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MUTUAL FUNDS, IDIOSYNCRATIC VARIANCE, AND ASSET RETURNS

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Abstract

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This paper documents two new facts. First, over the past 30 years variance has been negatively correlated with expected return for NYSE&AMEX stocks and this relationship is not accounted for by several well-known prespecified factors (e.g., the price-to-book ratio or size). More volatile stocks have lower returns, other things equal. In fact, one of the prespecified factors, size, obscures this inverse relationship. Second, I document that open-end mutual funds have strong preferences for stocks that are liquid, well-known, and most interestingly, highly volatile stocks.

Two previously documented facts suggest a simple story that explains these findings. First, Sirri and Tufano (1993) report that net money inflows to mutual funds are relatively insensitive to mutual fund performance, except for the best performing funds. The highest decile of mutual fund performers (in non risk-adjusted returns) receive a large inflow of funds; lower deciles show little sensitivity to performance. This nonlinear payoff creates an option-like payoff to portfolio manager performance, causing fund managers to prefer volatile stocks. Second, Shliefer (1986) and others have shown that stocks have upward sloping supply curves. The "exogenous" demand for volatile stocks and upward sloping supply curve form an explanation why volatile stocks have lower expected returns on average.

This thesis also documents several measurable characteristics of stocks that are correlated with mutual fund demand. Mutual funds prefer stocks with higher absolute prices, greater liquidity, higher age since initial listing on the exchange, more news

stories in major newspapers, and (for all but the small-cap sector) greater market capitalization. The preference of mutual funds for nontraditional measures of risk are relevant for models of asset markets with costly information, and studies of the determinants of stock supply elasticity.

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Chapter 1

Introduction

This paper documents two new facts. First, over the past 30 years on the NYSE&AMEX, stock variance has been negatively correlated with expected return. Controlling for size (i.e., market equity), idiosyncratic variance has a statistically significant negative correlation with risk-adjusted returns. Second, open-end mutual funds have strong preferences for particular stock characteristics such as liquidity and information proxies, and, most interestingly, for highly volatile stocks.

Two previously documented facts suggest a simple story that explains these findings. First, Sirri and Tufano (1993) report that net money inflows into mutual funds are relatively insensitive to mutual fund performance, except for the best performing funds. The highest decile of mutual fund performers (in non risk-adjusted returns) receive a large inflow of funds while lower deciles show little sensitivity to performance. This nonlinear payoff creates an option-like payoff to portfolio manager performance, causing fund managers to prefer volatile stocks. Data suggesting that individual stocks have upward sloping supply curves[1] implies that this "exogenous" demand for volatile stocks on the part of mutual funds may account for the lower expected returns of volatile stocks, even after adjusting for risk in various ways.

[1]See Shleifer (1986) or chapter 2 for a fuller discussion.

The presence of a principal-agent relationship causes deviations from a first-best equilibrium in almost every environment where such a relationship exists. Sirri and Tufano's findings suggest that delegated asset managers have an incentive to purchase more volatile securities, and chapter 3 corroborates this hypothesis. If investors were fully rational and able to act immediately on all arbitrage opportunities, arbitrageurs would counter the fund managers' preferences and no price effect would be observed. However, as pointed out by Merton (1987), markets dominated by rational agents may nevertheless produce anomalous behavior relative to models assuming perfect and complete information, as institutional complexities and information costs cause considerable variations in the speed at which different types of anomalies can be expected to be eliminated. For example, assume a subtle information problem creates an anomaly. Before it can be documented in the data with conventional levels of statistical confidence it must exist for a considerable amount of time. Once an anomaly has been documented, there remains the meta-statistical question of whether or not the anomaly was an aberration (i.e., 5% of all true nulls will be rejected at the 5% level). Finally, enough investors must implement strategies that eliminate this anomaly. The thesis of this dissertation is that just this sort of anomaly exists in cross sectional expected asset returns with respect to volatility. Though not explainable within frictionless models, it is consistent with a model of costly information.

The asset return findings in this thesis challenge standard asset pricing models such as the CAPM. Systematic or nondiversifiable risk should imply higher expected returns to compensate risk-averse investors for bearing this risk. Nonsystematic or diversifiable risk need not be tolerated (since it is diversifiable), and thus this risk should not add to an asset's expected return. While many papers have rejected the CAPM or shed doubt upon the APT,[2] this thesis documents for the first time that the correlation between variance and expected return has, with statistical significance, the "wrong" sign. I find that, controlling for size (i.e., market equity), total risk (diversifiable and nondiversifiable) is inversely correlated with absolute expected returns over the past 28 years. Factors extracted from the NYSE&AMEX only exacerbate the return premium to low variance stocks.

The negative relation between variance and expected return directly addresses what Lehman (1990) calls a "minor conundrum" in tests of the significance of residual risk. If a portfolio is not mean-variance efficient, then the residual variances from its market model regressions should help explain expected returns. That is, according to the APT, residual variances should in part reflect squared loadings on omitted risk factors (or for the CAPM, the squared beta on the mismeasured expected market return), and thus given that factors are not measured exactly, idiosyncratic variance should be positively related to expected return in large samples. Previous research has consistently rejected the existence of positive residual risk premiums, in spite of the evidence that suggests that usual market proxies or factors are not mean-variance efficient.[3] This paper suggests that this minor conundrum is actually a major conundrum: high residual risk assets receive a significant negative premium! That is, the null that idiosyncratic variance is unrelated to expected return (since it is diversifiable risk) is rejected, and the rejection is toward the alternative that idiosyncratic risk is *negatively* correlated with expected return, not

[2] For example, see Gibbons (1982), Fama and French (1992), or Gultekin and Gultekin (1986).

[3] For example Douglas (1968), Fama and MacBeth (1973), Roll and Ross (1980), and Dhrymes, Friend, and Gultekin (1984).

positively correlated as one might reasonably expect. Either risk factors are not correctly specified using conventional, formal econometric techniques, or investors are evaluating investments based on asset characteristics other than risk.

Previous empirical work has not documented the inverse correlation between expected return and volatility that I find due to the interference of size and price. Both small size and low prices have been found to be correlated with higher expected returns (see Banz (1981) and Jaffe et al (1985) or Bhardwaj and Brooks (1992), respectively). Since low prices and small size are also correlated with higher variance, an omitted variables problem arises. Prior tests have not found a negative relation between variance and expected return because simple correlations between variance and expected returns are obscured by the interference of price and size.

The mutual fund preferences I find are new, and this is due to several reasons. First, my source, MorningStar, has only put their mutual fund portfolio data on CD since 1991. Further, this data is not compiled in a manner easily amenable to academic research. There have been several studies of net mutual fund demand, using quarterly pension fund buy and sell records.[4] In contrast to these studies, the data I have are on mutual fund portfolio stocks, not flows, which is what mutual fund manager's presumably have preferences over. Also, other research on mutual fund behavior has focused on two specific hypotheses: trend following and herding by mutual fund managers. Because I use several stock characteristics in explaining mutual fund preferences. I can implicitly examine an alternative hypothesis to herding when observing the net purchasing of a particular stock by the mutual fund sector. Specifically, if mutual funds have preferences

[4] See Chapter 3 for a full review

for certain security characteristics, as securities acquire these characteristics mutual funds will be seen "herding" into them: the appearance of herding can just be the result of aggregate preferences for specific individual security characteristics.

In addition to mutual fund's revealed preference toward volatile stocks, this thesis reports several specific preferred security characteristics. Relevant to transaction costs, mutual funds show an aversion to low-price stocks and stocks with low liquidity (as measured by trading volume divided by the shares outstanding). Also, other than the small-cap sector, which specializes in small firms, funds show an aversion to small firms. Furthermore, companies that have generated more information, as measured by the number of major newspaper news stories or the number of months since listing on the exchange, are held in disproportionate amounts. The significance of these variables suggest potential proxies for risk, transaction costs, and information flows. These findings highlight stock characteristics correlated with institutional neglect.[5]

The mutual fund sector's strong aversion to low-priced stocks presents a potential measurement bias in detecting trend-following. Lower priced stocks tend to have lower previous returns, and I find evidence of trend following when I do not control for absolute price, but no evidence of trend following when I do control for absolute price. This highlights an important omitted variables problem in trend following tests that has not been addressed previously.

This paper is organized as follows. Chapter 2 discusses the hypothesis behind the empirical study. Chapter 3 estimates open-end mutual fund manager preferences for several security characteristics, based on the regressions of security characteristics with

[5] See Arbel, Corvell and Strebel (1983), Barry and Brown (1984) or Merton (1987) for models and empirical evidence that relate expected returns to the scope of investor ownership

aggregate mutual fund holdings. Chapter 4 previews the asset pricing results with some simple graphs and tables. Chapter 5 uses the methodology of Fama and MacBeth (1973) to test the hypothesis that idiosyncratic or total variance is negatively correlated with expected returns. Chapter 6 uses a grouping based strategy to assess the ability of factors (extracted using Connor and Korajczyk's (1986) principal components technique) to explain the return premium to low-variance stocks. Chapter 7 examines the theoretical basis of investor preferences and asset pricing anomaly in more detail, as well as alternative explanations to the main hypothesis. Chapter 8 concludes.

Chapter 2

Motivating the Empirical Tests

The purpose of this section is to develop a theory underlying the empirical tests this thesis reports. The main findings of these tests are that mutual funds hold disproportionate amounts of highly volatile stocks and, controlling for size, stocks with higher variance have a lower expected return than stocks with lower variance. Since these findings do not directly address standard outstanding hypotheses, such as herding by mutual funds or positive correlations between variance and expected returns, it is imperative to make clear what the findings represent and why they are interesting. Below I describe and document the premises from which the testable implications follow.

2.1 The Basic Hypothesis Tested in this Dissertation

Patel, Zeckhauser and Hendricks (1990) find that the flow of money into mutual funds is sensitive to the relative rank of prior performance, much more so than any cardinal measure of performance. More specifically, Sirri and Tufano (1993) note that mutual fund performance affects net capital inflows mainly for the highest returning portfolios.

Figure 2.1

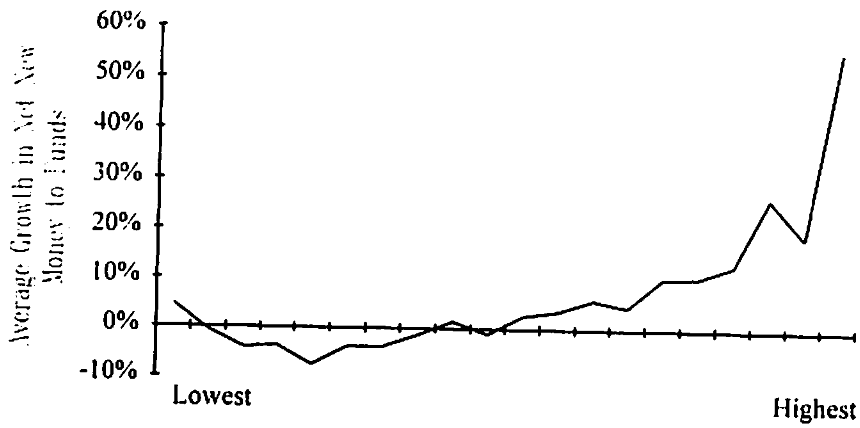

Figure 2.1 above represents the net growth in money to all mutual funds based on their prior relative performance, where the mutual funds are put into 20 different groupings.[1] We see that the top managers (ranked by absolute portfolio returns) receive large net inflows of new money, yet funds that perform poorly or average do not lose or gain many assets. Further, this result holds for virtually all subsamples of funds: different sized funds, funds employing different distribution methods, and for survivors versus dead funds. Since most funds receive compensation as a fixed percentage of assets managed, this creates a nonlinear payoff function to fund managers similar to that of a call option. As with call options, where higher variance of the underlying asset implies greater value to the option owner, this payoff suggests fund managers and fund complexes (which manage a group of funds) have an incentive to engage in volatile strategies. In sum,

[1] Data provided by Erik Sirri is greatly appreciated.

given the preference of investors toward the top-performing funds a revealed preference by fund managers towards volatility would be eminently rational.

Evidence that funds are choosing volatile portfolios in order to take advantage of this fact come from two sources. The first piece of evidence is documented in chapter 3: in aggregate, funds have a preference towards volatile securities. If one controls for price, which systematically biases measured variance, funds show a statistically significant preference toward securities with higher variance of monthly returns. Another piece of evidence is the growth of specialty funds that target specific industries or strategies. There are funds that specialize in industries, geographic regions or other strategies (e.g., high dividend stocks), so that currently there are more funds than there are stocks listed on the NYSE&AMEX. For example, many fund complexes (such as Fidelity) offer an array of specialized funds that appears suited for the nonlinear payoff to relative fund performance.[2]

The other fact relevant to this thesis is the existence of positively sloped supply curves for assets. Bradley, Desai, and Kim (1988) found the higher the fraction of target shares purchased by an acquiring firm, the higher the premium paid in interfirm tender offers. Holthausen, Leftwich, and Mayers (1990) find that buyers of large blocks of stock pay a premium above the price before the block transaction. Finally, Bagwell (1992) used information from Dutch auction stock repurchases to document that firms face upward-sloping supply curves when they repurchase shares. All of these studies imply that an increased demand for a stock will raise its price and thus lower its return; however, they could also reflect the revelation of insider information. Shleifer (1986) finds that the share price increase at the announcement of the inclusion of firms to the

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[2]The growth in specialty funds could also be an attempt to provide a more diverse menu of individual hedges.

S&P500 Index is positively related to the increase buying of shares by Index funds. Since being included in the Index does not necessarily signal any information about stock value, Shleifer provides the most convincing evidence of upward sloping supply curves for individual equities.

The revealed preferences of funds toward volatile stocks combined with the presence of upwardly sloping asset supply curves suggests this preference toward highly volatile stocks affects their equilibrium expected returns. The data from the NYSE&AMEX from 1962 to 1992 confirm this suspicion: holding constant size, variance is negatively correlated with expected returns, as documented in chapters 4, 5, 6. This negative correlation occurs in non risk-adjusted terms, and is exacerbated by controlling for measures of risk such as APT factors or beta.

2.2 Implications for the Possible Violation of Market Efficiency

The variance-expected return relation may provide an arbitrage opportunity and thus could violate the notion of market efficiency. Merton (1987) has emphasized that anomalies to frictionless models of asset pricing are consistent with rationality in a world of costly information, and thus they are not necessarily arbitrage opportunities. If correlations between various non-risk characteristics of a stock can arise unexpectedly in an evolving market structure, the correlation will necessarily have to persist before it can be eliminated. That is, the anomaly must exist, be detected, and then strategies exploiting this anomaly must be marketed and implemented. Merton developed a model of investor neglect to explain the size effect by arguing that since information on small firms was more costly for investors to gather, their neglect relative to larger firms distorted equilibrium expected returns relative to complete information asset pricing models. The investor neglect that was potentially responsible for this anomaly has been replaced by a situation today where funds explicitly targeting these stocks represent one of the largest mutual fund objectives. At the same time, the small firm effect was not present during the 1983-92 period, unlike in most of the prior decades. The variance-expected return relation may be a similar type of inefficiency that is costly to discern but ultimately temporary. Just as an occasional dollar bill found on the sidewalk is a violation of a frictionless version of the efficient markets hypothesis, anomalies will occasionally appear as exceptions to frictionless asset pricing models.

2.3 Conclusion

Only two facts are needed to generate the hypotheses tested in this thesis: the nonlinear payoff to portfolio manager returns (where the best receive large inflows and the rest are unaffected) and an upward sloping supply curve for stocks. Both facts have been documented. The payoff function to mutual funds implies the optimal strategy for fund managers is to engage in risky strategies, such as preferring volatile stocks. If mutual funds (and possibly other managers competing for investor's funds) prefer volatile stocks and if stocks have positively sloping supply curves, this could explain why volatile stocks have lower risk-adjusted expected returns than less volatile stocks. Merton's 1987 model is useful in explaining how anomalies such as this one can temporarily persist and reconciling these occurrences with conceptions of rational frictionless markets.

Chapter 3

Data and Estimation of Open-End Mutual Fund Preferences

One hypothesis explored in this thesis concerns the preference of mutual funds for characteristics of securities not directly related to their risk, where risk is defined by the CAPM. The data utilized in this chapter provide a method for testing this hypothesis by looking at open-end mutual fund portfolio holdings and documenting the revealed preferences for stock characteristics by these mutual funds.

To my knowledge this is the first use of the open-end mutual fund portfolio holdings data offered by the MorningStar company. These tests are also unique in methodology, in that they look for the cross-section of percentage ownership of a particular security by the entire mutual fund sector (or subsector). I look at stocks of holdings as opposed to flows of holdings, as has been done in most other studies of institutional ownership.

There appear to be several characteristics of stocks that are highly correlated with the mutual fund industry's ownership of a particular stock. The most indisputable conclusion that can be drawn from these data is that mutual fund preferences for stocks are not totally driven by conventional proxies for risk alone. Since portfolio theory (both the arbitrage pricing theory and the capital asset pricing model) assumes that investors choose portfolios solely based on risk (which implies a unique expected return), the clear deviation from this assumption could point to possible explanations for cross-sectional asset expected return anomalies. More relevant to this particular thesis, I find that mutual funds show a distinct preference for volatile securities, ceteris paribus.

In section 1, I will first review what other researchers have discovered that is relevant to the study here. In section 2, I will discuss how the data set was created, and what it comprises. Section 3 reviews the estimation technique used in this panel. Section 4 discusses the estimation results, and section 5 concludes.

3.1 Literature Review of Prior Theories and Evidence of Institutional Security Demand

There have been several studies of institutional demand for securities, specifically testing two main hypotheses: the existence of herding by portfolio managers into or out of specific securities, and the relation of net institutional demand to prior returns of that security (trend following or positive feedback trading). The empirical work done in this chapter on mutual fund preferences is implicitly a study of herding behavior. If mutual funds on average own a disproportional amount of, say, volatile stocks, then this implies that at one time there must have been herding into this security by the mutual fund sector (where herding is defined as the correlation of fund demand for securities in a particular period *or* the serial correlation of fund demand for particular securities).

Friend, Blume and Crockett (1970) found a significant tendency for groups of mutual funds to follow the prior investment choices of their more successful counterparts in 1968. Kraus and Stoll (1972) studied monthly trades for each of 229 mutual funds or bank trusts from January 1969 to September 1969 in order to determine the tendency of the institutions to herd in their trades. They did not find statistically significant dollar imbalances between purchases and sales of particular securities. Lakonishok, Shleifer and Vishny (1991, 1992) used 769 pension funds over the period 1985-89 to test both the for evidence of herding and for trend following behavior. They found weak evidence of contrarian strategies by the mutual funds. Recently there have been several studies that have supported the herding hypothesis. Grinblatt and Titman (1992) find positive persistence of net demand for stocks during the 1974-84 period using 279 mutual funds. Russ Wermers (1993) used the same data set as Grinblatt and Titman but a different metric of herding and found evidence of herding in the form of net demand or selling of a security during a quarter following similar demand or supply in the previous quarter. Peles (1993) looked at the trades of 4000 institutions covered by the Vickers Stock Research Corporation for about 1400 securities listed on the NYSEAMEX for the period 1986-1990. He also finds positive serial correlation in security demand.

