakonishok (1987) note that fund managers may make holdings decisions to improve the listed holdings around filing dates. There are countless reasons a fund manager might liquidate his holdings unique to each situation; I restrict the scope of my investigation to a subset of rational categories to draw inference about high-outflow funds liquidation selection.

Data and Methodology

The data used in this study combines holdings data from the CRSP Survivor-Bias-Free US Mutual Fund Database with CRSP and Compustat data. The sample period is restricted to December 2002 to December 2008 due to the availability of mutual fund holding data in CRSP. I impose several screens of the data to focus on large, US-based equity funds, similar to Coval and Stafford's (2007) examination of equity fund asset sales. First, I eliminate bond, specialty, international, and global funds from the holding data. Then, I eliminate funds that always have less than twenty holdings and those funds that always have more than $1 billion (2004 dollars) in total net assets[5], consistent with Coval and Stafford (2007). These larger funds are less likely to experience very large fund flows relative to their total net assets and should generally be more stable funds. These funds, which are then subject to large outflows relative to their large size, make them compelling research subjects.

Additionally, company stocks are eliminated if they are held by fewer than ten mutual funds. Finally, observations are deleted if the percent change in total net assets, defined as $100 * (TNA_{j,t} - TNA_{j,t-1} * (1 + R_{j,t}))/TNA_{j,t-1}$, is too extreme (i.e. less than -50% or greater than 200%). That corresponds to approximately the 1st and 99th percentile of changes. Mutual fund flows are defined following the literature as the change in total net assets, controlling for stock returns during the month. Here j indexes the mutual fund and t indexes the quarter:

$$flow_{j,t} = \frac{FLOW_{j,t}}{TNA_{j,t-1}}\ ; \qquad (4\text{-}1)$$

[5] The $1 billion cutoff is based on 2004 dollars with the CRSP Value-weighted Market Index used as the deflator.

and

$$FLOW_{j,t} = TNA_{j,t} - TNA_{j,t-1} * (1 + R_{j,t}). \quad (4\text{-}2)$$

This data is available from the CRSP Mutual Fund monthly return database. Flow-induced sales are measured for those funds experiencing flows below the 10th percentile of flows. Quantitatively, the cutoff for the 10th percentile of mutual fund flows is -0.087. That is, the bottom ten percent of funds experience quarterly outflows of at least 8.7% of total net assets.

Once the lowest flow funds (highest outflow funds) are identified, I sort by the quarterly change in market value of each stock in the portfolio (change in shares held x price), identifying the 10 stocks with the largest decrease. I implicitly assume that the change in stock price is reasonably small and it is the change in holdings that drives the change in market value of the stock holding.[6] This list of liquidated firms is re-matched against the CRSP database to calculate a one-year holding period return. Table 2 contains summary statistics for this subset of firms.

I compute the Amihud (2002) illiquidity measure for every holding by every fund to establish a baseline value of the liquidity of a fund's holdings. Amihud (2002) constructs a measure of illiquidity based on the price impact of sales, defined as the annual average of the ratio of the absolute value of returns to the dollar trading volume on that day. I multiply the daily ratio by 1,000,000 as a scaling factor. This measures the daily price impact of order flow and allows for comparisons across stocks. The formula is as follows:

[6] Alternatively, I considered a screen of the top ten percent of sales per fund, but rejected this because the mean number of securities per fund is just 35 and would result in a small sample set.

$$ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} 1000000 * {|R_{iyd}|}/{VOLD_{iyd}}, \quad (4\text{-}3)$$

where D_{iy} is the number of days with available data for stock *i* in year *y* and $VOLD_{iyd}$ is the daily volume times the absolute value of price.

In order to look at relative valuation, I begin with the Compustat database from 1982-2008. I continue using the RKRV decomposition technique to generate estimates of firm-specific misvaluation in my examination of strategic reevaluation. I need historical data for the valuation methodology, but I will later match this to the firms in the 2002 – 2008 window from the mutual fund data.[7] Using the basic method introduced in Chapter 1 and consistent with the original RKRV paper and the application in Chapter 3, I estimate total firm misvaluation using a 20-year historical estimation period. In Chapter 1's description of the technique, I illustrate that the decomposition specifies a long-run firm value estimate, independent of momentary valuation deviations, and a total firm misvaluation. If the RKRV methodology correctly identifies misvaluation and fund managers engage in strategic rebalancing, then I expect the fund manager, to reduce holdings of overvalued securities and increase holdings of undervalued securities.

