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HIGHER ORDER MOMENTS RESAMPLING

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ABSTRACT

This paper develops a set of portfolio optimization models that involve a resampling approach of the higher order moments of financial assets return distributions. Specifically, the first four moments are examined. The Resampled Efficiency (RE) techniques introduce Monte Carlo methods to properly represent investment information uncertainty in computing minimum variance (MV) portfolio optimality. Notwithstanding the central limit theorem, for both the academic and financial communities it is a well known fact that stock market returns exhibit latent higher moment risk in the form of negative skewness and high kurtosis. Taking cue from these considerations we have added higher-order moments to the resampling rule. We discuss the solution of the higher order moments resampling approach by replaying an investment game. The game compares the performance of a player using four portfolio schemes for determining portfolio weights using a Monte Carlo based resampling approach. Extensive computational results are obtained on a real-world dataset with two different resampling approaches. Surprisingly, when higher moments of stock return distributions are accounted for in the resampling optimisation algorithm success is mixed.

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KEYWORDS: higher-order moments, resampled efficiency (RE), Monte Carlo, MV portfolio optimality

INTRODUCTION

Optimal asset allocation has generated considerable interest in finance since the seminal papers by Merton (1969) and Samuelson (1969) but important caveats remain. One of these caveats is estimation error in parameters. Empirical evidence indicates that asset returns are partially predictable. Three methods are currently available to address estimation errors. One deals with changing the objective function to explicitly include estimation risk. One form of this approach is often called "robust" optimization and aims at explicitly incorporating estimation error into the portfolio optimisation process (Täutäuncău and Käoenig, 2004, Ceria and Stubbs, 2005). According to Täutäuncău and Käoenig (2004) robust optimization consists of finding solutions to optimization problems with uncertain input parameters. Uncertainty is described using an uncertainty set which includes all, or most, possible realizations of the uncertain input parameters. On this issue Sherer (2006) show that the optimality of robust optimisation critically depends on the complicated interplay between risk aversion and uncertainty aversion.

An alternate is Bayesian methods which have a very strong rooting in decision theory. This approach involves rescaling the input parameters to certainty equivalent values. This latter approach consist of using of quadrature methods (Ang and Bekaert (2001), Lynch (2001)) or resampling methods based on Monte Carlo simulations (Barberis (2000)) to find a range of optimal portfolios. The user picks the one preferred according to a certain objective function. Quadrature methods may not be very precise when the underlying asset return distributions are not Gaussian, as is strongly suggested by empirical research, (see Bollerslev et al., 1992 and Gallant and Tauchen, 1989). While Monte Carlo methods do not suffer from this problem, they can be computationally expensive to use as they rely on discretization of the state space and use grid methods. Besides with regard to other approaches, resampling methods have additional benefits related to trading costs. In this article we focus on the resampling approach. Resampling is based on a stochastic simulation procedure where resampled returns and standard deviations are derived stochastically using the original historical optimiser inputs (New Frontier Advisors, 2001).

Markowitz and Usmen (2003) show resampled efficiency optimized portfolios exhibited superior performance on average and in each of their 30 individual tests. Previous works have focused only on resampling the mean and variance ignoring higher order moments. They also focus their research effort on mean-variance approaches. This article enriches the previous literature on both fronts by using the higher moments resampling approach with regard to model portfolios. Specifically, we examine Markowitz Mean-Variance, Tracking Error Minimization (TEM), Mean Absolute Deviation Minimization (MADM) and Shortfall Probability Minimization Models (SPM). The remainder of the paper is organized as follows. In Section 2, we present the empirical methodology that we use in Section 3. In Section 3 we describe the data source and portfolio strategies. Next empirical results obtained from a dataset consisting of equity returns are presented. Section 4 summarizes the findings and provides some concluding remarks.

LITERATURE REVIEW

Many researchers in empirical and theoretical articles have argued that the higher moments of return distributions, such as skewness and Kurtosis, cannot be neglected unless there is reason to believe that the equity returns have a normal (symmetrical) probability distribution. When a set of asset returns has a multivariate normal distribution, the correlation matrix contains all the information about the statistical dependence among them. Unfortunately, as it has been observed in various recent papers (e.g. Embrechts et al., 2002), there is ample evidence that the behaviour of stock market returns does not agree with the frequently assumed normal distribution. Moreover, it is well known that stock market returns have negative skewness and excess kurtosis. This stylized fact has been supported by a huge collection of empirical studies. Some papers on this issue include Ibbotson, (1975), Prakash et al., (2001), Bates (1996), Jorion (1988), Hwang and Satchell (1999), and Harvey and Siddique (1999, 2000).

The role of higher moments has become increasingly important in the literature mainly because the traditional measure of risk, variance, has failed to fully capture the "true risk" of stock market returns. Homogeneous and severely asymmetric distributions show that the mean-variance criterion does not correctly approximate expected utility. In this case an higher moment optimization better approximates the expected utility (Athayde and Flôres, 2004). However analytical closed solutions are available only if marginal distributions have defined functions such as the multivariate skewed Student's t (Jondeau and Rockinger, 2005). Other marginal distributions do not have closed formulas to be applied yet.

Recently, elegant non-parametric solutions to the optimization problem with co-skewness and co-kurtosis matrix have been proposed by Jondeau and Rockinger (2006). However they propose an approximation of the utility function given by Taylor expansion up to order four and thus they rely on a defined utility function (CARA) for the investor. A recent work by Harvey, Liechty et al., (2004) propose a method to address both estimation risk and the inclusion of higher moments in the portfolio selection. They document that the multivariate normal distribution is not useful for modelling portfolio returns because it does not allow for skewness of returns. Also they suggest specifying a Bayesian probability model for the joint distribution of the asset returns when these returns are driven by a Skew Normal distribution. This allows us to capture the asymmetry of the returns and include it in the portfolio selection task. In such a Bayesian framework the expected utilities are then maximized using predictive returns.