The theories underlying these tests are motivated in large part by passages from Keynes' *General Theory* (1936). One such passage is the metaphor of the beauty contest where people pick not the most beautiful face (i.e., private estimates of true value), but who they think others consider the most beautiful face (i.e., conventional wisdom, p.156). Market value is a function of expectations of expectations *ad infinitum*. In such cases, there is a potential for under-weighting of private information as people may ignore their own private estimates after a sufficient amount of information about other's information is revealed through their purchases. The other passage is the remark that "worldly wisdom teaches that it is better for reputation to fail conventionally than to succeeded unconventionally (p.157)." This passage suggests that constraints on long run evaluation may create incentives for people to optimally mimic each other in the short run. In both cases, investors purchase assets not based wholly on their fundamental value, and in the process underweight private information. This insight has been used as the motivation for more rigorous theories of trend-following or herding. Interestingly, the inflow of money to top-performing mutual fund managers, and the preference towards volatility documented in this thesis both suggest an opposite interpretation: mutual fund managers consider risk-taking the conventional method of succeeding. That is, mutual fund managers are not trying to look alike, but instead are trying to distinguish themselves. In this environment they expose themselves to greater risk, and potentially overweigh private information.

There are two specific models that explain herding as a rational result in markets of incomplete information. First, herding has been independently modeled in a similar way by Welch (1992) and Bannerjee (1992). In these models, if agents receive private, noisy signals and can observe the choices of others, after watching a sufficient number of agents make a certain choice the following agents will then all make the same choice regardless of their private information. This amounts to people ignoring their own private information and herding into one choice. The outcomes in these environments are inefficient in that the aggregate information does not become public over time, which is what happens if many of the first to choose have atypical signals. Herding equilibria are multiple and fragile and depend on the small sample distributions of the signal (which suggests potential interaction with excessive volatility

In a different model, Scharfstein and Stein (1990) model an agency problem where agents receive noisy signals and know that they will be remunerated based on two criteria: their success that is stochastically related to their unknown type, and their investment choice's correlation with other investment choices. The latter criterion is used because smart investors receive correlated signals and the good investments all receive the same unanticipated shock, so that although smart investors may all choose the ex post "wrong" asset, they all make the same unforseeable mistake. On the other hand, dumb investors receive uncorrelated signals about investor choices and thus their singular mistakes reveal their poor type. This causes agents to not weight fully their own private information, since they know that contrarian investment decisions will be evaluated more harshly if they fail. In such an environment herding can occur as agents mimic those who choose before them. Like the prior models of Welch and Bannerjee, investor purchases can not affect price in these models, but the intuition behind them (as articulated by Keynes) makes them potentially relevant to securities markets.

If mutual funds have a comparative advantage in holding securities with certain characteristics, or if mutual funds face incentives that favor holding securities with certain characteristics, then as a security acquires these characteristics funds will desire and purchase them. The strength of this empirical study is that it identifies several of these characteristics. In this way I generate and test an alternative interpretation of revealed trend-following or herding behavior: as stocks acquire specific characteristics mutual funds are more likely to hold them. This may have nothing to do with under weighing private information or responding disproportionately to short run incentives. For example, I find that mutual funds show a strong aversion to low-priced stocks (price less than $5). Over time as a stock rises in price it will attract net mutual fund demand, evidence to those looking at net changes in mutual fund demand of herding and trend-following. In reality the effect may be due to the comparative disadvantage of large institutions buying low-priced stocks. Thus the empirical findings in this chapter provide alternatives to this line of research and at the least suggest variables to control for when testing for herding or trend-following.

3.2 Data Used In The Estimations

MorningStar's two CDs contain complete portfolio data on most open-end mutual funds for the years 1991 and 1992 (using the January 1992 and 1993 MorningStar CDs).[1] Using a stock's ticker, I am able to find the total percentage of a NYSE&AMEX stock owned by an open-end mutual fund in a particular year by matching the portfolio's share holding with security information from CRSP. Specifically, for each stock with 24 months of uninterrupted returns prior to the portfolio holdings year, I pull security information such as the stock's variance, volume, ticker, date of initial listing, beta, price and market capitalization as of the prior December. I also pull the shares outstanding for each month over the portfolio year. A fund's portfolio holdings menu lists the ticker and shares held of each stock the fund owns at the end of a specific month in the prior year (usually April or June). Using the date of the reported portfolio, I am able to construct how much of each stock is owned by each fund for the portfolio year by matching the tickers of the MorningStar and CRSP datasets. Though the ownership data is taken at different points within the portfolio year, they represent a noisy yet unbiased estimate of mutual fund demand in that year, as fluctuations in aggregate stock price levels do not affect the measure of stock ownership.

I test the relationship between security characteristics and aggregate mutual fund ownership in the following way. If all asset demanders, non-mutual funds and mutual funds, held similar portfolios, then the mutual fund industry as a whole would own equal proportions of each stock. For example, given that the open-end mutual fund sector as a whole owns, on average, 6% of every stock on the NYSE, if this same set of mutual funds

[1] Data previous to 1991 are not available on CD but only in hard copy, making an already onerous database creation procedure infeasible.

owns only 3% of IBM's shares, I can say that for some reason this sample of mutual funds was averse to holding IBM shares. This percentage holding of a particular stock by the mutual fund sample will be the independent variable in these tests.

The MorningStar data set contains portfolio holdings for 2,284 and 2,520 mutual funds in 1991 and 1992, respectively. I included only those mutual funds that hold more than 50% of their portfolio in equities, which leaves 1,087 and 1,174 funds in 1991 and 1992. This was done because funds with very small equity holdings relative to their bond portfolio frequently did not list their equity portfolios (they listed the bond holdings instead). Furthermore, it removed a rather small amount of net mutual fund equity holdings relative to the total. Summary statistics on the mutual funds are given in table 3.1. Note that the mean dollar value of a fund's equity ($340 million in 1992) is much greater than the median ($70 million in 1992), implying that there exists several large funds with several billion dollars in equity and many funds with only around $50 million in equity. Data relating to the size of the fund and the tenure of the fund manager were used to test whether aggregate preferences were driven by the new entrants or established funds. The mean portfolio turnover statistic was 95% in 1991 and 85% in 1992, indicating that on average funds hold a security for slightly less than one year. The mean percentage of assets in equity is 86%, implying that these are primarily equity investing mutual funds.

Table 3.2 displays summary statistics on mutual fund's total equity holdings of individual securities. Constructing this measure was done in the following manner. The portfolio holdings are from various dates within the year for different funds, so that some of the 1991 portfolio holdings correspond to April while others correspond to June or October of that year. 1991 data use only portfolio dates within 1991, while 1992 data use only data pertaining to portfolio dates within 1992. To get an estimate of the mutual fund industry's holdings of a particular stock in a particular year, for each fund's portfolio I divided the number of shares held of a particular company by the number of shares outstanding on that date (the date is listed in the fund's portfolio holdings menu), and then added up this quotient for all mutual funds that reported holdings within the year. This was my dependent variable: percentage ownership of a stock by open-end mutual funds. Specifically, let own_i represent the dependent variable. It is defined as the following

$$(3.1) \quad own_i = \sum_{m=1}^{M} \frac{\text{shares owned of stock i by fund m at time } t_m}{\text{shares outstanding of stock i at time } t_m}$$

where t_m represents the date to which the portfolio data correspond for fund m's holding of stock i and M is the total number of mutual funds in the specific category of interest (e.g., "growth" funds only). Tests of subsets of the mutual fund universe utilized only funds within the specified subset. For example, I test the explanatory power of a various set of variables not only on the entire mutual fund universe, but on small funds only, or only funds within the investment objective of "growth." In these cases, I summed only over these sub samples.

Table 3.2 shows that the mutual fund sector as a whole had zero holdings of approximately 17% of the securities passing the relevant criteria to be included in these tests (described below). The mean ownership statistic indicates that the mutual fund sector owns on average of 5.2% and 5.7% of the shares outstanding of stocks in 1991 and 1992 respectively. Thus the entire sample of open-end mutual funds represents a small yet significant portion of total equity ownership of the NYSE/AMEX.

Table 3.3 shows the importance of several investment objectives. Although MorningStar lists over 20 objectives, the top 6 represent the majority of equity ownership (over 75% of equity holdings). Furthermore, growth and growth-income alone represent about 60% of the total sample of mutual funds. The small company funds represent a sizable portion of investor demand and have obvious preferences for small companies. As we shall see, this sector's demand has a significant affect on the aggregate demand characteristics with regard to market capitalization. The largest 3 of these objectives are tested independently to determine if there is substantial heterogeneity between funds with different objectives.

The independent variables I used were all available as of December prior to the portfolio holdings year (i.e., 12/90 and 12/91 for years 1991 and 1992 respectively). Table 3.4 shows summary statistics for variables of interest in explaining mutual fund demand. Using all firms on the NYSE/AMEX return files from the Center for Research in Security Prices (hereafter CRSP) data set, I calculated these stock's standard deviations as of December of the prior year from the past 24-60 months, depending on availability. If at least 24 months of data or the price as of December were not available, I did not use the stock. Beta was derived by summing the slopes in a regression of the stock return on the current and prior month's market return (I used the NYSEAMEX value-weighted return for the market return). Age represents the number of months the security has been listed on the NYSE or AMEX as of the observation year with an initial date of January 1925 for the oldest stocks, the time of the beginning of the CRSP tapes. Given the criteria for determining variance, age was at least 24 months (since it needed this many months of uninterrupted returns to calculate the variance of the issue's return). News stories was determined by a search of the University Microfilms International (UMI) Newspaper Abstracts database. This contained the number of stories in major newspapers that contained a particular company's name. For the 1992 portfolio data I used the number of stories in 1991 and for the 1991 portfolio data I used the number of stories in 1990 and 1989 (due to the nature of the UMI data). Monthly volume divided by shares outstanding was taken in the December immediately prior to the portfolio year, and this ratio proxies for liquidity.

A discussion of the relevance of these variables is important. As we are mainly concerned with the connection between aggregate mutual fund holdings and idiosyncratic variance of a stock, it is important to control for potential omitted variables problems. The most prominent potentially misleading variables are price and size. Table 3.6 shows that both size and price are highly correlated with volatility. A substantial number of observations have very low prices and very small size. For example in 12/91, 15% of all securities listed on the NYSE/AMEX had a price less than 2.5, with a mean capitalization of only $21 million, representing only 0.2% of the NYSE/AMEX total market capitalization. SEC regulations discourage mutual funds from holding more that 10% of a firm, institutionally constraining many funds from taking a position in these stocks. Most funds in this case would be rational to avoid them. Further, given the documented existence of upwardly sloped supply curves for stocks, the ownership of a large proportion of a stock may entail a great amount of slippage in getting into or out of a position if that position is large, where slippage is defined as the difference between the posted market price immediately prior to trading and the effective price received or paid. Thus the small size of some firms might discourage buying by large funds who perceive significant transaction costs in buying and selling shares in an issue that can at best provide only a meager addition to total portfolio return. Finally, low prices are known to have greater bid-ask spreads as a percentage of their average price (see Blume and

Stambaugh, 1983). The greater transaction costs of these small, low-priced stocks provides reason for an institutional aversion outside the realm of risk preferences.

Another reason to control for price is that low-priced stocks have a bias in their measured variance due to their proportionally higher bid-ask spreads. A stock moving from bid to ask to bid adds a great deal to the return variance of low price stocks although this is not "real" stock price variance in the sense that it is not the variance of return relevant for a trader off the floor of the exchange. For example, a stock going back and forth from its bid of 1 to its ask of 1-1/4 will report a substantial variance, even though the true return remained constant at zero.[2] Stoll and Whaley (1983) find that the variance due to the bid-ask spread is 0.051% for small, lower-priced firms and only 0.001% for large firms, implying a significant upward bias for the measured variance of monthly returns for low-priced stocks. This implies low-priced stocks will have measured variance significantly above true variance. Since the relationship between price level of a stock and the bid-ask spread as a percentage of price is nonlinear and there are quite a few stocks with very low prices in this sample, I used the log of the price as an explanatory variable in the regressions.

Other variables include return variance and beta, clearly two characteristics of stocks that are of interest in their own right, in that this study is mainly of the relationship of a stock's volatility, systematic and nonsystematic, on the preferences for mutual fund ownership. I do not include residual variance because of its high correlation with total variance, so much so that residual variance added no information to total variance in

[2]Assuming that the bid and ask price have equal probability of being the last trade of the day, the variance using last trades due to the bid-ask spread is $\left(\frac{P_A - P_B}{P_A + P_B}\right)^2$, where P_A is the ask price and P^B is the bid price.

unreported tests. Volume as a percentage of shares outstanding is a proxy for the liquidity of the issue and may serve as a proxy for transaction costs or information flows pertaining to that issue, with highly liquid shares being the result of either. News stories and age can both proxy for aggregate information or the cost of information on particular stocks, with older stocks having a more established reputation and thus less estimation uncertainty of the riskiness of the stock, and the prevalence of news stories could proxy for the amount of recent information generated by a firm.

Table 3.5 is the same as table 3.4 except in this case I only use the stocks that had zero net ownership by the mutual fund sample. A comparison between table 3.4 (the entire sample) and table 3.5 (the sample of stocks with zero net mutual fund ownership) is done to see if any of the preferences I find in the econometric analysis stand out prominently through this simple sorting procedure. These stocks with zero net fund ownership have lower mean price levels, age since being listed, and news stories generated about them. While the mean return variance of the two samples is similar, the median is considerably lower, implying that mutual funds tended not to hold any of stocks that had very low return variances. The econometric estimation that follows supports these initial inferences.

Table 3.6 further highlights the high correlation between return variance, price and size. Further, panel A shows that there are many stocks with extremely low prices (below $5 per share). Note also that while the mean return variance was 1.6% for all stocks, for those stocks with a price less than or equal to 1 (over 5% of the sample) the mean return variance for this group was a considerably higher 6.0%. The correlation matrix in panel B of this table shows the simple correlations between variables. Again, note that variance of monthly return is highly correlated with both price and size, and points to the importance of separating the independent influence of these variables on the variable to be explained, specifically mutual fund ownership.

3.3 Estimation Technique

Although some of the funds held short positions, the great majority do not. In fact for no stock does the entire sample have a net short position. The institutional constraints on short positions imply that a censored model would be most appropriate. Thus the equation I estimated is a standard censored model of the form[3]

$$\text{(3.2)} \quad \begin{aligned} &\text{own}_i^* = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \\ &\text{own}_i = 0 \text{ if } \text{own}_i^* \leq 0 \\ &\text{own}_i = \text{own}_i^* \text{ if } \text{own}_i^* > 0 \end{aligned}$$

where the explanatory variables x_i are various security characteristics. I am primarily concerned with the hypothesis that funds are attracted to high variance stocks, ceteris paribus. In order to control as much as possible for possible omitted variables biases, I included not only a wide variety of other potentially relevant variables but their squares and cubes as well. The primary variables of interest other than monthly return variance were: price level, time since listed on the exchange (age), liquidity, news stories, market equity, prior year's return, and beta. I tried as much as possible to linearize these explanatory variables, and therefore took the logs of market equity, liquidity, age, and news stories.

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[3]See Maddala (1989) p.149 for an exposition of censored regression models.

For simple linear regressions heteroskedasticity leads to inefficient estimates, but with nonlinear regressions the estimates can be biased as well. For this reason, I estimated the parameters in equation (3.2) using Powell's censored least absolute deviations (CLAD) estimator (Powell 1984, 1986). The CLAD estimation technique relies on symmetry conditions imposed by a censored model, and in this way is semi-parametric and does not require assumptions of homoskedasticity or normality. The CLAD parameter estimates are unbiased, consistent and asymptotically normally distributed, with only a minimal restriction on the distribution of the error term (it must have a zero median). Unreported analysis suggests that the errors indeed are not homoskedastic, especially across capitalization. Both years had to be estimated independently since both methods assume the samples are identically and independently distributed. To get standard errors I bootstrap the data by taking 500 independent draws from the original sample (with replacement), and utilizing the standard deviation of the resulting collection of estimates as parameter standard errors.

3.4 Estimation Results

Table 3.7 reports the main cross-sectional results for years 1991 and 1992.[4] The first regression uses standard deviation as the sole explanatory variable for mutual fund ownership. The coefficient on standard deviation is negative and significant. Since standard deviation is highly contaminated by the price of the security, both due to measurement error of standard deviation and perhaps an omitted risk factor associated with low-priced stocks,[5] in the second regression I control for price. Here I found the

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[4] Bo Honore graciously supplied the Gauss program utilized to calculate the CLAD estimates.

[5] As implied by the studies that have found low-priced stocks outperforming high-priced stocks, for example see Bhardwaj and Brooks (1992)

coefficient on standard deviation to be positive and significant. Mutual funds showed an aversion to low-priced stocks, especially the very low price stocks as evidenced by the fact that I am using the log of the price level. The third regression in table 3.7 is the standard regression utilized in tests on subsamples of the mutual fund industry, as it includes all of the significant other explanatory variables. With 5 other variables, the coefficient on standard deviation is positive and significant at the 1% level, strong evidence that mutual funds truly prefer highly volatile stocks since a variety of other potential explanations are controlled for. Using the coefficient estimate on standard deviation for the year 1991 in the third estimation, a doubling of monthly return standard deviation from 10% to 20% per month corresponds to an increase in mutual fund holding of 2.0% of a company's total shares outstanding. Putting this in context, the average percentage holding of an NYSE/AMEX fund by this sample is around 6%.

The third regression in table 3.7 contains coefficient estimates that are all significant at the 5% level. We see that mutual funds prefer stocks with higher prices, age since listing on the exchange, volatility, liquidity, news stories, and are averse to size. Though unreported, the price effect is mainly a strong aversion for stocks with prices below $5. Stocks with a price greater than $15 show no mutual fund preference This is implicit in the significance of the logged value of price. It appears that mutual funds are only affected by price when it is very low.

Liquidity, as measured by the volume of the stock divided by the number of the shares outstanding, also has a highly nonlinear relationship with mutual fund ownership. Mutual funds prefer stocks with higher liquidity, which seems related to a transaction cost story. That is, either liquidity directly proxy's transaction costs (a high volume of trade implies low costs of trading), or the relationship is more indirect. Specifically, higher liquidity may proxy for high information flows which implies a greater amount of portfolio rebalancing or changing speculative positions taken in this stock, which in turn implies greater liquidity. Higher information flows could be related to lower transaction costs (as the cost of acquiring information is lower) or higher risk (if one believes that changing risk is itself a risk factor).

The number of months since the stock's initial listing, its "age," is also highly significant. Barry and Brown (1984) looked explicitly at the relation between period since initial listing and expected returns, and found that for the period 1931-1981 older stocks had significantly lower returns than the newly listed stocks, controlling for size and beta. They argued that estimation uncertainty surrounding newly listed firms made them riskier and was responsible for the higher returns. One might think this is due to the obvious correlation between age and size, but even in regressions that include size, its square and its cube, the coefficient on the log of age remains positive and significant. Age could proxy for information costs and risk. The older an issue is the greater precision in estimating its risk characteristics, and thus age could proxy for the uncertainty of the risk estimation and thus risk itself. Also, older stocks have more time to get the word out about its product, etc., and thus older stocks have lower information costs; analysts are not compelled to discover the stocks in an obscure database, but are already apprised of its existence just because the stock has been around for a while.