I screen Compustat for firms that have non-missing values for common shares outstanding; net income; and fiscal year-end share price. I exclude observations with a negative value for total assets or common equity. Following RKRV, firms are also excluded if their book-to-market ratio exceeds 100 or if the market value of equity is below $10 million, eliminating small market firms. Return on assets (ROA) and return on equity (ROE) are defined as net income in year *t* divided by book assets (BA) or book

[7] At this point, my valuation sample is restricted to the overlap of 2002 – 2006, but I am working on extending that sample.

equity in year *t*-1, respectively. I winsorize the performance measures at the 1st and 99th percentiles to eliminate extreme values (e.g. values exceeding the 99th percentile are set equal to the 99th percentile). I report two measures of leverage: book leverage (1-book equity/total book assets) and market leverage (1-market equity/market value). Firms are sorted into the Fama French twelve industry categories (French, 2012).

Results

Table 4-1 shows some summary statistics about the mutual funds with the highest outflows. On average, these funds have returns of -0.7% and hold 136 unique stocks in a given quarter. The bottom 10% of outflows are -8.7%, which leaves a mean quarterly outflow of the sample of -17.5%. Table 4-2 gives summary statistics for the holdings of the highest outflow funds. These are the stocks that managers can choose from when liquidating positions for cash. Columns A and B show all holdings for all quarters. Columns C and D show just the unique holdings for the quarter (without duplicates across funds). I show that the mean of prior year returns is 11-14% (Columns A and C), while the mean of future returns is about -1 to 3%. This discrepancy is caused in part by the difference in mutual fund holding observations over time. There are far more observations in 2008, when the next year returns encompass relatively poorer 2009 returns.

I also note in Table 4-2 that nearly 60% of mutual fund holdings in the sample have experienced positive prior-year returns. Table 4-3 splits these stocks out into winners and losers to examine their returns. It appears that while the winners tend to have significantly lower (though not negative) returns over the next year, the prior-year losers have higher, though still negative, returns on average. This seems to indicate the presence of a mean-reversion or counter-momentum effect. If this is the case, then

selling winners may be a smart strategy to take, as these holdings may tend to be overvalued. I later examine this possibility.

Table 4-4 aggregates the holdings by portfolio to show that the average portfolio has had positive prior-year returns of approximately 14%, illustrating that even high outflow funds can have positive average returns in an up market—a rising tide lifts all boats. In Table 4-5, I examine whether the liquidation choice is motivated by recent price increase or decrease and related features. I begin my investigation by examining transactions of high economic value. I sort each portfolio by dollar change in holdings, which combines change in shares held times price. For the top ten most liquidated holdings per portfolio, I calculate a prior-year mean return of 19.25% among 4,129 fund quarters. Of these holding reductions, 67.3% are stocks with positive prior-year returns, which I define as “winners,” while stocks with negative prior-year returns, i.e. “losers,” comprise 32.7% of the most-liquidated holdings. These results suggest that there may be some preference for selling winners rather than losers.

I extend my analysis to consider a complementary possibility—perhaps the fund managers have a preference for liquidity. Table 4-6 examines the liquidity of the fund holdings. The mean of the Amihud (2002) illiquidity measure for all holdings is reported in Column A as 0.017. However, when I look at unique holdings in either Column B or C, this number increases. This indicates that more liquid holdings are held more frequently, as their repeated inclusion increases the overall liquidity of the holdings. (Recall that lower Amihud illiquidity values imply greater liquidity.) In Column E, I examine the liquidity of the most liquidated stocks. Once again, these are the ten stocks

with the greatest dollar change in holdings. The evidence shows that the most liquidated securities are statistically significantly more liquid than the average holdings.

Table 4-8 shows that the mean liquidity of prior-year winners is greater than that of prior-year losers. This is consistent with Odean (1998) who argues that stocks with a previous price run-up will tend to be more liquid than those with a prior price decline. This may explain the tendency of funds to sell previous winners. However, Table 4-7 shows that while winners are more liquid, on average, than losers, the stocks sold are on average less liquid than those that are held. This indicates that the stocks sold are not necessarily the most liquid of the holdings. I also see that, on average, the stocks sold actually outperform those with no change and those that are bought. This is not indicative of a successful effort at stock picking. Overall, these results are not consistent with managers selling either the most liquid of their holdings, the most overvalued, or the worst future performers.

It is possible that fund managers are strategically rebalancing their portfolio in their liquidation choice. For a given quantity held, stocks with a larger increase in value will comprise a larger percentage of a fund's portfolio. Holding aside any fundamental valuation analysis, fund managers may simply rebalance holdings (including liquidation) if the asset allocations change. To test this hypothesis, I calculate an unbalanced weighting of each holding, *i*, for each portfolio, *j*, as if there were no change in holdings between periods to estimate the effects of price changes on the portfolio allocations:

$$UnbalancedWeighting_{i,j,t} = \frac{(Q_{i,j,t-1} \times P_{i,t}) - (Q_{i,j,t-1} \times P_{i,t-1})}{tna_{j,t-1}}. \quad (4\text{-}4)$$

Holdings with higher price increases or larger quantities held will have higher relative weights by this measure. I expect that firms that strategically rebalance will choose to

liquidate the holdings with the highest unbalanced weighting because they now comprise a higher percentage of the portfolio.

