Redefining Risk:
An Investigation into the Role of Sequencing

by

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(ABSTRACT)

Mehra and Prescott's(1985) equity premium puzzle has stirred continued debate on just why the average return on equity has been so high relative to the risk-free rate. Recent work by Backus, Gregory, and Zin(1989), Knez and Snow(1992), and Trainor(1992) have also documented a liquidity premium puzzle. In addition, Fama and French(1992) have found that beta has no explanatory power in explaining an asset's excess return.

These studies point out that current financial models are unable to explain even the most basic premise that assets with greater risk have higher returns. The question that now arises is why are these financial models failing to explain excess returns? One obvious answer to this question which has been completely ignored is that the proxy being used to define risk is wrong.

It is the contention of this proposal that investors are concerned about buying into an asset and subsequently experiencing a sequence of below average or negative returns. Under this premise, using the variance of returns as a measure of risk is inadequate and a new risk measure must be derived. This study demonstrates that measuring the deviation of an investor's wealth level from buying a risky asset in relation to what an investor's wealth level would have been from buying a risk-free asset discerns both the deviation of returns and the propensity of returns to sequence.

It is then shown that sequencing risk and the slope of the term structure are integrally related. Specifically, the steeper the yield curve, the greater sequencing risk will be priced since a negative sequence could result in forced borrowing by investors

when rates are high to maintain a constant consumption rate.

Empirically, it is shown that measuring an asset's risk by the contribution it makes to a portfolio's propensity to sequence rather than to a portfolio's variance more accurately explains portfolio returns within a CAPM type framework. Additionally, size does not usurp the explanatory power of this new beta. Surprisingly, it is found that the explanatory power of the traditional beta and size are contingent upon the slope of the term structure being fairly flat. The wealth beta seems to be unaffected. The conclusion of the study suggests that current financial models are seriously flawed due to the erroneous definition and mis-measurement of risk.

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"Why was the equity premium so large? The obvious answer is 'risk.'"
-Andrew B. Abel, "The Equity Premium Puzzle", 1991

I. Introduction

Despite the apparent clarity of Abel's answer to his tautology, the financial literature has been unable to explain Mehra and Prescott's(1985) equity premium puzzle. A second similar puzzle now involves the liquidity premium as pointed out by Backus, Gregory, and Zin(1989), Knez and Snow(1992), and Trainor(1992). Additionally, Fama and French(1992) have established that beta has no explanatory power in explaining an asset's excess returns.

These studies demonstrate that current financial models are lacking in even the most basic pursuit of explaining why certain assets have higher returns. If the answer is the simple fact that assets with higher returns are more risky, than a more serious question arises as to why the literature has been unable to explain these higher returns. A possible answer to this second question is that risk has been erroneously defined.

Since the beginning of time, or more precisely Markowitz(1952), the definition of risk has been taken to be the variance of returns. Indeed, the common factor that plagues all of the previously mentioned studies is that the variance or covariance of returns is used to measure risk. If these measurements are a poor proxy for risk, than these models are doomed to fail.

Therefore, I have attempted to redefine exactly what risk is in the ambitious pursuit of explaining why certain assets have higher returns. Specifically, I explore how an asset's returns affect investor's wealth rather than just examining the asset's returns. If one considers that investors are concerned about an asset's returns by how it affects their wealth, then it would seem prudent to examine how an investor's wealth changes with a given set of returns. In addition, since it may be posited that individuals are concerned about their wealth at all points in time, than using variance which is a one period probability measure of the dispersion of returns as a measure of risk is grossly inadequate.

The risk measure that I have developed is based on the deviation of an investor's wealth level from buying a risky asset in relation to what an investor's wealth level would have been from buying a risk-free asset. Since consumers are uncertain about when they will need or use their wealth for consumption purposes, they are fearful of placing their wealth into any asset that may reduce their wealth over time, not just over the next period. Consumers are concerned with how long and how far their wealth can fall from buying a risky asset. The variance of returns does not adequately measure this risk.

In redefining risk, the question is asked under what circumstances is variance even priced? It is shown that without credit constraints, the variance of an asset's returns will not be priced regardless of the risk aversion by consumers. It is then shown that the sequencing of an asset's returns directly affects the borrowing-deposit differential. If the slope of the term structure proxies for this borrowing-deposit differential, than the steeper the term structure, the greater sequencing risk will be priced.

The empirical results suggest that using the variance of wealth rather than the variance of returns does indeed explain portfolio returns. In a Beta type setup, using the covariance of a portfolio's wealth sequence with the market's wealth sequence outperforms the traditional beta and maintains significance even after adding size to the regressions. The wealth beta is robust to different market proxies and different time periods where as the traditional beta is not.

Additionally, it is found that the wealth beta and size are completely unrelated. Size is insignificant when sorting by the wealth beta and the wealth beta is insignificant when portfolios are ranked on size. This was due to the fact that the dispersion in values for the variable that was not ranked was minimal. Combining this with the fact that size has additional explanatory power within each wealth beta ranking, while the wealth beta has additional explanatory power within each size ranking, leads to the conclusion that apparently these two variables are measuring two different types of risk.

Surprisingly, it is found that the explanatory power of the traditional beta and size are contingent upon the slope of the term structure being fairly flat. The wealth beta seems to be unaffected. The explanation of this result is unclear, but may narrow the focus of future research on exactly what risk size is measuring.

The layout of this study is as follows. Section II reviews some literature which has examined the sequencing nature of asset returns. Section III explains the relationship between the variance of returns, their sequence, and the effect on credit rationing and expected returns. Section IV explains the intuition behind the variance of wealth while Section V derives the formal definition. Section VI derives a wealth beta which is an application of measuring risk as the variance of wealth. Section VII describes the empirical methodology used and section VIII empirically applies the CAPM analysis using the wealth beta. The proposal concludes by suggesting that current financial models are seriously flawed due to the erroneous definition and mis-measurement of risk.

II. Literature Review

> "If the random walk does not apply, much of quantitative analysis collapses, especially the Capital Asset Pricing Model and the concept of risk as standard deviation or volatility."
> -Edgar E. Peters, *Chaos and Order in the Capital Markets*, 1991 p.66.

Associating risk with sequencing in the capital markets is not an entirely new concept. Peters(1989 and 1991) in two papers dealing with fractal structure, or the fact that there are trends in the capital markets, defines a similar concept which he calls "persistence". Peters has found that the events in one period influence all the periods that follow in both the stock and bond market. The problem is determining which way the market is trending. To quote,

> While the stock market shows persistent trends, the relatively low level of H also implies a good deal of noise.[1] We can thus expect that attempts to forecast the stock market over the short term will be difficult, given the level of short-term noise. The H of 0.61, however, shows that it may be possible. In addition, attempts to find "deterministic chaos" in the stock market will be difficult because of the level of noise in the data. The same is true of the bond market. ... Finally, the results show that pure random walk theory does not apply to the capital markets. The capital markets instead follow a biased random walk. The trick is to determine the current bias as well as to anticipate when the "joker" will crop up to change the bias.[2] ... The next phase involves models that explain these dynamics and statistical techniques for estimating risk.[3]

Unlike Peters' work, this study is not trying to prove there are predictable trends in the financial markets, only the fact that they are there whether it is found that

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[1]H refers to the Hurst exponent which measures whether a series shows persistence or not. H can vary between 0 and 1 where an H = 0.5 implies a pure random walk while an H less that 0.5 implies anti-persistent behavior and an H greater than 0.5 implies persistence. See Peters(1989) for further explanation and references.

[2]See Peters(1989), p36.

[3]See Peters(1991), p.62.

they can be predicted or not. In fact, I contend that because the trends cannot be predicted, investors require an additional risk premium to compensate them from buying into the market when it may be experiencing a downward trend. As Peters alludes to, determining the trends is difficult if not impossible. The risk premium required for holding equity or long-term bonds may be more of a result of aversion to negative sequences rather than some measure called variance.

Peters also applied rescaled range analysis to individual stocks.[4] When applied to Apple Computer and ConEd, Peters had this to say,

> Because both stocks have H values greater than 0.5, they are both fractal, and application of standard statistical analysis becomes of questionable value. Variances are undefined, or infinite, which makes volatility a useless and possibly misleading estimate of risk. (1991, p. 89)

This is precisely the point I am trying to make. As it turned out, Apple had a beta of 1.2, and an H = 0.68, while ConEd had a beta of 0.60 and an H = 0.58. Peters goes on however, and makes a statement where we differentiate in opinion. Peters argues that ConEd is perhaps the riskier stock because it has an H closer to 0.5 which shows less persistence or more random behavior.

There are two problems with this argument. The first is that from a portfolio framework, one cannot examine H alone, much like a variance of a stock does not define its risk in the CAPM framework. It is apparent to me that one would need to know the contribution of a stock to a diversified portfolio's trend to correctly assess its risk. The second point is that a higher Hurst index does not imply a stock is less risky. In fact, to quote Peters,

> Fractal analysis not only fails to explain, it also offers little in terms of forecasting trends. ... "this methodology, still in its infancy, has given

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[4]Rescaled range analysis is used to estimate the Hurst index. Note the Hurst index is considered a very robust indicator, regardless of the underlying distribution. (See Mandelbrot and Wallis, 1969)

> us new insights into the functioning of the markets, but it does not yet offer forecasting ability. (1991, p.163)

As I have pointed out before, if these trends are not predictable, then assets that have a greater propensity to trend would be more risky, not less.

In concluding this section, Peters' results seem to confirm my original hypothesis that sequencing is a major risk factor. Since in general, the yield on assets increase with their maturity, stocks being an infinitely lived asset, the higher yields associated with longer maturity assets seems to be directly proportional to the magnitude of the Hurst index, or rather the greater propensity of these assets to sequence.

III. Variance, Sequencing, and Credit Rationing

Since I am redefining risk in an attempt to explain the risk premium, the first question that must be answered is what gives rise to a risk premium in the first place? The answer to this question is not as obvious as it seems.

Imagine a representative agent with positive but decreasing marginal utility of consumption. Let every consumer's wealth be entirely composed of a risky asset that has a payoff B with probability 1/2 and a payoff G with probability 1/2 where G > B. Let the expected payoff be E and assume there are no lending or borrowing constraints.

Examining this situation over time and assuming the coefficient for intertemporal substitution is zero, the consumer wishes to equivocate consumption across periods. If the consumer could costlessly transfer wealth between the good and bad states, the distribution of an asset would not matter, only its expected value.

Risk as ordinarily defined is now zero even though there is positive variance about expected values. The reason the distribution is irrelevant is because if the asset paid off B, the consumer could make up the shortfall by borrowing the amount E minus B. This amount is easily paid off during a good state when the risky asset pays off G. As long as there are no borrowing constraints, the consumer is unconcerned about the variability of outcomes.

If the variance of returns does not by itself cause risk premiums to exist, then what factors are needed for a risk premium to exist? One answer is borrowing constraints combined with the variance of returns. Agents are limited by the amount they may borrow and at the rate they may borrow. Due to the borrowing constraints and the possibility that the agent may not be able to borrow to make up income shortfalls, the agent will place some wealth in the form of cash. This allows the agent to make up income shortfalls if a poor stated is realized. It is this mechanism which causes the variance to be priced, regardless of whether risk neutrality or risk aversion is assumed.

This would be the end of the story except for the fact that another important question has not been answered. Since I have assumed frictionless markets, what causes there to be borrowing constraints? To explain, assume that agents have limited wealth and limited life spans. Then when an asset realizes a negative return, this return may exceed an agent's wealth. If the agent's wealth is sufficiently reduced, then the agent would be unable to repay a loan. Since this is a possibility, credit is rationed. This leads directly to cash holdings by the agent and required risk premiums for assets with higher variances. In essence than, the variance of an asset gives an indication of the probability that an asset's negative return could reduce an agent's wealth to zero and affect the agent's ability to repay loans.

However, it is my contention that the variance of returns is an inadequate proxy to indicate the probability that an asset's returns could wipe out an agent's wealth. Using the variance of returns does not discern the propensity of an asset to experience a sequence of negative returns and wipe out or seriously deplete an investor's wealth. If stocks tend to fall in value and stay there for long periods of time, than these assets will be avoided. The variance only gives the probability of how far an asset will fall, and gives no indication of how long it may remain below what it was purchased for.

Therefore, an investor faces borrowing constraints based not only on his portfolio's variance, but also on its propensity to sequence. Since any potential lender would limit credit and charge higher rates to investors with portfolios that have a high variance and/or a high propensity to sequence, investors will require these portfolios to have higher expected returns.

With this in mind, it would make more sense to examine how an investor's wealth changes with each change in the value of the asset. This would incorporate all the asset's returns, and most importantly, measure the asset's propensity to sequence.

The only reason the variance of returns is associated with the asset premiums is that it does measure part of the riskiness of an asset. The reason it hasn't performed well in explaining premiums is that it neglects the sequencing risk of an asset.

Therefore, the greater the variance and sequencing potential of returns, the greater the deposit-borrowing rate differential will be. This results since investors do not want to be forced to borrow when the borrowing rate is relatively high. When the borrowing-deposit rate differential is large, the greater the variance and sequencing components of an asset will be priced.

IV. The Variance of Wealth

When investors are deciding to move capital from a risk-free asset to a risky asset, investors are concerned with how their wealth will move through time if placed in the risky asset in relationship to how their wealth would have grown if they had left their capital in the risk-free asset. Therefore, the true riskiness of an asset is the possibility that the wealth level from investing in that asset falls below what it would have been if left in the risk-free asset. The larger and longer wealth deviates below what it would have been if left in the risk-free asset, the more risky the asset, and to compensate investors for this risk, the higher the asset's expected return must be.

Theoretically, if past wealth paths are an indicator of future paths, the true measure of asset's riskiness is to determine how often and for how long the wealth level from investing in a risky asset falls below the risk-free asset's wealth path. Encompassing standard portfolio analysis, the true risk of a security should be how this wealth short fall (below the risk-less wealth level) covaries with the market's short fall. Unfortunately, this measure would be both empirically and theoretically problematic. Risk would often be measured as zero since positive estimates of risk would only be recorded when both the security and the market wealth levels are below the risk-free asset's wealth level.

Using longer estimation periods to measure this risk would run into theoretical problems since over long periods of time, the wealth level of risky securities tends to always be larger than that of a risk-free asset to compensate investors for those asset's greater risk. A more important theoretical consideration in measuring risk this way is that any area measured below the risk-free wealth level would critically depend upon the beginning date from which the wealth path is created.