Konno et al. (1993) consider the problem where the portfolio's skewness is maximized under constraints on expected return and variance. In the presence of higher order moments, optimizing with respect to mean and variance only can lead to highly undesirable effects, as the mean-variance optimization problem is oblivious to skewness and kurtosis. Trying to circumvent some of the failures of the MV approach, several researchers have proposed advances to the traditional mean variance theory in order to include higher moments in the portfolio optimisation task (see Athayde and Flores (2001), Adcock (2002), Jondeau and Rockinger (2004) among others). For example, Harvey and Siddique (1999, 2000) pointed out that the skewness of stock returns is relevant to portfolio selection. Their argument is if asset returns have no diversifiable co-skewness, expected returns must reward for it. Lai (1991), Chunhachinda et al. (1997), Prakash et al. (2003) and Sun and Yan (2003) have applied the polynomial goal programming method (PGP), introduced in financial research by Tayi and Leonard (1988), to the portfolio selection with skewness. In the hedge fund context, recent research has proposed new methods to include higher moments in the hedge fund portfolio selection. A work by Bacmann and Bosshard (2003) suggests using an asymmetric risk measure in order to penalise fat negative tailed investments and reward investments with fat positive tails. The role of skewness and kurtosis has also been remarked by Niu and Cui (2002), and Sun and Yan (2003). This suggests that true risk may be a multi-dimensional concept and that other measures of distributional shape such as higher moments can be useful in obtaining a better description of multi-dimensional risk.

Resampled Efficiency™ (RE) optimization and rebalancing, first proposed in Michaud (1998), introduces a multivariate normal Monte Carlo simulation for asset returns whose parameters are calibrated on the historical vectors of average returns, average standard deviations and the correlation coefficient matrix, to more realistically reflect the uncertainty in investment information. The process of stochastic simulations, otherwise known as Monte Carlo simulations, is a mathematical technique that factors in randomness (Kautt, 2001). Parametric Resampling converts all input parameters into a multivariate normal distribution and takes random draws from the multivariate normal to generate new scenarios. An optimal portfolio for each scenario formed and a method to average across all optimal portfolios to find a good compromise is developed.

RE technology also includes statistically rigorous portfolio trading and monitoring rules and tests for assets avoiding the often ineffective and costly rebalancings typical of the MV optimization asset management process making resampled portfolios more stable and have the added benefits of simplifying the management of a portfolio. In this regard Michaud (1998) suggests that data input resampling leads to asset allocations that are more robust and intuitive relative to classic mean-variance analysis using historical data. It is worth noting that Michaud's approach does not consider tail dependences and extreme (negative) returns (tail risk), not assumed in the classical multinormality assumption.

To cover this gap in literature, we replay an investment game that compares the performance of a player using Monte Carlo based resampling approach advocated in Michaud (1998), with a player that uses a resampling approach in which also high moments namely skewness and kurtosis are taken into account. Moreover, we perform high order resampling with regard to several model portfolios. Specifically, Mean-Variance, Tracking Error Minimization (TEM), Mean Absolute Deviation Minimization (MADM) and Shortfall Probability Minimization Models (SPM). The proposed heuristic method can be analytically divided in four steps that we perform for each portfolio model.

Step 1. Sample a mean vector and covariance matrix of returns from a distribution of both cantered at the original (point estimate) values normally used in portfolio optimization. Unlike all previous applications found in literature we consider the first four moments for each sample distribution namely mean, variance Kurtosis and Skewness. The kurtosis is a function of both the second and fourth central moments of the underlying distribution; that is, the kurtosis is a multi-dimensional measure of risk. It then follows, in general, that risk is multidimensional and depends not only on the scale but also the shape of the underlying distribution of returns.

THE MODEL

We consider every stock return, as a process $\{y_t\}_{t=1,2,..,N}$ assuming that the y_t's are independent and identically distributed with a cumulative distribution function *F*. The conventional coefficients of skewness and kurtosis for y_t are given by:

$$SK_t = E\left(\frac{y_t-\mu}{\sigma}\right)^3 \qquad KR_t = E\left(\frac{y_t-\mu}{\sigma}\right)^4 - 3 \tag{1}$$

where $\mu = E(y_t)$ and $\sigma^2 = E(y_t - \mu)^2$, and expectation E is taken with respect to F. Given the data $\{y_t\}_{t=1,2,..,N}$ SK_t and KR_t are usually estimated by the sample averages

$$\widehat{SK}_t = T^{-1}\sum_{t=1}^{N}\left(\frac{y_t-\hat{\mu}}{\hat{\sigma}}\right)^3 \qquad \widehat{KR}_t = T^{-1}\sum_{t=1}^{N}\left(\frac{y_t-\hat{\mu}}{\hat{\sigma}}\right)^4 - 3 \tag{2}$$

where $\hat{\mu}=T^{-1}\sum_{t=1}^{N} y_t$, $\widehat{\sigma^2}=T^{-1}\sum_{t=1}^{N}(y_t - \hat{\mu})^2$

Step 2. The simulated resampled data were used as data inputs for the optimizer, in other words these stochastically derived inputs are, in turn, used as inputs into a portfolio optimization algorithms. Step 3, the simulation (repetition of Step 1 and Step 2) was subjected to 500 trials. We get 500 mean vectors and covariance matrices. Given the level of uncertainty inherent in determining inputs, the resampling process leads to many alternative outcomes based on the original inputs. The number of simulated observations is a free parameter of the RE optimization process and is a natural way to model the amount of confidence an investor has in their risk-return estimates. So the number of simulated observations is a mechanism for tuning the optimization process according to the level of certainty and time horizon associated with estimates. Step 4, the listed asset allocation percentages were averaged for the respective portfolios.

It is possible to divide portfolio models, at least chronologically, into two families: the 'traditional models' (CAPM, Markowitz), which constitute the modern theory of portfolio choices, and the so-called 'post-modern' models (MADM, TEV, SPM).