Related to age is the number of news stories related to a firm in several large daily newspapers.[6] As with age, news stories could proxy transactions costs by increasing the precision of risk estimation and lowering information costs. These firms' low profiles might also require greater search costs in highlighting them as securities desirable within

[6]Specifically, these newspapers included the Atlanta Constitution, Boston Globe, Chicago Tribune, Christian Science Monitor, L.A. Times, N.Y. Times, USA Today, Wall Street Journal, and the Washington Post.

a portfolio. Funds show a significant preference towards stocks that are in newspapers, though using the log of news stories indicates that this may be more accurately characterized as an aversion to stocks that are very rarely in the news.

Size, as measured by the log of market equity, is negatively correlated with mutual fund ownership and this coefficient has the weakest significance of all of the explanatory variables. In the breakdown of mutual fund ownership in table 3.11, we see this aggregate relation obscures a highly significant but conflicting preference within fund objectives. Table 3.11 estimates the preference of different fund objectives for the previously mentioned stock characteristics. The separation of the small company objective shows that the seeming weak aversion to size we see in aggregate masks stark heterogeneity between objectives. The small company subsector as a whole has a predictable strong affinity toward small stocks. The rest of the funds (indicated by the No Small Company heading, which includes all objectives except small company) show a strong preference toward large stocks. Given the size of the small company objective (around 6% of the sample), in aggregate the preference for volatility is weakly negative.

In table 3.8 I include size, its square and its cube in order to see if size is driving the results on any of the other explanatory variables. I see that size subtracts nothing from the significance of the other variables, and does not itself become highly significant in aggregate. Other unreported regressions using polynomial expansions of other variables did not diminish the significance of any other explanatory variables and so were left unreported. This is why I use regression 3 of table 3.7 as the standard regression on the subsamples of the mutual fund industry.

Also in table 3.8 we can see the nonlinear aspect of the demand for volatile stocks. Using the standard deviation and variance, we see the coefficient on standard deviation is strongly positive while it is strongly negative for variance. This implies that mutual fund ownership is concave in variance. For example using the coefficients from 1992 in table 3.8, second regression, the coefficient on return standard deviation and variance is 14.2 and -0.502 respectively. The median return variance of a stock used in the 1992 regressions was 1% (annualized, using table 3.4), so that at the median volatility induced a 9.2% level of mutual fund ownership. At the level of 8% volatility (well above the median) there is no effect, and at 10% volatility induced a -5.3% level of mutual fund ownership, *ceteris paribus*. Since mutual fund holdings are censored at 0%, this would imply that funds did not hold any of these highly volatile stocks, other things equal.

Table 3.8 examines the hypothesis that it is not idiosyncratic volatility that attracts mutual funds but the systematic volatility of a stock that attracts mutual funds. We see that beta, however, is not significant in a regression with other parameters. Although beta is known to be difficult to measure accurately (see Ross and Roll 1994), it appears unlikely that beta can explain the preference of mutual funds for volatile stocks.

The findings related to the effect of prior return on mutual fund ownership are useful in highlighting an important omitted variables problem in tests for trend-following. Table 3.9 examines the trend-following hypothesis. When prior return is used alone in explaining mutual fund ownership, we see that its coefficient is positive and significant. This correlation could easily be interpreted as a preference for stocks that have risen in price, or alternatively an aversion to stocks that have fallen in price. When I include other variables, however, we see that this inference is mistaken. Using price and prior return, the coefficient on prior return becomes insignificant in 1992 and for 1991 it becomes negative (and significant). This implies that the aversion to low-priced stocks could be driving the simple correlation between prior return and mutual fund demand in prior studies. Low-prices are correlated with low prior returns, and the strong aversion to low-priced stocks by the mutual fund sector will show up in a simple correlation between ownership and prior return, providing the unwary econometrician with evidence of positive-feedback investing (i.e., buying stocks that have gone up). Using all of the other explanatory variables we see the prior return coefficient for 1991 becomes insignificant while for 1992 it becomes negative and significant. Prior stock returns do not appear to have a strong explanatory power in regressions with other variables.

Table 3.10 breaks down the basic set of parameters by mutual fund subsets to determine if some coefficients are driven by the size of the fund or the tenure of the portfolio manager. Large (small) funds are those with assets greater (smaller) than the median fund. Old and young pertain to manager tenure, which is reported (though with considerable error) in the MorningStar data. Old (young) funds are those with tenure longer (shorter) then the median fund. Note that the coefficient's absolute magnitudes are not directly comparable between regressions here since the size of the dependent variable will change across subsections (e.g., large funds will hold more of all stocks than the small funds even if they have identical preferences due to budget constraints alone). The only coefficient that differs significantly in sign and significance from the aggregate results of tables 3.7 - 3.9 is the coefficient on size. Younger and smaller funds appear to prefer large firms. However, this result is driven more by the distribution of fund objectives within these groups. A disproportionate number of the funds specializing in small firms are older and larger than average, which naturally leads to finding that the older and larger funds have a preference toward smaller firms. Most importantly, the small and large funds, and the less experienced and more experienced managers all show positive and significant preferences toward volatile securities. Thus we cannot say that the mutual fund sector's preference for volatile stocks is driven by a strategy that emerging funds use to break into the industry.

Table 3.11 breaks the mutual fund sector down by objective. The CLAD estimation technique has difficulty converging for panels with few positive observations, and thus funds with less prominent objectives are not examined since they hold so few of the total number of available stocks. I break down the mutual funds into growth (about 35% of the fund sample), growth-income (about 28%), small cap (about 6%) and all funds but the small cap funds (about 94%). The preference towards volatile stocks is strong among the growth and growth-income objectives, as well as all funds excluding the small cap objective. The small cap sector itself displays no preference toward volatile stocks. The positive preference towards size is clear in all but the small cap objective, which shows a predictable preference towards small firms. The most consistent preference among the objectives is the aversion to low priced stocks, which is strongly significant across all objectives.

The strongest preference revealed by mutual funds is the aversion to low-priced stocks, which comprise a large portion of the NYSE&AMEX. If this is a transaction costs or regulatory issue, where the size of most mutual funds makes purchasing a low-priced stock prohibitively expensive or legally infeasible, an equal-weighted index may be an especially ill-suited index with which to compare these mutual funds. An equal-weighted index gives disproportionate weight to low-priced stocks, and therefore utilizing the equal-weighted index is misleading since it includes securities that mutual funds can not seem to hold.

3.5 Conclusion

The data estimation in this chapter documents for the first time several specific security characteristics that mutual funds prefer. Price, volatility, liquidity, news stories, age, and size are all significant in explaining aggregate mutual fund holdings of stocks. Most important to the remainder of this thesis, funds show a preference for volatile stocks. These results have sundry relevancies. First, the aversion to low priced stocks creates the appearance of trend following by mutual funds even if it is not occurring, and thus is an important variable to control for in these tests. The aversion to low-priced stocks also highlights why certain indexes such as the equal-weighted NYSE&AMEX can be misleading benchmarks of mutual fund performance. The sensitivity of mutual funds to proxies for transaction costs and information flows suggests that although funds provide diversified portfolios to investors, they do not provide full diversification to equity risk. Perhaps most interestingly, certain security characteristics correlated with mutual fund neglect may help explain certain anomalies in cross sectional asset pricing. In the following chapters I examine the effect of asset return variance and cross-sectional equity returns. The mutual fund preferences toward volatile stocks may help explain the negative correlation between variance and expected returns I find in these estimations.

Table 3.1
Summary Statistics on Mutual Funds

Below are characteristics of the mutual funds used in the censored regressions. Datasets were pulled from MorningStar's *Mutual Funds OnDisc*, January 1993 and January 1992. The January 1993 CD contains portfolio data for funds for the prior year, and similarly for the January 1992 CD.

	Year	
	1991	1992
Total number of Funds Covered by MorningStar	2,284	2,520
Number of Funds Utilized (w/ equity>50% of portfolio)	1,087	1,174
Total Value of Utilized Fund's Equity Holding	$275 billion	$340 billion
Mean Value of Utilized Fund's Equity Holding	$253 million	$290 million
Median Value of Utilized Fund's Equity Holding	$57 million	$70 million
Mean Portfolio Manager Tenure	4.4 years	4.6 years
Median Portfolio Manager Tenure	3 years	3 years
Mean Portfolio Turnover	95%	85%
Mean Percent of Assets in Equity	86%	86%
Mean Percent of Assets in Cash	8.8%	8.7%
Mean Percent of Assets in Bonds	3.7%	3.5%

Table 3.2
Summary Statistics on Mutual Fund's Total Equity Holdings

The variable own_i represents the estimated proportion of security i owned by the sample of mutual funds during the year. This is the dependent variable used in the censored regressions.

$$own_i = \sum_{m=1}^{M} \frac{\text{shares owned by fund m at time } t_m}{\text{shares outstanding at time } t_m}$$

where M is the total number of mutual funds in the specified sample.

	Year	
	1991	1992
Total observations	2,133	2,221
Number with own_i=0 (i.e., mutual funds held no shares)	356	380
Mean own_i	5.2%	5.7%
Median own_i	3.6%	3.9%
Max own_i	78%	94%

Table 3.3
Total Equity Holdings by Investment Objective

	% of Total Equity Holdings	
	1991	1992
Growth	34.9%	37.5%
Growth-Income	26.4%	28.7%
Small Company funds	5.6%	6.7%
Equity-Income	4.4%	4.9%
Balanced	4.5%	3.3%
Aggressive Growth	2.5%	2.5%

Table 3.4
Summary Statistics on NYSE&AMEX Securities Used in Censored Regressions

These are various statistics on stocks utilized with the MorningStar data in the censored regressions. Utilized stocks are a subset of CRSP's NYSE&AMEX stock database. 1992 utilized data have 24 months of uninterrupted returns for the period 12/89-12/91, this holds similarly for 1991 data. ME represents market equity. Beta is computed as the sum of the slopes in the regression of the return on the current and prior month's value-weighted market return. Monthly variance is the total variance of monthly returns for the prior 2-5 years, depending on availability. News Stories is the number of news stories found in the UMI data file of major newspapers for the two-year period prior to 1991 and the one-period prior to 1992. Age is the number of months since the stock was listed prior to the observation year. Monthly Vol./Shares Out. is a proxy for the security's liquidity.

1991 Data 2,133 Observations

	% Return Variance	Beta	Price ($)	Age Months	News Stories	Monthly Vol. /Shares Out.	Market Equity
mean	1.49	1.08	17.9	231	31	39	2,190 ($mill.)
med	1.01	1.07	11.6	187	15	29	144 ($mill.)
max	44.77	4.35	459.1	780	1641	484	410,000 ($mill.)
min	0.03	-2.80	0.016	24	0	0	0.15 ($mill.)

1992 Data 2,221 Observations

	% Return Variance	Beta	Price ($)	Age Months	News Stories	Monthly Vol. /Shares Out.	Market Equity
mean	1.72	1.14	21.8	231	16	51	2,731($mill.)
med	1.04	1.11	15.4	162	8	36	201 ($mill.)
max	51.27	6.25	433.5	792	844	5257	385,000 ($mill.)
min	0.03	-0.66	0.05	24	0	0	0.49 ($mill.)

Table 3.5
Summary Statistics on the NYSE&AMEX Securities with Zero Mutual Fund Ownership

These are various statistics on stocks utilized with the MorningStar data in the censored regressions. This table is analogous to table 4 except the securities utilized here are only those securities that are not owned by any mutual funds in the MorningStar dataset.

1991 Data 356 Observations

	% Return Variance	Beta	Price	Age	News Stories	Monthly Vol. /Shares Out.	Market Equity
mean	1.59	0.83	10.4	113	11	34	2,587 ($mill.)
med	0.66	0.69	7.3	50	5	25	188 ($mill.)
max	44.77	3.71	89.5	780	355	484	410 ($bill.)
min	0.03	-0.93	0.03	24	0	0	150 ($thous.)

1992 Data 380 Observations

	% Return Variance	Beta	Price	Age	News Stories	Monthly Vol. /Shares Out.	Market Equity
mean	1.69	0.86	11.7	107	6	38	3,250 ($mill.)
med	0.62	0.72	9.1	57	1	26	286 ($mill.)
max	51.27	6.25	122.6	792	114	819	385 ($bill.)
min	0.03	-0.66	0.05	24	0	0	493 ($thous.)

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Table 3.6
Correlation Statistics on NYSE&AMEX Securities Used in Censored Regressions for 1991

These are various statistics on stocks utilized with the MorningStar data in the censored regressions. Utilized stocks are a subset of CRSP's NYSE&AMEX stock database. 1992 utilized data have 24 months of uninterrupted returns for the period 12/89-12/91, this holds similarly for 1991 data.

Panel A

Price Category	% of Sample	mean ME ($millions)	mean β	mean variance (% return)
Total	100%	2,833	1.13	1.6
Price≤1	5.1%	21	1.52	6.0
1<Price≤2	4.3%	26	1.30	3.6
2<Price≤3	3.4%	41	1.20	2.9
3<Price≤5	6.5%	61	1.29	2.5
5<Price≤10	16.6%	174	1.15	1.6
10<Price≤15	12.6%	592	1.03	1.2
15<Price	51.5%	5,282	1.07	0.9

Panel B

Correlation Matrix

	log(Prc+1)	Log(ME)	Steve	Variance	Log(Liq)	Log(News)	Log(Age)	Beta
Log(Prc+1)	1	.83	-0.60	-0.49	-0.03	0.27	0.29	-0.18
Log(ME)	0.83	1	-0.51	-0.43	0.04	0.37	0.26	-0.11
Stdev	-0.60	-0.51	1	0.91	0.12	-0.06	-0.07	0.51
Variance	-0.49	-0.43	0.91	1	0.08	-0.10	-0.07	0.34
Log(Liq.)	-0.03	0.04	0.13	0.08	1	0.17	0.07	0.24
Log(News)	0.27	0.37	-0.06	-0.10	0.16	1	0.28	0.12
Log(Age)	0.29	0.26	-0.07	-0.07	0.07	0.28	1	-0.02
Beta	-0.18	-0.11	0.51	0.35	0.24	0.12	-0.02	1

Prc-price.
ME-market equity.
Beta- computed as the sum of the slopes in the regression of the return on the current and prior month's value-weighted market return.
Stdev-total standard deviation -of monthly returns for the prior 2-5 years, depending on availability.
Variance-Stdev squared.
News-news stories found in the UMI data file of major newspapers for the two-year period prior to 1991 and the one-period prior to 1992.
Age-number of months since the stock was listed prior to the observation year.
Liq.-proxy for liquidity and is defined as Monthly Vol./Shares Out.

Table 3.7
Censored Least Absolute Deviations Model of Mutual Fund Demand (standard errors in parentheses)

Independent variables were taken from the December prior to the dependent variable year and are defined below. Censored Least Absolute Deviation standard errors were bootstrapped, using 500 random draws. Intercept omitted.

Dependent Variable: Own_i (see table 2). Percent ownership of stock outstanding held by entire sample mutual funds (e.g., 14.5% ownership by the mutual fund sector is input as 145).

	91	92	91	92	91	92
stdev*10	-12.2	-13.4	34.8	30.7	19.8	12.3
	(1.75)**	(1.60)**	(3.18)**	(4.43)**	(3.90)**	(2.58)**
log(1+prc)			65.2	78.5	60.20	68.7
			(3.52)**	(6.02)**	(6.61)**	(7.48)**
log(liq)					34.9	46.7
					(4.36)**	(4.37)**
log(news)/10					96.0	16.4
					(2.91)**	(3.12)**
log(age)/10					121.4	10.6
					(2.86)**	(3.09)**
log(ME)/10					-33.7	-28.4
					(11.27)**	(12.27)*

log(1+prc)-Log of (1+price).
log(age)-Log of the age of the security, where age is the number of months since the security has been listed on the NYSEAMEX.
log(news)-Log of (1+news stories), where news stories were found from a search of the UMI database containing the number of stories pertaining to a company in major newspapers.
log(liq)-Log of liquidity, where liquidity is defined as the monthly trading volume divided by the shares outstanding.
log(ME)-Log of market equity, where market equity is in $millions.
stdev-standard deviation of monthly returns for the prior 24-60 months, depending on availability.
** significant at the 1% level
* significant at the 5% level

Table 3.8
Censored Least Absolute Deviations Model of Mutual Fund Demand
(standard errors in parentheses)

Independent variables were taken from the December prior to the dependent variable year and are defined below. Censored Least Absolute Deviation standard errors were bootstrapped, using 500 random draws. Intercept omitted. 1991 data had 2,133 observations, with 356 censored (i.e., zero mutual fund holdings) observations. 1992 data had 2,221 observations with 380 observations.

Dependent Variable: Own_j (see table 2). Percent ownership of stock outstanding held by entire sample mutual funds (e.g., 14.5% ownership by the mutual fund sector is input as 145).

	91	92	91	92	91	92
stdev*10	26.4	20.6	128	142	132.3	136.1
	(4.66)**	(5.66)**	(15.2)**	(13.9)**	(19.3)**	(16.5)**
variance*100			-43.3	-50.2	-45.5	-50.7
			(7.49)**	(6.51)*	(8.95)**	(7.83)**
log(1+prc)	57.4	64.5	-57.6	58.4	57.1	57.6
	(5.91)**	(6.18)**	(5.17)**	(5.15)**	(5.36)**	(5.67)**
log(liq)	34.6	47.5	31.9	43.6	33.3	42.7
	(4.23)**	(4.74)**	(3.31)**	(3.24)**	(3.66)**	(3.22)**
log(news)/10	124.5	19.8	39.1	6.49	41.5	6.62
	(29.5)**	(3.60)**	(20.25)**	(3.89)	(22.5)	(3.78)
log(age)/10	117	12.2	95.6	8.87	97.9	8.90
	(25.8)**	(3.04)**	(21.62)**	(2.41)**	(22.4)**	(2.20)**
log(ME)/10	-9.48	479	-25.2	-6.94	-24.3	-9.18
	(459)	(1151)	(10.43)*	(12.20)	(10.8)**	(12.3)
log(ME)2	188	-46.1				
	(349)*	(1079)				
log(ME)3*10	-101	-72.4				
	(88)	(255)				
Beta/10					-5.26	5.38
					(33.30)	(3.96)

variance-variance of monthly returns.
log(ME)2-log(ME) squared
log(ME)3-log(ME) cubed.
Beta-the sum of a regression of the securities on the value-weighted market and its lagged return.

** significant at the 1% level
* significant at the 5% level

Table 3.9

Censored Least Absolute Deviations Model of Mutual Fund Demand (standard errors in parentheses)

Independent variables were taken from the December prior to the dependent variable year and are defined below. Censored Least Absolute Deviation standard errors were bootstrapped, using 500 random draws. Intercept omitted. 1991 data had 2,133 observations, with 356 censored observations. 1992 data had 2,221 observations with 380 observations.

Dependent Variable: Own_j (see table 2). Percent ownership of stock outstanding held by entire sample mutual funds (e.g., 14.5% ownership by the mutual fund sector is input as 145).

	91	92	91	92	91	92
stdev*10					20.7	16.6
					(3.75)**	(2.81)**
l(1+prc)			46.6	46.6	64.4	78.6
			(4.26)**	(3.56)**	(7.31)**	(8.40)**
log(liq)					35.0	50.3
					(4.30)**	(4.99)**
log(news)/10					87.4	13.4
					(27.7)**	(3.44)**
log(age)/10					121	9.65
					(29.81)**	(2.87)**
log(ME)/10					-33.8	-33.0
					(11.8)**	(12.38)**
Ret(-1)	29.8	11.3	-17.9	2.05	-5.33	-4.39
	(3.83)**	(3.60)**	(6.39)**	(2.12)	(5.47)	(1.61)**

Ret(-1)-stock's stock return in year prior

** significant at the 1% level
* significant at the 5% level

Table 3.10
Censored Least Absolute Deviations Model of Mutual Fund Demand (standard errors in parentheses)

Independent variables were taken from the December prior to the dependent variable year. Each regression Large funds have assets greater than the median, while small funds have assets less than the median. Old tenure refers to funds run by managers with greater than median tenure (i.e., 3 years as reported in table 3.1), while young tenure is defined as funds run by managers with less than or equal to median tenured managers.