Fortunately, there is a measure that is both empirically and theoretically valid. Rather than measuring the covariance of an asset's wealth short falls with the market's short fall, I can measure the covariance of deviation around the risk-free wealth level, regardless of whether it is above or below this trend. From a theoretical standpoint, there should be a one to one correspondence between the area above the risk-free wealth trend and below. If an asset has a larger area above the risk-free wealth trend, it must be because it also has the possibility of having a larger area below the risk-free wealth trend. If not, investors are being over overcompensated for this asset's risk implying markets are inefficient. This measure is also not contingent upon which date wealth is accumulated as the area enlarges or shrinks based on every return.

To see exactly how the area between the wealth path of a risky asset and a risk-free asset arises, consider the following two return sequences along with the growth path of wealth for two different assets.

Time	Asset 1-Returns	Asset 2-Returns	Asset 1-Wealth	Asset 2-Wealth
1	0.02	-0.01	1.02	0.99
2	-0.07	0.08	0.95	1.07
3	0.03	0.03	0.98	1.10
4	-0.02	-0.04	0.96	1.05
5	-0.04	0.08	0.92	1.14
6	0.06	0.05	0.97	1.20
7	-0.01	0.07	0.96	1.28
8	0.05	-0.07	1.01	1.19
9	0.08	0.02	1.09	1.22
10	0.07	0.07	1.17	1.30
11	0.07	-0.02	1.25	1.28
12	0.08	0.06	1.35	1.35

Both assets have the exact same returns except for their order. The average return for both assets is 2.55% with a standard deviation of 5.31%. Under traditional measures of risk, the risk premium should be the same for both assets.[5]

On examination though, it is apparent that the ordering of returns for asset 1 has a greater propensity to sequence than asset 2. This is represented in the fact that most of the smaller returns for asset 1 come in the early periods and most of the larger returns come in the latter periods. This type of return sequence is of concern to investors. Investors are fearful of buying into an asset and subsequently experiencing a rash of below average or negative returns. This risk is not detected by the standard deviation of returns.

Since wealth grows geometrically, the ending wealth level for both return sequences is the same since they both experience the same exact returns except for the order. Assuming a risk-free rate of 2%, if the assets were risk-free, they would both have zero variance and wealth would grow to $1.02^{12} = 1.27$. By graphing the growth of actual wealth against this risk-free growth rate of wealth, the magnitude of the sequencing risk can be seen since both assets have the same standard deviation of returns.[6]

Figure 1 highlights the difference in how wealth evolves over time for each asset. Note how wealth for asset 1 deviates from the risk-free wealth line to a much greater extent than asset 2. Graphically, it becomes obvious that the return sequence for asset 1 embodies an additional risk that is not associated with asset 2.

Since the variance of returns is unresponsive to this sequencing risk, a new measure of risk must be derived that increases both with an increase in the variance of returns and greater sequencing. Measuring the area between the wealth path of the

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[5]At this point, I am ignoring one factor models that measure an asset's risk by its covariance with the market. The reader may want to consider the returns as market returns at two different points in time. In any case, either asset could be contrived to have the larger beta or equal beta's.

[6]Again to remind the reader, the deviation between the wealth path of these assets would in reality be taken from the wealth path of an actual risk-free asset and not from the realized mean growth path of the two assets. This is made clear in the next section.

risky asset and the risk-free asset through time does just that.

Note that the riskiness of asset 1 over asset 2 does not depend on whether the wealth path rises above or below the risk-free wealth path. The critical difference is the propensity of asset 1 to sequence more than asset 2. Consider the mirror images of the wealth paths for assets 1 and 2 in figure 1. The risk for these two assets is the same regardless of whether the wealth path rises above the risk-free wealth path or below.

Another way to look at this risk is from a liquidity standpoint. For asset 2, the timing of when to buy is less relevant since the wealth path of asset 2 never deviates far from the risk-free wealth path. However, for asset 1, the timing is more critical. Even if the asset has experienced a negative sequence, one does not know if the asset will experience another negative sequence, or as figure 1 shows, experiences a positive sequence after period 6. It may be that the wealth path in the first 6 periods for asset 1 repeats itself. I contend that one can only measure an asset's propensity to sequence and not its direction. Because of this, investors will require higher expected returns from assets that have a tendency to sequence more than other assets.

V. Formal Definition of the Variance of Wealth

Conventional analysis has restricted itself to a one period framework. This however neglects a very important aspect of an investor's decision. When an investor is making a decision about allocating wealth to certain assets, the concern is not only what the asset will do for the next period, but for n periods after that. Investors are fearful of buying into an asset and subsequently experiencing a rash of below average or negative returns. With stationary and nonstationary distributions alike, the variance of returns does not measure this risk.

Most expected utility functions now recognize that an investor is concerned with both current and future levels of consumption. In general, these expected utility functions are written as

$$EU(c) = \sum_{t=0}^{\infty} \beta^{t} EU(c_t) \tag{1}$$

where β is a parameter for time preference. Although the time separable assumption of von Neuman Morgenstern utility functions has been relaxed in many papers, research up to the present has mainly concentrated on the interrelationships between consumption at different periods or separating risk aversion and intertemporal substitution. If present utility level is determined by the consumption level at all points in time, then it should also be affected by how an asset's return affects wealth through all points in time. This is why the sequence of an asset's returns is critical. If there is a propensity for an asset's returns to sequence, whether it is positive or negative, the value and riskiness of that asset is based on how it affects current and future levels of consumption.

One way to detect this type of risk is to examine how returns affect investor's wealth. Assume wealth follows a random walk around zero, than wealth at time t will equal

$$W_t = W_{t-1} - \epsilon_t \tag{2}$$

This is equivalent to the assumption that stock prices follow a random walk with an investor's wealth composed of one or more stocks. A one period variance measure equivalent to the variance of returns would be

$$\epsilon_1^2 = W_t - W_{t-1} = \sigma_\epsilon^2 \tag{3}$$

Extending this to two periods, the error would be

$$\epsilon_2 = W_t - W_{t-2} = W_{t-2} + \epsilon_t + \epsilon_{t-1} - W_{t-2} = \epsilon_t + \epsilon_{t-1} \tag{4}$$

so the variance measure would be

$$\frac{(\epsilon_t + \epsilon_{t-1})^2}{2} = \frac{(\acute{o}^2_{\epsilon_t} + \acute{o}^2_{\epsilon_{t-1}} + 2 \text{ cov } (\epsilon_t , \epsilon_{t-1}))}{2} \tag{5}$$

Standard analysis has assumed ε_t and ε_{t-1} are independent and has used the variance as a measure of risk which in this case would be $2\sigma_\varepsilon^2/2 = \sigma_\varepsilon^2$. Since the covariance term has been assumed to be equal to zero, using the variance of returns measures the same risk as the variance of wealth would in equation 5. But this only holds in the special case when returns are independent. With sequencing in the returns, the covariance term in equation 5 is not zero.

By only using the variance as a measure of risk, the actual risk of an asset is understated by a factor of $\{(n-1)/2\} \times n$ covariance terms for any historical estimation of risk using n periods or for any prediction of wealth n periods into the future. Standard analysis shows the forecast error increases with the square root of n, but this is only correct if the returns are independent. If the returns sequence, than the errors are not independent and the covariance terms must be measured. With sequencing, the forecast error increases faster than the square root of n. For risk averse investors, this wider confidence interval will require higher expected returns.

Several important notes should be made at this time. The variance of wealth is not analogous to correcting for autocorrelation or measuring covariance terms. Over any time period, autocorrelation can take on a variety of values. If within some time period autocorrelation is negative than turns positive, the measured autocorrelation would be zero. As will be seen, the variance of wealth is immune to this problem. The variance of wealth will measure all sequencing in returns, regardless of the autocorrelation. In essence, the variance of wealth takes account of the relationship between every e_t and e_{t-1} and places no restriction on what the correlation between any e_t and e_{t-1} can be.

The variance of wealth also measures the magnitude of the returns for any given autocorrelation. Two assets can have the same autocorrelation, but quite different variance of wealth magnitudes. As an example, consider the returns of two assets which both exhibit perfect autocorrelation. One asset's return sequence increases incrementally by 0.1% while the other asset's return sequence increases incrementally by 1.0%. The wealth path of the asset whose returns increase by 1% will deviate much further from the wealth path of the risk-free asset than the asset whose returns only increase by 0.1%.

To formally derive the variance of wealth, consider that the value of wealth through time is written as

$$W = \Pi_{i=1}^{n} (1 + R_i) \tag{6}$$

where R_t is the return of an asset in each period t. Since wealth grows geometrically, the ending wealth for any return sequence will be the same for any ordering of a given set of returns. Thus the geometric average growth rate for any n and any sequence of returns is

$$u_g = (W_n / W_0)^{1/n} - 1 \tag{7}$$

where W_0 = 1 or some initial constant.

Now consider how wealth grows through time for different assets. For a risk-free asset with a constant yield, wealth grows at a constant rate through time.[7] Mathematically, this growth path is

$$RFG_t = (1 + r_f)^t \tag{8}$$

where RFG_t is the value of wealth at any t that has grown at the risk-free rate of growth. Graphing wealth through time, we would find that wealth grows linearly in logs over any time frame for a risk-free asset. Since this growth line represents how wealth would grow if the investor owned a risk-free asset, the greater wealth deviates from this line, the more risky the asset must be.

The deviation of wealth at every point in time from what wealth would be if it were to grow at the risk-free rate of growth can result from two sources. The first pertains to the variance of returns. The deviation of wealth at any point in time from the risk-free trend is written as W_t - RFG_t. Since W_t at any point in time is determined by the product of $(1+R_t)$ from t=0 to t, the greater the variance of the R_t's, the greater W_t will deviate from a constant growth rate of wealth. This is represented graphically in figure 2.

The second source in the deviation of wealth results from the particular sequence of returns. For any given variance of returns over any n, the more random the returns, the smaller wealth will deviate from the wealth derived from a constant rate of growth. This is a direct result of the fact that wealth at any particular t

[7] It is acknowledged that even the one-month T-bill which may be considered the closest to a risk-free asset has a dynamic yield. Obviously is this case the risk-free growth path would not grow at a constant rate but this in no way affects the results.

critically depends on the sequence of returns. Therefore, returns that exhibit a higher degree of sequencing will cause the deviation of wealth from the risk-free wealth trend to be much larger. This was graphically shown in figure 1.

Since it has now been shown that the deviation of actual wealth from a risk-free wealth trend will increase both with an increase in the variance of returns and their propensity to sequence, I contend that a more accurate measure of risk would be to measure the area between the risk-free wealth line and the actual wealth line rather than the variance of returns. One easy measure of this area is to use the squared deviations of the risky asset's wealth path from the wealth path of the risk-free asset. This can simply be called the variance of wealth, or if the square root of this sum is taken, we have what I call the standard deviation of wealth. This is written as

$$\sigma_w = \left[\frac{\sum_{t=1}^{n} (W_t - RFG_t)^2}{n} \right]^{0.5} \tag{9}$$

Using the variance of wealth around the risk-free or average geometric growth rate of wealth embodies all the properties of the variance of returns, with the additional advantage of discerning the risk associated with the sequencing of returns.

In essence, it can now be stated that the riskier the asset, the greater the area between the risk-free wealth line and the actual wealth line. Referring back to the numerical example and using equation (4) to measure the area between the risky asset's wealth path and the risk-free asset's wealth path, the standard deviation of wealth for asset 1 is 12.3% while for asset 2, the standard deviation of wealth is 6.4%. The standard deviation of wealth for asset 1 in this example is almost two times that of asset 2, exemplifying the fact it has greater sequencing risk. It becomes apparent that using the standard deviation of returns as a measure of risk is inferior compared to using the standard deviation of wealth.

VI. The Wealth Beta

In applying the variance of wealth to standard portfolio analysis, the risk of a security can now be measure by the asset's contribution to the portfolio's variance of wealth, rather than to the portfolio's variance. In essence, an asset's beta is now measured by how an asset's wealth path covaries with the market's wealth path.

With this in mind, rather than calculating the covariance as

$$\sigma_{i,m} = \frac{\sum_{i=1}^{n} [R_i - E(R_i)] \times [R_m - E(R_m)]}{n} \tag{10}$$

I have redefined the covariance of an asset to be

$$\sigma_{i,m} = \frac{\sum_{i=1}^{n} [R_i - R_f] \times [R_m - R_f]}{n} \tag{11}$$

where R_f is the risk-free rate which replaces $E(R_i)$ and $E(R_m)$.

This leads to four unique beta calculations. The original beta, (β_o), a second beta that differs from the original only by replacing the expected return calculation by the risk-free rate, (β_r), a wealth beta, (β_w), and a second wealth beta (β_{wg}), similar in stature to the original beta where deviations around an asset's actual growth trend are measured, rather than from the risk-free rate of growth which is how β_w is calculated. Mathematically, the four betas are given below.

$$\beta_o = \frac{\sigma_{i,m}}{\sigma_m^2} = \frac{\sum_{i=1}^{n} [R_i - E(R_i)] \times [R_m - E(R_m)]}{[R_m - E(R_m)]^2} \tag{12}$$

$$\beta_r = \frac{\sigma_{i,m}}{\sigma_m^2} = \frac{\sum_{i=1}^{n} [R_i - R_f] \times [R_m - R_f]}{[R_m - R_f]^2} \tag{13}$$

$$\beta_w = \frac{\sigma_{i,m}}{\sigma_m^2} = \frac{\sum_{i=1}^{n} [W_i - RFG] \times [W_m - RFG]}{[W_m - RFG]^2} \tag{14}$$

$$\beta_{wg} = \frac{\sigma_{i,m}}{\sigma_m^2} = \frac{\sum_{i=1}^{n} [W_i - \mu_{gi}] \times [W_m - \mu_{gm}]}{[W_m - \mu_{gm}]^2} \tag{15}$$

where W_i and W_m are defined in equation (6), μ_g is defined in equation (7), and RFG is defined in equation (8).

In the empirical work, I call these betas Abeta(Sharpe-Litner beta), Rbeta(risk-free beta), Wbeta(wealth beta), and Wbetg(wealth growth beta) which again is similar to the actual beta except wealth is used rather than returns. Theoretically, the wealth beta(Wbeta, equation 14) is my new measure of risk. The other betas are tested for comparison purposes only. With the betas thus defined, my new measure of risk can now be empirically tested.