For each portfolio, I calculate a median unbalanced weighting measure and compare to the portfolio-specific holding's score. Stocks with high unbalanced weighting scores (greater than the portfolio median) are 49% of the liquidation choice, while 51% of the liquidated holdings have below median scores. On the surface, this suggests that strategic rebalancing is not occurring, as less than half of the liquidated observations come from the portion of holdings that are now overweighted in the portfolio.

In Table 4-9, I further evaluate whether extremely high unbalanced weighting scores has an impact on the liquidation decision. I compare the weighting score of the portfolio holdings to quartile cutoffs and find that 25.9% of the liquidated holdings occur among the top quartile (i.e., highest relative increase) in portfolio weighting, while 23.2% of the liquidated holdings occur among lowest quartile (i.e., lowest relative increase). Though a means difference test between the top and bottom quartile is significant, there appears to be little economic difference between the categories. It appears that funds equally liquidate holdings across quartiles of portfolio unbalanced weighting scores. Thus a desire to rebalance towards an original or target allocation does not seem to motivate a fund's selling decisions.

Though I show that funds sell winners rather than losers and that funds are not rebalancing (in economic terms) following price changes, I argue that these results may not be at odds. I reconcile these facts by suggesting that over the sample period, the typical median unbalanced weighting score is positive. If the reallocation is fairly even

across all quartiles of this score, there will be more stocks with positive returns—it is simply that some stocks had much greater increases in value.

Table 4-10 uses the RKRV methodology to examine the relative over or undervaluation of those stocks that are sold. For each portfolio holding, I calculate the RKRV firm-specific error, time-series sector-error, and long-run value-to-book (FSE, TSSE, and LRVTB in the Hertzel and Li (2010) notation) using a 20-year historical observation window, matching as closely as possible to the original specification of RKRV. However, I deviate from the original RKRV model following Hertzel and Li (outlined in Chapter 2), to use only historical accounting information (up to the fiscal year prior to the fund's liquidation decision) in the estimation of the valuation errors. Hertzel and Li address the RKRV assertion that their method is biased because it includes future accounting information that would be unknowable to investors at the time. Hertzel and Li's modification attempts to minimize this bias by including data that is available to investors at the time of action. Table 4-10 shows that, on average, the sold stocks have a lower firm-specific misvaluation than the retained stocks (retained holdings include increased or zero change), but with a means difference t-statistic of -1.45, it is not significantly different at the 90% level. It appears that the funds are not systematically liquidating stocks that are overvalued by the firm-specific misvaluation metric.

Finally, I conduct a probit analysis to estimate the likelihood that a holding of high-outflow funds will be liquidated, using liquidity (AMIHUD), prior return, naïve rebalancing, firm-specific mispricing, and fund flow characteristics. The dependent variable for this regression is a dummy representing whether a holding's size was

reduced by a fund in the quarter. The coefficient results of this probit model reported in Table 4-11 generally align with the interpretation of the summary statistics. Stocks held by funds facing large outflows, FLOW, are more likely to be sold. More liquid stocks (low AMIHUD values) are more likely to be sold and prior positive one-year returns (PRIORRET) increase the likelihood of sale. As noted in the earlier discussion, it does not appear that funds change holdings to address naïve rebalancing and a negative (and statistically insignificant) coefficient on NAÏVE supports this finding. At the same time, a negative coefficient on the firm's relative valuation measure (FSE) suggests that overvaluation (high FSE) leads to less selling, while low overvaluation (i.e., undervaluation) results in more selling. This result is inconsistent with a managers' goal to retain or increase holdings poised for future gains while reducing positions that will have future losses. I expect exactly the opposite result—a positive coefficient for the FSE variable. If the RKRV method is correctly identifying relative valuation, then these mutual fund managers are selling the undervalued securities while retaining positions in the overvalued securities. There are two potential explanations: perhaps holding the undervalued and selling the overvalued is not the fund managers' goal, or the RKRV FSE measure is not correctly identifying the same mispricing as the fund managers.

Analysis

This study focuses on the behavior of high-outflow funds, which see large redemptions from investors and must usually liquidate holdings to generate sufficient cash to satisfy demands. Investors actively chase mutual fund returns by reallocating capital across mutual funds so that recently strong performing funds often experience cash inflows, while other funds may suffer redemption demands and cash outflows. This paper examines some of the responses of managers facing redemptions by focusing

specifically on the actions of fund managers facing investment pressure; those managers who are forced to make decisions to raise cash in satisfying redemptions. I investigate whether the changes in the high outflow portfolio were correlated with prior stock performance. I discover that these funds liquidate prior stock winners more frequently than losers in the holding, illustrated in Table 4-7. Perhaps the winners are sold more frequently because they make up a higher percentage of the portfolio.