Dependent Variable: Percent ownership of stock outstanding held by the particular sample mutual funds.

	Young Tenure 642 Censored		Old Tenure 413 Censored		Small Funds 717 Censored		Large Funds 400 Censored	
	91	92	91	92	91	92	91	92
stdev*10	8.38	4.29	9.21	6.93	0.748	0.721	20.0	12.93
	(1.46)**	(1.03)**	(2.58)**	(1.93)**	(0.20)**	(0.256)**	(3.43)**	(2.69)**
log(1+prc)	20.1	18.73	37.8	41.5	2.66	3.695	58.61	64.47
	(2.57)**	(2.37)**	(4.83)**	(5.09)**	(0.513)**	(0.843)**	(5.85)**	(7.33)**
log(liq)	20.9	22.12	17.7	25.7	2.102	4.65	33.11	43.65
	(2.25)**	(1.91)**	(2.16)**	(3.53)**	(0.303)**	(0.503)**	(4.10)**	(4.48)**
log(news)/10	14.8	2.07	74.5	10.34	3.076	0.617	95.95	14.04
	(11.27)	(1.29)	(15.22)**	(2.05)**	(1.581)	(0.281)**	(25.14)**	(2.89)**
log(age)/10	30.5	3.71	96.35	7.79	6.45	1.092	109.3	8.88
	(9.8)**	(1.2)**	(15.43)**	(1.93)**	(1.92)**	(0.298)**	(26.29)**	(2.72)**
log(ME)/10	16	17.9	-37.32	-24.9	-1.055	2.67	-29.87	-21.8
	(4.9)**	(4.24)**	(7.31)**	(7.4)**	(0.839)	(1.34)*	(9.99)**	(12.75)

** significant at the 1% level
* significant at the 5% level

Table 3.11

Censored Least Absolute Deviations Model of Mutual Fund Demand (standard errors in parentheses)

Independent variables were taken from the December prior to the dependent variable year. "No small company" represents the entire sample of mutual funds without the small company objective

Dependent Variable: Percent ownership of stock outstanding held by particular sample mutual funds.

	Growth		Growth-Income		Small-Cap		No Small Cap	
	91	92	91	92	91	92	91	92
stdev*10	14.2	8.14	-0.529	-3.67	-1.12	1.86	18.98	8.78
	(1.94)**	(1.61)**	(1.57)	(1.38)**	(1.99)	(1.49)	(3.15)**	(2.83)**
log(1+prc)	30.7	24.25	9.816	6.978	17.03	21.77	54.99	46.5
	(4.3)**	(3.83)**	(2.2)**	(2.1)**	(3.29)**	(5.38)**	(5.97)**	(7.63)**
log(liq)	27.8	30.69	16.23	20.08	-1.327	2.23	50.96	61.71
	(2.99)**	(4.4)**	(2.24)**	(2.287)**	(1.73)	(2.28)	(4.96)**	(5.85)**
log(news)/10	20.9	3.74	12.388	2.21	50.24	4.56	53.38	9.15
	(13.68)	(1.6)*	(9.93)	(0.834)**	(15.15)**	(2.31)	(19.6)**	(3.31)*
log(age)/10	-1.31	0.7077	58.81	7.355	98.41	5.93	86.05	7.35
	(14.18)	(1.56)	(11.42)**	(1.17)	(29.67)**	(3.36)	(26.85)**	(3.06)*
log(ME)/10	11.3	27.87	22.93	35.72	-76.14	-72.32	31.72	67.78
	(5.54)*	(7.56)**	(3.77)**	(5.89)**	(9.36)**	(18.4)**	(11.75)**	(13.05)**

** significant at the 1% level
* significant at the 5% level

Chapter 4

Introduction to Asset Pricing Tests of the Variance-Expected return Relationship

Chapter 3 documents that mutual funds prefer volatile stocks, which seems entirely rational given the reaction of investors to mutual fund performance. The presence of upward sloping stock supply curves suggests that this demand may affect cross sectional equity expected returns, and indeed we find that volatility is negatively correlated with equity expected returns in the following chapters. This chapter gives a visual introduction to the relation between variance and expected expected return over the past 28 years that is tested more rigorously in chapters 5 and 6. It clearly shows that higher variance stocks seem to have lower expected returns than low variance stocks, and this relationship is the exact opposite of what is implied by the market covariance of these stocks. By presenting size sorted portfolios along with the variance sorted portfolios, we can see how this new anomaly compares to a well-known one. Also, I document the bias in measured expected returns caused by arithmetic averaging and show that conventional tests using monthly expected return observations will be biased towards a positive relation between variance and expected return.

4.1 Returns to Sorted Portfolios, 1965-92

The relationship between variance and expected return is best introduced with a series of graphs. Figure 4.1 shows the return and market covariance characteristics of portfolios formed on the basis of total variance. The portfolios were formed in the following way. Each December I presorted the data into those with prices between $5 and $12.5, $12.5 and $20, and those with prices above $20. I then sorted into size quintiles within these three groups. Within these 15 groups I sorted by total variance into quartiles, and then grouped all of the variance quartiles from all of the 15 groups. The presort was done to control for mismeasurement of variance that is correlated with price, as well as the potential that the correlation between variance and expected return may be obscured by the size effect (the correlation between size and variance). The period 1/1965 to 12/1992 was used because August 1962 is when AMEX was added to the CRSP tapes, and we need at least 2 years to form variance estimates for these observations. I also excluded those stocks with prices below 5 to give credibility to the actual costs of implementing this strategy. Stocks with very low prices have substantially higher bid-ask spreads as a percentage of price, and thus the actual cost of implementing a strategy with these stocks could be substantial. There are times when stocks with prices below $5 (around 27% of all stocks in 1967 and 1991) represent a large number of stocks listed, and given the extra costs associated with purchasing these low-priced stocks, I did not want to bias the results in any way by using returns that do not accurately reflect the return obtainable to an investor off the floor who pays a bid-ask spread. Though unreported, removing the low-price stocks this does not alter the graphs in any significant way.

The returns represent the geometric mean annual return to portfolios formed at the end of December and then held for 12 months, from 1 January to 31 December the next year. The infrequency with which the portfolios were constructed was also utilized to give the results a better reflection of what the feasible return is on portfolios formed on the basis of variance or size. For example, if the extra return is 5% per year on one portfolio relative to the market, this would have no economic significance if it involved reformulating a portfolio every month, as round-trip transaction costs would undoubtedly exceed 5% per year with this amount of portfolio turnover.[1] If a stock is delisted during the year its delisting return was utilized, and then the remaining investment was distributed equally over all remaining securities within the originally targeted portfolio for the rest of the year.

Figure 4.1 shows the continuous compounding mean return to portfolios formed by their total variance. Note that the line in figure 4.1 is downward sloping, that is, the portfolios with the higher average total variance have lower returns. The columns in figure 4.1 represent the ex post betas of these portfolios. Specifically, the columns reflect the beta of the annual portfolio excess return with the market excess return, using the 28 annual return observations from the portfolios and the equal-weighted market index. I am trying to give beta the best chance of explaining the data, and thus I am using the equal-weighted index since it seems to outperform the valued weighted index in cross-sectional asset pricing tests. Further, by using ex post betas as opposed to the ex ante betas, this reduces the differences in beta that would occur if we used ex ante betas. The results show that ex post betas are positively correlated with the total variance of the stocks within the portfolio, as one would expect. The quartiles with the more volatile stocks tend to have higher portfolio betas. The higher returns to the lower variance portfolios do not seem to be explainable by beta, since the betas predict a positive relation between total variance and return. The empirical investigations in chapters 5 and 6 corroborate

[1]Stoll and Whaley (1983) estimate the total round-trip costs of investing in a stock to be 2.4% of the stock price for the 1960-79 period.

this simple interpretation: controlling for size, higher total variance is correlated with lower returns.

Figure 4.2 looks at portfolios formed over the same period using the same methodology as above except here I sorted only by size, again for stocks with prices greater the $5. This gives context to figure 4.1. In figure 4.2, note how the size effect (where size is inversely related to returns) is potentially explainable by beta. The higher returning small-size portfolios have higher betas, suggesting that the risk-adjusted returns are not related to size, while size proxies for risk factors such as beta. The variance-return relationship in figure 4.1 clearly does not have this obvious alternative hypothesis. Also, the measured betas in figure 4.1 suggest risk-adjusting the returns will only accentuate the high variance-low return implication.

Figure 4.3 breaks up the returns into three sub periods ('65-'73, '74-'82, '83-'92) to explore the stability of the variance-return relationship. All show the same slightly downward slope, where the highest variance portfolio has a lower return than the lowest variance portfolio. Again, in order to give context to this finding, figure 4.4 does a similar break-up of the size portfolios examined in figure 4.2. Here we see the size effect is not stable over long periods of time. The last period (1983-92) shows a positive relationship between size and return in contrast to the aggregate negative relationship. This finding suggests the size effect might have disappeared, which could be for two reasons. First, the finding of this effect may have created its own undoing. Early publication of the size effect occurred in the beginning of the eighties (specifically, Banz (1980), and Reinganum (1981)). There are now many mutual funds that specialize in the small firms, and as with all trading rules, successful ones should generate their own obsolescence in rational markets. Secondly, the size effect could be due to data snooping. For example, Fisher Black argued that the size effect "sounds like people searched over thousands of rules till they found one that worked in the past. Then they reported it, as if past performance were indicative of future performance. As we might expect, in real life the rule did not work any more" (Black, 1992). This argument is not as applicable to the volatility anomaly documented in this dissertation since variance is not an *ad hoc* characteristic of a stock, as it has had an integral relationship with expected return since the beginnings of modern portfolio theory.

4.2 The Zero-Cost Portfolio and Its Beta

The APT tests in chapter 6 utilize a zero-cost portfolio in assessing the volatility anomaly. The portfolio is zero-cost since it goes short an equivalent amount of securities that it goes long, and since there are no free lunches in equilibrium, it should generate zero risk-adjusted returns. To see why this zero-cost portfolio generates large abnormal risk-adjusted returns, we need only look at the return of this portfolio relative to the market. Figure 4.5 graphs the equal-weighted market return and the return to a zero-cost portfolio that is long the low variance portfolio and short the highest variance portfolio used in figure 4.1. As seen in figure 4.5, the zero-cost portfolio's return is negatively related to the market (its beta is -0.26 against the equal-weighted market portfolio). This porfolio acts as insurance, providing good returns during periods of market declines, and vice versa. Accordingly, it should should generate a negative return in equlibrium. The positive absolute return it generates implies that in risk-adjusted terms, the abnormal return is much greater. The APT tests confirm this result, as the zero-cost variance sorted portfolio's factor loadings are primarily negative. The positive return on this zero-cost portfolio, as implied by the difference in returns to the high and low volatility portfolios, is clearly even greater in a risk-adjusted sense.

4.3 Variance Bias to Estimated Returns

Blume and Stambaugh (1983) have documented the bias induced by nonsynchronous trading and bid-ask spreads on estimates of average portfolio returns. Using the fact that closing prices are unbiased yet inexact estimates of the "true price" (due to non-synchronous trading and bid-ask spreads), and that an arithmetic average implies rebalancing to equal weights each period, Jensen's inequality can be used to demonstrate that arithmetically averaged portfolio returns are upwardly biased.[2] This finding is especially relevant to securities with large bid-ask spreads relative to the price of the securities, which are predominantly low-priced stocks. For example, Reinganum (1982) found that during the 1964-78 period the average return for NYSE&AMEX firms in the lowest market-value decile exceeded the average return for the highest decile firms by more than 30% per year! In contrast, using the same data and controlling for portfolio rebalancing by utilizing buy-and-hold portfolios, Blume and Stambaugh found this differential reduced to 15% per year.

The statistical tests in this thesis are subject to this rebalancing bias. I limit the effects of this bias in various ways in these graphs. First, these graphs do not utilize low-priced stocks that have greater pricing errors. Secondly, since mispricing due to bid-ask spreads is corrected in subsequent months for a particular security a buy-and-hold portfolio alleviates this problem. This is because if the closing price is randomly distributed around the true price, a return overestimation one period will be offset by a subsequent underestimation for a particular stock within a portfolio. For example, a stock price that jumps from its bid of \$1 to its ask of \$1.25 and then back to its bid of \$1 will have an average monthly return of 2.5% if rebalanced (the average of 25% and -20%), but

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[2]See Appendix 1 for proof.

the buy-and-hold methodology will correctly document of return of 0% (since $1 is its initial and ending price).

The bias imparted by bid-ask spreads in returns is constant over all investment horizons for a security, so increases in the holding period length of the security reduces its severity. The returns to the portfolios formed in this chapter represent the monthly returns to an equal weighted initial investment in each security in the portfolio at the beginning of each year. A security that is delisted included its delisting return, and the proceeds left over were then distributed equally over all remaining securities within the particular portfolio for the rest of that year. Thus the portfolio returns are the returns to a strategy that is implemented in real time, without hindsight, based on a sorting mechanism utilized once at the beginning of each year.

4.4 A Neglected Bias Induced by Variance on Relevant Asset Returns

There exists another bias to arithmetic average returns distinct from the rebalancing problem that is more difficult to control for in the FM and APT tests. Since most asset pricing tests utilize monthly returns they are tests of mean monthly returns. This bias is not due to pricing errors, that is, from deviations of the closing price from the true price. For example, a stock with a return of 50% one month and -50% the next has an arithmetic average return is 0%, while its continuous compounding average return is -25% (1.5*0.5=.75). The continuous compounding average is the relevant return to investors since it best mimics actual investment experience. Most actual portfolios pursue a buy and hold strategy within a given review period with only minor modification induced by new information about particular individual issues. Deviations from the continuous compounding average caused by arithmetic averages are therefore biased to the degree they misstate continuous compounding returns. This bias is important in measuring the relation of variance to return because there exists a fundamental relationship between the bias in arithmetic returns and the variance of the asset, and thus a consistent overestimation of return proportional to the variance of the actual returns.[3]

This is directly relevant to this study since it is variance and expected return that we are examining. Table 4.1 shows the returns to portfolios formed on the basis of size each year, which are used in figures 4.2 and 4.4. Note that even controlling for pricing errors in various ways (by excluding low-priced stocks, and using 12 month long buy and hold portfolios), the difference between the small and large size stock portfolio returns from 1964 to 1992 is 8.0% using the arithmetic averages of the annual returns but only 5.3% using a continuous compounding average, a 2.7% reduction in the return differential. This follows from the fact that the lowest sized portfolio return has a greater variance than the highest sized portfolio.

In Table 4.1, notice how the arithmetic return bias affects the reported returns for the variance-sorted portfolios used in Figures 4.1 and 4.3. Here the premium to the high variance quartile is 2.6% arithmetically, but *increases* to 3.9% using a continuous compounding average. This is because the higher variance portfolio has a higher bias in the reported arithmetic return than the less volatile portfolio. This is directly related to the findings here on the return differentials between the various portfolios. When portfolios are sorted by variance, the higher variance portfolio has a greater bias in its arithmetic return than the low variance portfolio, and thus continuous compounding

[3] See Appendix 2 for proof and exposition.

averages increase the return differential between the high and low variance return portfolios.[4]

To see the effect of the bias more clearly, the 28-year cumulative return differential between the extremum groups for the size and variance sorted portfolios is listed in table 4.1. The cumulative return demonstrates the importance of the bias imparted by arithmetic returns. The actual cumulative return differential was 425% for the size-sorted portfolio, which is equal to its continuous compounding return differential. The arithmetic return differential was a much larger 863%. Thus arithmetic returns overstate the estimated end-of-period savings using the size strategy by a factor of 2 over a reasonable lifetime investment horizon (28 years). The variance-sorted portfolio returns are not as grossly distorted by the bias imparted by arithmetic averaging, but it is important to note the arithmetic bias *obscurs* the variance-return relation as opposed to exaggerating it.

Table 4.1 demonstrates that even using annual returns, we still produce a substantial bias if we average the returns arithmetically as opposed to geometrically (as in continuous compounding). A continuous compounding average annual return gives an accurate picture of the cumulative return over the entire period, while an arithmetic average annual return portrays the unorthodox strategy of investing a constant amount of principal each year. Tests of regression coefficients on variables explaining monthly returns are implicitly utilizing monthly arithmetic averages, that is, they estimate the mean monthly returns correlated with various independent variables. Unfortunately, the use of longer periods such as the 28 year cumulative returns used in these graphs would

[4] This is because the average geometric return for the high variance portfolio is much less than its average arithmetic return, while the average geometric return for the low variance portfolio is only slightly lower than its average arithmetic return

create even larger problems. First, it would severely reduce the number of observations, reducing test power. Further, a multi-year return would require assuming multi-year risk stationarity for the tested securities (as it is the risk-adjusted returns we are interested in), and it seems probable that securities have varying risk over shorter time horizons. The Fama-MacBeth regressions and the APT grouping tests basically utilize monthly returns, which will bias the tests towards finding a positive relationship between volatile securities and expected returns.

4.5 Conclusion

These simple graphs and tables are meant to convey 2 points. First, controlling for size there appears to be an inverse relation between variance and expected return. Second, this anomaly to the CAPM and factor models is potentially more severe than the size effect for several reasons. Measured return biases that plague the size effect do not accentuate the anomaly, they hide it. Return biases caused by rebalancing overstate the monthly returns of low-price stocks and thus, given the correlation between low-price and measured monthly return variance, high variance stocks. Further, the bias caused by variance alone (unrelated to pricing errors) also works to mask and not accentuate the variance-return relation hypothesized here. A zero-cost portfolio sorted by variance produces an absolute annual return of 3.9%, and this return is only *increased* in risk-adjusted returns since the portfolio is negatively correlated with the market return. Finally, the relationship is more stable over the past 28 years than the size effect, which shows signs of possibly fading over the recent decade. In chapter 6 we will also see that the total variance effect is not primarily a January phenomenon, unlike the size effect. The following chapters try to measure this return premium by accounting for risk more carefully.