VII. Empirical Methodology

Before delving into the empirical methods dealing with the wealth beta, some initial empirical work was performed to test the contention in section IV that the slope of the term structure is directly related to sequencing risk inherent in inflation. Section V also hypothesized that the borrowing-deposit rate differential would make sequencing in returns more risky and therefore cause higher expected returns for the stock market. To test these two hypothesis, monthly yield data was taken from the CRSP bond and stock files and monthly inflation rates were taken from Ibbotson Associate's *Stocks, Bonds, Bills, and Inflation: 1993 Yearbook*. The time period examined was from January, 1953 to December, 1992. Since banks tend to lend long term and borrow short, to proxy for the deposit-borrowing differential, I used the difference between the two year rate on Fama's two year discount bond and the one month T-bill.[8]

To derive a sequencing measure for inflation, the preceding 24 months of inflation data was used to derive a sequencing measure before January of each year. Two proxies were used. The first determined the sequencing of inflation around the average geometric growth rate experienced over the preceding two years. This is very much like the Wbetg calculation. The second took the inflation rate from the 24th month preceding the year to be examined and used that rate to derive the expected growth rate of inflation. This rate was used assuming investors expected the current rate of inflation 24 months ago to continue for the following 24 months. The variance of inflation was also calculated around both the average inflation rate over the preceding 24 months and around the inflation rate from the preceding 24th month.

This is done each year resulting in 40 observations.[9] Regressions were run on

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[8]The two year rate was used since two years have been used to estimate the sequencing variables. The one, three, and five year yield was also tested with no change in the results.

[9] Month be month data is not used due to the problems of overlapping data.

the differential in yields to see if the slope in the term structure can be partially explained by sequencing in inflation. Realizing that several factors affect the term structure, apriori, the r-squares are expected to be small. Since there is no reason to expect the sequencing of inflation to be correlated with other variables, the t-stats hopefully are not biased.

The empirical work dealing with the wealth beta was based on return data from January 1926 to December 1992. Using the CRSP NYSE/AMEX monthly stock files and the CRSP bond files, the four betas derived in section III were calculated for all stocks each year from January 1941 to December 1992 using the CRSP value weighted and equally weighted market proxies. Betas were calculated using both monthly and yearly returns. Monthly betas used monthly returns for the preceding two years and the yearly betas used yearly returns for the preceding 15 years of data[10]

The reason yearly betas were calculated is that there has been recent evidence that beta and the return interval are integrally related. (See Chan and Chen, 1988 and Handa, Kothari, and Wasley, 1989 and 1993). Results have generally shown that extending the return estimation interval for the traditional beta's(Abeta) calculations has removed the size effect and have resulted in Abeta being significant. Concerns about parameter stationarity over 15 years has been partially alleviated due to Chan and Chen's(1988) results that show betas estimated using monthly returns over 5 and 15 year estimation periods are highly correlated.[11]

However, no such tests for the wealth beta(Wbeta) have been performed. Additionally, there is as yet no empirical reason to use yearly returns for Wbeta. More importantly, there is no economic justification for using yearly returns to

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[10]The two year estimation period was selected to correspond to Fama and French's(1992) shorter estimation period and due to parameter non-stationarity concerns for the wealth beta which has not been investigated.

[11] The 15 year estimation period was used to correspond to the above work.

estimate Wbeta. Since Wbeta is a measure of the sequencing risk when buying into an asset, it is unlikely investors are considering the sequencing risk over yearly periods. Indeed, the entire contention of this dissertation is that the equity premiums are due to the immediate sequencing risk, not sequencing after one year.

Despite the above reasons for not using yearly returns to estimate Wbeta, in an effort to compare how Wbeta compares with Abeta using yearly returns, all four betas were also calculated using yearly returns for the preceding 15 years. Other than using yearly data, the empirical work follows the same format as used with the monthly betas. Note that for a stock to be included in the sample now, 16 years of data had to be available. This reduced the total sample size from 60,085 to 17,717 observations for the 1941-92 period and from 37,554 to 10,388 observation for the 1966-92 period. This in itself leads to some selection bias. The exact effect is unknown, but it can be conjectured that larger stocks will be over represented.

The final set of results from this study examines the contention that sequencing risk is increasingly priced the steeper the term structure. To empirically test this, the period between 1953 and 1992 was split in half based on the difference between the two year bond yield and the annual yield on the one month T-bill on December 31 of the prior year. It is expected that Wbeta will be larger for the years subsequent to a steeper yield curve. It may also be hypothesized that if Abeta is a poor proxy for risk, it will do much worse in the years following a highly sloped term structure. If it is a good proxy for risk, Abeta should also be larger in the years following a highly sloped term structure.

For all the results, twenty portfolios were formed and ranked by the different betas and the natural logarithm of size as calculated in December of each year. Each portfolio contains (to within one) the same number of securities. Each portfolio's average equally weighted return was then calculated for the following year.[12]

Additionally, regressions were also performed on data that was first ranked by size and the four betas. After the first ranking, twenty portfolios were again formed within each preceding ranked group by size and each of the four betas. The four betas and size were then regressed on average mean excess returns. This will tell us whether within Abeta or sized ranked portfolios, Wbeta has additional explanatory power.

All regressions are done under simple OLS without any corrections for autocorrelation. There are several reasons more complicated regressions were not run. As for correcting for autocorrelation, Fama and French(1992, p.431) said corrections for autocorrelation "lead to trivial changes in the β's." From a theoretical standpoint, if β correctly measured risk in the first place, these corrections would not have to be made. A major impetus behind the wealth beta is that it already measures this type of risk. This argument also applies to correcting for heteroskedasticity by using GLS.

GLS was also not used since Handa, Kothari, and Wasley(1989) said their GLS and OLS results were very similar. More importantly, by just using OLS, if the wealth beta works, than my results are not subject to Roll and Ross's(1994) criticism of GLS. To quote,

> Unless the index proxy is grossly inefficient, with expected return less than or equal to r_0, a GLS regression would almost certainly find a significant and positive mean-beta relation in large samples. But what would this really imply about the validity of the CAPM, about whether the true market portfolio of all assets is ex ante mean-variance efficient. If the mean return-beta relation is positive for every possible market

[12]Note that at this point in the empirical work, the portfolio returns are the weighted average of each stock's yearly return and not the weighted average of the monthly returns. Thus the regressions are on 40 years of data rather than 600 monthly average returns. This was done due to computer limitations. It reduced the number of observation from over 1 million to approximately 70,000 and since the betas are only estimated yearly, using the next 12 months of returns for each stock or each stock's next years return should not affect the results.

> proxy whose mean return exceeds r_0, what conceivable set of empirical results would cause us to reject the CAPM? p.114

As Roll and Ross put more succinctly, "Nonetheless, we think it is appropriate to bring attention to the bizarre idea that the very range of possible findings can be affected by the econometric technique."

Finally, although the empirical work used two market proxies, theoretically the value weighted index is more relevant since it is the total value of all investor's wealth. To again quote Roll and Ross(1994),

> Beating or trailing a value-weighted index has become the most widely accepted criterion of investment performance. It is an appropriate criterion relative to the wealth-weighted average returns of other investors. p.116

The 1941-92 time period was used for both the monthly and yearly betas so results using the different estimation lengths would be comparable. Also in an effort to compare this study with other such notable results as Fama and French(1992), Handa, Kothari, and Wasley(1993) among others, the 1941-1992 time period was roughly split in half and regression results were recalculated for the 1966-1992 period which roughly corresponds to Fama and French 1963-90, HKW 64-82. This was mainly done since the relationship between beta and average return has been found to be nonexistent over this time period.

VIII. Empirical results

A. Inflation Sequencing

The first results deal with whether the sequencing in inflation can explain the slope of the term structure. From table 1, neither the sequencing or variance measure turned out to be significant in explaining the slope of the term structure. The results did not change whether the one, three or five year bond was used to replace the two year bond.[13]

To determine if a steeper term structure is associated with higher expected returns, the difference between the two year bond and the one month bill at the end of December of each year was regressed on the following year's return of the CRSP value and equally weighted market returns. The regression results are also given in table 1. As one can see, both t-stats are of the expected sign and greater than 1.5, but obviously not highly significant. Economically though, a 1% change in the difference between the two year bond yield and the one month bond yield does indicate that the expected value weighted market return should increase by approximately 4.5%. Results again did not qualitatively change whether the one, three or five year bond was used to replace the two year bond.

Based on these two simple regressions, the implication is that the connection between sequencing in inflation and the slope of term structure is simply not there. One might also conclude that the connection between the slope of the term structure and the market premium is also not that strong based on the t-stats, but as will be seen later, the slope of the term structure plays a critical role on the importance of the different beta measures and size.

Before I report the results for the CAPM type tests, the following abbreviations

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[13]The sequencing of inflation was also regressed on market returns each year and also came up insignificant.

will be used in the discussion that follows. Abeta, Rbeta, Wbeta, and Wbetg followed by a v or an e indicates whether that beta was calculated using the value weighted or equally weighted index respectively. Lame stands for the natural logarithm of market equity as calculated in December of each year by multiplying the shares outstanding of each stock by the stock price. If in the text a 'v' or an 'e' does not follow the beta's name, I am discussing the beta within the context of both indexes.

Although results for all four betas and size will be discussed, the discussion will mainly emphasize the differences between the Sharpe-Litner beta (Abeta), the wealth beta (Wbeta), and size. The reasoning behind this is that Rbeta's results were qualitatively similar to Abeta's results and Wbetg's results were qualitatively similar to Wbeta's. Therefore, tabulated results and figures will be limited to those dealing with Abeta, Wbeta, and size.

B. Initial Rankings - Monthly Returns

1941-1992

Table 2 summarizes the regression results for the 1941-92 period when portfolios are ranked by Abeta, Wbeta, and the natural logarithm of size. From table 2, when ranking by Abeta, one can see that Abeta is significantly positive using either the value weighted or equally weighted index as the market proxy. Adding size to the regressions does not change the results and in fact size has the wrong sign. Although not shown, when adding Wbetav to the regression, Abetav no longer remains significant. However, Abetae did remain significant.

When portfolios are ranked by Wbeta, Wbeta is also significant and size as well as Abeta(not shown) is insignificantly negative when added to the regression. When portfolios are ranked by size, size alone explains 92% of the deviation in average excess returns as opposed to 77% for Wbetav and 50% for Abetav. Adding Abeta or Wbeta to the regressions does not change the result and in fact, they come in significantly negative, but this is more likely due to multicollinearity problems.

1966-1992

Table 3 summarizes the regression results for the 1966-92. Comparing these results to table 2, it is found that when ranking by Abetav and using Abetav as the only explanatory variable, similar to Fama and French and others, Abetav is found to have no significant explanatory power and is in fact slightly negative, (see figure 3). Abetae remains significant except when Wbetae is added to the regression..

Wbeta does not succumb to the same problems as Abeta does, (see figure 4). It remains positively significant even after adding size or Abeta to the regressions. When ranking by size, size remains the single most important variable as it again explains 92% of the deviation in mean average returns, (see figure 5). Abeta and Wbeta both are insignificantly negative when added to these regressions.

Initial conclusions

Thus far, it is apparent that the Sharpe-Litner beta does not perform nearly as well as the wealth beta in explaining average returns. Positive results for both Abeta and Rbeta are continent upon which market proxy is used and which time period is examined. In contrast, results for Wbeta are robust to these changes. In addition, where it has been found that Abeta loses significance when Wbeta is added to the regression, Wbeta remains significant when Abeta is added.

Second Rankings - Monthly Data

1941-1992

The next investigation into Wbeta's merits over Abeta was to see if after sorting by Abeta, would a second sort by Wbeta add further explanatory power. Table 4 summarizes the regression results for when portfolios are first ranked by Abeta, Wbeta, and size, and then ranked by one of the other variables. For example, portfolios are first ranked by Abeta, then each ranked portfolio by Abeta is ranked again by Wbeta or size.

Table 4 shows that within each Abeta ranked portfolio, by ranking the portfolios again by Wbeta or size, that significant explanatory power within each Abeta ranked portfolio is still available. Although not shown, adding other variables to these second ranked portfolios did not affect the initial variable used for the second ranking. One important note, even though size had the highest absolute value t-stat, Wbeta produced an adjusted r-square of 0.69 while size only produced an adjusted r-square 0.25.

Table 4 also shows that when portfolios are first ranked by Wbeta and then Abeta, Abeta is significant. However, even though Abeta is significant, the adjusted R-square for Abetav is only 0.18 as opposed to Wbetav's 0.69 when portfolios are first sorted by Abetav. On the other hand, a second ranking by Abetae had an R-square of 76%. When portfolios are first ranked by size and than Abeta, only Abetae came in significant. Second rankings by Wbeta were significant under both indexes.

1966-1992

Once again, Abeta does not stand up to the test of time. After portfolios are first ranked by Abeta, Wbeta and size remain significant in explaining returns within each portfolio. When portfolios are first ranked by Wbeta or size and then Abeta, Abeta does not explain returns within each of these ranked portfolios. Table 5 summarizes the results. Again note that even though size had larger t-stats, the r-square on size is not as large as Wbeta's within the Abeta ranked portfolios.

Final Conclusions Using Monthly Returns

In terms of the traditional beta, it is readily apparent that Wbeta does a much better job in explaining mean average excess returns across groupings of portfolios than Abeta or Rbeta. Wbeta is robust to both changes in the time period and the market index proxy that is used in answer to Roll and Ross's criticism of Abeta. However, it is not apparent that Wbeta does a better job than the logarithm of size in explaining the deviation in portfolio returns.

It may be hypothesized that the reason size explains returns is that size proxies for the greater sequencing risk in smaller firms. Smaller firms may have the tendency to trend in specific directions for long periods of time as information is disseminated or becomes available more slowly. If this is the case though, why is it that in the 1966-92 period when ranking by size, 92% of the deviation in mean excess returns is explained while when ranking by Wbetav, only 52% of the deviation in mean excess returns is explained? Additional information has led me to dismiss any relationship between size and Wbeta.

In checking the relationships between Abeta, Wbeta, and size during the 1966-92 period, in the unreported results, it was found that ranking by Abeta and using only size as a single regressor led to significant results for size. The same held true for ranking by size and using Abeta as a single regressor. In fact, Abeta had greater significance when ranking by size rather than by itself. This relationship has been well documented and is due to the strong correlation between the two variables.

However, ranking by Wbeta and using size as the single regressor led to insignificant results for size. The analogous situation held for ranking by size and using Wbeta as the single regressor. The problem was that the deviation in the wealth betas was too evenly distributed when ranking by size. The analogous situation held for size when ranking by Wbeta. As an example, ranking by Wbetav led to a distribution of betas between -2.27 and 4.84. Ranking by size led to a distribution of Wbetav between 0.46 to 0.97. The distribution for size when ranking by Wbetav was 13.69 to 14.25 compared with 9.26 to 16.45 when ranked by size.

Combine the above information with the fact within each Wbeta ranking, size has additional explanatory power and within each size ranking, Wbeta has additional explanatory power, leads me to conclude that these two variables are picking up two different kinds of risk. The risk Wbeta is measuring is sequencing risk. The risk size proxies for is still in question. What I can say is that size is not proxying for sequencing risk.