The Tracking Error Minimization Model (TEM) is a parametric model based on two factors: the expected return and the variance of the differential between the performance of the portfolio and the performance of the benchmark, which is the square of the Tracking Error Volatility. The objective is to seek a weight to assign to each asset in the portfolio, in order to obtain the minimum portfolio tracking error, with the constraints that the expected returns to be achieved, are equal to or below a preset level, and that the weightings of the activities are positive and have sums equal to 1.

A generalization of the structure of the constraints is also permitted, in the sense that the presence of arbitrary linear constraints on the structure of the portfolio or lower (upper) bound is permitted.

The objective function to minimize is:

$$\textit{Min variance} \sum(\omega_i \cdot r_i) - \sum(\chi_i \cdot r_i) \tag{3}$$

where:

χ_i = fraction of the benchmark portfolio held in asset i.

$\sum(\chi_i \cdot r_i) = r_t$ (benchmark return)

ω_i = asset i's weight by optimization process

The Mean Absolute Deviation Minimization Model (MADM) is a non-parametric model, based on the idea of finding a benchmark, against which a predetermined over-performance is required. It seeks therefore to achieve a certain return trying, at the same time, not to depart too much from the chosen benchmark. As the risk measure, the distance from the benchmark is adopted, represented by the absolute median difference, calculated over a predetermined period of time. The goal is to find the weight to assign to each security in the portfolio, with the condition of minimum absolute mean deviation, and the security return, or better the portfolio return, expected to be achieved, is equal to or less than a value set in advance. Moreover, the weights of all activities must be positive and of sum equal to 1. It also permits the presence of arbitrary linear constraints in the structure of the portfolio. The model does not take into account hypotheses on the shape of the distribution returns, the only implicit assumption is that the return distribution, observed in the past, remains in the future. The objective function to minimize is:

$$Min_{\omega} \sum \left| \sum (\omega_i \cdot r_i) - \sum (\chi_i \cdot r_{it}) \right| \qquad (4)$$

where:

r_i = asset i's return

ω_i = asset i's weight by optimization process

χ_i = fraction of the benchmark portfolio held in asset i.

$\sum (\chi_i \cdot r_{it}) = r_{bt}$ = benchmark return

Remaining with models designed to optimize performance against a benchmark, the Shortfall Probability Minimization (SPM) model aims to reduce the probability of occurrence of an underperformance of the portfolio against a benchmark. The probability of shortfall is estimated over time, by relating the number of periods in which there was a shortfall to the total over the time periods preselected.

The aim of the model of minimizing the shortfall probability is, therefore, to find the weight assigned to each financial instrument so that in a given timeframe, the shortfall frequency is minimal, with the constraint that the expected return is equal to or less than a value to be assigned, and the sum of the weightings is equal to 1. Other restrictions can also be imposed on the linear weights of financial assets.
In this model, as with the previous, the only assumptions on the distribution of returns made are that, they are the product of a stationary process (in this way the past contains useful information for future distribution). The objective function to minimize is:

$$\min_{\omega} \sum_{t=1}^{M} \frac{I_t}{m} \qquad (5)$$

where:
It = dichotomic variable, which assumes value equal to 1, in the event that at time t, shortfall occurs, otherwise it assumes value equal to 0.
m = number of sample periods in the time domain considered.

For all portfolio we assume constraints as follow:

The sum of all weights in the portfolio is unity:

$$\sum_{i=1}^{N} w_i = 1$$

And all the weights are positive (no short selling):

$$w_i \geq 0$$

For *Markowitz Portfolio Optimization* we have

$$w_{mv}^{*} = arg_{w\epsilon C} max\, w^T \bar{\mu} - \frac{\lambda}{2} w^T \Omega w \quad (6)$$

The traditional optimization problem is given by

$$L(w, \theta) = w^T \bar{\mu} - \frac{\lambda}{2} w^T \Omega w + \theta(w^T I - 1) \quad (7)$$

where θ denotes the multiplier associated with the full investment constraint ($w^T I = 1$).

After taking first-order derivatives with respect to the Lagrange multiplier and the vector of portfolio weights, solving for the Lagrange multiplier and substituting this back into the derivative with respect to portfolio weights we arrive at the familiar solution:

$$w_{mv}^{*} = \frac{1}{\lambda} \Omega^{-1} \left(\bar{\mu} - \frac{\mu^T \Omega^{-1} 1}{1^T \Omega^{-1} 1} 1 \right) + \frac{\Omega^{-1} 1}{1^T \Omega^{-1} 1} \quad (8)$$

The Resampled Efficient Frontier is the collection of all possible RE optimal portfolios with risk aversion parameters from expected utility curves ranging from total risk aversion to total risk indifference. The REF plots below the classical efficient frontier because it expects less return and restricts risk to a narrower range.

RESULTS

In order to compare the performance of robust optimization approaches detailed in the previous section with traditional mean-variance and minimum-variance portfolios, we applied a "rolling horizon" procedure similar as in DeMiguel and Nogales (2006). First, the sample estimates of mean returns and covariances are made using an estimation window of *T*=52 weekly observations, which for weekly data corresponds to 1 year. Two, using these samples estimates we compute the optimal portfolio policies according to each strategy. Three, we repeat this procedure for the next period, by including data for the new date and dropping the data for the earliest period. We continue doing this until the end of the data set is reached. At the end of this process, we have generated *L* - *T* portfolio weight vectors for each strategy, where *L* is the total number of samples The out-of-sample performance of each strategy is evaluated according to the following statistics: Total Return, Average Return, Standard Deviation, Downside Risk, Tem, Tev, Information Ratio, Sharpe, Sortino, Beta and Treynor.