What drives this behavior? One explanation is that recent winners are more liquid (Odean (1998)). The fund manager may sell the stocks that are more liquid, which are coincidentally winners (or vice versa). To confirm this, I plot the holdings by the Amihud illiquidity measure (Table 4-8) and show that the winners are more liquid than the losers across the portfolio. Among the choice of liquidation, the winners within the portfolio are significantly more liquid than the losers. It is possible that the liquidity of the security drives the choice, but it this is an inconclusive result.

Another explanation suggests that recent winners' increase in value leads to overweighting "by default." Therefore, more frequent liquidations of winners could also be characterized as an effort to rebalance towards a previous allocation. Some selling may be attributed to this naïve rebalancing effort, though it appears that the choice of liquidation is evenly spread across a measure of naïve rebalancing.

I further investigate whether the portfolio decisions are made more strategically, attributing managers' decisions to choices based on fundamentals. For example, a recent winning stock could still be undervalued, if it was even more undervalued in the past. Only fairly- or overvalued stocks that then experience a recent run-up in price should be considered overvalued. This investigation examines whether we can link fund

manager liquidation decisions with a measure of firm-specific valuation error. Since recent stock performance alone does not necessarily indicate a stock's relative value (or valuation error), I use the RKRV decomposition technique to estimate how a stock's market value deviates from its intrinsic value. If fund managers are actively, strategically rebalancing their holdings and the RKRV measure is useful at identifying relative value, then I expect that the liquidation choice is heavily skewed towards overvalued stocks, characterized by the RKRV overvaluation measure. Moreover, if fund performance is expected to improve, I might further expect that the retention choices are under- or even fairly-valued. However, neither pattern is in evidence. The liquidated stocks are not systematically overvalued, which suggests that the retention picks are not skewed towards the undervalued and may be skewed towards the overvalued.

The reasons for selling individual securities comprising a portfolio are limitless, yet I find results that suggest firms are selling on a consistent pattern. Specifically, I show that the highest outflow funds tend to sell recent (one-year) winners rather than losers. A growing line of research investigates the behavior of investors and generally concludes that they are not the perfectly rational actors expected in classic economic theory. That is, investors often behave in their own self-interest, but not always, and often in predictably irrational ways. Does similar irrationality extend to experts, professional investors who might be immune to behavioral problems? This paper does not answer this question specifically, but sheds some light on how experts may behave when an action is required, enabling further examination of the underlying behavioral causes.

Table 4-1. Summary statistics of the highest outflow funds

	N	Min	Max	Mean	Median	Std Dev
Quarterly TNA ($million)	4,129	-96.80	75,056.3	496.6	96.3	2,110.6
Quarterly Fund Return	4,129	-45.6%	51.7%	-0.7%	-0.6%	8.5%
Fund Flow	4,129	-50.0%	-8.7%	-17.5%	-13.8%	9.5%
Number of Stocks Held	4,129	1.0	2,671.0	135.8	68.0	236.8

Note: Data comprise holdings of Top Decile of Highest Outflow Funds over the period 2002-2008, totaling 4,129 fund-quarters from the CRSP Survivor-Bias-Free US Mutual Fund Database. Total Net Assets (TNA) comprise the sum of assets of all classes of a mutual fund. I measure fund *j* outflows per quarter, *t*, as $flow_{j,t} = \frac{FLOW_{j,t}}{TNA_{j,t-1}}$; $FLOW_{j,t} = TNA_{j,t} - TNA_{j,t-1} * (1 + R_{j,t})$. Consistent with Coval and Stafford (2007), bond, specialty, international, and global funds are eliminated. Funds are eliminated if they never hold at least 20 unique stocks in a single quarter during the sample period (it is possible for a fund to have as few as 1 holding, so long as there exists a quarter in the sample period that it held at least 20). Observations of company stocks that are held by fewer than 10 funds are removed. Funds are removed if their percent change in TNA are extreme (i.e., greater than 200% or less than -50%).