C. Initial and Secondary Rankings - Yearly Returns

1941-1992 and 1966-1992

Although results for yearly returns are not tabulated, one finds that Abetav and Abetae are significant, but become insignificant as soon as size is added. Rbetav and Rbetae are significantly negative. Wbetav is significantly positive but Wbetae is significantly negative, while Wbetgv is significantly positive and Wbetge is insignificantly positive. The results do not indicate that using yearly returns to estimate beta lead to improvements in any beta's explanation of mean average returns. The conclusion one would reach using yearly returns to explain average mean returns over this time period is that none of the betas seem to work.

These results are not entirely inconsistent with previous research as previous research concentrated on attempting to remove the size effect. Using yearly return intervals to estimate betas has achieved that goal to some degree. When secondary rankings are performed, after initially ranking portfolios by any of the four betas, the t-stats on size have been significantly reduced. In fact, after sorting by Abetae or Rbetav and then sorting on size, size is insignificantly negative.

Abeta is also redeemed after initially sorting by Wbeta. After making a second ranking by Abeta, Abeta is significantly positive. The same is not true for secondary rankings by Wbeta after first sorting by Abeta. These results were expected though based on the fact that the risk Wbeta measures deals with sequencing risk associated at all points in time, not at yearly intervals. Remember also that this sample is probably biased towards larger stocks.

Using the reduced sample associated with the yearly betas, size is still a significant variable when it comes to explaining returns. The r-square associated with size in this sample is 0.73 as opposed to only 0.40 for portfolios ranked and regressed on Abetav and only 0.20 for Abetae. However, consistent with previous research, after sorting by size and adding Abetav to the regression, size becomes insignificant. Abetae however did not have such an effect.

Final Conclusions Using Yearly Returns

Despite the fact that Abeta has been partially resuscitated using yearly returns, it still falls short when compared to Wbeta using monthly returns or size. Both betas were regressed on yearly returns, so if anything, Abeta using yearly returns should have the advantage. Comparing r-squares though, Wbetav and Wbetae had r-squares around 50% for the 1966-92 time period while Abetav and Abetae using yearly returns had r-squares of 40% and 20% respectively. Comparing just Abeta and Wbeta, Wbeta is still superior whether Abeta is estimated using monthly or yearly return data. Comparing either variable to size, size still dominates.

D. Betas and the Term Structure

If the tests ended here, perhaps Abeta could be laid to rest in support of Wbeta or size. But what started out as a test to see if Wbeta would turn out to be more significant when the term structure is steep as compared to when it is flat, actually may have inadvertently given the profession a new empirical fact to ponder.

Using data from 1953 to 1992, two samples were created. One sample corresponds to the years following the 20 smallest yield differentials and the other to the 20 largest. Table 6 specifies which years are associated with each sample and the spread in annual percentage terms between the two year bond and the one month T-bill for each year. For the "flat" years, the difference varies from -0.91% in 1974 to 0.87% in 1971 with a mean of 0.32%. For the steep years, the difference varies from 0.89% in 1960 to 3.63% in 1988 with a mean of 1.57%.

Initial Rankings

Tables 7 and 8 report on the dramatic difference between the two samples using the value weighted and equally weighted index as the market proxy. As one can see from tables 7 and 8 or figures 6 and 7, when the yield curve is fairly flat, Abetav and Abetae are significantly positive in explaining mean average returns over the following year. On the other hand, when the yield curve is steep, Abetav and Abetae are significantly negative. Size does not reduce the significance of Abeta when the yield curve is flat although Abeta does lose significance when Wbeta is added to the regression(not shown). However, when size is added to the regression when the yield curve is steep, Abetav does become insignificant and size is significantly positive.

When ranking portfolios by Wbetav or Wbetae(see figures 8 and 9), Wbeta is also significantly positive when the yield curve is flat and when the yield curve is steep except for Wbetav which is only marginally positive when the yield curve is steep(t-stat =1.9). Wbeta also maintains significance when size is added to the regressions. What is disappointing is that Wbeta's coefficient is larger when the yield curve is flat as opposed to when it is steep which is the exact opposite of what I would expect.

A second dramatic results deals with size. When the term structure is flat, size is significantly negative with a T-stat of -13.65 and a parameter estimate of -.026. When the term structure is steep, size is still significantly negative, but only has a t-stat of -2.37 and a parameter estimate of -.00256 which is approximately 10 times smaller than when the term structure is flat. Obviously the economic effect of size critically depends on how flat or steep the term structure is. Additionally, when the term structure is steep, the significance of size is lost when Abetav is added to the regression.

Figure 10 highlights the difference between the effects of size when the term structure is flat versus when it is steep. When the term structure is flat, excess returns(remember these returns are in excess of the risk-free rate) fall from approximately 21% to 3% as the value of the logarithm of size goes from 8.9 to 15.84. Compare this to the 0.05 percent change in going from the smallest to the largest size portfolio when the term structure is steep.

Second Rankings

With such surprising results, second rankings were also done in attempt to determine what is going on. In table 9, within each Abetav ranked portfolio, rankings were done again by Wbetav and size. Wbetav came up significantly positive under both the flat and steep term structure samples while size again had dramatic differences in effect between the flat and steep samples..

When portfolios are first ranked by Wbetav then Abetav, Abetav is again significantly positive when the term structure is flat and significantly negative when the term structure is steep. The difference in the size result carries through no matter which variable is ranked first. Table 10 reports identical results for the equally weighted index.

Within each size ranking, when the yield curve is flat, Abeta is significantly positive. When the yield curve is steep, Abeta is significantly negative. This holds for either index. The difference in the slope of the yield curve apparently does not affect Wbeta as it comes in insignificantly positive under either term structure shape although the t-stats are all above 1.

Final Conclusions About Betas and the Term Structure

Strangely enough, Abeta works in explaining portfolio's mean average returns when the term structure is flat. When it is steep, Abeta is significantly negative. Wbeta does not seem to be affected but size is significantly affected. When the term structure is flat, size explains 91% of portfolio mean returns as opposed to 20% when the term structure is steep. These findings are difficult to explain.

If it is the case that sequencing risk is priced to a much greater extent when the term structure is steep, and Abeta does not pick up this risk, than perhaps Abeta's results can be explained. When the term structure is flat, Abeta adequately measures risk, when the term structure is steep, it fails. However, this is not confirmed by larger parameter values for Wbeta when the term structure is steep.

Size is in a similar situation. Despite the countless papers that have tried to eliminate size as an explanatory variable and/or attain significance for beta by remeasuring beta with longer time intervals, longer return intervals, numerous econometric fixes, and all other parlor tricks, it seems that the slope of the term structure is critical to the importance of beta and size as explanatory variables. One only needs to look at figure 10 to see when size is and is not important in explaining mean average portfolio returns.

E. Overall Conclusions From Empirical Results

At the very least, these results lead to the conclusion that using the variance of returns as a proxy for risk is inadequate. Using the variance of wealth not only seems to be a superior proxy, but has resuscitated CAPM to some degree. The significance of the wealth beta in relation to the traditional beta either measured by yearly or monthly returns is not subject to the same capriciousness as the traditional beta. The wealth beta is robust to changes in the index proxy, the time period studied, and even to the term structure phenomena.

When it comes to just ranking portfolios and explaining returns, the logarithm of size remains the most important variable, except when the term structure is steep at which time Abetav has the highest r-square of 39%, albeit with a negative coefficient. Adding size to the regression does move the r-square up to 85%, but Lame also has the wrong sign. The economic justification for the sign of these variables alludes me which leads me to place little confidence on their reliability.

Obviously, ranking just on size is not the final answer. Wbeta had explanatory power within each size ranking. Apparently, size and the wealth beta measure two different types of risk. The question that now needs to be answered is why does the importance of size and Abeta depend on the term structure being fairly flat?

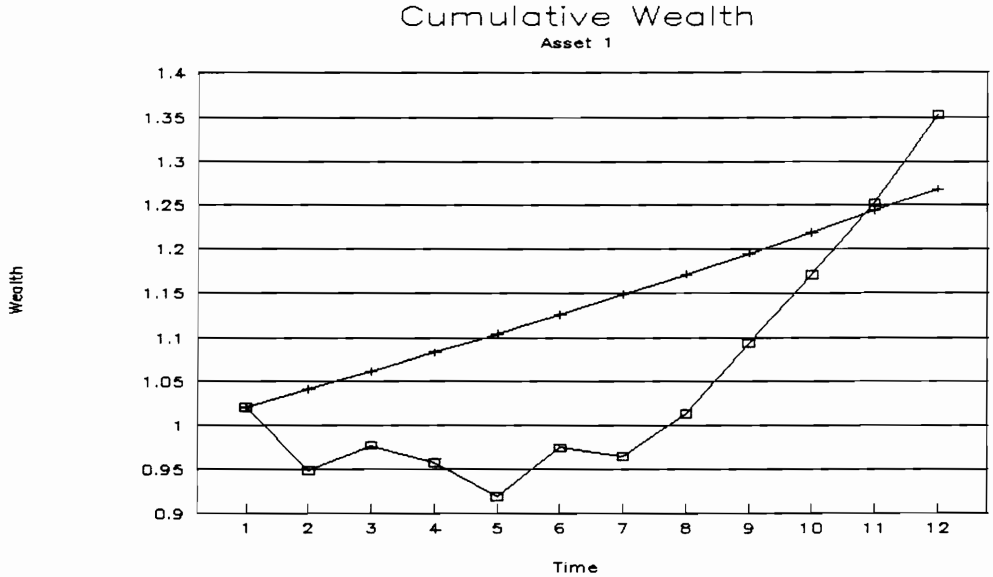
IX. Conclusion

This proposal has set forth a new measure of risk that encompasses both the variance of returns and their sequencing risk. The empirical results have established that a wealth beta which measures the covariance of an asset's wealth path with the market wealth path outperforms the Sharp-Litner beta, which in its current form, does not explain portfolio returns. It has also been established that the slope of the term structure critically affects both size and the traditional beta's ability in explaining average mean portfolio returns.

An important result is that the wealth beta and size are not related. Apparently they measure two different types of risk. The importance of size in explaining mean excess returns seems to be mainly confined to those years subsequent to a fairly flat term structure. The exact risk that the size variable is proxying for is unknown. I can only say it is not sequencing risk.

Possible directions for future research on this new measure of risk are numerous. Where ever the variance of returns has been used, the variance of wealth could also be used. It will be interesting to see if this new risk measure can explain the equity and liquidity premium puzzles. Its application to capital budgeting and the determination of positive NPV projects should also lead to interesting work.

In conclusion, whether future empirical work reinforces my particular risk measure or not, using the standard deviation of returns as a measure of risk is grossly inadequate. The one period discrete time framework which uses the variance as measure of risk has proven that it cannot explain the risk premiums that we have witnessed over the past half century. Continual fine tuning of these financial models is not going to give us a clear picture if we are on the wrong channel. It is time that we re-examine the assumptions we have made and accept the increasing probability that the past 40 years of financial research is seriously flawed.



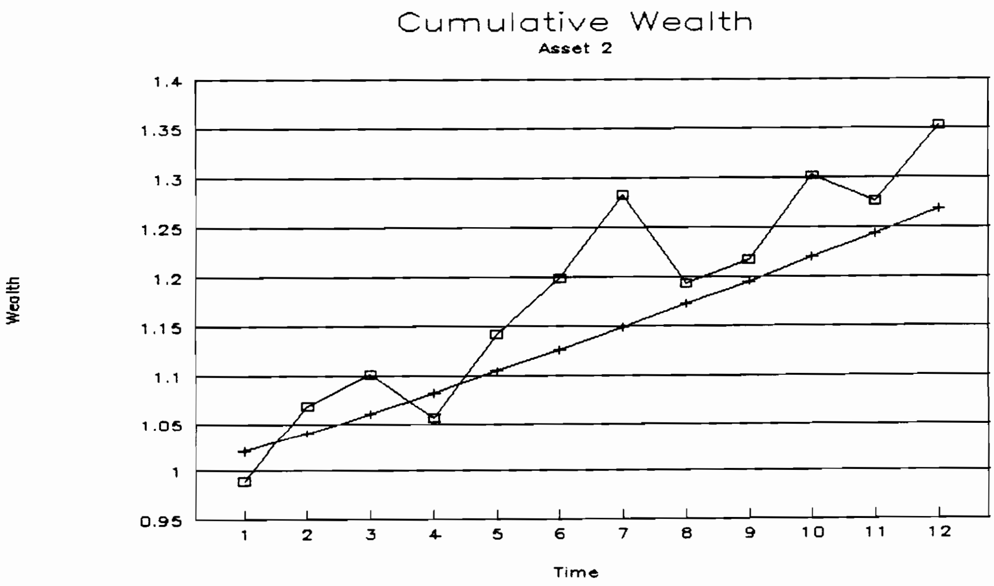
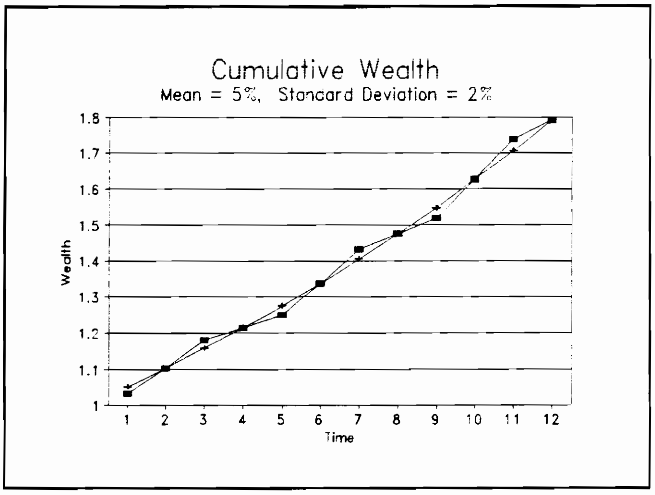


Figure 1

Comparison of the growth of actual wealth against the risk-free trend rate of growth for assets 1 and 2. The risk-free rate was set equal to 2%. Both assets have the exact same returns except for their order. The average return for both assets is 2.55% with a standard deviation of 5.31%. Asset 1 has a greater propensity to sequence since small or negative returns tend to be followed by small returns while large returns tend to be followed by large returns.