The stocks were selected according to market capitalization (large cap stocks) for the top Blue Chip equities for each stock index. We collect weekly data on 3 international indices from yahoo finance from 12/01/2001 to 04/05/2007. The price series for each stock index are subsequently converted to return series. So we define the one-period rate of return during the interval (*j-1*) to *j* as:

$$r_j = \frac{P_j - P_{j-1}}{P_{j-1}} \quad (9)$$

Not surprisingly, the assumption of a Gaussian normal distribution can be rejected for all of the assets both with a Jarque–Bera, Kolmogorov–Smirnov test and Mardia's test of multivariate skewness and kurtosis. Specifically Mardia's test is based on the Mahalanobis distance of data vector from its sample mean and it allows to reject the hypothesis of the normality if the sample has no significant skew and the measure of kurtosis deviates from expectancy only randomly.

Starting from introduced models, we examine eight investment strategies for each index, for a period of 330 weeks (from 12/01/2001 to 04/05/2007). In this application four models were considered : Madm, Spm, Tev, Markowiztz for each of these two variants were proposed: 1) the application, to the reference model, of the technique of Resampling using Gaussian distributions where one considers only the mean and standard deviation for formulating hypotheses on the distribution of asset returns in the index, (these models will be called with the following code: "model name+ res", eg. Madmres) and 2) the application, to the reference model, of High Order Resampling in which not only we take account of mean and the standard deviation to make assumptions on the distribution of asset returns, but also of Skewness and the Kurtosis (these models will be called with the following code: "model name + resdd such as Madmresdd)

Sp Mib Results

Results for the Madm model, in Table1 show how the application of the Resampling technique has brought a benefit to the reference model in terms of return (average return of +0.04% on a weekly basis compared to the model) and in terms of risk. With reference to this last, it must be noted that this improvement is measured not only in terms of lower standard deviation (-0.04% on a weekly basis) but also in terms of lower Downside Risk (-0.18% on a weekly basis) and Tev (-0.27% on a weekly basis). In light the above discussion, a logical consequence emerges from Rap measures in this regard. Analyzing the Sharpe ratio, Sortino and Information Ratio it can be concluded that the technique of Resampling, model "res", have improved the original model (Madm) in terms not only of risk and return, but also in terms of Rap measures that benefits in terms of risk-adjusted profitability. The same considerations made with respect to the Madmres model in terms of Rap measures can be made to the Madmresdd model. For this model it shows an improvement compared to model Madm in terms of performance (+0.10% on a weekly basis) and SD (-0.29% on a weekly basis) and in terms of the Sharpe Ratio (+4.56%). However there is a deterioration in terms of down-side risk (+0.27% on a weekly basis). Starting from this very last finding it becomes necessary to understand if the rising performance produced by the model is associated with an increase in the acceptable down-side risk than characterized in the Madm model.

To answer this question you need to compare Information Ratio indices. The measure reports an increase of 2.95%. This result allows us to conclude that with the increase in the down-side risk, there is an increase of excess return (relative to the benchmark model Madmresdd) more than proportional to the Madm model or an improvement in terms of adjusted risk return calculated by Information Ratio. Analyzing Spmres and Spmresdd models, a lower performance of the latter emerges in terms of average weekly return (respectively -0.06% and -0.07%,) compared to the Spm model. With regard to risk (Standard Deviation, Down Side risk, Tev), models based on resampling improved the reference model. So it becomes essential to analyze the Rap measures to highlight any improvements made by the Spmresdd and Spmres to the Spm model. In this case, and for these models, in all cases a benefit is shown by using the Resampling techniques on the Reference Model (Spm). It can be concluded with reference to the Spm model that Resampling techniques have brought an increase in the risk-adjusted performance even though there has been, both for Spmres and for Spmresdd, a worsening in terms of weekly average return.

For the Tev model, particularly with regard to Tevres and Tevresdd variants, there are two opposing scenarios from a standpoint of efficiency and risk, for which you can reach the same conclusions with regard to Rap measures. Taking the average weekly return, one can observe a positive differential in relation to the Tevres model (+0.08%) and a negative differential in respect to the Tevresdd model (-0.03%). Conversely, for risk measures an improvement to the Tev model is observed, -0.57% with reference to standard deviation, as a result of the Tevresdd model and a worsening to the Tevresdd model for the Down side risk and Tev (-1.03% and -0.09% respectively). However both Tevres and Tevresdd models improve the Rap indicators of the Tev model. Finally, regarding the application of Resampling techniques to the Markowitz model, the Markres model has a differential output compared to the reference model, negative. The differential for the risk measures, as for that of performance is negative, this evidence is reversed on the Rap indicators leads to a negative differential. The Markresdd model presents characteristics diametrically opposed. It is possible to observe improvements in performance, risk and Rap. In this case the "Resdd" model has not only improved the initial model in all the components of risk and return analyzed, but also has improved version of "res" of that model.

In summary, if we exclude the Markeres models in all other cases the Resampling techniques made an improvement of the Rap indicators compared with strategies derived from the application of reference models. Hitherto Resampling techniques have been considered as an evolution of the reference model, in a way that we can consider the “resdd” models, as evolutions of the “res” models. In fact in the application of “resdd” models, distribution hypotheses can be considered closer to reality than the “res” models, as a matter of fact often the returns can present fat tails or positive and negative asymmetry, not captured by the standard “res” models. In reference to this observation, considering the Rap measures, "resdd" models have a positive differential compared to "res". This means that, except for Sharpe indicators for Tev and Spm models, the application of the technique of "resdd” results in an improvement with respect to the “res” technique. For Tev and Spm models, data shows no valid improvements in terms of Rap. It is noted that the differentials of negative Sharpe are principally a result of the income component, the fact the Dsr, which expresses the negative volatility of the standard deviation, has a negative differential. In conclusion, for the models analyzed, result shows how Resampling techniques identify investment strategies that improve the Rap measures of the portfolios selected compared to standard models. Still, the application of the “resdd" technique led to an improvement in the Rap indicators of the portfolio compared with the “res” technique.