Table 4-2. Returns of highest outflow fund portfolio holdings

Statistic	(A) *t*-4 to *t*	(B) *t* to *t*+4	(C) *t*-4 to *t*	(D) *t* to *t*+4
Observations	456,122	456,122	98,469	98,469
Mean	11.11%	-0.82%	14.00%	2.75%
Maximum	5366.28%	2508.00%	5366.28%	2508.00%
Minimum	-98.43%	-99.93%	-98.43%	-99.93%
Standard Deviation	51.09%	48.12%	62.81%	50.90%
% Winners	58.25%	47.79%	59.36%	50.90%
% Losers	41.74%	52.20%	40.63%	49.07%

Note: Data comprise holdings of Top Decile of Highest Outflow Funds over the period 2002-2008, totaling 4,129 fund-quarters from the CRSP Survivor-Bias-Free US Mutual Fund Database. I measure fund outflows as of quarter *t*, and present summary statistics of the holdings of the top outflow funds. The holdings' returns are reported over the prior four quarters, *t*-4 through *t*, and the subsequent four quarters, *t* through *t*+4. Column A presents the summary returns of all holdings of all 4,129 fund-quarters over the prior four quarters *t*-4 through *t*. Column B presents the summary returns of all holdings over the subsequent four quarters, *t* though *t*+4, regardless of whether a holding remained in a fund. Column C presents summary returns of unique holdings per fund-quarter over the *t*-4 through *t*. Column D presents summary returns of unique holdings per fund-quarter of the subsequent four quarters, *t* through *t*+4, regardless of whether a holding remained in a fund. % Winners illustrates the percentage of the holdings that had positive returns over the one-year windows; Columns A and B for all holdings over the 4-quarter windows, while Columns C and D comprise the unique holdings. % Losers illustrates the percentage of the holdings with negative returns over the one-year returns windows; Columns A and B for all holdings over the 4-quarter windows, while Columns C and D comprise the unique holdings.

Table 4-3. Returns of portfolio winners and losers

	Winners		Losers	
	(A)	(B)	(C)	(D)
Statistic	*t*-4 to *t*	*t* to *t*+4	*t*-4 to *t*	*t* to *t*+4
Observations	265,710	265,710	190,394	190,394
Mean	36.75%	0.67%	-24.66%	-2.90%
Maximum	5366.70%	454.34%	0.00%	2508.00%
Minimum	0.00%	-99.12%	-98.43%	-99.93%
Standard Deviation	51.38%	38.71%	19.31%	58.71%
% Winners	100.00%	50.71%	0.00%	43.71%
% Losers	0.00%	49.28%	100%	56.28%
Difference of means (past winners/losers) future returns t-statistic:			23.19	***

Note: Data comprise holdings with prior one-year positive returns (Winners) and negative returns (Losers) of top decile of highest outflow funds over the period 2002-2008, totaling 4,129 fund-quarters. Column A presents the summary data of returns of winners over the prior four quarters *t*-4 through *t*. Column B presents the summary data of returns of winners over the subsequent four quarters, *t* though *t*+4, regardless of whether a holding remained in a fund. Column C presents the summary data of returns of unique winners over the prior four quarters *t*-4 through *t*. Column D presents the summary data of returns of all winners over the subsequent four quarters, *t* though *t*+4, regardless of whether a holding remained in a fund. % Winners illustrates the percentage of winners that had positive returns over the one-year returns windows; % Losers illustrates the percentage of losers with negative returns over the one-year returns windows. The difference of means t-statistic between the winners' and losers' future returns (unique holdings) is reported at the bottom. *** indicates significance at the 99% level.

Table 4-4. Summary statistics of mean portfolio returns

Statistic	Value
Observations	4,129
Mean	14.41%
Maximum	416.18%
Minimum	-90.05%
Standard Deviation	30.99%

Note: Table presents the summary statistics of aggregated fund holding returns of the highest outflow funds. Data comprise holdings of top decile of highest outflow funds over the period 2002-2008, totaling 4,129 fund-quarters.

Table 4-5. Returns of the most liquidated holdings

Statistic	(A) *t*-4 to *t*	(B) *t* to *t*+4	(C) *t*-4 to *t*	(D) *t* to *t*+4
Observations	37,224	37,224	21,782	20,999
Mean	19.25%	-0.25%	21.22%	0.52%
Maximum	1692.78%	506.19%	1692.78%	506.19%
Minimum	-99.90%	-99.65%	-99.90%	-99.65%
Standard Deviation	49.42%	39.44%	54.57%	41.44%
% Winners	67.27%	48.82%	67.20%	48.54%
% Losers	32.68%	51.11%	32.76%	51.39%
Difference of means (past v future returns) t-stat:		59.50 ***	44.28 ***	

Note: Data comprise holdings of the top decile of highest outflow funds over the period 2002-2008, totaling 4,129 fund-quarters. We calculate the ten largest decreases in dollar value change in holdings for each fund per quarter. Column A presents the summary returns of all holdings of all 4,129 fund-quarters over the prior four quarters *t*-4 through *t*. Column B presents the summary returns of all holdings over the subsequent four quarters, *t* though *t*+4, regardless of whether a holding remained in a fund. Column C presents summary returns of unique holdings per fund-quarter over the *t*-4 through *t*. Column D presents summary returns of unique holdings per fund-quarter of the subsequent four quarters, *t* through *t*+4, regardless of whether a holding remained in a fund. % Winners illustrates the percentage of winners that had positive returns over the one-year returns windows; % Losers illustrates the percentage of losers with negative returns over the one-year returns windows. The difference of means t-statistic between past and future returns of the most liquidated stocks is reported at the bottom. *** indicates significance at the 99% level.