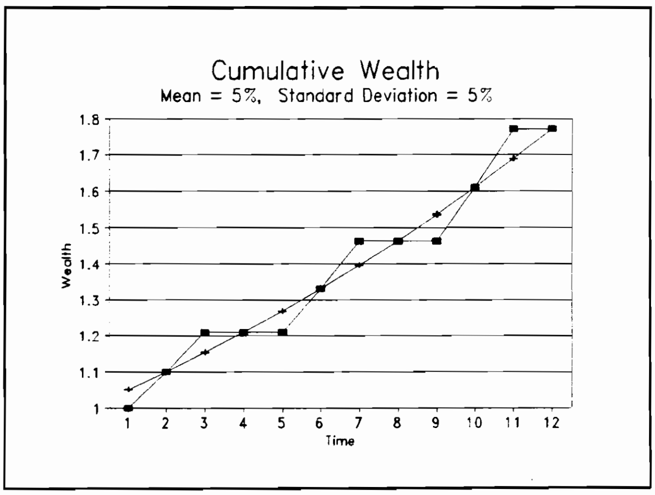
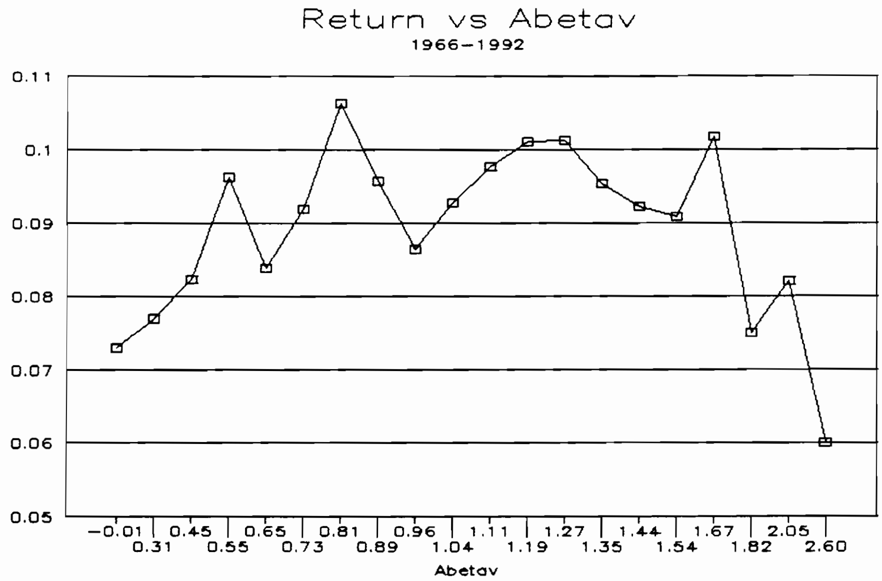


Figure 2

Comparison of the standard deviation of wealth when returns have a standard deviation of 2% versus 5% in relationship to a risk-free asset which has a constant return of 5%.



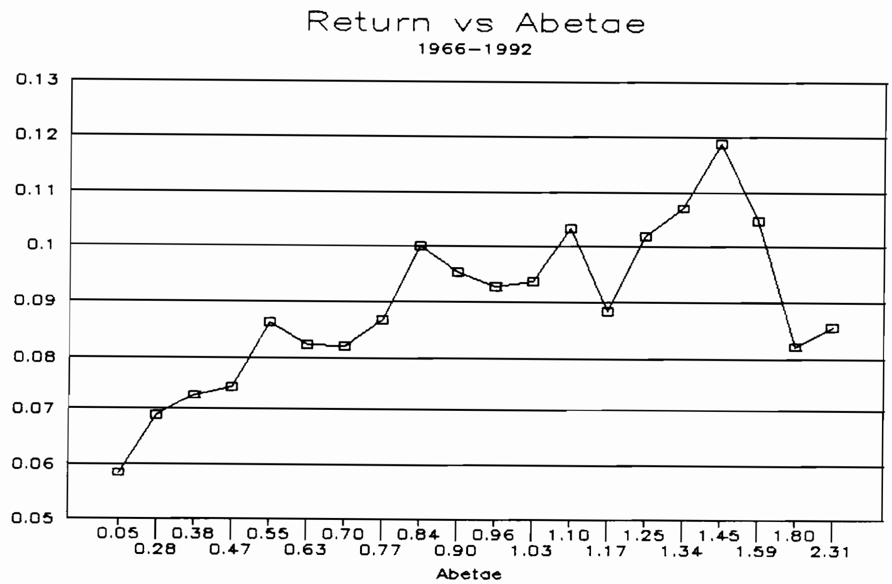
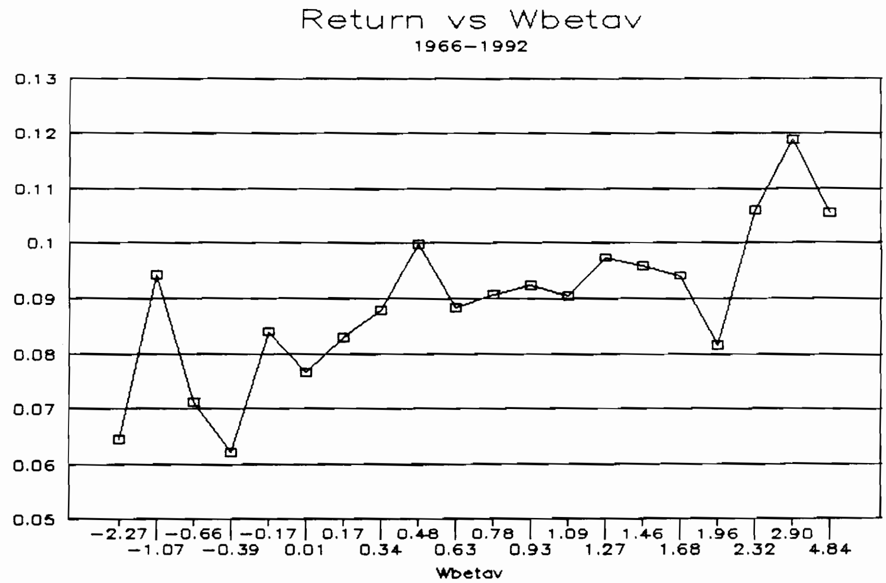


Figure 3

Figure 3 shows the relationship between the value of Abetav and Abetae at the beginning of each year with mean average portfolio returns over the subsequent year for the 1966-1992 period. The betas are calculated using the previous two years of monthly data.



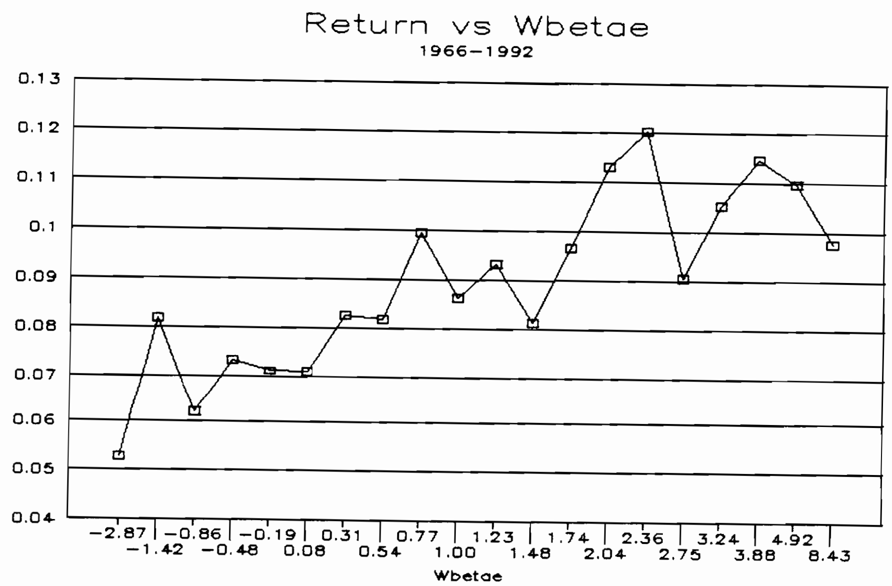


Figure 4

Figure 4 shows the relationship between the value of Wbetav and Wbetae at the beginning of each year with mean average portfolio returns over the subsequent year for the 1966-1992 period. The betas are calculated using the previous two years of monthly data.

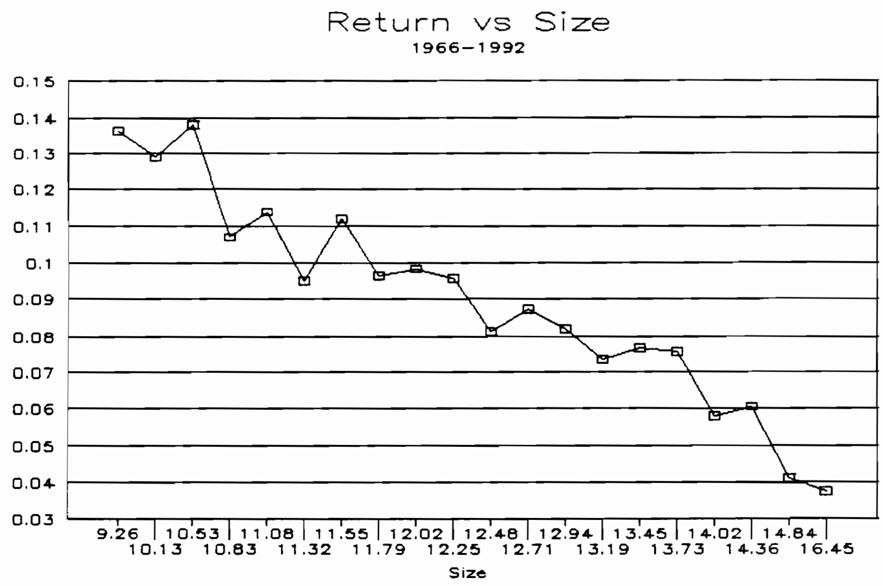
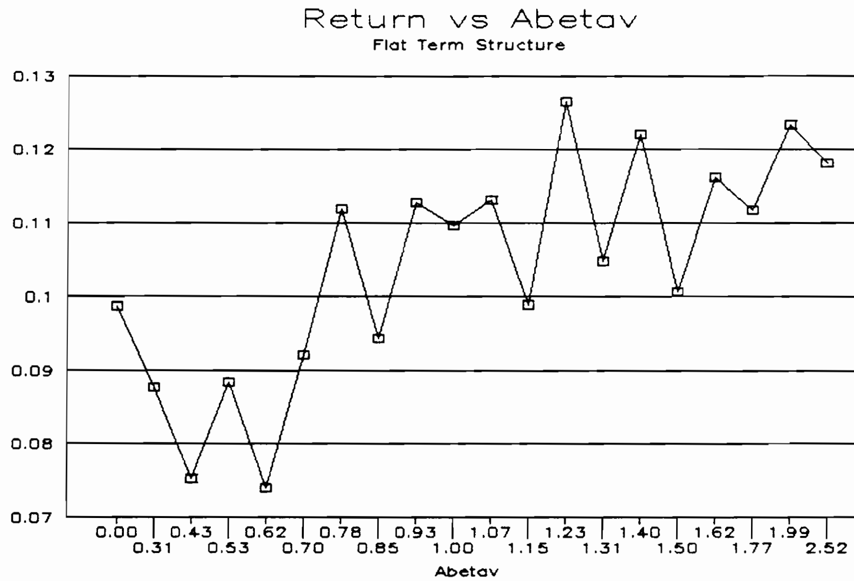


Figure 5

Figure 5 shows the relationship between the logarithm of size at the beginning of each year and mean average portfolio returns over the subsequent year for the 1966-1992 period. The betas are calculated using the previous two years of monthly data.



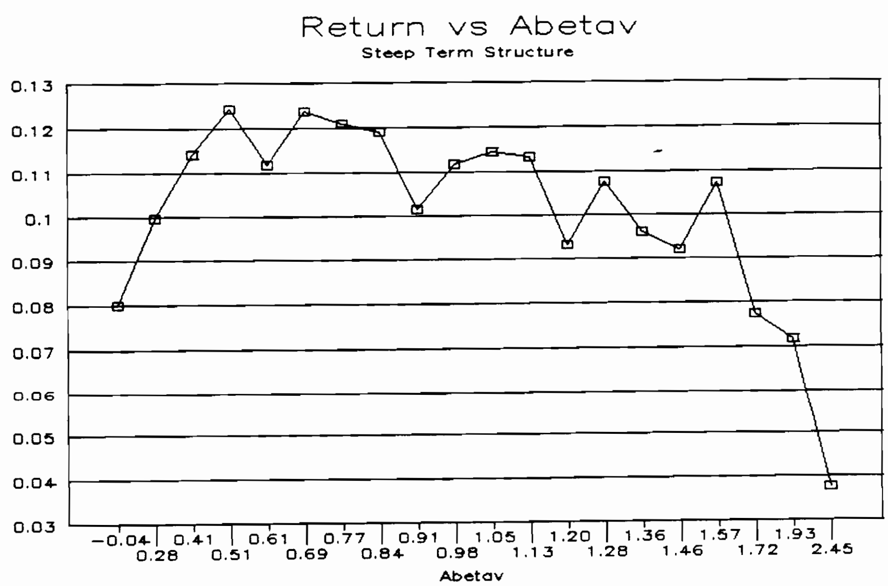


Figure 6

Figure 6 shows the difference in the relationship between Abetav and mean average portfolio returns in years subsequent to the smallest and largest differential between the two year bond yield and the one month T-bill for the years 1953-1992.