<u>Eux 50 Results</u>

The use of portfolio model strategies on the Eux 50 index did not lead, unlike those used on the SPMib, to a significant improvement from a passive strategy (Table 2). One can try to understand whether the application of Resampling techniques has nevertheless brought a benefit in terms of Rap measures for the models taken into account. Table 2, shows how the Madmres and Madmresdd models have improved not only the Rap indicators of the reference model but also the weekly average return and the various risk indicators. Increasing profitability and reducing risk by the "res" and "resdd" applied to this model reflects, in general, what has been previously discussed with regard to the result shown in Table 1.

Data on average returns shows negative differentials per the related risk measures. Resampling techniques have reduced the risk of the reference model, namely SPM, but not increased profitability. The impact on the Rap measures was opposite to that which occurred in Table 2. For the Spm model, the impact of the condition described above on the Rap measures is positive. In this case there was a worsening of the Rap measures. It can be concluded, that the Res and Resdd techniques created a less risky strategy "sacrificing" the income component of the Rap indicators. The Tevres model empirical findings presents a weekly average return higher than the Tev model but has also led to a worsening of risk components. The Tevresdd model has improved the income component, as Tevres, improving risk measures. Both variants improve the Rap measures of the original model, this means that the Tevresdd model has worked more effectively than Tevres as it has increased profitability by reducing the average risk. Even the Markres and Markresdd models improve in terms of Rap the Rap reference model (Table 2). Summarize comparing applications of the "res" and "resdd" models to the Eux index 50 we can make the following observations: 1) For the Madm model, the Rap differences between “res” and “resdd" models is close to 0. This leads to the conclusion that, given that both techniques improve the basic model, the choice between “resdd” and "res" techniques is, for the Madm model, almost indifferent. 2) For the Spm model, variant “ressdd” provides no benefit over the application of "res"; 3) The variants “resdd” with respect to the variants "res", applied to Tev model, improve Rap measures and risk – return components. 4) The

Markes model and the Markresdd model do not differ in terms of Sortino and Information Ratio Index, whereas variant “resdd" does not make any improvement to the variant "res" in terms of Sharpe Ratio as a result of excessively negative return differential while generating a differential negative standard deviation.

Table 1: Spmib40 Model Results

	Madm	Madmres	Madmddres	Madmres vs	Madmddres vs Madm
Total Return	265.05%	301.34%	377.88%	36.29%	112.83%
Average Return	0.34%	0.38%	0.44%	0.04%	0.10%
Standard Deviation	3.01%	2.97%	2.71%	-0.04%	-0.29%
Downside risk	2.98%	2.80%	3.25%	-0.18%	0.27%
Tem	0.53%	0.62%	0.74%	0.09%	0.20%
Tev	2.93%	2.66%	3.03%	-0.27%	0.10%
Information Ratio	9.91%	11.91%	12.14%	2.00%	2.23%
Sharpe	8.35%	9.74%	12.91%	1.39%	4.56%
Sortino	10.08%	12.53%	13.03%	2.45%	2.95%
Beta	53.58%	62.10%	39.17%	8.52%	-14.41%
Treynor	0.55%	0.54%	1.01%	-0.01%	0.46%
	Spm	**Spmres**	**Spmddres**	**Spmres vs Spm**	**Spmddres vs Spm**
Total Return	379.37%	342.75%	335.90%	-36.62%	-43.46%
Average Return	0.49%	0.43%	0.42%	-0.07%	-0.07%
Standard Deviation	4.24%	3.30%	3.24%	-0.94%	-0.99%
Downside risk	4.36%	3.29%	3.01%	-1.07%	-1.34%
Tem	0.85%	0.70%	0.68%	-0.15%	-0.17%
Tev	3.99%	3.14%	2.86%	-0.85%	-1.13%
Information Ratio	10.28%	11.63%	12.43%	1.35%	2.15%
Sharpe	9.53%	10.25%	10.19%	0.72%	0.66%
Sortino	11.23%	12.20%	13.09%	0.97%	1.87%
Beta	64.72%	57.94%	66.25%	-6.78%	1.53%
Treynor	0.69%	0.66%	0.57%	-0.03%	-0.13%
	Tev	**Tevres**	**Tevddres**	**Tevres vs Tev**	**Tevddres vs Tev**
Total Return	252.94%	325.55%	239.04%	72.61%	-13.91%
Average Return	0.32%	0.41%	0.29%	0.08%	-0.03%
Standard Deviation	2.90%	3.15%	2.33%	0.25%	-0.57%
Downside risk	2.67%	2.96%	1.64%	0.29%	-1.03%
Tem	0.51%	0.67%	0.42%	0.16%	-0.09%
Tev	2.58%	2.79%	1.63%	0.21%	-0.95%
Information Ratio	10.41%	12.22%	15.03%	1.81%	4.62%
Sharpe	8.05%	10.09%	8.64%	2.04%	0.60%
Sortino	10.77%	12.96%	15.05%	2.19%	4.28%
Beta	62.17%	64.86%	68.65%	2.69%	6.48%
Treynor	0.45%	0.56%	0.36%	0.11%	-0.09%
	Markowitz	**Markres**	**Markresdd**	**Markres vs Mark**	**Markresdd vs Mark**
Total Return	393.45%	310.86%	407.37%	-82.59%	13.92%
Average Return	0.45%	0.38%	0.45%	-0.07%	0.00%
Standard Deviation	2.63%	2.66%	2.12%	0.03%	-0.50%
Downside risk	3.04%	3.09%	2.79%	0.05%	-0.25%
Tem	0.72%	0.63%	0.74%	-0.09%	0.02%
Tev	2.90%	2.88%	2.72%	-0.01%	-0.17%
Information Ratio	13.32%	10.81%	14.45%	-2.51%	1.13%
Sharpe	13.72%	10.89%	16.92%	-2.83%	3.20%
Sortino	13.97%	11.57%	14.80%	-2.40%	0.83%
Beta	41.33%	42.56%	31.94%	1.23%	-9.39%
Treynor	0.98%	0.78%	1.26%	-0.19%	0.28%

This table shows the Spmib40 Model results.