Table 4-6. Liquidity of holdings, portfolios, and most liquidated holdings

Statistic	(A)	(B)	(C)	(D)	(E)
Observations	456,114	98,465	20,089	4,121	36,014
Mean	0.0166	0.0318	0.0780	0.0069	0.0022
Maximum	76.4142	76.4140	76.4140	2.3515	2.4575
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.4311	0.6105	1.1334	0.0574	0.0226

Note: Table presents summary statistics of the annual Amihud (2002) illiquidity measure (AIM) for the sample of portfolio holdings. AIM is defined as the annual average of the ratio of the absolute value of returns to the dollar trading volume on that day, multiplied by one million (as a scaling factor): $ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} 1000000 * {|R_{iyd}|}/{VOLD_{iyd}}$, where D_{iy} is the number of days with available data for stock *i* in year *y* and $VOLD_{iyd}$ is the daily volume times the absolute value of price. AIM is a unitless, relative measure. Low values represent less illiquid stocks, i.e., greater liquidity. Column A presents the summary statistics of AIM for all holdings for all firm-quarters. Column B restricts the sample to unique firms in a quarter. Column C further restricts to unique firms per year. Column D presents the mean annual AIM for the portfolios in the

sample. Column E gives the mean annual AIM for the stocks comprising the ten largest decreases in dollar change in holdings for each fund per quarter.

Table 4-7. Liquidity and returns by changes in holdings

	Sold	No Change	Bought	Buy or Hold
Observations	253,406	53,182	149,448	202,658
Mean Prior Return	6.83%	0.99%	17.89%	16.46%
Standard Deviation	*44.84%*	*24.10%*	*62.10%*	*57.53%*
% Winners	54.66%	62.00%	63.00%	62.74%
% Losers	45.33%	38.00%	36.99%	37.25%
Mean Future Return	0.42%	-3.90%	-1.84%	-2.38%
Standard Deviation	*50.12%*	*43.75%*	*46.02%*	*45.44%*
Future % Winners	48.47%	45.61%	47.39%	46.93%
Future % Losers	49.98%	54.38%	52.59%	53.06%
Mean Amihud	0.0137	0.0099	0.0239	0.0203
Standard Deviation	*0.2560*	*0.2410*	*0.6598*	*0.5799*

Note: Table presents the mean returns and liquidity of holdings grouped by disposition: buy, sell, or no change. "Buy or Hold" combines the Bought and No Change dispositions. Prior Return is the mean return of the holdings over the *t*-4 to *t* period. Future return is the return of the holding over the *t* to *t*+4 period regardless of whether a fund continued to hold the stock. Mean Amihud is the average annual Amihud (2002) illiquidity measure (AIM) for the sample by disposition category. AIM is a unitless, relative measure. Low values represent less illiquid stocks, i.e., greater liquidity. Standard deviations of the disposition means are listed below each mean in italics.

Table 4-8. Liquidity of winners and losers

Statistic	Winners	Losers
Observations	265,710	190,404
Mean	0.0050	0.0327
Maximum	17.7602	46.4142
Minimum	0.0000	0.0000
Standard Deviation	0.0844	0.6594
Difference of means (winners v losers) t-stat:	18.210 ***	

Note: Table presents summary statistics of the annual Amihud (2002) illiquidity measure (AIM) for stocks with positive returns (winners) and negative returns (losers) over the *t*-4 to *t* period. AIM is a unitless, relative measure. Low values represent less illiquid stocks, i.e., greater liquidity. A difference of means t-statistic between the winners and losers is reported at the bottom. *** indicates significance at the 99% level.

Table 4-9. Non-initiating naïve rebalancing measure

Unbalanced Weighting Score	Mean	Standard Deviation
High Quartile	25.85%	43.78%
Top Half	48.96%	49.99%
Bottom Quartile	23.18%	42.20%
Observations	145,992	

Note: Table presents mean and standard deviations of high outflow funds' unbalanced weighting scores. The unbalanced weighting score (UWS) measures how a fund's portfolio allocation can change due to the holdings' quarterly returns. For each portfolio holding (Q), I calculate the percentage change in value of a holding driven by changes in share price (P), per fund Total Net Asset, TNA, in the prior quarter (t-1): $[Q_{(t-1)}*P_{(t)}] - [Q_{(t-1)}*P_{(t-1)}] / TNA_{(t-1)}$. This captures the percentage change in portfolio composition due to changes in share price, without respect to changes in holding quantity, using the prior quarter composition as a benchmark allocation. Holdings are sorted into quartiles by percentage change per fund, per quarter. Naïve rebalancing occurs when fund manager liquidates holdings that experienced high relative change in fund composition due to changes in price. The observations represent non-initiating changes in holding, i.e., purchases if a stock is already among the holdings, or sales of any existing holding.