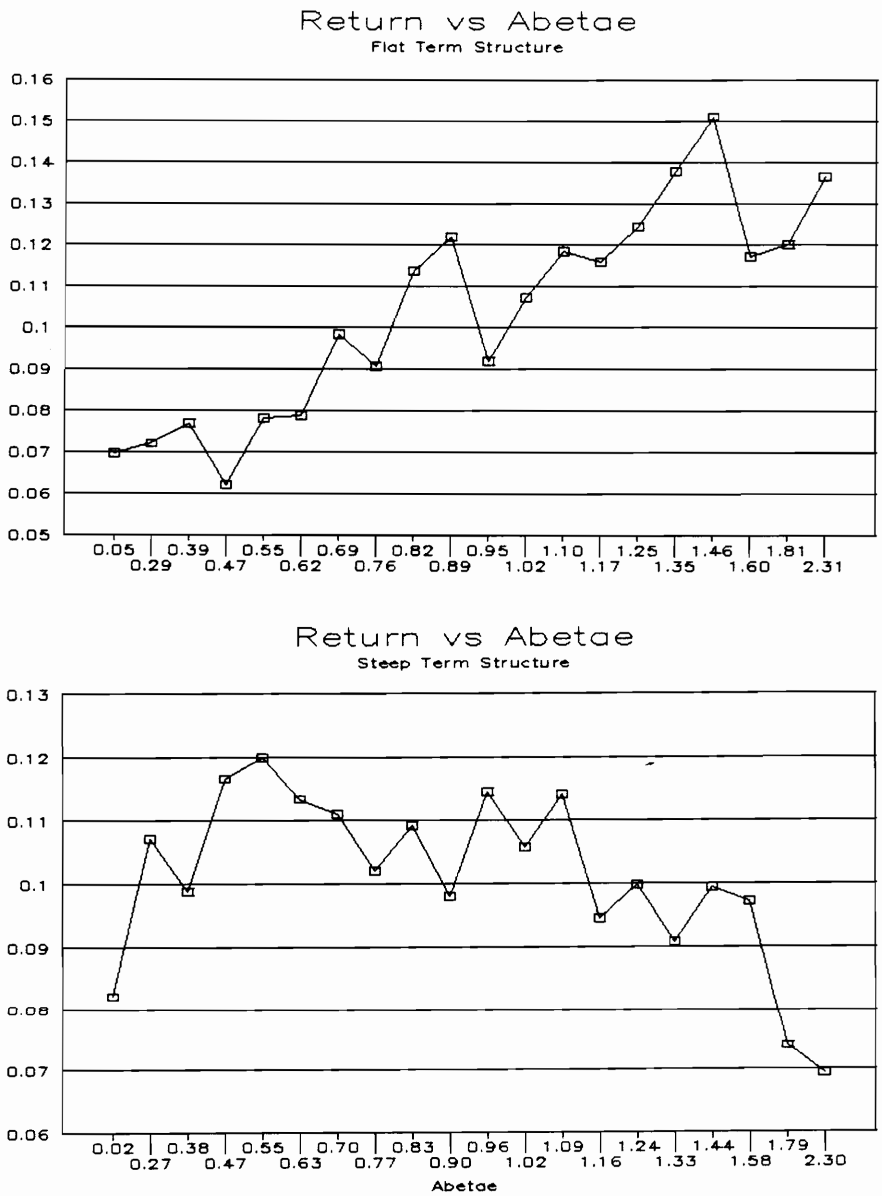


Figure 7

Figure 7 shows the difference in the relationship between Abetae and mean average portfolio returns in years subsequent to the smallest and largest differential between the two year bond yield and the one month T-bill for the years 1953-1992.

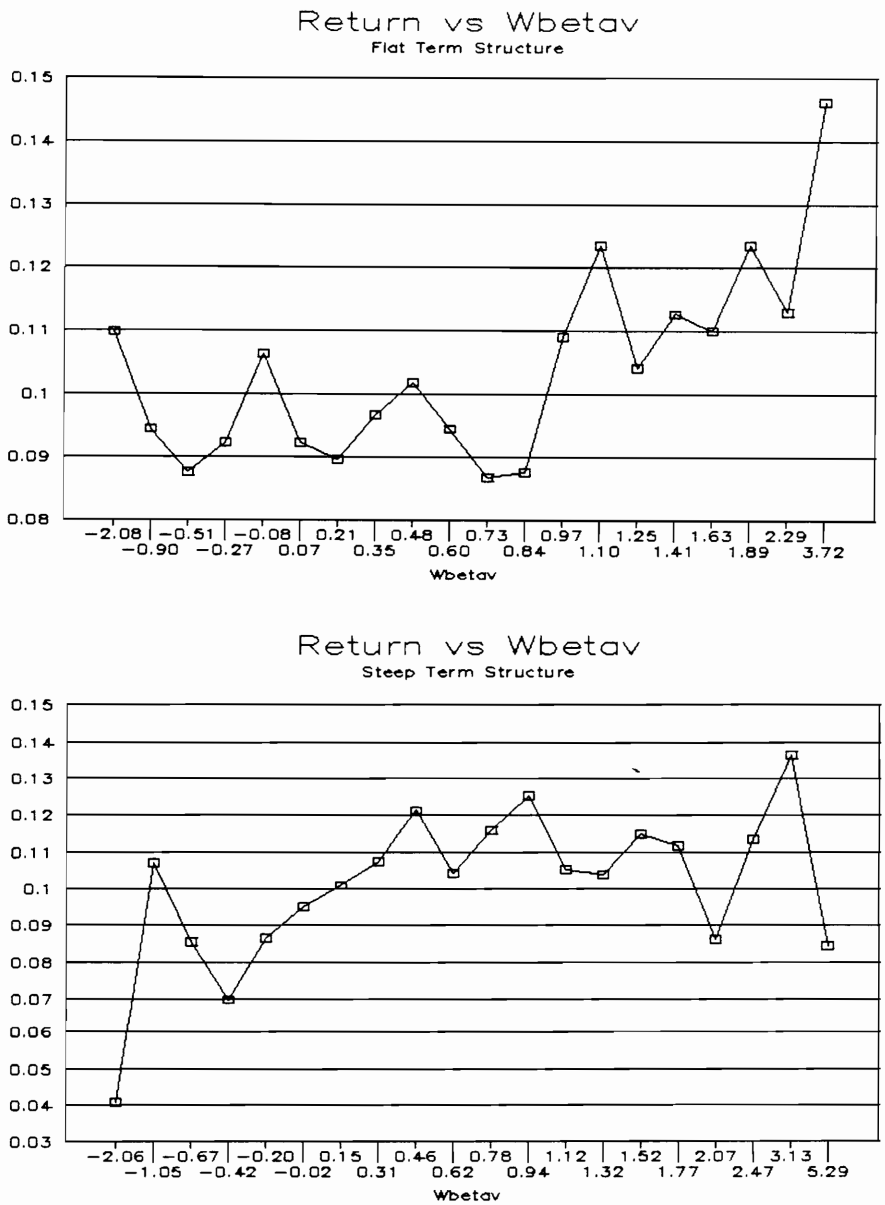


Figure 8

Figure 8 shows the difference in the relationship between Wbetav and mean average portfolio returns in years subsequent to the smallest and largest differential between the two year bond yield and the one month T-bill for the years 1953-1992.

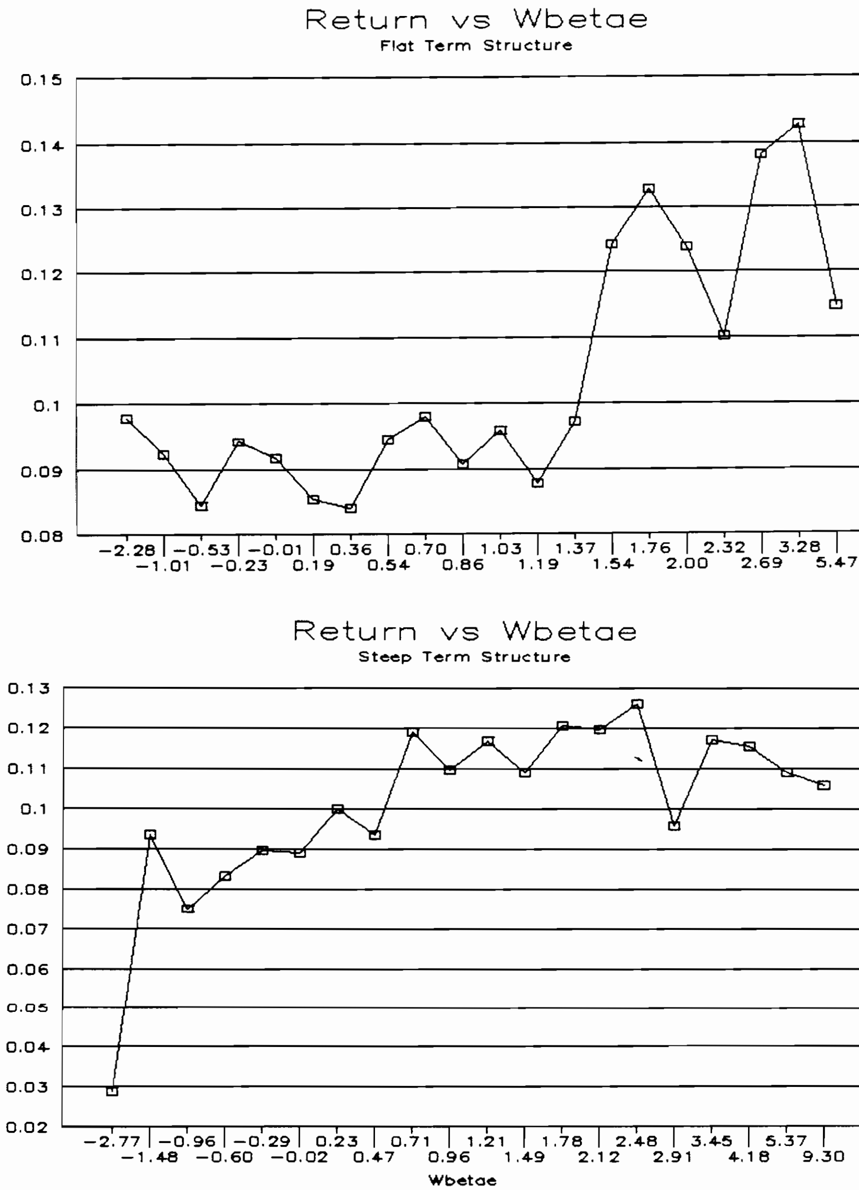
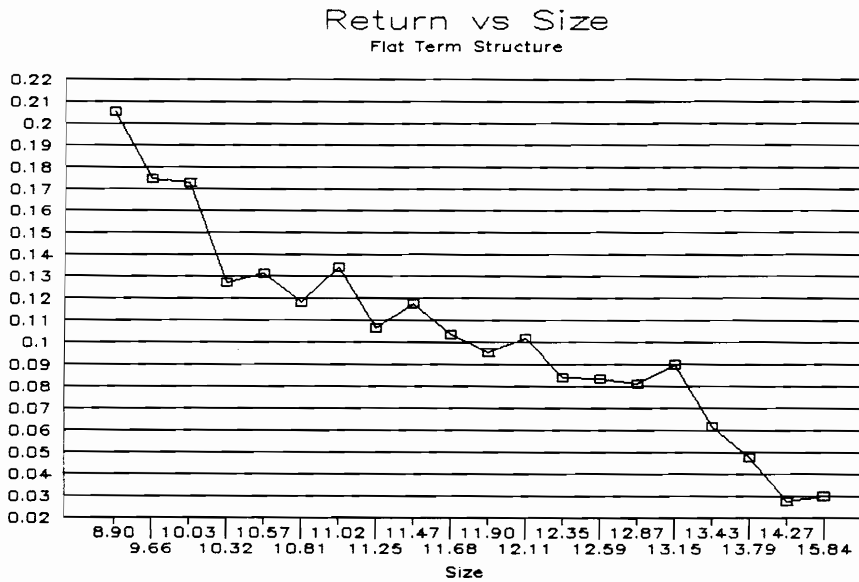


Figure 9

Figure 9 shows the difference in the relationship between Wbetae and mean average portfolio returns in years subsequent to the smallest and largest differential between the two year bond yield and the one month T-bill for the years 1953-1992.



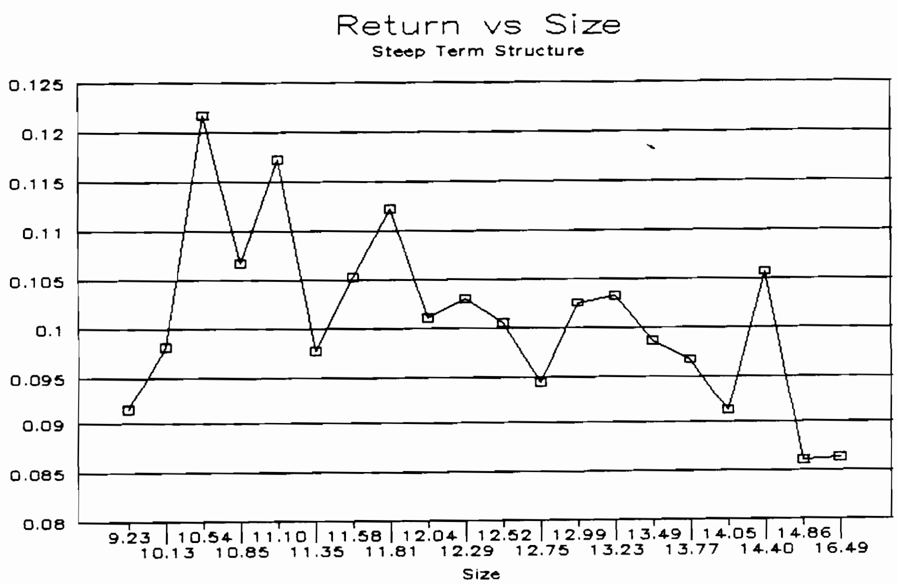


Figure 10

Figure 10 shows the dramatic difference in the relationship between the logarithm of size and mean average portfolio returns in years subsequent to the smallest and largest differential between the two year bond yield and the one month T-bill for the years 1953-1992.

Table 1

The following are regression results to determine whether the sequencing in inflation can explain the slope of the term structure, and whether the slope of the term structure explains higher market returns. TWMONE is the differential between the two year bond's annual yield and the one month T-bill's annual yield. VWO and VRO are the sequencing and variance measures respectively taken around the inflation rate on the 24th preceeding month. VW and VR and are the sequencing and variance measures respectively taken around the geometric average inflation rate over the preceeding 24 months. This is done for each year from 1953 to 1992 resulting in a total of 40 observations.

The regressions on the value weighted(VWMR) and equally weighted(EWMR) market indexes are done during the same time period. The value of the independent variable(TWMONE) is derived at the end of December for each preceeding year and regressed on the return of the index over the following year.