Table 2: Ex50 Model Results

	Madm	Madmres	Madmddres	Madmres vs Madm	Madmddres vs Madm
Total Return	61.56%	77.98%	74.28%	16.42%	12.72%
Average Return	-0.09%	-0.03%	-0.05%	0.06%	0.04%
Standard Deviation	3.33%	2.96%	2.91%	-0.37%	-0.42%
Downside risk	2.69%	2.45%	2.77%	-0.24%	0.08%
Tem	-0.23%	-0.11%	-0.15%	0.12%	0.08%
Tev	2.76%	2.40%	2.69%	-0.35%	-0.07%
Information Ratio	-4.26%	-2.23%	-2.56%	2.03%	1.70%
Sharpe	-5.46%	-4.11%	-4.74%	1.34%	0.72%
Sortino	-4.16%	-2.27%	-2.64%	1.88%	1.52%
Beta	70.76%	67.75%	57.45%	-3.00%	-13.30%
Treynor	-0.16%	-0.08%	-0.12%	0.08%	0.04%
	Spm	Spmres	Spmddres	Spmres vs Spm	Spmddres vs Spm
Total Return	103.50%	88.69%	80.30%	-14.81%	-23.20%
Average Return	0.08%	0.01%	-0.02%	-0.06%	-0.09%
Standard Deviation	3.61%	3.16%	3.11%	-0.45%	-0.50%
Downside risk	3.33%	2.75%	2.65%	-0.58%	-0.69%
Tem	0.11%	-0.02%	-0.09%	-0.13%	-0.20%
Tev	3.18%	2.56%	2.53%	-0.62%	-0.65%
Information Ratio	1.57%	-0.36%	-1.55%	-1.92%	-3.12%
Sharpe	-0.41%	-2.43%	-3.48%	-2.02%	-3.07%
Sortino	1.64%	-0.38%	-1.63%	-2.02%	-3.27%
Beta	67.33%	70.45%	69.48%	3.12%	2.15%
Treynor	0.08%	-0.01%	-0.06%	-0.09%	-0.14%
	Tev	Tevres	Tevddres	Tevres vs Tev	Tevddres vs Tev
Total Return	58.39%	73.15%	115.04%	14.76%	56.66%
Average Return	-0.12%	-0.05%	0.08%	0.07%	0.19%
Standard Deviation	3.06%	3.10%	2.67%	0.04%	-0.39%
Downside risk	2.28%	2.62%	0.83%	0.35%	-1.44%
Tem	-0.29%	-0.15%	0.10%	0.13%	0.39%
Tev	2.33%	2.50%	0.79%	0.17%	-1.54%
Information Ratio	-6.11%	-2.66%	6.63%	3.45%	12.74%
Sharpe	-6.74%	-4.42%	-0.44%	2.32%	6.30%
Sortino	-5.97%	-2.79%	6.97%	3.18%	12.94%
Beta	73.49%	69.92%	88.74%	-3.57%	15.24%
Treynor	-0.19%	-0.10%	0.06%	0.09%	0.25%
	Markowitz	Markres	Markresdd	Markres vs Mark	Markresdd vs Mark
Total Return	68.37%	134.37%	114.77%	66.00%	46.40%
Average Return	-0.07%	0.21%	0.07%	0.28%	0.14%
Standard Deviation	2.89%	4.16%	2.37%	1.27%	-0.52%
Downside risk	3.72%	3.73%	1.14%	0.01%	-2.58%
Tem	0.51%	0.52%	0.09%	0.00%	-0.42%
Tev	3.65%	3.61%	1.16%	-0.04%	-2.49%
Information Ratio	7.54%	7.37%	4.10%	-0.17%	-3.44%
Sharpe	2.87%	2.80%	-0.85%	-0.07%	-3.72%
Sortino	7.69%	7.62%	4.04%	-0.07%	-3.64%
Beta	85.40%	81.66%	75.34%	-3.75%	-10.07%
Treynor	0.33%	0.34%	0.06%	0.01%	-0.27%

This table shows the Ex50 Model results.

Sp 100 Results

For both reference models, "res" and "resdd", resampling techniques improved not only Rap measures, but also measures of performance and risk. The Tevres model shows an increase in performance compared to a general increase in all measures of risk. This increase did not negatively affect Rap measures. For Rap, positive differentials are reported. Tevresdd worsened the performance of the reference model but reduced the risk producing a net positive effect (excluding the Sharpe Ratio) on the Rap measures. Unlike with Tevresdd, Markresdd and Markres models while presenting the same characteristics in the income and risk components (respectively worsening and improvement over the reference model), has a worsening in Rap measures.