Figure 4.1

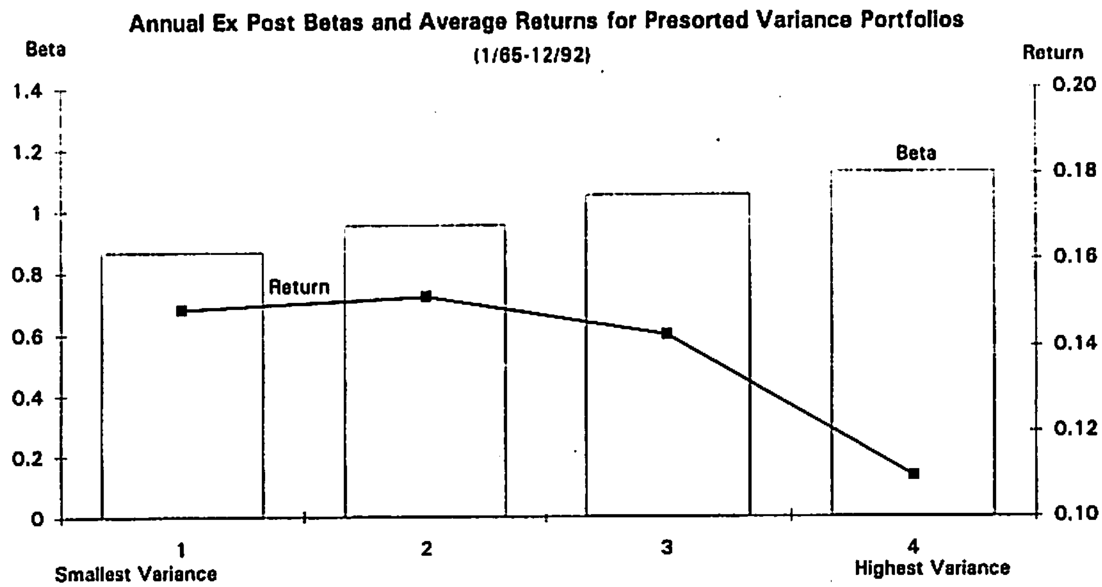

Figure 4.2

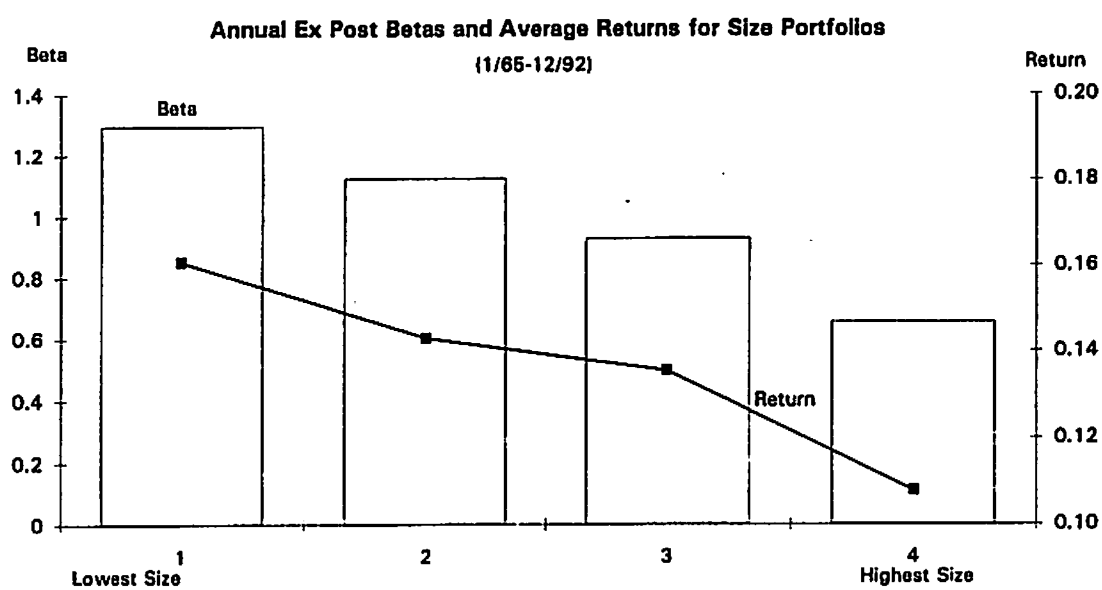

Figure 4.3

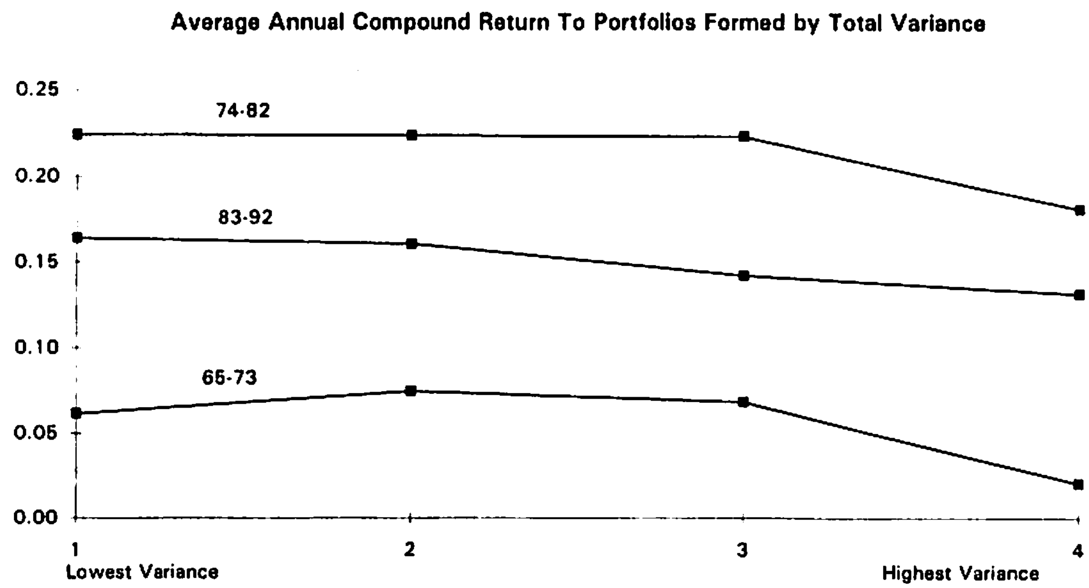

Figure 4.4

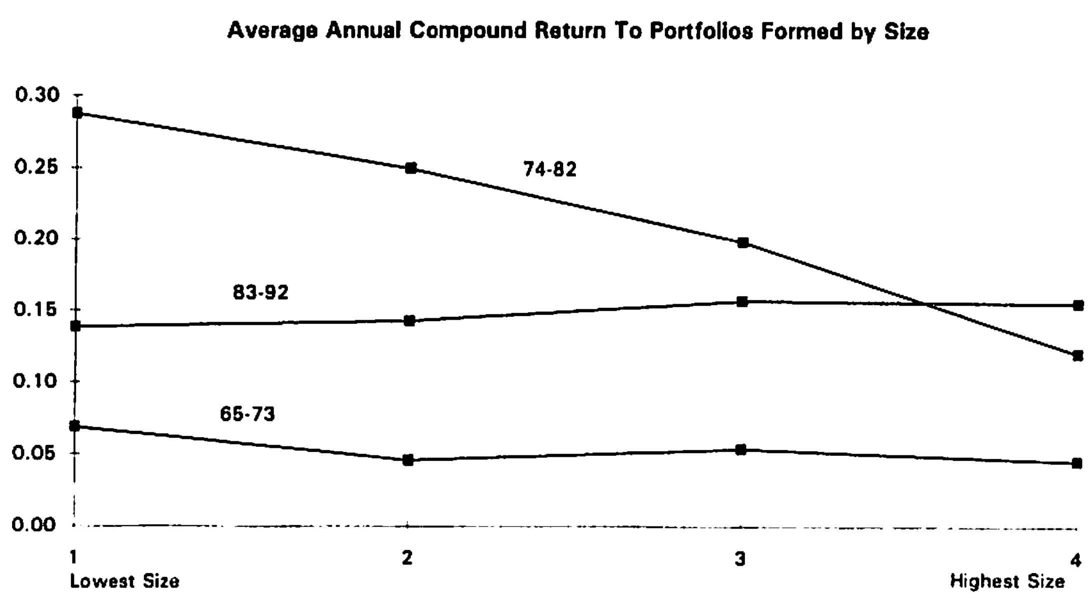

Figure 4.5

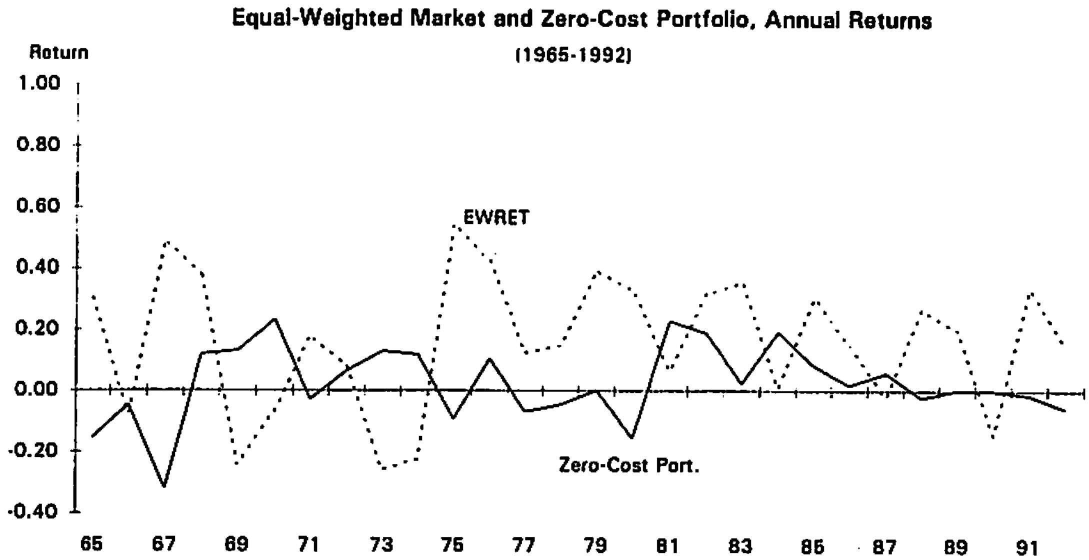
Equal-Weighted Market and Zero-Cost Portfolio, Annual Returns
(1965-1992)
Return
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
EWRET
Zero-Cost Port.
65
67
69
71
73
75
77
79
81
83
85
87
89
91

Table 4.1

Comparison of Arithmetic and Continuous Compounding Average Annual Returns for Size and Presorted Variance Portfolios, 1/1965-12/1992

Portfolios were formed each October, generating 28 annual return observations. Securities with prices less than $5 at the end of September were excluded. If a security was delisted during the year, its delisting return was utilized and then the security was replaced by the value-weighted index return. The variance-sorted portfolio was presorted by price and size in order to minimize these influences (described in the text). Continuous compounding averages will be denoted geometric averages, which is the same thing.

Size-Sorted Portfolios

	Smallest			Largest
Arithmetic Avg. Ann.Return	20.1%	17.3%	15.7%	12.1%
Geometric Avg. Ann. Return	16.1%	14.3%	13.5%	10.8%

Difference Between the Size Extremum Portfolios, 1965-1992

Arithmetic. Annual Average Return	8.0%
Arithmetic Cumulative Return	863%
Geometric. Annual Average Return	5.3%
Geometric Cumulative Return	425%

Variance-Sorted Portfolios

	Smallest			Largest
Arith. Avg. Ann. Return	16.8%	17.3%	16.8%	14.2%
Geo. Avg. Ann. Return	14.9%	15.2%	14.3%	11.0%

Difference Between the Variance Extremum Portfolios, 1965-1992

Arithmetic. Annual Average Return	2.6%
Arithmetic Cumulative Return	205%
Geometric. Annual Average Return	3.9%
Geometric Cumulative Return	292%

Chapter 5

The High Variance-Low Return Correlation Within Fama-MacBeth Regressions

The variance-return implication is now addressed more formally. Specifically, the hypothesis is that high variance stocks have lower expected returns than low variance stocks. In testing for this I must account for other potentially relevant factors affecting cross-sectional asset returns. In this test for the significance of residual variance on expected returns, I emulate rather closely the methodology Fama and French (1992, hereafter denoted as F&F). These regressions are called Fama-MacBeth regressions because Fama and MacBeth introduced them in their classic test of the CAPM in 1973, where they utilized a new econometric methodology in order to control for problems unique to cross-sectional asset pricing (this technique is discussed in section 5.4).

5.1 Data

For tests without book-to-market equity I used securities that had the following characteristics.

1) exist on the NYSE and AMEX return files on the CRSP files
2) had at least 24 months of uninterrupted returns prior to the return month
3) listed capitalization for the month prior to the return month

In tests that use the book-to-market equity factor, the qualifications for inclusion were restricted further to include

A) nonfinancial firms

B) had a book equity listing in the prior December

C) post 1962

The latter qualifications are because the book equity data is not generally available prior to 1962 (COMPUSTAT item 60), and the book-to-market equity variable is systematically different for highly levered financial firms. For the first set of Fama-MacBeth regressions, the utilized number of firms per month is less than the total number of firms extant on the CRSP tapes at the beginning of the year (this is because firms had to have 24 months of uninterrupted data as well as a price listed for the prior month to get capitalization). The set utilized in the FM regressions with book equity are smaller still for the mentioned above.

Firms are required to file their 10-K reports with the SEC within 90 days of their fiscal yearends, but significant numbers do not comply. Furthermore, of those that do get their 10-K reports in by the end of March, almost half experience of 120-day delay until their reports are made public. To ensure that book value is in most investor's information sets before the measured expected returns, I match the accounting data for all fiscal yearends in calendar year t-1 (1962-1990) with the returns for July of year t to June of t+1 (as in F&F).

I use a firm's market equity at the end of December of year t-1 to compute its book-to-market ratio for t-1, and use its market equity for the month prior to the measured return to measure its size. This is different from F&F who utilize June of year t as the market equity variable for the entire year, July of year t to June of year $t+1$. Since market equity data is available to investors on a monthly basis I see no reason why old data (from the prior June) would be more relevant than current data, and presume the F&F used June because it made constructing the database easier. Further, unreported results show that this modification does not change the regression coefficients very much. Thus to be included in the return tests for, say, November of year t, a firm must have a CRSP stock price for October of year t. It must also have monthly returns for at least 24 months preceding October of year t (for β and σ^2 estimates, discussed below).

CRSP begins its coverage of AMEX in July 1962. Prior to this it has only NYSE data. Given potential systematic differences between NYSE and AMEX stocks (NYSE stocks being larger on average), the FM tests were done on separate samples: 7/1928-6/1964 and 7/1964-6/1992. Unlike F&F, I use the recent period of July 1964 to June 1992 as opposed to July 1962 to June 1990. This is for two reasons. First, time has passed and I have more data. Secondly, the latter period is distinguished from the prior period (1928-63) by the addition of AMEX returns. Since 24 months of data are required to form estimates of variance, starting the latter period in 1962 implies there will be two years worth of observations with no AMEX stocks. For example, in 1963 there averaged 1,033 firms eligible for regressions in the tests without book-to-market equity, while in 1964 this number jumped sharply to 1,603, reflecting the additional AMEX stocks. Thus if the intent of separating samples is to control for the addition of AMEX to the original NYSE stocks, it is appropriate to use July 1964 as the starting date for the latter sample, and June 1963 as the ending date for the earlier sample.

5.2 Estimating Market β's

The asset pricing tests use the cross-sectional regression approach of FM. Each month the cross-section of returns on stocks is regressed on variables hypothesized to explain expected returns. The mean of the collection of monthly regression slopes then provides a standard test of whether different explanatory variables are on average priced (see 5.4 for more detail).

Unlike FM but like F&F I do not use portfolios for the final tests for the significance of β and other factors in explaining cross-sectional returns. I estimate βs for portfolios and then assign a portfolio β to each individual stock. Using portfolios has the advantage a providing better estimates of β, but its drawback is that is does not generate sufficient variation in other parameters of interest such as size or idiosyncratic variance. That is, the FM portfolios are formed after sorting them by pre-ranking beta, and this sort does not generate sufficient variation in the other parameters of interest to give sufficient power to test the significance of variables such as size and idiosyncratic variance in explaining expected returns.

5.3 β Estimation: Details

Each month, all NYSE&AMEX stocks on CRSP are sorted by size (ME) to determine the NYSEAMEX decile breakpoints for ME. I estimated portfolio βs separately for the FM tests without book equity and the FM tests with book equity during the 7/1964-6/1992 period.

I form portfolios on size because of the high correlation between market equity and β of size-sorted portfolios (Chan and Chen (1988)). To allow for variation in β that is unrelated to size, I subdivide each size decile into 10 portfolios on the basis of pre-ranking βs for individual stocks. Pre-ranking βs are the sum of the slopes in the regression of the stock return on the current and prior month's market return (I used the NYSEAMEX value-weighted return for the market return). The sum βs are meant to adjust for nonsynchronous trading (Dimson (1979)).[1] The pre-ranking βs are estimated on 24 to 60 months of prior returns (as available). F&F estimate β for a stock using the 2-5 years of data prior to July of year *t*. I utilize the 2-5 years of data prior to the return month. Thus for July of year *t* our β portfolio formation procedure is identical, for August I utilize a time period one period later than their time period. For each month, I sort the data first into size deciles (using the prior month's size) and then into pre-ranking β deciles (using the prior 24-60 month's returns). This creates 100 size–β portfolios.

Over two separate samples within the period 7/64-6/92 I obtained post-ranking monthly returns for each of the 100 size–β portfolios, weighing each stock within each portfolio equally (one sample pertaining to the regression run without book-to-market equity, the other pertaining to the more constricted sample that used book-to-market equity as an explanatory variable). These size-β portfolio estimates used the full sample (348 observations for 7/64-6/92, 420 observations for 1/28-12/64) of the 100 portfolio returns with the NYSEAMEX value weighted portfolio (using Dimson's methodology). These estimates will be called the post-ranking β of a size-β portfolio.

5.4 Fama-MacBeth Regressions

An FM regression consists of the following. Each month I determine to which size–β portfolio each stock belongs by first separating the securities into size deciles and then into pre-ranking β deciles. I then assign one of the 100 portfolio βs to each stock,

[1] While this approach does not produce theoretically consistent beta estimates in the presence of nonsynchronous trading, in practice adding the sum of other market lead and lag coefficients does not alter the estimates significantly. As in F&F, I thus kept with the simpler Dimson methodology.

and do this separately each month. To determine the residual variance for each stock using the prior 24-60 months' data I calculate total variance and the concurrent market variance. Depending on what is available for the individual stock, using the formula $res\,\mathrm{var} = \mathrm{var}(r_i) - \beta^2\,\mathrm{var}(r_m)$, where r_i is the monthly return on stocks and r_m is the monthly market return over the same period. β is from the size–β portfolio to which it was assigned.

The second pass regression for each month is of the form

$$(5.1) \quad R_{it} = \alpha_t + \gamma_{1t}x_{it}^1 + \gamma_{2t}x_{it}^2 + \gamma_{3t}x_{it}^3 + \ldots + \varepsilon_{it}$$

where the x's represent various potential combinations of independent variables, such as the portfolio beta, the log of market equity, variance, etc. Most importantly, R_{it} is the monthly return for stock i.

The generated sample of coefficients are a sample of estimates. That is, monthly FM regressions generate 348 observed γ coefficients on the independent variables for the 1964-92 period. Assuming that the mean of a γ coefficient has a t-distribution with the estimated mean equaling the sample mean, and the estimated variance of the mean equaling the sample variance of γ divided by the square root of the number of observations, we can test for whether γ_i=0 for a particular i. The generated sample of coefficients are estimated with error, however, and thus standard inference techniques are not strictly valid.

Given that the β estimates are inevitably measured with error in this framework, it is reasonable to question the relevance of these results. The strength of the F&F methodology, which uses pre-ranking β and size separated portfolio βs, and applies these to individual stocks, comes from two sources.

First, there are several other variables of interest in explaining expected returns, such as size, the book-to-market ratio, and idiosyncratic variance. This problem is that there will be little variation across other variables of interest if the portfolios were sorted by pre-ranking β and size alone. This implies tests like mine that utilize several independent factors in explaining returns will have to use a cross-section of stocks, not portfolios. This makes it inappropriate to assume that β estimates are consistent for a particular asset, since the true betas are not the same for all the stocks in a particular size-β.