Table 4-10. Market-to-book decomposition of sold and retained holdings

Variable	Sold Holding	Retained Holding	T-statistic	
Ln(M2B)	1.062	1.090	-9.959	***
	0.660	*0.665*		
FSE	0.136	0.138	-1.451	
	0.464	*0.471*		
TSSE	0.153	0.143	17.037	***
	0.137	*0.131*		
LRVTB	0.773	0.808	-16.928	***
	0.488	*0.482*		
Observations	122,314	104,337		

Note: Table reports the mean of the market-to-book ratio and of its three components through the Rhodes-Kropf, Robinson, Viswanathan (2005) decomposition technique for our sample of high outflow fund holdings. Ln(M2B) is the natural log of the market capitalization to book value of equity ratio. The three components are firm specific error (FSE), time-series sector error (TSSE), and the long-run value-to-book (LRVTB). The column T-statistic reports the difference of means t-statistic that retained holdings have the same average market-to-book ratio (or component) as the sold holdings. Retained holdings include stocks that are increased in a portfolio or unchanged. *** indicates significance at the 99% level.

Table 4-11. High outflow funds' liquidation choice probit

Variable	Estimate	Standard Error	
Intercept	-0.229	0.0037	***
Amihud	-0.4118	0.1212	***
PriorRet	0.0574	0.0068	***
Naïve	-0.0008	0.005	
FSE	-0.0156	0.0069	**
Flow	0.0235	0.0057	***
Observations		226,671	

Note: Table reports probit regression coefficients and standard errors to predict which holdings will be liquidated by high outflow funds. Probit regression uses sold stock dummy as dependent variable. Independent variables include the Amihud (2002) illiquidity measure (AIM), the holding's prior return over the *t*-4 to *t* period, the naïve rebalancing measure, the firm-specific error (FSE) component of the market-to-book decomposition, and the fund's flow. ** and *** indicate significance of the coefficients at the 95% and 99% levels, respectively.

CHAPTER 5
CONCLUSION

Market-to-book ratios are basic metrics describing the market's assessment of a firm relative to the accounting value of the firm. A growing line of literature details efforts to extract additional information about the firm by separating the firm's underlying value from any contemporaneous market mispricing. One specific effort, the Rhodes-Kropf, Robinson, and Viswanathan (2005) decomposition technique, is utilized in explanations of corporate finance decisions deriving from a paradigm of market mispricing. Much of the existing literature uses the decomposition to confirm that managerial behavior is related to misvaluation. For example, in the original RKRV (2005) paper, managers' choice of merger and acquisition financing correlates with an estimate of relative valuation. Other papers (for example, Lin, Pantzalis, and Park (2010); Glegg, Harris, Madura, and Ngo (2011); and Harris and Madura (2011)) use the decomposition technique in conjunction with other misvaluation estimates. Hertzel and Li (2010) document that SEO-issuing firms are correlated with overvalued firms, as characterized by the RKRV misvaluation measures. Significantly, among the existing literature, only the Hertzel and Li (2010) research notes that the original RKRV specification includes information unknowable to investors, and modifies the decomposition to include only contemporaneously available information.

Extending this line of literature, I modify the existing decomposition methodology to use only publicly available past information, to demonstrate what usefulness the market-to-book decomposition has to firm outsiders. I conclude that the methodology has some value in corroborating the decisions of firm management as explored in a variety of existing research, but it fails to extend to uses external to the firm. I

investigate how the decomposition can be used by external parties to identify firm misvaluation and improve returns. My results suggest that the decomposition does not provide significantly useful contemporaneous indications of misvaluation for an external observer of the firm.

Though Hertzel and Li (2010) note that SEO-issuing firms are overvalued by the RKRV components, my initial study does not find a reliable trading pattern using a valuation sorting on their misvaluation. The results of my initial study suggest that a sophisticated investor probably could not capitalize on the relative mispricing measured using the RKRV decomposition to capture abnormal returns relative to broad market indices. The initial results, using overlapping construction periods, suggest that there may be tenuously small profits, but more stringent tests using either three- or five-year non-overlapping portfolio creation periods, based only on publicly available information at the time of construction, suggest that a sophisticated investor could not earn consistent abnormal returns, net of transactions costs over a one- or two-year holding period. These findings suggest that the RKRV method, which explicitly claims to identify mispricing, does not yield a reliably profitable trading strategy.