Table 3: Sp100 Model Results

	Madm	**Madmres**	**Madmddres**	**Madmres vs Madm**	**Madmddres vs Madm**
Total Return	86.52%	153.43%	134.81%	66.91%	48.29%
Average Return	0.07%	0.22%	0.18%	0.15%	0.10%
Standard Deviation	4.90%	4.37%	4.23%	-0.53%	-0.67%
Downside risk	4.34%	3.74%	3.97%	-0.60%	-0.37%
Tem	0.27%	0.52%	0.46%	0.25%	0.19%
Tev	4.25%	3.68%	3.82%	-0.57%	-0.43%
Information Ratio	3.31%	7.84%	6.23%	4.54%	2.92%
Sharpe	-0.31%	3.08%	2.10%	3.39%	2.41%
Sortino	3.38%	7.97%	6.48%	4.59%	3.10%
Beta	93.16%	91.06%	74.20%	-2.10%	-18.96%
Treynor	0.15%	0.32%	0.33%	0.17%	0.18%
	Spm	**Spmres**	**Spmddres**	**Spmres vs Spm**	**Spmddres vs Spm**
Total Return	118.15%	266.12%	232.12%	147.97%	113.97%
Average Return	0.21%	0.40%	0.36%	0.18%	0.15%
Standard Deviation	5.77%	4.44%	4.68%	-1.34%	-1.09%
Downside risk	5.41%	3.66%	4.09%	-1.75%	-1.32%
Tem	0.53%	0.78%	0.75%	0.25%	0.21%
Tev	5.07%	3.71%	3.97%	-1.36%	-1.10%
Information Ratio	5.22%	12.67%	10.58%	7.45%	5.36%
Sharpe	2.15%	6.88%	5.84%	4.73%	3.70%
Sortino	5.57%	12.49%	10.88%	6.92%	5.31%
Beta	105.82%	94.29%	96.01%	-11.53%	-9.81%
Treynor	0.27%	0.49%	0.45%	0.22%	0.18%
	Tev	**Tevres**	**Tevddres**	**Tevres vs Tev**	**Tevddres vs Tev**
Total Return	163.82%	199.67%	110.55%	35.86%	-53.27%
Average Return	0.24%	0.31%	0.08%	0.07%	-0.16%
Standard Deviation	4.26%	4.51%	2.98%	0.25%	-1.29%
Downside risk	3.54%	3.86%	1.32%	0.32%	-2.21%
Tem	0.55%	0.68%	0.23%	0.13%	-0.32%
Tev	3.49%	3.77%	1.59%	0.28%	-1.91%
Information Ratio	8.72%	9.83%	10.85%	1.10%	2.13%
Sharpe	3.52%	4.89%	-0.50%	1.37%	-4.02%
Sortino	8.83%	10.06%	9.05%	1.22%	0.21%
Beta	93.99%	95.53%	96.18%	1.54%	2.19%
Treynor	0.33%	0.40%	0.15%	0.07%	-0.18%
	Markowitz	**Markres**	**Markresdd**	**Markres vs Mark**	**Markresdd vs Mark**
Total Return	149.57%	148.67%	130.62%	-0.90%	-18.95%
Average Return	0.21%	0.21%	0.11%	-0.01%	-0.10%
Standard Deviation	4.26%	4.16%	2.58%	-0.10%	-1.68%
Downside risk	3.72%	3.73%	2.22%	0.01%	-1.50%
Tem	0.51%	0.52%	0.33%	0.00%	-0.18%
Tev	3.65%	3.61%	2.18%	-0.04%	-1.47%
Information Ratio	7.54%	7.37%	8.20%	-0.17%	0.67%
Sharpe	2.87%	2.80%	0.93%	-0.07%	-1.94%
Sortino	7.69%	7.62%	8.37%	-0.07%	0.69%
Beta	85.40%	81.66%	64.03%	-3.75%	-21.38%
Treynor	0.33%	0.34%	0.29%	0.01%	-0.04%

This table shows the Sp100 Model results.

CONCLUSIONS

Optimal asset allocation has generated considerable interest in finance but important caveats remain. Once caveat is estimation error in the parameters. Empirical evidence indicates that the behaviour of stock market returns does not agree with the frequently assumed normal distribution. In the presence of higher order moments, optimizing with respect to mean and variance only can lead to highly undesirable effects. According to Markowitz and Usmen (2003) Resampled Efficiency optimized portfolios exhibited superior performance on average. RE technology also avoid the often ineffective and costly rebalancings making resampled portfolios more stable and have the added benefits of simplifying portfolio management. It is worth noting that Michaud's approach does not consider tail dependences and extreme (negative) returns (tail risk).

Other research focuses on the mean-variance approaches. To cover this gap in literature we perform high order resampling, taking into account Skewness and Kurtosis, with regard to several model portfolios. Specifically, we examine Mean-Variance, Tracking Error Minimization (TEM), Mean Absolute Deviation Minimization (MADM) and Shortfall Probability Minimization Models (SPM). We apply the method to a set of blue chip equities from 3 stock indexes (Sp100, Smib40, Ex50). Our result show that the Resampling techniques improved all three markets considered, the Rap measures of the portfolio in 70% of cases analyzed. Considering individual markets: 80% for the Ex 50 index, 63% for the SP100 index and 80% for the Spmib index. High order moments resampling techniques have improved the Rap measures of the respective standard resampling technique in 48% of cases. The results suggest procedures for improving the investment value of estimates are always worthwhile.

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OPTIMAL INVESTMENT FOR INSTITUTIONAL INVESTORS UNDER VALUE-AT-RISK CONSTRAINTS IN CHINESE STOCK MARKETS

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ABSTRACT

Value at Risk (VaR) is defined as the worst expected loss under normal market conditions over a specific time interval at a given confidence level. Given the widespread usage of VaR, it becomes increasingly important to study the effects of the portfolio optimization subject to the VaR constraint set by the fund manager. In this paper, we examine the classical portfolio optimization models and the most popular VaR methodologies. We show that the portfolio optimization models under VaR constraint provide the clear insight to the mean-variance decision. We also consider the problem with the extra tracking error constraint. Furthermore, we provide an empirical analysis on the model by using China's market data. VaR estimates are produced via Monte Carlo simulations.

JEL: G11; G15; G32

Keywords: Portfolio optimization, mean-variance, VaR, Monte Carlo

INTRODUCTION

Many investment fund managers choose Mean-Variance analysis and Value at Risk (VaR) as their most important supporting tools in their asset allocation and portfolio allocation decision-making. Nowadays, the fund managers turn to focus on the downside possibility of portfolio and the new benchmark for the measure of risk is Value at Risk.