Also, there is the problem of the collinearity between size and β. Chan and Chen (1988) report that portfolio βs formed by pre-ranking βs alone are almost perfectly correlated (-.98) with size (ln(ME)), so it is difficult to distinguish between the role of size and β in explaining average returns. The independent variation in β provided by subdividing size deciles using the pre-ranking βs of individual stocks results in strong variation in β that is independent of size. Fama and French report that the correlation between the portfolio's average size and post-ranking β goes down to -0.50 from -0.98. The lower correlation means that bivariate regressions of returns on β and size are more likely to distinguish true size effects from true β effects in average returns. The β-size portfolio βs separate strong correlation of β with size, so much so that power to distinguish between β and size would be difficult.

5.5 Results

Table 5.1 shows time series averages of the slopes from the month-by-month FM regressions of the cross-section of stock returns on size, β, residual variance, total variance, and a price dummy for the period July 1964 to July 1992. The explained return used in these regressions was multiplied by 100 (so a return of 5% is listed as 5). The coefficient on β alone is positive but insignificant, while both size and a price dummy alone are individually significant. Residual (idiosyncratic) variance and total variance both display no significance when used alone to explain returns. When size is added to a regression with variance, however, the coefficient on residual and total variance is negative and significant, implying a negative relation with expected returns. Given that mean residual variance was about 1% for monthly returns from 62-92, the coefficient of -16 on residual variance indicates that a doubling in residual variance to 2% per month would correspond to a 0.16% decrease in monthly expected return (1.9% annualized rate). The negative and significant coefficient on total variance or residual variance occurs in all regressions that include size: a price dummy or β does not affect the significance of the negative coefficient on variance. Size appears necessary to elicit a variance effect. With only a price dummy, the variance effect is not significant. As in Fama and French, the addition of size reduces the value of the coefficient on β and it becomes insignificantly different from zero. In fact, the coefficient on β becomes negative for most of regressions with size.

Table 5.2 performs the same tests over the same period using only nonfinancial firms that also listed book equity data with COMPUSTAT. This dataset not only utilizes book value, a potentially relevant explanatory variable, but it reduces the data set by about 23% since not only do we exclude nonfinancial firms but firms must have data on COMPUSTAT, and this biases the data sample towards larger, more successful firms. The results are similar to table 5.1 for regressions on the individual stock characteristics and for regressions that include β and size. The coefficients on variance are not significant in regressions with size and variance, although they are negative. The coefficients on variance and residual variance are significant in regressions with β and size or book-to-market and size. This difference could be due to the reduction in power that comes from the smaller sample or the bias that comes from the relatively larger firms that meet the COMPUSTAT requirements, but as the parameter estimates do not change much this difference appears innocuous. Using the most inclusive set of regressors, the coefficients on variance and residual variance are significantly negative. Consistent with prior studies, the book-to-market, price dummy, and size are all highly significant throughout the sample, while β is not.

Table 5.3 looks at the 1928-64 time period. Book-to-equity variable was not used since this data was not available then. The coefficients on variance or residual variance are in general not significant in this period, although they are negative. The coefficient on β in a regression by itself produces a slope near 1 that is significant; however, this coefficient falls in value and loses significance in regressions with size. The price dummy for stocks less than $2.5 and for size are significant throughout the sample in regressions. Though unreported, the coefficient on idiosyncratic variance reaches its 1964-1992 level of around -16 at around 1950. The APT tests below corroborate the hypothesis that the inverse relation between variance and expected return began around this time.

5.6 Conclusion

The only previous papers that have examined the relation between idiosyncratic variance, size and expected return were Tinic and West (1986) and Lakonishok and Shapiro (1986). Both studies find idiosyncratic variance to be insignificant in explaining expected returns. While Tinic and West sorted by pre-ranking beta only, Lakonishok and Shapiro sorted by variance as well (both utilized the Fama-MacBeth portfolio methodology). In both cases they utilized a more onerous inclusion requirement (at least 7 years of uninterrupted data), and only NYSE data. The different data sample (their data consisting of larger and older firms), and the lack of variation in size and variance compared to my study presumably made for the different results.

There is a possible effect of volatility on return mismeasurement. As mentioned in chapter 4, highly volatile stocks in a portfolio will cause returns to be overestimated if rebalancing occurs frequently. This effect should only bias the results against my hypothesis, as I am conjecturing high variance implies low return, ceteris paribus. The reported average slopes are a monthly arithmetic average, with a larger bias the greater the volatility of the return relation. This could be the driving force behind the significance of the low-price dummy in all of the regressions, as these stocks' returns have a large variance in their expected returns due to pricing errors. It seems probable, given how low the prices of these stocks are, that the positive coefficient on the price dummy is a statistical illusion due to a systematic bias caused by pricing errors.[2] Most importantly, the variance related return bias will tend increase the coefficient on variance, since the bias is positively correlated with variance. This makes the significance of the variance coefficients, in the negative direction, that much more striking.

[2]For example, if a stock is priced at 1-1 1/2, a recorded close at the bid, then the ask, then the bid would generate a rebalanced return of 0.5(0.50-0.33)=0.083, even though its true return was 0. For a stock price at 101-101 1/2, this same recording at bid, ask, then bid would only produce a spurious return of 0.000012.

Table 5.1

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1964 to June 1992

Stocks are assigned the post-ranking β of the size-β portfolio they are in at the end of the prior month. Portfolios are formed monthly. Each size decile is subdivided into 10 β portfolios using pre-ranking βs of individual stocks, estimated with 2 to 5 years of prior monthly returns (as available). The equal-weighted monthly returns on the resulting 100 portfolios are then calculated for each month. The post-ranking β use the full (7/64-6/92) sample of post-ranking returns for each portfolio. The pre- and post-ranking βs are the sum of the slopes from a regression of monthly returns on the current and prior month's returns on the value-weighted portfolio of the NYSE&AMEX stocks.

To be listed, a security must have at least 24 months of uninterrupted returns, and must have a capitalization listing for the prior month. On average, there are 1931 stocks in the monthly regressions, with data after 1969 showing basically no change in number of stocks. ME is market equity, and is drawn from the month directly prior to the return month. The average slope is the time-series average of the monthly regression slopes for July 1963 to June 1992, and the t-statistic is the average slope divided by its time-series standard error (348 observations). Residual Variance = Tot. Var - β^2Market Var.

The listings are in the form:

Variable
estimate
(standard error)
(t-stat)

Beta	ME	Variance	Resid. Var.	Price<2.5
0.472				
(0.354)				
(1.336)				
	-0.180			
	(0.067)			
	(-2.698)*			
		0.632		
		(9.060)		
		(0.070)		
			-0.586	
			(10.064)	
			(-0.058)	
				1.789
				(0.658)
				(2.719)*

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.1 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1964 to June 1992

Beta	ME	Variance	Resid. Var.	Price<2.5
-0.166	-0.203			
(0.303	(0.058)			
(-0.547	(-3.501)**			
0.201	-0.215	-15.991		
(0.263)	(0.056)	(5.325)		
(0.766)	(-3.839)**	(-3.003)**		
-0.013	-0.224		-16.395	
(0.280)	(0.055)		(5.750)	
(-0.046)	(-4.063)**		(-2.851)**	
-0.189	-0.174			1.281
(0.299)	(0.050)			(0.573)
(-0.633)	(-3.483)**			(2.235)*
0.209	-0.186	-17.587		1.370
(0.262)	(0.049)	(5.141)		(0.562)
(0.796)	(-3.774)**	(-3.421)**		(2.439)*
	-0.232	-14.786		
	(0.056)	(7.065)		
	(-4.154)**	(-2.093)*		
	-0.224		-18.302	
	(0.057)		(7.150)	
	(-3.926)**		(-2.560)*	
	-0.148			1.281
	(0.057)			(0.577)
	(-2.612)*			(2.221)*

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.1 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1964 to June 1992

Beta	ME	Variance	Resid. Var.	Price<2.5
	-0.203	-16.293		1.350
	(0.048)	(6.923)		(0.564)
	(-4.180)**	(-2.353)*		(2.393)*
	-0.195		-20.495	1.374
	(0.050)		(6.964)	(0.562)
	(-3.913)**		(-2.943)**	(2.443)*
		-4.333		1.727
		(8.164)		(0.606)
		(-0.531)		(2.850)**
			-7.107	1.732
			(8.841)	(0.604)
			(-0.804)	(2.866)

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.2

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on Book-to-Market Equity and Previous Variables: July 1964 to June 1992

BE is from COMPUSTAT's item 60, representing book value at the end of the fiscal year. BE and ME data are from December of year t-1 for returns from July of year t through June of year t+1. Regressions using BE utilized a smaller data set, as we exclude financial firms and firms without COMPUSTAT data for these regressions. Residual Variance and Price data were available the month prior the measured return. There are an average of 1492 firms each period, with basically no trend since 1971.

Only NYSE&AMEX nonfinancial firms with listed book equity and market capitalization, as well as 24 months of uninterrupted prior returns were included in this estimation. Residual Variance = Tot. Var - β^2Market Var.

Beta	ME	Variance	Resid. Var.	Price<2.5	Book/ME
0.503					
(0.356)					
(1.416)					
	-0.176				
	(0.064)				
	(-2.756)**				
		4.491			
		(10.257)			
		(0.438)			
			3.971		
			(11.342)		
			(0.350)		
				1.678	
				(0.556)	
				(3.018)**	
-0.121	-0.193				
(0.312)	(0.056)				
(-0.390)	(-3.478)**				
0.221	-0.205	-14.829			
(0.266)	(0.054)	(6.368)			
(0.832)	(-3.801)**	(-2.329)*			

** significant at the 1% level for a two-sided t-test with H_0: parameter=0

* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.2 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on Book-to-Market Equity and Previous Variables: July 1964 to June 1992

Beta	ME	Variance	Resid. Var.	Price<2.5
0.011	-0.214		-15.084	
(0.286)	(0.053)		(6.833)	
(0.039	(-4.019)**		(-2.208)*	
-0.138	-0.166			1.226
(0.309)	(0.049)			(0.473)
(-0.446)	(-3.404)**			(2.592)*
0.243	-0.178	-16.736		1.344
(0.265)	(0.048)	(6.250)		(0.465)
(0.916)	(-3.679)**	(-2.678)*		(2.892)**
	-0.221	-12.390		
	(0.053)	(8.324)		
	(-4.167)**	(-1.489)		
	-0.215		-15.953	
	(0.055)		(8.437)	
	(-3.943)**		(-1.891)	
	-0.147			1.271
	(0.056)			(0.480)
	(-2.631)*			(2.646)**
	-0.196	-14.070		1.329
	(0.047)	(8.241)		(0.467)
	(-4.130)**	(-1.707)		(2.847)**
	-0.190		-18.376	1.376
	(0.049)		(8.329)	(0.467)
	(-3.877)**		(-2.206)*	(2.944)**

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.2 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on Book-to-Market Equity and Previous Variables: July 1964 to June 1992

Beta	ME	Variance	Resid. Var.	Price<2.5	Book/ME
					0.368
					(0.091
					(4.036)**
-0.046	-0.157				0.181
(0.302)	(0.053)				(0.059)
(-0.153)	(-2.983)**				(3.082)**
0.261	-0.147	-14.726		1.325	0.147
(0.263)	(0.046)	(6.208)		(0.468)	(0.058)
(0.993)	(-3.229)**	(-2.372)*		(2.832)**	(2.547)*
0.052	-0.156		-15.366	1.325	0.151
(0.280)	(0.045)		(6.618)	(0.467)	(0.058)
(0.185)	(-3.439)**		(-2.322)*	(2.838)**	(2.622)*
	-0.149				0.198
	(0.064)				(0.069)
	(-2.345)*				(2.895)**
		-0.017		1.536	
		(9.596)		(0.496)	
		(-0.002)		(3.094)**	
			-2.111	1.568	
			(10.418)	(0.497)	
			(-0.203)	(3.154)**	

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

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Table 5.3

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1928 to June 1964

Stocks are assigned the post-ranking β of the size-β portfolio they are in at the end of the prior month. Portfolios are formed monthly. Each size decile is subdivided into 10 β portfolios using pre-ranking βs of individual stocks, estimated with 2 to 5 years of prior monthly returns (as available). The equal-weighted monthly returns on the resulting 100 portfolios are then calculated for each month. The post-ranking β use the full (7/28-6/64) sample of post-ranking returns for each portfolio. The pre- and post-ranking βs are the sum of the slopes from a regression of monthly returns on the current and prior month's returns on the value-weighted portfolio of the NYSE&AMEX stocks.

To be listed, a security must have at least 24 months of uninterrupted returns, and must have a capitalization listing for the prior month. ME is market equity, and is drawn from the month directly prior to the return month. The average slope is the time-series average of the monthly regression slopes for July 1928 to June 1964, and the t-statistic is the average slope divided by its time-series standard error (420 observations).

Beta	ME	Variance	Resid. Var.	Price<2.5
1.022*				
(0.391)				
(2.614)				
	-0.300			
	(0.080)			
	(-3.738)**			
		-2.328		
		(8.312)		
		(-0.280)		
			-0.472	
			(8.771)	
			(-0.054)	
				2.192
				(0.598)
				(3.663)**
0.192	-0.272			
(0.347)	(0.057)			
(0.553)	(-4.761)**			

** significant at the 1% level for a two-sided t-test with H_0: parameter=0

* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.3 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1928 to June 1964

Beta	ME	Variance	Resid. Var.	Price<2.5
0.253	-0.273	-10.874		
(0.330)	(0.055)	(6.517)		
(0.767)	(-4.926)**	(-1.669)		
0.183	-0.272		-8.237	
(0.339)	(0.055)		(6.924)	
(0.541	(-4.960)**		(-1.190)	
0.124	-0.206			1.601
(0.334)	(0.046)			(0.504)
(0.371)	(-4.503)**			(3.177)**
0.267	-0.209	-14.499		1.849
(0.321)	(0.046)	(6.510)		(0.497)
0.831)	(-4.580)**	(-2.227)		(3.721)**
	-0.309	-10.326		
	(0.069)	(7.687)		
	(-4.475)**	(-1.343)		
	-0.300		-9.021	
	(0.074)		(7.721)	
	(-4.078)**		(-1.168)	
	-0.215			1.658
	(0.063)			(0.511)
	(-3.411)**			(3.242)**
	-0.243	-13.823		1.867
	(0.057)	(7.728)		(0.499)
	(-4.242)**	(-1.789)		(3.739)**

** significant at the 1% level for a two-sided t-test with H_0: parameter=0

* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 5.3 Continued

Average Slopes (standard errors, t-Statistics) from Month-by-Month Regressions of Stock Returns on β, Size, Total Variance, Residual Variance and Low Prices: July 1928 to June 1964

Beta	ME	Variance	Resid. Var.	Price<2.5
	-0.231		-13.191	1.839
	(0.061)		(7.718)	(0.500)
	(-3.809)**		(-1.709)	(3.681)**
		-8.622		2.250
		(8.060)		(0.546)
		(-1.070)		(4.120)**
			-7.808	2.248
			(8.349)	(0.556)
			(-0.935)	(4.041)**

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Chapter 6

Grouping-Based Factor Tests

6.1 Preliminaries

I am interested in whether residual variance is inversely correlated with expected return, and if the above mentioned correlation between idiosyncratic variance and expected return can be explained by risk. The FM regressions suggest that the prespecified factors β, size, book-to-market equity, or low-price cannot explain the premium on low variance stocks. This chapter utilizes a grouping strategy and APT factors to test the hypothesis that variance is related to expected return. Grouping is appealing because the hypothesis against the null hypothesis of no relation between the sorting variable and the dependent variable relies only on weak assumptions regarding the potential functional relation. The rank-ordered securities are grouped and abnormal returns corresponding to a trading strategy of a long position in one extreme group and a short position in the other extreme group are computed, where abnormal is defined as returns outside the context of a posited equilibrium model of asset returns. This approach has been utilized in tests of market efficiency (for example see Jegadeesh (1990), Lehman (1990b), or Chopra et al (1992)). Using a factor analysis framework, I can test for the nonfactor significance of idiosyncratic variance by forming an arbitrage portfolio consisting of being long a portfolio of low variance assets and short an equivalently sized portfolio of high variance assets. The resulting equation I test is

$$(6.1) \quad R_{Lt} - R_{Ht} = (\alpha_L - \alpha_H) + (\beta_L - \beta_H)F_t + \varepsilon_t$$

where R_{Lt} and R_{Ht} are the return on the low and high variance portfolio, respectively, F_t is a kx1 vector of factor returns, and B_L and B_H are 1xk vectors representing the factor loadings on low and high variance portfolios. The quantity R_{Lt}-R_{Ht} represents the return of a zero-cost portfolio that is long an equal-weighted portfolio of low variance stocks plus the return on a portfolio short high variance stocks. The portfolio is zero-cost because the proceeds from the short position presumably could be used to purchase the long position. The zero-cost portfolio return is thus the long position's return minus the short position's return. If a difference in returns to this portfolio is due to a difference in factor loadings, it should show up in the term $(\beta_L - \beta_H)F_t$, since something that costs zero should produce no risk-adjusted return. If a difference in returns is due to something outside the factors utilized, $(\alpha_L - \alpha_H)$, the intercept, will be significantly different that zero. I will call the portfolios constructed zero-cost portfolios since the return represents a portfolio that utilizes its short proceeds to obtain its long position, and thus absent credit market imperfections is costless. Under the assumptions of the APT these portfolios should yield an abnormal return, $(\alpha_L - \alpha_H)$of zero if the factors are completely specified. Discussion of this model of asset returns and the method of deriving the factors are explained below in section 6.2.

6.2 Asymptotic Principal Components Estimation of the Factors

To derive the factors utilized in testing equation (6.1) I utilize the asymptotic principal components procedure derived in Connor and Korajczyk (1986). In their procedure they assume an economy of the following sort. Assume that asset returns follow an approximate factor model,

$$(6.2)\quad \begin{aligned} &\tilde{r}_t = E(\tilde{r}_t) + B\tilde{f}_t + \tilde{\varepsilon}_t \\ &E(\tilde{\varepsilon}_t | f_t) = 0, \quad E(\tilde{f}_t) = 0, \quad E(\tilde{\varepsilon}_t \tilde{\varepsilon}_t') = V \end{aligned}$$

where r_t is a countably infinite vector of returns to a countably infinite set of traded assets, f_t is a k-vector of pervasive economic factors, B is an $\infty \times k$ matrix of the factor sensitivities of the assets, and ε_t is the vector of idiosyncratic returns.

Two conditions must be satisfied. A finite upper bound on the maximum eigenvalue of V^n as n goes to infinity is equivalent to a condition that all nonfactor risk is diversifiable. To ensure that each risk factor affects many assets in the economy a pervasiveness condition is required such that $B^{n\prime}B^n$ has a minimum eigenvalue going to infinity with n (the number of assets).

The equilibrium version of the APT implies that

$$(6.3)\quad E(\tilde{r}_t) = r_{ft} i + B\gamma_t$$

where r_{ft} represents the return on a riskless asset, i is a vector of ones, and γ_t is a k-vector of factor risk premiums.

Combining (6.2) and (6.3) gives

$$(6.4)\quad \tilde{r}_t - r_{ft} i = B(\gamma_t + f_t) + \tilde{\varepsilon}_t$$

This equation serves as the basis for the factor model tests of the grouped portfolio.