Variable	Parameter Estimate	Standard Error	T-stat	Significance
Dep. Var. - TWMONE				
R-square	0.0065	Adj R-sq	-0.0472	
INTERCEP	1.055	0.4203	2.51	0.0166
VWO	-0.0155	14.785	-0.008	0.9938
VRO	-30.8914	248.25	-0.124	0.9016
Dep. Var. - TWMONE				
R-square	0.0231	Adj R-sq	-0.0297	
INTERCEP	0.1006	0.4319	0.233	0.817
VW	-8.8978	45.624	-0.195	0.8464
VR	183.746	282.008	0.652	0.5187
Dep. Var. - VWMR				
R-square	0.0596	Adj R-sq	0.0349	
INTERCEP	0.08568	0.0384	2.23	0.0318
TYMONE	0.0453	0.0292	1.552	0.1289
Dep. Var. - EWMR				
R-square	0.0231	Adj R-sq	-0.0297	
INTERCEP	0.1301	0.0525	2.477	0.0178
TYMONE	0.02941	0.0399	0.736	0.466

Table 2

Table 2 summarizes regression results for 20 ranked portfolios with equal number of stocks. All betas are estimated with 24 months of data, placed in ranked portfolios and regressed on the subsequent year's return minus the return from holding one month T-bills. This is done for each year from 1941 to 1992. The letter 'V' at the end of a variable corresponds to the value weighted index while the letter 'E' stands for the equally weighted index.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
Ranked by Abetav					**Ranked by Abetae**				
R-square	0.4969	Adj R-sq	0.469		R-square	0.8486	Adj R-sq	0.8402	
INTERCEP	0.109361	0.00293	37.327	0.0001	INTERCEP	0.09326	0.003069	30.385	0.0001
ABETAV	0.009855	0.002337	4.217	0.0005	ABETAE	0.027729	0.002761	10.044	0.0001
R-square	0.6974	Adj R-sq	0.6618		R-square	0.8572	Adj R-sq	0.8404	
INTERCEP	-0.0726	0.054282	-1.337	0.1987	INTERCEP	-0.00182	0.094024	-0.019	0.9848
ABETAV	0.016822	0.002791	6.027	0.0001	ABETAE	0.034756	0.007473	4.651	0.0002
LAME	0.012894	0.003843	3.355	0.0038	LAME	0.006567	0.006491	1.012	0.3258
Ranked by Wbetav					**Ranked by Wbetae**				
R-square	0.7704	Adj R-sq	0.7576		R-square	0.6463	Adj R-sq	0.6267	
INTERCEP	0.112515	0.001938	58.061	0.0001	INTERCEP	0.112255	0.002594	43.282	0.0001
WBETAV	0.009855	0.001268	7.771	0.0001	WBETAE	0.006195	0.00108	5.736	0.0001
R-square	0.7735	Adj R-sq	0.7468		R-square	0.6513	Adj R-sq	0.6103	
INTERCEP	0.191133	0.162633	1.175	0.2561	INTERCEP	0.006716	0.214339	0.031	0.9754
WBETAV	0.010049	0.001357	7.408	0.0001	WBETAE	0.006112	0.001116	5.476	0.0001
LAME	-0.0058	0.011997	-0.483	0.635	LAME	0.007778	0.015795	0.492	0.6287
Ranked by Size					**Ranked by Size**				
R-square	0.9289	Adj R-sq	0.9249						
INTERCEP	0.323202	0.01333	24.246	0.0001					
LAME	-0.01677	0.001093	-15.332	0.0001					
R-square	0.9536	Adj R-sq	0.9481		R-square	0.9289	Adj R-sq	0.9205	
INTERCEP	0.652187	0.109872	5.936	0.0001	INTERCEP	0.323312	0.245083	1.319	0.2046
LAME	-0.02384	0.002519	-9.463	0.0001	LAME	-0.01677	0.009256	-1.812	0.0877
ABETAV	-0.22049	0.073262	-3.01	0.0079	ABETAE	-6.1E-05	0.137111	0	0.9996
R-square	0.9637	Adj R-sq	0.9595		R-square	0.9672	Adj R-sq	0.9633	
INTERCEP	0.379408	0.017007	22.309	0.0001	INTERCEP	0.387773	0.017226	22.511	0.0001
LAME	-0.01675	0.000803	-20.852	0.0001	LAME	-0.01854	0.000862	-21.514	0.0001
WBETAV	-0.07163	0.017719	-4.043	0.0008	WBETAE	-0.03338	0.007491	-4.456	0.0003

Table 3

Table 3 summarizes regression results for 20 ranked portfolios with equal number of stocks. All betas are estimated with 24 months of data, placed in ranked portfolios and regressed on the subsequent year's return minus the return from holding one month T-bills. This is done for each year from 1966 to 1992. The letter 'V' at the end of a variable corresponds to the value weighted index while the letter 'E' stands for the equally weighted index.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
Ranked by Abetav					**Ranked by Abetae**				
R-square	0.0289	Adj R-sq	-0.025		R-square	0.3425	Adj R-sq	0.306	
INTERCEP	0.092732	0.005521	16.797	0.0001	INTERCEP	0.074075	0.005654	13.101	0.0001
ABETAV	-0.00317	0.004324	-0.732	0.4735	ABETAE	0.015537	0.005074	3.062	0.0067
R-square	0.5935	Adj R-sq	0.5457		R-square	0.3777	Adj R-sq	0.3045	
INTERCEP	-0.32611	0.086279	-3.78	0.0015	INTERCEP	-0.09592	0.173484	-0.553	0.5875
ABETAV	0.013032	0.004405	2.959	0.0088	ABETAE	0.028137	0.013819	2.036	0.0576
LAME	0.02883	0.005933	4.859	0.0001	LAME	0.011412	0.01164	0.98	0.3406
Ranked by Wbetav					**Ranked by Wbetae**				
R-square	0.5472	Adj R-sq	0.5221		R-square	0.4937	Adj R-sq	0.4656	
INTERCEP	0.083754	0.002448	34.216	0.0001	INTERCEP	0.081705	0.003477	23.498	0.0001
WBETAV	0.006702	0.001437	4.664	0.0002	WBETAE	0.005181	0.001237	4.189	0.0006
R-square	0.5546	Adj R-sq	0.5022		R-square	0.5193	Adj R-sq	0.4627	
INTERCEP	0.194051	0.207439	0.935	0.3627	INTERCEP	-0.18954	0.285291	-0.664	0.5154
WBETAV	0.006957	0.001543	4.509	0.0003	WBETAE	0.004959	0.001262	3.93	0.0011
LAME	-0.00791	0.014873	-0.532	0.6018	LAME	0.019434	0.020439	0.951	0.355
Ranked by Size					**Ranked by Size**				
R-square	0.9286	Adj R-sq	0.9246						
INTERCEP	0.285269	0.0129	22.114	0.0001					
LAME	-0.01571	0.001027	-15.295	0.0001					
R-square	0.9333	Adj R-sq	0.9255		R-square	0.9335	Adj R-sq	0.9257	
INTERCEP	0.381322	0.088234	4.322	0.0005	INTERCEP	0.483353	0.175863	2.748	0.0137
LAME	-0.01769	0.002074	-8.529	0.0001	LAME	-0.02318	0.006694	-3.462	0.003
ABETAV	-0.06362	0.057815	-1.1	0.2865	ABETAE	-0.10744	0.095132	-1.129	0.2744
R-square	0.9326	Adj R-sq	0.9246		R-square	0.9305	Adj R-sq	0.9223	
INTERCEP	0.296211	0.01688	17.548	0.0001	INTERCEP	0.294334	0.018584	15.838	0.0001
LAME	-0.01566	0.001028	-15.242	0.0001	LAME	-0.01594	0.001097	-14.529	0.0001
WBETAV	-0.0141	0.01403	-1.005	0.3291	WBETAE	-0.00424	0.006164	-0.687	0.5011

Table 4

Table 4 summarizes regression results for 20 ranked portfolios with equal number of stocks which are first ranked by Abeta, Wbeta, or size, and then within each initial ranking are ranked again based on Abeta, Wbeta, or size. All betas are estimated with 24 months of data and regressed on the subsequent year's return minus the return from holding one month T-bills. This is done for each year from 1941 to 1992. The letter 'V' at the end of a variable corresponds to the value weighted index while the letter 'E' stands for the equally weighted index. The second rankings are done by the first variable in each regression excluding the intercept.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
First Ranked by Abetav					**First Ranked by Abetae**				
R-square	0.7101	Adj R-sq	0.694		R-square	0.5863	Adj R-sq	0.5633	
INTERCEP	0.112156	0.002233	50.221	0.0001	INTERCEP	0.114471	0.001977	57.909	0.0001
WBETAV	0.010148	0.001528	6.641	0.0001	WBETAE	0.004401	0.000871	5.051	0.0001
R-square	0.2968	Adj R-sq	0.2577		R-square	0.3103	Adj R-sq	0.272	
INTERCEP	0.126743	0.005644	22.455	0.0001	INTERCEP	0.126429	0.005057	25.002	0.0001
LAME	-0.01747	0.001405	-12.434	0.0001	LAME	-0.01606	0.001354	-11.867	0.0001
First Ranked by Wbetav					**First Ranked by Wbetae**				
R-square	0.2312	Adj R-sq	0.1884		R-square	0.7772	Adj R-sq	0.7648	
INTERCEP	0.109877	0.004867	22.575	0.0001	INTERCEP	0.097811	0.003168	30.874	0.0001
ABETAV	0.0092	0.003955	2.326	0.0319	ABETAE	0.023072	0.002912	7.923	0.0001
R-square	0.2518	Adj R-sq	0.2102		R-square	0.2058	Adj R-sq	0.1617	
INTERCEP	0.126259	0.005748	21.967	0.0001	INTERCEP	0.125662	0.005711	22.005	0.0001
LAME	-0.01744	0.001447	-12.048	0.0001	LAME	-0.01666	-0.0015	-11.131	0.0001
First ranked by size					**First ranked by size**				
R-square	0.0397	Adj R-sq	-0.0136		R-square	0.2971	Adj R-sq	0.258	
INTERCEP	0.115852	0.005326	21.752	0.0001	INTERCEP	0.108744	0.004587	23.706	0.0001
ABETAV	0.003683	0.004267	0.863	0.3994	ABETAE	0.01149	0.004166	2.758	0.0129
R-square	0.4702	Adj R-sq	0.4408		R-square	0.3555	Adj R-sq	0.3196	
INTERCEP	0.11524	0.002266	50.846	0.0001	INTERCEP	0.115436	0.002644	43.667	0.0001
WBETAV	0.006063	0.001517	3.997	0.0008	WBETAE	0.003542	0.001124	3.151	0.0055

Table 5

Table 5 summarizes regression results for 20 ranked portfolios with equal number of stocks which are first ranked by Abeta, Wbeta, or size, and then within each initial ranking, are ranked again based on Abeta, Wbeta, or size. All betas are estimated with 24 months of data and regressed on the subsequent year's return minus the return from holding one month T-bills. This is done for each year from 1966 to 1992. The letter 'V' at the end of a variable corresponds to the value weighted index while the letter 'E' stands for the equally weighted index. The second rankings are done by the first variable in each regression excluding the intercept.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
First Ranked by Abetav					**First Ranked by Abetae**				
R-square	0.5785	Adj R-sq	0.5551		R-square	0.4535	Adj R-sq	0.4231	
INTERCEP	0.082663	0.002528	32.695	0.0001	INTERCEP	0.083144	0.00281	29.59	0.0001
WBETAV	0.007716	0.001553	4.97	0.0001	WBETAE	0.004083	0.001056	3.865	0.0011
R-square	0.3312	Adj R-sq	0.2941		R-square	0.3915	Adj R-sq	0.3577	
INTERCEP	0.096545	0.006075	15.893	0.0001	INTERCEP	0.096736	0.005342	18.107	0.0001
LAME	-0.01832	0.001784	-10.27	0.0001	LAME	-0.01767	0.001441	-12.263	0.0001
First Ranked by Wbetav					**First Ranked by Wbetae**				
R-square	0.0072	Adj R-sq	-0.0479		R-square	0.1851	Adj R-sq	0.1398	
INTERCEP	0.090975	0.006783	13.412	0.0001	INTERCEP	0.078284	0.005958	13.138	0.0001
ABETAV	-0.00195	0.005405	-0.362	0.7219	ABETAE	0.011033	0.005456	2.022	0.0583
R-square	0.269	Adj R-sq	0.2284		R-square	0.1733	Adj R-sq	0.1274	
INTERCEP	0.09558	0.005789	16.509	0.0001	INTERCEP	0.094488	0.006067	15.574	0.0001
LAME	-0.01782	0.001422	-12.53	0.0001	LAME	-0.01684	0.001753	-9.604	0.0001
First ranked by size					**First ranked by size**				
R-square	0.0848	Adj R-sq	0.0339		R-square	0.0006	Adj R-sq	-0.0549	
INTERCEP	0.097865	0.008088	12.101	0.0001	INTERCEP	0.089418	0.006826	13.1	0.0001
ABETAV	-0.0082	0.006354	-1.291	0.213	ABETAE	-0.00066	0.006177	-0.107	0.9156
R-square	0.135	Adj R-sq	0.0869		R-square	0.2284	Adj R-sq	0.1856	
INTERCEP	0.086509	0.002919	29.632	0.0001	INTERCEP	0.084913	0.003305	25.689	0.0001
WBETAV	0.002947	0.001758	1.676	0.111	WBETAE	0.002784	0.001206	2.308	0.0331

Table 6

The information below delineates those years between 1953 and 1992 that are associated with the flatest and steepest rise in the term structure as measured by the difference between the annual yield on the two year bond and the annualized yield on the one month T-bill. Each year refers to the value as of December 31 of the preceeding year. Values are given for the 2 year T-bill, the one month T-bill, the difference between the two bills, the value weighted market return for each year, and the equally weighted market return for each year.

Flat						Steep					
Year	**2yr**	**1mth**	**2yr-1m**	**VW**	**EW**	**Year**	**2yr**	**1mth**	**2yr-1m**	**VW**	**EW**
1953	2.19	1.97	0.22	0.33	-2.87	1960	4.92	4.03	0.89	0.86	-1.52
1954	1.80	1.25	0.55	50.25	57.06	1961	2.78	1.87	0.91	27.44	29.47
1955	1.48	0.94	0.55	25.31	20.38	1962	3.38	2.43	0.95	-9.96	-12.74
1956	2.63	2.38	0.24	8.41	6.90	1968	5.70	4.43	1.27	12.74	30.23
1957	3.58	3.08	0.49	-10.55	-14.33	1970	8.11	7.00	1.11	1.29	-2.94
1958	2.55	2.72	-0.18	44.81	59.84	1972	4.83	3.40	1.42	17.64	8.44
1959	3.12	2.33	0.79	13.10	15.49	1973	5.92	4.97	0.94	-16.92	-29.30
1963	3.20	2.99	0.21	21.40	18.68	1976	6.61	5.29	1.32	26.24	45.49
1964	3.91	3.54	0.37	16.35	18.17	1977	5.30	4.29	1.00	-4.84	9.51
1965	3.93	3.48	0.45	14.07	28.67	1978	7.08	5.78	1.30	7.33	13.98
1966	4.81	4.35	0.46	-8.85	-7.11	1980	10.84	9.68	1.15	32.64	30.87
1967	4.79	4.56	0.23	26.83	50.14	1982	13.21	9.65	3.56	20.99	29.57
1969	6.29	6.27	0.02	-9.75	-20.40	1984	10.53	8.86	1.67	5.80	0.77
1971	5.40	4.53	0.87	15.85	19.48	1985	9.79	8.15	1.63	31.73	29.94
1974	6.69	7.61	-0.92	-26.77	-26.50	1986	7.85	6.54	1.31	17.31	14.36
1975	7.17	6.73	0.44	37.67	61.81	1987	6.30	4.78	1.51	2.92	-2.77
1979	9.63	8.95	0.68	21.87	35.38	1988	7.64	4.01	3.63	17.62	22.15
1981	12.39	13.10	-0.71	-4.15	5.87	1989	8.94	5.75	3.18	29.52	16.78
1983	9.27	8.53	0.74	22.76	33.40	1990	7.73	6.60	1.13	-4.34	-17.61
1992	4.73	3.88	0.85	8.26	17.99	1991	7.05	5.61	1.44	30.69	38.90
Mean =	4.98	4.66	0.32	13.36	18.90		7.23	5.66	1.57	12.33	12.68

Table 7

Table 7 compares results for 20 ranked portfolios with equal number of stocks for those years in which at the beginning of those years, the difference between the two year bond yield and the one month T-bill yield was the smallest and the largest as specified in table 5. All betas are estimated with 24 months of data using CRSP's value weighted index as the market proxy, placed in ranked portfolios, and regressed on the proceedings year's yearly return minus the return from holding one month T-bills. This is done for each year that is relevant within the 1953 to 1992 time period.