This study also examines the impact of market valuations on prediction models of credit ratings. I hypothesize that market leverage can provide additional information to models of default risk and demonstrate that replacing book leverage with market leverage in similar models provides results that are both more accurate and precise in predicting credit ratings. This means corporate managers can adjust capital structures in targeting credit ratings by evaluating effects in market valuations, consistent with financial literature, rather than also considering book value implications to satisfy the

rating agencies. Using estimates of long-run value generated through the RKRV decomposition technique, I examine whether firms with growth options are treated differently by rating agencies and illustrate how firms might adjust their mix of tangible and intangible assets to improve ratings. If growth options have long-term value for a firm, and lower the default probability for the firm, rating agencies should award a higher rating to a firm with more growth options, given similar accounting valuations. I find small improvements in ratings for firms with more growth opportunities, so long as they have a sufficiently large asset base. These results are largely consistent with the existing literature, which primarily emphasize profitability, stability, and size. This essay also notes that there is credit rating improvement available by changing the asset mix in certain circumstances.

In a third essay, I explore the characteristics of holdings changes by mutual fund managers facing high outflows. These high outflow funds sell recent winners more frequently than recent losers. The winners tend to be more liquid than other holdings in their portfolios. Finally, I use the RKRV metric to assess whether fund managers act in response to misvaluation. I determine that when mutual fund managers are forced to liquidate holdings in response to outflows, relative valuation is a less important factor than liquidity and momentum in deciding which stocks to sell. The results suggest that managers do not make good stock picking decisions when faced with outflows.

Though my research does not show significant positive application for the RKRV decomposition, none of these results rules out the decomposition's use in the literature. Instead, this research aims to explore the boundaries of its application. Where Hertzel and Li (2010) find that SEO-issuing firms are characterized by overvaluation and

subsequently underperform, I note that it is difficult for an investor to screen stocks based on the misvaluation metric and earn abnormal profits. There may be other firm characteristics that also correlate with SEO issuance and future underperformance that are not represented by all firms identified as overvalued by RKRV. Future research could investigate what characteristics distinguish the merely overvalued from the overvalued and SEO-issuing. Although my research indicates that investors would have trouble profiting using this stock screen, that does not mean that the RKRV methodology is useless at sorting stocks by relative valuation. Instead, I argue that identifying a trading strategy sets a higher bar for accuracy than previously required by the literature. While the RKRV measure does not achieve that height, it may nonetheless still be useful enough to corroborate theories of managerial behavior in response to misvaluation.

My investigation of mutual fund holdings changes uses the RKRV misvaluation estimate to shed light on whether fund managers sell stocks that are overvalued, while increasing or extending holdings that are undervalued. My conclusions indicate that there is little evidence that the choice of liquidated holdings correlate with the RKRV overvalued characteristic. This conclusion admittedly rests with the notion that the RKRV decomposition does correctly identify over- and undervalued stocks, seemingly a joint hypothesis problem. Though several papers show corporate behavior that aligns with predictions of responses to misvaluation (e.g., issuing equity when overvalued (Hertzel and Li (2010)), using cash to finance acquisitions when undervalued (Rhodes-Kropf, Robinson, and Viswanathan (2005))), there is little concrete evidence that the methodology definitively identifies the misvaluation. The joint hypothesis problem vexes

the efficient markets literature (Campbell, Lo, and MacKinlay (1996)) and extends to the evaluation of the RKRV decomposition. Future research could focus on this problem examining how proficiently the methodology identifies misvaluation.

By extending the RKRV application in a variety of applications, I show that the RKRV market-to-book decomposition has limits in usefulness for external parties. I conclude that while the methodology has value in testing firm management decisions against financial theory, it has less utility in identifying mispricing to execute a successful trading strategy. Although the existing finance literature uses the RKRV methodology in drawing inferences about the potential misvaluation of companies, it does not appear that the methodology sufficiently measures misvaluation to an extent satisfactory for an external investor.

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BIOGRAPHICAL SKETCH

Aaron Gubin is a tax-deduction baby, born New Years' Eve, 1976. Though born in New York City, he grew up in small-town, rural Alabama. He earned a bachelor's degree in economics from New College of Florida in 1998 and a Master of Business Administration from the University of Florida in 2005, with concentrations in finance, security analysis, and competitive strategy. He continued his studies at the University of Florida, earning his doctorate in finance in the fall of 2012.

In his career, he worked for Arthur Andersen's A-Plus Tax Software group; evaluated startups at New South Ventures, a venture capital shop in Sarasota, Florida; and research projects at Capitalink, a boutique investment bank in Miami. He continues teaching at East Carolina University in Greenville, North Carolina. He loves to travel and is seldom without a camera, taking photographs of landscapes, animals, and architecture.