Let R^n denote an $n \times T$ matrix consisting of the observed returns on n assets over T periods. Let r_F denote a T-vector of observed returns on the riskless asset. The $n \times T$ matrix of excess returns (returns in excess of the riskless return) is given by $R^n = r^n - i^n r_f'$. Using (6.4) we can write the excess returns as

(6.5) $R^n = BF + \varepsilon^n$

where F is the kxT matrix of realizations of $(\gamma_t + f_t)$ over the period and ε^n is the nxT matrix of realizations of ε_t. In the empirical specification of the APT used here we allow for time variation in the factor risk premiums but assume that the factor sensitivities (B^n) are time-invariant.

The asymptotic principal components procedure exploits the fact that the k-factor estimates equal the first k eigenvectors of the TxT cross-product matrix of security excess returns (in excess of the one-month treasury bill return), $R^{n\prime}R^n/n$. Thus for each 5-year period I used $R^{n\prime}R^n/n$ as F, the sum of the factors and the risk premiums (which may vary over time). In other words, the sample period is divided into thirteen 5-year subperiods from 1928-1992. In each subperiod, the asymptotic principal components technique is applied to the excess returns for all firms without any missing monthly returns over the subinterval (CRSP data on NYSE and AMEX as available). These portfolio excess return are used as F_t (the factor-mimicking portfolio returns) in (6.1) to test whether the difference between high and low variance portfolio can be explained by extracted factors, i.e., whether the intercept is equal to zero as implied by the APT (applying equation (6.5) to the high and low variance portfolios).

6.3 Grouping Methodology for the Abitrage Portfolio

Given the known correlation between variance, price level, and size mentioned above and the well-know correlation between size, price and expected return (see table 3.6), I find it appropriate to control for these variables. Also, as mentioned in chapter 3 the measured variance of low priced stocks will tend to be overestimated. Previous research (Douglass (1968), Fama and MacBeth (1973), Ross and Roll (1980), Gultekin, Drymes, Friend, and Gultekin (1985)) has examined the hypothesis that an asset's own standard deviation has incremental power over the asset's factor sensitivities in explaining mean returns. Their results seem to suggest either no explanatory power or a slightly positive correlation between own standard deviation and expected return. My results run strongly in the opposite direction, and this is probably because in prior studies own standard deviation was proxying for size and contaminated by low-price variance estimation.

To control for price and size for reasons mentioned above, I first presort the data by price into 2 groups: those securities with prices greater than \$5 and less than \$10, and those with prices greater than \$10 as of the prior December. Since very low price securities have highly mismeasured variances (i.e., the bid-ask spread as a proportion of a stock's price), those stocks with prices less than \$5 are excluded (though unreported, including them does not change the results significantly if one utilizes a category for a price less than \$5). Within these two categories, I sort into three capitalization categories. This creates 6 categories within which I sort by total variance to form an equal weighted long portfolio of the stocks with the lowest variance, and then subtract the returns of an equal weighted portfolio of the stocks with the highest variance.

When forming arbitrage portfolios based on a long position in low variance assets and a short position in high variance assets, I must consider what cutoff to use in defining "high" and "low" variance. Different definitions yield different samples, and given enough samples the data may show spurious cross-sectional correlations between many irrelevant characteristics and returns. Grouping strategies in the literature have used from 1 to 20% of the available observations in the two extreme portfolios (and in one case 35 of the top and bottom grouped stocks, DeBondt and Thaler (1985)). My grouping strategy is motivated by Lys and Sabino (1992), who show that test power is maximized when the two extreme groups each contain 27% of the sample, a much larger percentage than that typically used. Intuitively, this is because as the size of the extremum groups increases, the pure variance of these portfolios decreases. At the null of no correlation between the grouping variable and the dependent variable, the 27% extremums maximize test power. That is, deciles may have more extreme mean sorting values, but this beneficial attribute is offset by the higher total variance of these smaller groups under the null. This result is not sensitive to the distribution of the dependent variable.

Portfolios are formed only once a year, each December. The benefit of this approach is that it mitigates the errors caused by portfolio rebalancing. This approach makes no sense in the FM regressions since there we are necessarily looking at mean monthly returns of individual stocks, and cannot avoid the portfolio rebalancing bias. This is one of the benefits of the grouping methodology. To be included a security must have at least 24 months of uninterrupted returns and listed market capitalization. Variance is determined by the prior 24-60 months, depending on availability. Stocks that leave the dataset after formation of the portfolio use the delisted return when the stock is leaves the CRSP dataset, and then the value-weighted market return is used in the place of the individual stock's return for the remainder of the year. This biases the tests towards the null of no return outside pure factor returns, since it makes the two extremum portfolios more similar (like the value-weighted market).

6.4 Estimated Equations

I tested for abnormal returns using both extracted factors and using the value-weighted NYSEAMEX return as a prespecified factor. For the 5 factor model the equations I tested were of the form

$$(6.6)\quad \left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$$

$$(6.7)\quad \left(R_{Lt} - R_{Ht}\right) = \alpha_{NJ} + \delta_{Jan} + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$$

equation (6.6) is a test for whether α, the monthly return not accounted for by the extracted factors, is significantly different from 0. Equation (6.7) breaks this down into January and nonJanuary returns, where α_{Jan} is 1 during January and 0 otherwise, and α_{NJ} is 1 during nonJanuary months and 0 otherwise.

I also looked at the larger samples from 1928-62 and 1963-92 using the CAPM model. I broke the sample at 1962 since this is when AMEX was added to the CRSP tapes and thus there was a discrete shift in the nature of the firms in the data. This approach highlights the ability of a competing model of equilibrium market returns to explain the premium on low-variance stocks. The equations are similar to the ones described above except here the factors have been replaced with the excess market return. These equations are thus

$$(6.8)\quad \left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1\left(R_m - R_f\right) + \varepsilon_t$$

$$(6.9)\quad \left(R_{Lt} - R_{Ht}\right) = \alpha_{NJ} + \delta_{Jan} + \beta_1\left(R_m - R_f\right) + \varepsilon_t$$

In the tests of equations 6.6-6.9, two different zero-cost portfolios are formed. One zero-cost portfolio is sorted by variance after presorting by price and size, and another simply sorted by size. The size portfolio is long the smallest 27% and short the largest 27% of stocks, where every stock is equal weighted. The latter portfolio was formed for the sake of comparison.

OLS regressions estimate α, α_{NJ}, and α_{Jan}. White standard errors[1] are then calculated because they are asymptotically consistent under the assumption of heteroskedasticity, a well-documented phenomenon in asset markets (noted first by Mandelbroit (1963), later discussed by French et al (1987)). The estimation of the factors creates measurement error in the factors used in the regression. Connor and Korajczyk (1988) do simulations to show that for finite samples (of comparable size to ones used in actual estimation) the estimation errors of their procedure do not cause "large" factor estimation errors, and thus I ignore potential measurement error problems in this analysis.

6.5 Results

Table 6.1 displays the excess returns from a five factor model for thirteen five-year periods during the 1928-1992 period. A test of the APT model is that the monthly return unaccountable by the factors, α, should be zero. For 9 of the 13 five-year periods, and 9 of the last 10 periods, the zero-cost portfolio long low variance assets and short high variance assets (presorted by price and size) achieved significant positive excess monthly returns (at the 1% level). This portfolio's returns should be accounted for by the factor sensitivities and the expected value of the factors. This portfolio average return is 0.6% per month in excess returns over the 63-92 period. In a separate test include in

[1]Which are heteroskedasticity consistent standard errors for the OLS estimates of parameters. See White (1980).

table 6.1 that separated the January from the non January abnormal returns, the coefficients are positive and significant in 8 of the 13 months for both the January dummy and the intercept for the non January months. These tests indicate that this phenomenon is not primarily a January or non January phenomenon.

Table 6.2 allows us to compare the variance-sorted portfolio anomaly to the size anomaly. For a portfolio long low-cap stocks and short high-cap stocks (using the same cut-off of top and bottom 27%) the coefficient of excess monthly returns, α, is positive and significant at the 1% level in only 7 of the 13 periods, less than for the presorted variance portfolio. Further, the average excess monthly return over the more recent and broader (in terms of number of stocks) 1963-92 period is only 0.5% compared to the presorted variance portfolio's 0.6%. Unlike Connor and Korajczyk (1988) but like Lehman and Modest (1988), I do not find the nonfactor size effect to be primarily a non January phenomenon over the 1963-92, perhaps due to my grouping strategy that used the 27% extremums. In fact, the size effect unaccounted for by factors appears much more prominent in January, being significant in 8 of the 13 periods for January months, while only significant in 3 of the 13 periods for nonJanuary months.

Table 6.3 forms a zero-cost portfolio by sorting by variance without controlling for low prices or stock size (through presorting). This was done to show how important controlling for price and size are. The intercept is significant in 7 as opposed to 9 of the 13 periods, and its mean magnitude in the past 30 years is 0.43% as opposed to 0.60%. Thus APT tests do not necessitate controlling for these factors in order to see the abnormal returns to a portfolio formed by total variance, but controlling for size and price accentuates the results.

Table 6.4 lists the factor sensitivities and the White standard errors for the five factor model on a zero-cost portfolio presorted by price and size. Usually 3 or four of the factor sensitivities are significant and negative, with a few being significant and positive. The mean value of the factors during the five-year period allows us to compute the expected return to these portfolios. That is, the expected return on this zero-cost portfolio, assuming the APT is correct and the factors have been measured accurately, should equal the sum of the products of the factor sensitivities and the mean of the vector representing factor risk premiums. This expected return is listed for each 5-year time period from 1963 to 1992. The mean of these expected returns is -0.45% per month. The average abnormal return of the presorted zero-cost arbitrage formula is 0.60% per month over this same period. Thus the mean absolute monthly return to this portfolio is only 0.15% per month, but the negative factor sensitivities of the portfolio imply that the portfolio provides a form of insurance and should have a negative return. Unlike the size anomaly, where the large absolute returns seem too large for the factor sensitivities of the portfolio, here the absolute return is rather small but the negative factor loadings make it a greater rejection of the APT model.

Table 6.5 illustrates the monthly returns left unexplained by a simple CAPM model. The change in the sample in 1962 suggests that it would be appropriate to split the sample in two: 1928-62 and 1963-92. The portfolios tested here are just like the ones formed for the tested in tables 6.1 and 6.3 (based on presorted variance and size only). The estimated covariance with the market for these portfolios shows that while the size-based portfolio had a positive β, the variance portfolios clearly have a negative correlation with the value-weighted market return. The presorted variance portfolio generates a 0.41% monthly abnormal return in the first and second periods. In the latter period (1963-92) the January excess return loses significance in the presorted variance portfolio.

The pure size portfolio shows that the size effect is mainly a January phenomenon in a CAPM context. The excess returns are negative for the nonJanuary months for both the 1928-62 and the 1963-92 period. Most importantly for comparison with the variance effect, the size portfolio's monthly excess return is of lower statistical significance than for the presorted variance portfolio.

Table 6.1

NonFactor Returns from a Portfolio Long Low Variance Securities and Short High Variance Securities, Presorted by Price and Capitalization Monthly Return Estimates (White Standard Errors) 1928-1962

Data are all CRSP NYSE&AMEX data with at least 24 months of uninterrupted returns and listed capitalization. The portfolio was formed each month sorting all stocks by variance within 6 pre-sorted groups. The data are presorted into the following manner: firms are first sorted into two price categories, and then within these categories sorted into three market equity categories based on size. The price categories are 5 to 10 and above 10. Securities with prices less than 5 were omitted. Within the resulting 6 groups, I then sort into top and bottom 27%. Portfolios were formed every January using data available at the end of the prior December. I then take the equal-weighted returns of these groups, subtracting the high variance return portfolio from low variance portfolio. Delisted securities within a portfolio utilized the delisting return and then used the value-weighted market return in its place within the equal-weighted portfolio. Five factors were drawn over six 5-year period using Connor and Korajczyk's asymptotic principal components procedure. Factor making portfolios have 429, 621, 715, 765, 916, 953, 939, 1521, 1703, 1836, 1822, 1614, and 1761 securities, drawn from CRSPs NYSEAMEX file, respectively over the 13 five-year periods Returns are in percent per month so a represent the monthly percent return for this parameter (e.g., α=0.36 implies that the portfolio had a +0.36% return per month not accounted for by the extracted factors). α_{NJ} is a dummy variable equal to 1 for all nonJanuary months, while δ_{Jan} is a dummy equal to 1 for January months.

equation 1 $$\left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$$

equation 2 $$\left(R_{Lt} - R_{Ht}\right) = \alpha_{NJ} + \delta_{Jan} + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$$

	equation 1 (no Jan. dummy)	equation 2 (with Jan. dummy)	
Time Period	α (White s.e.)	α_{NJ} (White s.e.)	α_{Jan} (White s.e.)
1928-32	-0.07	-0.21	1.50
	(0.32)	(0.34)	(1.29)
1933-37	0.66	0.36	3.98*
	(0.39)	(0.39)	(1.48)
1938-42	0.54	0.22	4.26
	(0.32)	(0.33)	(0.63)**
1943-47	0.61	0.54	1.59
	(0.16)**	(0.17)**	(0.57)**
1948-52	0.53	0.38	1.74
	(0.14)**	(0.12)**	(0.47)**
1953-57	0.71	0.62	1.29
	(0.15)**	(0.16)**	(0.33)**
1958-62	0.79	0.48	3.19
	(0.15)**	(0.15)**	(0.54)**

Table 6.1 Continued

NonFactor Returns from a Portfolio Long Low Variance Securities and Short High Variance Securities, Presorted by Price and Capitalization Monthly Return Estimates (White Standard Errors) 1963-1992

	equation 1 (no Jan. dummy)	equation 2 (with Jan. dummy)	
Time Period	α (White s.e.)	α_{NJ} (White s.e.)	α_{Jan} (White s.e.)
1963-67	0.36	0.30	1.85
	(0.19)	(0.20)	(1.01)
1968-72	0.86	0.65	2.48
	(0.21)**	(0.25)*	(1.08)*
1973-77	0.62	0.44	2.92
	(0.23)**	(0.22)*	(0.89)**
1978-82	0.59	0.54	1.25
	(0.15)**	(0.16)**	(0.57)*
1983-87	0.74	0.64	1.61
	(0.16)**	(0.17)**	(0.44)**
1988-92	0.45	0.29	2.20
	(0.22)**	(0.22)	(1.95)

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 6.2

NonFactor Returns from a Portfolio Long Small Capitalization Securities and Short High Capitalization Securities
Monthly Return Estimates (White Standard Errors)
1928-1962

Data are all CRSP NYSE&AMEX data with at least 24 months of returns and listed capitalization. The portfolio was formed each month sorting all stocks by size into top and bottom 27 percentiles. Portfolios were formed every January using data available at the end of the prior December. I then take the equal-weighted returns of these groups, subtracting the large sized portfolio from low sized portfolio. Delisted securities within a portfolio utilized the delisting return and then used the value-weighted market return in its place within the equal-weighted portfolio. All other details are as described in Table 6.1.

equation 1 $$\left(R_{Lt}-R_{Ht}\right)=\alpha+\beta_1 f_{1t}+\beta_2 f_{2t}+\beta_3 f_{3t}+\beta_4 f_{4t}+\beta_5 f_{5t}+\varepsilon_t$$

equation 2 $$\left(R_{Lt}-R_{Ht}\right)=\alpha_{NJ}+\delta_{Jan}+\beta_1 f_{1t}+\beta_2 f_{2t}+\beta_3 f_{3t}+\beta_4 f_{4t}+\beta_5 f_{5t}+\varepsilon_t$$

	equation 1 (no Jan. dummy)	equation 2 (with Jan. dummy)	
Time Period	α (White s.e.)	αNJ (White s.e.)	αJan (White s.e.)
1928-32	0.66	0.42	3.31
	(0.47)	(0.50)	(1.62)*
1933-37	0.33	-0.01	4.05
	(0.37)	(0.38)	(0.54)**
1938-42	0.04	0.03	4.30
	(0.35)	(0.34)	(1.80)
1943-47	0.30	0.26	0.84
	(0.17)	(0.17)	(0.17)**
1948-52	0.17	0.08	0.91
	(0.10)	(0.11)	(0.29)**
1953-57	0.67	0.53	1.60
	(0.13)**	(0.14)**	(0.34)**
1958-62	0.38	0.21	1.66
	(0.13)**	(0.12)	(0.68)*

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 6.2 Continued

NonFactor Returns from a Portfolio Long Small Capitalization Securities and Short High Capitalization Securities
Monthly Return Estimates (White Standard Errors)
1962-1992

	equation 1 (no Jan. dummy)	equation 2 (with Jan. dummy)	
Time Period	α (White s.e.)	α_{NJ} (White s.e.)	α_{Jan} (White s.e.)
1963-67	0.46	0.47	0.22
	(0.23)	(0.22)*	(0.95)
1968-72	0.38	0.26	1.31
	(0.17)*	(0.17)	(0.59)*
1973-77	1.04	0.90	2.88
	(0.24)**	(0.25)**	(1.36)*
1978-82	0.56	0.46	1.79
	(0.22)*	(0.22)*	(0.93)
1983-87	0.54	0.38	1.94
	(0.24)*	(0.24)	(1.02)
1988-92	0.06	-0.10	1.97
	(0.22)	(0.23)	(1.08)

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 6.3

NonFactor Returns from a Portfolio Long Low Variance Securities and Short High Variance Securities, NOT Presorted by Price and Capitalization
Monthly Return Estimates (Standard Errors)
1928-1962

Data are all CRSP NYSE&AMEX data with at least 24 months of uninterrupted returns and listed capitalization. The portfolio was formed each month sorting all stocks by variance into top and bottom 27%. Portfolios were formed every January using data available at the end of the prior December. I then take the equal-weighted returns of these groups, subtracting the high variance return portfolio from low variance portfolio. Delisted securities within a portfolio utilized the delisting return and then used the value-weighted market return in its place within the equal-weighted portfolio. All other details are as described in Table 6.1.

equation 1 $\left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$

equation 2 $\left(R_{Lt} - R_{Ht}\right) = \alpha_{NJ} + \delta_{Jan} + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$

Time Period	equation 1 (no Jan. dummy) α (White s.e.)	equation 2 (with Jan. dummy) αNJ (White s.e.)	αJan (White s.e.)
1928-32	-0.86	-0.80	-1.54
	(0.42)*	(0.48)	(1.52)
1933-37	0.18	0.02	1.92
	(0.30)	(0.32)	(1.44)
1938-42	0.27	0.29	-0.04
	(0.34)	(0.36)	(1.33)
1943-47	0.19	0.11	1.25
	(0.16)	(0.15)	(0.97)
1948-52	0.31	0.24	0.83
	(0.10)**	(0.09)*	(0.43)
1953-57	0.40	0.37	0.59
	(0.15)	(0.16)	(0.26)*
1958-62	0.46	0.21	2.41
	(0.14)**	(0.14)	(0.62)**

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 6.3 Continued

NonFactor Returns from a Portfolio Long Low Variance Securities and Short High Variance Securities, Not Presorted by Price and Capitalization
Monthly Return Estimates (Standard Errors)
1962-1992

	equation 1 (no Jan. dummy)	equation 2 (with Jan. dummy)	
Time Period	α (White s.e.)	α_{NJ} (White s.e.)	α_{Jan} (White s.e.)
1963-67	0.26	0.21	1.47
	(0.24)	(0.24)	(1.06)
1968-72	0.61	0.53	1.27
	(0.19)**	(0.70)	(0.78)
1973-77	0.15	0.05	1.46
	(0.24)	(0.23)	(1.50)
1978-82	0.37	0.35	0.55
	(0.14)*	(0.15)*	(0.72)
1983-87	0.65	0.60	1.10
	(0.15)**	(0.16)**	(0.44)
1988-92	0.55	0.41	2.18
	(0.23)*	(0.23)	(1.62)