Variable	**Par. Estimate**	**Standard Error**	**T-Stat**	**Sig.**	**Variable**	**Par. Estimate**	**Standard Error**	**T-Stat**	**Sig.**
Flat Term Structure - Ranked by Abetav					**Steep Term Structure - Ranked by Abetav**				
R-square	0.4565	Adj R-sq	0.4263		R-square	0.3899	Adj R-sq	0.356	
INTERCEP	0.085701	0.005373	15.949	0.0001	INTERCEP	0.124406	0.007932	15.685	0.0001
ABETAV	0.016886	0.004343	3.888	0.0011	ABETAV	-0.02232	0.006582	-3.391	0.0033
R-square	0.4567	Adj R-sq	0.3928		R-square	0.8504	Adj R-sq	0.8328	
INTERCEP	0.095489	0.110522	0.864	0.3996	INTERCEP	-0.52744	0.090213	-5.847	0.0001
ABETAV	0.016568	0.005723	2.895	0.0101	ABETAV	0.003315	0.00488	0.679	0.5061
LAME	-0.00071	0.008007	-0.089	0.9304	LAME	0.044855	0.006202	7.233	0.0001
Flat Term Structure - Ranked by Wbetav					**Steep Term Structure - Ranked by Wbetav**				
R-square	0.4161	Adj R-sq	0.3836		R-square	0.1673	Adj R-sq	0.121	
INTERCEP	0.098683	0.003045	32.406	0.0001	INTERCEP	0.09608	0.005116	18.781	0.0001
WBETAV	0.007865	0.002196	3.581	0.0021	WBETAV	0.005404	0.002842	1.901	0.0734
R-square	0.5759	Adj R-sq	0.526		R-square	0.1685	Adj R-sq	0.0706	
INTERCEP	0.397336	0.118047	3.366	0.0037	INTERCEP	0.14263	0.296876	0.48	0.637
WBETAV	0.008865	0.001966	4.509	0.0003	WBETAV	0.005551	0.003069	1.809	0.0882
LAME	-0.02242	0.00886	-2.531	0.0216	LAME	-0.00334	0.021271	-0.157	0.8772
Flat Term Structure - Ranked by Size					**Steep Term Structure - Ranked by Size**				
R-square	0.9119	Adj R-sq	0.907		R-square	0.2379	Adj R-sq	0.1956	
INTERCEP	0.414067	0.022869	18.106	0.0001	INTERCEP	0.132929	0.013599	9.775	0.0001
LAME	-0.02598	0.001903	-13.65	0.0001	LAME	-0.00256	0.00108	-2.37	0.0291
R-square	0.9226	Adj R-sq	0.9135		R-square	0.2732	Adj R-sq	0.1877	
INTERCEP	0.599065	0.122921	4.874	0.0001	INTERCEP	0.055127	0.086693	0.636	0.5333
LAME	-0.02871	0.002558	-11.222	0.0001	LAME	-0.00152	0.001577	-0.965	0.3481
ABETAV	-0.14058	0.091888	-1.53	0.1444	ABETAV	0.061422	0.067585	0.909	0.3762
R-square	0.9434	Adj R-sq	0.9367		R-square	0.3493	Adj R-sq	0.2728	
INTERCEP	0.494484	0.032241	15.337	0.0001	INTERCEP	0.124125	0.013921	8.916	0.0001
LAME	-0.02799	0.0017	-16.461	0.0001	LAME	-0.00364	0.001207	-3.018	0.0078
WBETAV	-0.08268	0.026883	-3.075	0.0069	WBETAV	0.025421	0.014898	1.706	0.1061

Table 8

Table 8 compares results for 20 ranked portfolios with equal number of stocks for those years in which at the beginning of those years, the difference between the two year bond yield and the one month T-bill yield was the smallest and the largest as specified in table 13. All betas are estimated with 24 months of data using CRSP's equally weighted index as the market proxy, placed in ranked portfolios and regressed on the proceedings year's yearly return minus the return from holding one month T-bills. This is done for each year that is relevant within the 1953 to 1992 time period.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
Flat Term Structure - Ranked by Abetae					**Steep Term Structure - Ranked by Abetae**				
R-square	0.6938	Adj R-sq	0.6768		R-square	0.309	Adj R-sq	0.2706	
INTERCEP	0.06636	0.006741	9.844	0.0001	INTERCEP	0.114459	0.005463	20.952	0.0001
ABETAE	0.038619	0.006048	6.386	0.0001	ABETAE	-0.01398	0.004927	-2.837	0.0109
R-square	0.7035	Adj R-sq	0.6687		R-square	0.6823	Adj R-sq	0.645	
INTERCEP	0.19516	0.172324	1.133	0.2731	INTERCEP	-0.40179	0.115558	-3.477	0.0029
ABETAE	0.029763	0.013329	2.233	0.0393	ABETAE	0.023918	0.009149	2.614	0.0181
LAME	-0.00908	0.01214	-0.748	0.4647	LAME	0.034611	0.007743	4.47	0.0003
Flat Term Structure - Ranked by Wbetae					**Steep Term Structure - Ranked by Wbetae**				
R-square	0.4153	Adj R-sq	0.3828		R-square	0.3126	Adj R-sq	0.2744	
INTERCEP	0.096317	0.003934	24.485	0.0001	INTERCEP	0.093797	0.004865	19.281	0.0001
WBETAE	0.007245	0.002026	3.575	0.0022	WBETAE	0.004595	0.001606	2.861	0.0104
R-square	0.4161	Adj R-sq	0.3474		R-square	0.3426	Adj R-sq	0.2653	
INTERCEP	0.124128	0.176828	0.702	0.4922	INTERCEP	-0.25085	0.391515	-0.641	0.5303
WBETAE	0.007242	0.002084	3.476	0.0029	WBETAE	0.004174	0.001685	2.477	0.0241
LAME	-0.00208	0.013236	-0.157	0.8768	LAME	0.024653	0.028004	0.88	0.3909
Flat Term Structure - Ranked by Size					**Steep Term Structure - Ranked by Size**				
R-square	0.9119	Adj R-sq	0.907		R-square	0.2379	Adj R-sq	0.1956	
INTERCEP	0.414067	0.022869	18.106	0.0001	INTERCEP	0.132929	0.013599	9.775	0.0001
LAME	-0.02598	0.001903	-13.65	0.0001	LAME	-0.00256	0.00108	-2.37	0.0291
R-square	0.9124	Adj R-sq	0.9021		R-square	0.238	Adj R-sq	0.1483	
INTERCEP	0.48496	0.229545	2.113	0.0497	INTERCEP	0.139829	0.156973	0.891	0.3855
LAME	-0.02836	0.007916	-3.583	0.0023	LAME	-0.0028	0.005554	-0.504	0.6206
ABETAE	-0.04354	0.140251	-0.31	0.76	ABETAE	-0.00402	0.091115	-0.044	0.9653
R-square	0.9436	Adj R-sq	0.937		R-square	0.3858	Adj R-sq	0.3136	
INTERCEP	0.490214	0.030999	15.814	0.0001	INTERCEP	0.112724	0.016048	7.024	0.0001
LAME	-0.02861	0.001782	-16.053	0.0001	LAME	-0.00248	0.000999	-2.479	0.024
WBETAE	-0.04234	0.013693	-3.092	0.0066	WBETAE	0.012558	0.006206	2.023	0.059

Table 9

Table 9 compares regression results for 20 ranked portfolios with equal number of stocks which are first ranked by Abetav, Rbetav, Wbetav, or Wbetgv and then within each initial ranking, are ranked again based on Abetav, Rbetav, Wbetav, Wbetgv, or size. The comparison is between those years in which the difference between the two year bond yield and the one month T-bill yield was the smallest and the largest as specified in table 13 between 1953 and 1992. All betas are estimated with 24 months of data and regressed on the subsequent year's return minus the return from holding one month T-bills. The letter 'V' at the end of a variable stands for the value weighted index. The second rankings are done by the first variable in each regression excluding the intercept.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
Flat Term Structure - First ranked by Abetav					**Steep Term Structure - First ranked by Abetav**				
R-square	0.3519	Adj R-sq	0.3159		R-square	0.4563	Adj R-sq	0.4261	
INTERCEP	0.09719	0.004024	24.154	0.0001	INTERCEP	0.094584	0.002968	31.865	0.0001
WBETAV	0.009424	0.003015	3.126	0.0058	WBETAV	0.006669	0.001716	3.887	0.0011
R-square	0.9245	Adj R-sq	0.9203		R-square	0.2257	Adj R-sq	0.1827	
INTERCEP	0.444805	0.023055	19.293	0.0001	INTERCEP	0.153855	0.022912	6.715	0.0001
LAME	-0.02931	0.001974	-14.85	0.0001	LAME	-0.00425	0.001855	-2.291	0.0343
Flat Term Structure - First ranked by Wbetav					**Steep Term Structure - First ranked by Wbetav**				
R-square	0.3205	Adj R-sq	0.2828		R-square	0.2823	Adj R-sq	0.2425	
INTERCEP	0.088126	0.005979	14.74	0.0001	INTERCEP	0.119547	0.008126	14.712	0.0001
ABETAV	0.01429	0.004904	2.914	0.0093	ABETAV	-0.01825	0.006857	-2.661	0.0159
R-square	0.9224	Adj R-sq	0.9181		R-square	0.5838	Adj R-sq	0.5607	
INTERCEP	0.386553	0.019394	19.931	0.0001	INTERCEP	0.197783	0.019209	10.296	0.0001
LAME	-0.0243	0.001661	-14.63	0.0001	LAME	-0.00782	0.001555	-5.025	0.0001
Flat Term Structure - First ranked by Size					**Steep Term Structure - First ranked by Size**				
R-square	0.1949	Adj R-sq	0.1502		R-square	0.3851	Adj R-sq	0.351	
INTERCEP	0.089733	0.007405	12.117	0.0001	INTERCEP	0.127578	0.009202	13.865	0.0001
ABETAV	0.012515	0.005996	2.087	0.0513	ABETAV	-0.0257	0.007654	-3.358	0.0035
R-square	0.1094	Adj R-sq	0.0599		R-square	0.0811	Adj R-sq	0.0301	
INTERCEP	0.100862	0.003473	29.045	0.0001	INTERCEP	0.098084	0.00384	25.544	0.0001
WBETAV	0.003826	0.002573	1.487	0.1544	WBETAV	0.002727	0.002164	1.261	0.2236

Table 10

Table 10 compares regression results for 20 ranked portfolios with equal number of stocks which are first ranked by Abetae, Rbetae, Wbetae, or Wbetge, and then within each initial ranking are ranked again based on Abetae, Rbetae, Wbetae, Wbetge, or size. The comparison is between those years in which the difference between the two year bond yield and the one month T-bill yield was the smallest and the largest as specified in table 13 between 1953 and 1992. All betas are estimated with 24 months of data and regressed on the subsequent year's return minus the return from holding one month T-bills. The letter 'E' at the end of a variable corresponds to the equally weighted index. The second rankings are done by the first variable in each regression excluding the intercept.

Variable	Par. Estimate	Standard Error	T-Stat	Sig.	Variable	Par. Estimate	Standard Error	T-Stat	Sig.
Flat Term Structure - First ranked by Abetae					**Steep Term Structure - First ranked by Abetae**				
R-square	0.2932	Adj R-sq	0.2539		R-square	0.3762	Adj R-sq	0.3415	
INTERCEP	0.099561	0.002887	34.489	0.0001	INTERCEP	0.093513	0.003961	23.608	0.0001
WBETAE	0.004218	0.001544	2.732	0.0137	WBETAE	0.004563	0.001385	3.294	0.004
R-square	0.8957	Adj R-sq	0.8899		R-square	0.2575	Adj R-sq	0.2163	
INTERCEP	0.425802	0.025984	16.387	0.0001	INTERCEP	0.15711	0.022304	7.044	0.0001
LAME	-0.02767	0.002225	-12.432	0.0001	LAME	-0.00451	0.001806	-2.499	0.0224
Flat Term Structure - First ranked by Wbetae					**Steep Term Structure - First ranked by Wbetae**				
R-square	0.5902	Adj R-sq	0.5674		R-square	0.2022	Adj R-sq	0.1579	
INTERCEP	0.076744	0.005925	12.953	0.0001	INTERCEP	0.113128	0.006419	17.623	0.0001
ABETAE	0.027574	0.005416	5.092	0.0001	ABETAE	-0.01261	0.005902	-2.136	0.0467
R-square	0.9137	Adj R-sq	0.9089		R-square	0.3234	Adj R-sq	0.2859	
INTERCEP	0.388069	0.020662	18.782	0.0001	INTERCEP	0.173454	0.024499	7.08	0.0001
LAME	-0.02443	0.00177	-13.806	0.0001	LAME	-0.00582	0.001984	-2.934	0.0089
Flat Term Structure - First ranked by Size					**Steep Term Structure - First ranked by Size**				
R-square	0.3774	Adj R-sq	0.3428		R-square	0.4632	Adj R-sq	0.4334	
INTERCEP	0.082394	0.007207	11.432	0.0001	INTERCEP	0.122488	0.00631	19.412	0.0001
ABETAE	0.021492	0.006506	3.303	0.004	ABETAE	-0.0226	0.005733	-3.941	0.001
R-square	0.0737	Adj R-sq	0.0222		R-square	0.2838	Adj R-sq	0.244	
INTERCEP	0.099878	0.005001	19.974	0.0001	INTERCEP	0.096142	0.003263	29.463	0.0001
WBETAE	0.003176	0.002654	1.197	0.2469	WBETAE	0.002918	0.001093	2.671	0.0156

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