** significant at the 1% level for a two-sided t-test with H_0: parameter=0
* significant at the 5% level for a two-sided t-test with H_0: parameter=0

Table 6.4

Factor Sensitivities and Expected Monthly Returns for the Pre-Sorted Arbitrage Portfolio in Table 16 (White Standard Errors)

Expected return and abnormal return are for the zero-cost portfolio long low-variance stocks and short high variance stocks, presorted using the method described in the text. The returns are in 0.0% and pertain to months, so that 0.36 represents a 0.36% monthly return.

$$\left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \beta_4 f_{4t} + \beta_5 f_{5t} + \varepsilon_t$$

		Factor Sensitivities			Expected Return	Abnormal Return
β_1	β_2	β_3	β_4	β_5	$E(B'F)$	α
			1963-67			
-.22 (.019)	-0.018 (0.015)	-0.069 (0.024)	-0.046 (0.013)	-0.0097 (0.016)	-1.23	0.36
			1968-72			
.30 (.017)	-0.0022 (0.017)	0.067 (0.012)	-0.093 (0.017)	0.0045 (0.006)	0.14	0.86
			1973-77			
-.17 (0.018)	-0.16 (0.015)	-0.069 (0.015)	0.081 (0.020)	0.009 (0.020)	-0.16	0.62
			1978-82			
-0.27 (0.014)	0.098 (0.015)	-0.011 (0.013)	-0.068 (0.013)	-0.049 (0.012)	-0.79	0.59
			1983-87			
-.24 (0.011)	0.063 (0.010)	0.049 (0.010)	0.018 (0.011)	-0.078 (0.009)	-0.07	0.74
			1988-92			
-0.20 (.011)	-0.12 (0.011)	-0.028 (0.009)	-0.004 (0.012)	-0.014 (0.011)	-0.56	0.45

Table 6.5

CAPM Test of a Portfolio Long Low Variance Securities and Short High Variance Securities, Presorted by Price and Capitalization Monthly Return Estimates (White Standard Errors)

Portfolio formation procedure and data are as described in tables 6.1 and 6.2. The value-weighted market return is used for R_m. Returns are in percent per month so a represents the monthly percent return for this parameter (e.g., a=0.41 implies that the portfolio had a +0.41% return per month not accounted for by the measured market return).

equation 3 $\left(R_{Lt} - R_{Ht}\right) = \alpha + \beta_1\left(R_m - R_f\right) + \varepsilon_t$

equation 4 $\left(R_{Lt} - R_{Ht}\right) = \alpha_{NJ} + \delta_{Jan} + \beta_1\left(R_m - R_f\right) + \varepsilon_t$

Time Period	equation 3 (no Jan. dummy) α (White s.e.)	equation 4 (with Jan. dummy) α_{NJ} (White s.e.)	α_{Jan} (White s.e.)
Portfolio Presorted by Price and Size, Low minus High Variance Portfolios			
1928-62	0.41	0.33	1.21
$\beta_1 = -.51$	(0.14)**	(0.15)*	(0.40)**
1963-92	0.41	0.41	0.45
$\beta_1 = -.61$	(0.14)**	(0.14)**	(0.61)
Low minus High Capitalization Portfolios			
1928-62	0.45	-0.22	7.96
$\beta_1 = .55$	(0.28)	(0.26)	(1.33)**
1963-92	0.62	-0.17	9.62
$\beta_1 = .15$	(0.26)*	(0.22)	(1.31)**

** significant at the 1% level
* significant at the 5% level

Chapter 7

Theoretical Extensions and Alternatives to the Hypothesis Tested in This Dissertation

I only utilize two facts from which to generate the hypotheses tested in this thesis: the nonlinear payoff to portfolio manager returns (where the best receive large inflows and the rest are unaffected) and an upward sloping supply curve for stocks. Nonlinear payoffs to portfolio managers can explain the preference by managers for volatile stocks, and with the preference of mutual funds (and possibly other fiduciaries) for volatile stocks and upward sloping supply curves we get lower returns for these volatile stocks. The assumptions have been documented in previous work while the implications are tested and documented in this thesis.[1] The main theoretical questions raised by these findings are: (1) What kind of information structure leads to the preference of investors toward top-performing funds and (2) Why is this asset pricing result not arbitraged away in cross-sectional returns?

[1]See Bradley, Desai and Kim (1988), Holhausen, Leftwich and Mayers (1990) and Bagwell (1992) for the positively sloped supply curve and Sirri and Tufano (1993) for the mutual fund investor preferences.

7.1 A Simple Model of Investor Preferences Toward Top-Performing Funds

One simple model of this nonlinear relationship, where average and below average funds have little change of money inflow while top performers receive sizable inflows, can be easily explained by the switching costs of funds and wasteful managers. Assume that it is costly for existing mutual fund shareholders to switch funds. These would be information costs, tax consequences or explicit penalties for early withdrawal. If differences in manager ability are minor a sizable cost in switching funds would make existing fund holders indifferent to manager performance. New fund holders, however, have a clear incentive to utilize the best managers.

Good and bad manager types can be explained by assuming certain managers waste money. For example, it is easy to achieve negative risk-adjusted returns by engaging in costly strategies or having high overhead costs. Frequent trading, costly derivative strategies, or high employee expenses will all subtract from portfolio returns. Indeed, Sirri and Tufano (1993), and Patel, Hendricks, and Zeckhauser (1993) find that the persistence in performance is greatest among poorly performing mutual funds.

Given these two assumptions, the nonlinear reaction function of new money to mutual fund performance is rather straightforward. Assume that there are many managers who each generate a portfolio return P_m, which is distributed normally with identical mean μ and variance σ^2. Some of the managers consistently waste money, which could be from perks that do not generate utility for the investors or costly, misguided derivative strategies. Thus there are two distributions of managers, those who are frugal have a portfolio return with mean μ while those who are spendthrifts have a portfolio return with a mean of μ-c, where c>0 represents wasted spending. Both sets of managers have the same variance of returns. For investors trying to infer which manager belongs to which class, Bayesian updating implies those with the highest returns will have the highest probability of being from the frugal class of portfolio managers. If we assume the costs of determining relative rank limits the ability to determine the supremum manger and that only new investors allocate money based on the perceived type of the manager, the top performing managers will receive the new inflows of money into mutual funds. This is consistent with the graph money inflows and fund performance in chapter 2.

7.2 Investor Neglect and Asset Pricing Anomalies

Given the payoff function to portfolio managers it is optimal for funds to engage in risky strategies. Since investors dislike risk this will probably take a subtler form than leveraging a position in a single security. Fund complexes will offer an array of specialty funds that maximize the expected net inflow of money and within a fund's chosen strategy it will concentrate on the more volatile securities. If there exists a positively sloped supply curve for assets, this extra demand for the highly volatile stocks will translate into higher prices and thus lower returns for these securities.

The persistence of a seemingly irrational equilibrium similar to the one outlined here has been modeled by Merton (1987). Unlike the capital equilibrium model of Sharpe, Lintner, and Mossin (i.e., the CAPM), in Merton's model investors only invest in those securities of which they are "aware." The motivation is that information about firms is costly to transmit from firm to the investor. For example, the firm must market their securities directly through its shareholder relations division or indirectly through underwriters, both costly endeavors. Less conspicuously, the investor must pay receiver costs, such as the time and energy necessary to investigate a firm. Since both sender and receiver costs are significant, there will be many firms that are unknown to the investor. With this assumption, Merton shows that expected return is a function of factors in addition to market risk.

Merton's model was motivated by two strands of literature, the size effect and the listing on the stock exchange's effect on a stock's. Arguably, the investor base for small firms is smaller than for large firms. These small firms find it more costly to transmit information about them to potential investors, and Merton's model would therefore be relevant to the size effect. Further, a listing on the NYSE is associated with increased investor recognition that is believed to accompany listing on a major exchange. For example, Barry and Brown (1984) and Kadlec and McConnell (1994) note the positive return effect from listing on the NYSE, controlling for such factors as the increase in liquidity, beta, and size. Arbel, Corvell and Strebel (1983) find institutional holdings relevant in explaining expected returns, controlling for beta and size.

Merton's model has a clear application to the size effect, as Merton intended. The investor neglect that was potentially responsible for this anomaly has been replaced by a situation today where funds explicitly testing these stocks represent one of the largest mutual fund objectives. At the same time, the small firm effect was not present during the 1983-92 period, unlike the prior two decades. The variance-return relation may be a similar type of inefficiency that is costly to discern, ultimately temporary, but consistent with a model an equilibrium asset-pricing model with costly information.

7.3 Alternative Explanations of the Empirical Findings

There are several other potential explanations of the empirical findings in this dissertation. First among alternative explanations for the volatility anomaly is a tax-based explanation. Low variance stocks appear to receive a premium. If low variance stocks have a relatively higher dividend payout ratio, their return would be taxed at a relatively higher rate. Smaller stocks and stocks with low book-to-market equity ratios are typically "growth" stocks that generate returns primarily in capital gains. However,

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the tests control for this possibility somewhat by controlling for size and the book-to-market ratio.

Interestingly, the low volatility stocks tend to be closed-end mutual funds, which makes obvious sense. Mutual funds are well diversified and their returns should be expected to be less volatile than your average stock. Further, the prevalence of discounts in these funds relative to their net asset value indicates that these assets are undervalued, giving them higher returns over long periods of time. Exclusion of close-end funds from the asset pricing tests does not alter the volatility-return results significantly, however, so that these stocks are not the main driving force of these results.[2]

Another rational explanation of the volatility anomaly is that while true, the correlation is a chance occurrence; given thousands of researchers and many stock characteristics, chance correlations are bound to occur. Research on other exchanges, such as NASDAQ and other countries would be illuminating in this regard. Most importantly, however, unlike other reported correlates with expected return total variance is not a seemingly innocuous characteristic of a stock, as size and book-to-market equity might be interpreted. Variance has been presumed to have a special relationship with asset returns since the beginnings of modern portfolio theory.

The investor preference for top-performing mutual funds may be related to the success of large state lotteries. Within the variety of lotteries offered by states, the highest jackpot lotteries such as lotto (as opposed to the daily games) bring in the most revenue (see Mikesell and Zorn, 1986). This behavior implies that among people willing to take risks, these people may be risk-loving. The investor preference for top-performing mutual funds could be interpreted similarly: among people willing to invest in

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equities, these people prefer portfolio managers who can potentially provide extremely large payoffs.

Two nonrational explanations are relevant to this thesis. First, the phenomenon could be the result of the winner's curse in an environment with short sale constraints and heterogeneous beliefs (see Miller, 1977). In contrast to Varian's finding that greater belief dispersion may lead to lower risk adjusted returns, Miller takes a simpler approach based on short-sales constraints. If we assume that higher variance stocks will have a higher dispersion of beliefs, in a market with no short selling a stock with a larger dispersion of beliefs will have a larger amount of demand, since on average each buyer will believe the equilibrium price is exceptionally undervalued. We know this is not rational because in these situations bidders should appropriately downwardly adjust their private valuations (Milgrom and Weber, 1985). That is, they should be aware that their willingness to buy a stock signals they are at the upper tail of an unbiased distribution, and they should appropriately downwardly adjust their expectations. Furthermore, this explanation is inconsistent with the mutual fund findings, in that it would apply equally to individual investors and professionals. If anyone is sophisticated enough to account for the winner's curse, it should be the institutions and not the households.

A second nonrational explanation of the volatility anomaly is the "Lake Woebegon" effect, where every stock picker thinks they are above average. If everyone believes they can spot undervalued companies, then it is optimal to search out highly volatile stocks that have significant upside. The basic intuition is that if you can spot stocks that will outperform the market on a risk adjusted basis, you might as well choose the stocks that outperform the market by large amounts rather than stocks that can at most offer only a modest outperformance. Such stocks would have a large unconditional variance. While plausible, this situation would clearly be an nonrational equilibrium, since it would imply that most managers believe they are above average.

Chapter 8

Conclusion

In this thesis I document two empirical facts that are potentially related. The first is that idiosyncratic variance is inversely correlated with expected return for NYSE&AMEX securities once one controls for size. This effect is anomalous to factor models like the size anomaly. Furthermore, I document that open-end mutual funds have a strong preference for high volatility assets once one controls for price or size. The preference of mutual fund investors for top-performing funds and the existence of positively-sloped supply curves for stocks suggests a simply story that explains these findings: professional investors have an incentive to exploit the option-like characteristics of investor preferences by buying volatile stocks, and this extra demand raises the price and lowers the return of volatile stocks.

Alternatively, the mutual fund preference toward volatile stocks could be unrelated to the positive risk-adjusted returns earned by volatile assets. In this scenario, APT factor extraction techniques or practical measures of beta are incomplete. The asset pricing tests are implicitly joint tests of the mean-variance optimization *and* the particular specification of risk used in the tests. If this interpretation is correct, the volatility-return results are relevant to providing harsher practical tests of asset pricing models.

I also document several measurable characteristics of stocks that are correlated with mutual fund demand. Mutual funds prefer stocks with higher prices, greater liquidity, higher age since initial listing on the exchange, more news stories in major newspapers, and (for all but the small-cap sector) greater market capitalization. The preference of mutual funds for nontraditional measures of risk may be relevant models of asset markets with costly information, or studies of the determinants of stock supply elasticity.

β is difficult to measure with satisfaction, and the results here are not intended to add to the debate over the relevance of β. The importance of these cross-sectional results is that in regressions including several well-known correlates with expected return, variance (total or idiosyncratic) has a statistically significant negative correlation with expected returns in the 1964-92 time period. This presents a serious puzzle to portfolio theory, which says that total variance should be positively correlated with expected return to the degree it is correlated with β. Unless one were to argue that the estimates of variance are so poor that they are negatively correlated with β, a new and troubling anomaly with respect to variance and returns is presented. Even though all theories are technically incorrect, Newton's laws are indistinguishable from Einstein's for earthbound objects visible to light; the CAPM seems a considerably worse approximation. An implication of the CAPM is that idiosyncratic variance is not correlated with return and that total variance is correlated with return to the degree that variance contains systematic risk. However it appears that, holding constant size, more volatility is not compensated by higher returns. In fact, higher volatility seems to imply lower return.

The variance anomaly documented here is not subject to the myriad biases that help to exaggerate the high return to small-sized stocks. Portfolio rebalancing, the overestimation of the relevant expected return created by using arithmetic averages, and appropriate market risk premiums all tend to conceal the negative correlation between idiosyncratic variance and expected return. In a frictionless asset market with risk-averse investors, positive correlates with high returns must proxy for risk. A straightforward application of this reasoning would seem inappropriate here (i.e., low idiosyncratic variance must proxy for high risk). The findings in this paper suggest there exists a group of investors large enough to affect equilibrium returns whose investment decisions are not solely based on risk and return

Appendix 1

Return Bias Created by Pricing Errors Such as Bid-Ask Spreads

Suppose the bid-ask spread is the only source of measurement errors in observed prices (though price discreteness and nonsynchronous trading also can produce similar mismeasurement). Instead of observing the true price of a security, P_{it}, we observe $\hat{P}_{it}$, which could be the bid or the ask. Specifically

(1) $$\hat{P}_{it} = P_{it}(1+\theta_{it})$$

$$E(\theta_{it}) = 0,\ \ \theta_{it}\ \text{i.i.d.},\ \ \mathrm{Var}(\theta_{it}) > 0$$

The true return to security i over a period t is defined as

(2) $$R_{it} = \frac{P_{it}}{P_{it-1}}$$

Yet the measure return is

(3) $$\hat{R}_{it} = \frac{\hat{P}_{it}}{\hat{P}_{it-1}} = \frac{P_{it}(1+\theta_{it})}{P_{it-1}(1+\theta_{it-1})}$$

Equations (2) and (3) give

(4) $$\hat{R}_{it} = \frac{(1+\theta_{it})}{(1+\theta_{it-1})}R_{it}$$

Thus

(5) $$E(\hat{R}_{it}) = E\left(\frac{1+\theta_{it}}{1+\theta_{it-1}}\right)E(R_{it})$$

By Jensen's inequality, $E\left(\frac{1+\theta_{it}}{1+\theta_{it-1}}\right) > 1$, and thus

(5) $$E(\hat{R}_{it}) > E(R_{it})$$

upward bias in single-period measure returns can be approximated using a Taylor's series, which gives

(6) $$E(\hat{R}_{it}) = E(R_{it}) + \sigma^2(\theta)$$

The variance of θ, $\sigma^2(\theta)$, is larger for the low-priced stocks than for high-priced stocks, which implies the "mispricing bias" is greater for the lower-priced stocks.

Appendix 2

Formally, the relation between variance and bias in arithmetic return is of the following form. Assume the gross return of an asset has a lognormal return of the form

$$\text{(A2.1)}\quad R_t \sim LN(\mu, \sigma^2)$$

The arithmetic average return over T periods is

$$\text{(A2.2)}\quad R_{AT} = \frac{\sum_{t=1}^{T} R_t}{T}$$

which equals

$$R_{AT} = \frac{\sum_{t=1}^{T} \exp(\ln R_t)}{T}$$

Letting $r_t = \ln R_t \sim N(\mu, \sigma^2)$. we can use the moment generating function for normally distributed random variables, because we can see that $E(R_{AT})=E(\exp(r_t))$ where $r_t \sim N(\mu, \sigma^2)$. Thus the arithmetic expected average return is

$$\text{(A2.3)}\quad E(R_{AT}) = \exp(\mu + \sigma^2/2)$$

The continuous compounding average return over T periods is

$$\text{(A2.4)}\quad R_{GT} = \left(\prod_{t=1}^{T} R_t\right)^{1/T}$$

which equals $R_{GT} = \left(\prod_{t=1}^{T} \exp(\ln R_t)\right)^{1/T}$

again letting $r_t = \ln R_t \sim N(\mu, \sigma^2)$ we have

(A2.5) $$R_{GT} = \left(\exp\left(\sum_{t=1}^{T} r_t\right)\right)^{\frac{1}{T}} = \exp\left(\frac{1}{T}\sum_{t=1}^{T} r_t\right)$$

Again we can use the moment generating function for normally distributed random variables, but in this case E(RGT)= $E\left(\exp(\bar{r})\right)$ where $\bar{r} \sim N\left(\mu, \sigma^2/T\right)$, thus

by the moment generating function we have

(A2.6) $$E\left(R_{GT}\right) = \exp\left(\mu + \sigma^2/2T\right)$$

Using (A2.3) and (A2.6), the upward bias in arithmetic returns is clear from the fact

(A2.7) $$E\left(R_{AT} - R_{GT}\right) = \exp\left(\mu + \sigma^2/2\right) - \exp\left(\mu + \sigma^2/2T\right) > 0 \quad \text{for all T>1}$$

Further, the bias increases with the variance in the return process, that is

(A2.8) $$\frac{\partial E\left(R_{AT} - R_{GT}\right)}{\partial \sigma^2} = \sigma \exp\left(\mu + \sigma^2/2\right) - \frac{\sigma}{T}\exp\left(\mu + \sigma^2/2T\right) > 0 \quad \text{for all T>1}$$

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