After VaR was introduced by Philippe Jorion (2001), some researchers also discuss the relationship between Mean-Variance analysis and VaR. However, most of their analyses are in terms of absolute return of portfolio, without taking the benchmark into account. In this paper, we try to highlight the similarities and differences between Mean-Variance analysis and Value at Risk and find out how institutional investors, who care about the relative performance of their portfolio to the benchmark, do their risk-return management under Value at Risk constraint using returns relative to the benchmarks.

We will further investigate to solve the institutional investor's utility maximization problem subject to VaR constraint. In other words, we introduce VaR restriction into the problem of Knight (2005) and extend its research. Furthermore, we use the data from Chinese market to examine and support our conclusion. As a young emerging market, China's stock market has experienced extraordinary growth since the inceptions of the Shanghai and Shenzhen Stock Exchange in late 1990s. On its way to go to the matured market, it has a lot of specialties which make our findings more interesting.

The paper is organized as follows. We present the previous studies in Section II. In Section III, we derive the solution for the constrained maximum problem in mathematical framework. In Section IV we further explain the reason why we choose Chinese capital market as our research objectives and illustrate the characteristics of the data. Section V The conclusions are made in Section VI.

LITERATURE REVIEW

VaR was first introduced and popularized in 1994 by J.P. Morgan's famous RiskMetrics software. The subsequent research works, such as Pichler and Selitch (1999), Jorion (2001) and Alexander (2003) provide a complete analysis of VaR methodology and successfully help VaR become a standard concept in risk management. The two most important components of VaR measures are the length of time period over which market risk is to be measured and the confidence or significance level at which market risk is to be measured. In other words, VaR is used as an estimate of the minimum expected loss (alternatively, the maximum loss) over a set time period at a desired level of significance (alternatively, at a desired level of confidence). For example, a 5% VaR of $1,000 for a 10-day holding period implies that, given the standard deviation and distribution of returns for the portfolio, there is a 5% probability that the portfolio will lose a minimum of (at least) $1,000 over the next 10 days. Stated differently, there is 95% confidence the loss will be no greater than $1,000.

However, Rochefellar and Uryasev (2002) imply that as a quantile, VaR has its own serious shortcomings because it has no reason to be convex. Uryasev (1998) provides an alternative risk measure to VaR, called Conditional Value at Risk (CVaR). Pflug (2000) shows that CVaR is a coherent risk measure that it has many attractive properties including convexity. Conditional Value at Risk is also known as mean excess loss, mean shortfall or tail VaR. So, CVaR is the expected loss given that the loss exceeds VaR.

In this paper, we suppose the institutional investors care more about the whole maximum loss of their investment than the potential excess loss. In this respect, we will continue to use VaR, not CVaR, as the risk constraint in this paper in order to simplify the question.

In recent years, there are a lot of research papers that focus on the effects of CAPM and optimal portfolio selection under VaR constraint(Campbell et al (2001), Basak and Shapiro (2001)). The usual discussion is to develop a mean-risk model and a CAPM or utility maximization subject to a VaR constraint and find out some surprising features of VaR usage. Huisman et al (1999) uses mean variance approach to develop an asset allocation model which allocates assets by maximizing expected return subject to the constraint that the expected maximum loss should meet the Value at Risk limits set by the risk manager. Gaivoronski and Pflug (2000) combine the notion of VaR with portfolio optimality and develop a theory similar to Markowitz theory for optimal mean variance portfolios under VaR constraint. Alexander et al (2003) focus on the portfolio selection problem which yields a portfolio of the minimum CVaR with a specified rate of return.

In all listed papers above, the analysis is in terms of the absolute return of the portfolio. None of them take the benchmark into consideration. Today's portfolio managers, especially institutional investors, are usually evaluated by comparing their outperforming performance to that of their peers or to a benchmark published in guidelines made available to investors. There are some research papers that incorporate the benchmarks into the specific utility functions when they deal with the portfolio optimization problem. This type of performance evaluation method obviously motivates the fund managers to pursue the active management return. Markowitz (1987), Roll (1992), Sharpe (1992), Chan, Karceski, and Lakonishok (1999) and some other papers have introduced a related quadratic tracking approach to minimize the variance of the return difference between the managed portfolio and the benchmark. Recently, to better capture the manager's motivation, Morton et al (2003) consider optimal portfolio allocation under four non-standard benchmark-based utility functions. On the other hand, Knight (2005) represents a mathematical solution to the institutional investors' portfolio optimization in terms of the return relative to their benchmark.

Although these previous works consider the fund manager's aim to outperform of the benchmark through the investment process, they fail to formulate risk management requirements in terms of percentiles of loss distribution. The proposal of this paper is to find out a new approach to optimal portfolio allocation method for institutional investors in Value-at-Risk framework. To some extent, this paper is more closely related to Knight (2005), who study efficient portfolios for institutional investors' utility functions with general risk level constraints, than to Campbell et al (2001), who effectively replace mean variance preferences by mean VaR preferences.

Knight (2005) investigates the problem of calculating the exact distribution of optimal investments in a mean variance world under multivariate normality. The main contribution of Knight's paper is that their risk analysis is based on mean-variance analysis using not absolute or unbenchmarked returns, but relative returns to the benchmark. Under the assumption of normal distribution, Knight (2005) considers the institutional investors' expected utility in terms of relative returns and calculates the exact properties of measures. Campbell et al (2001) consider an optimal portfolio selection model which maximizes the expected return of the portfolio subject to Value-at-Risk constraint rather than standard deviation alone. In their paper, Campbell and his co-authors derive an optimal portfolio such that the maximum expected loss would not exceed the VaR for a chosen investment horizon at a given confidence level. The investors' problem described in Campbell et al (2001) is to maximize the expected level of final wealth under downside risk constraint which is measured by VaR. We can easily find out that there is no assumption of normally distributed returns in Campbell et al (2001) model. However, the analysis in Campbell's paper is obviously put on the absolute portfolio.

In this study, what we are going to do is combine the models analyzed in both Campbell et al (2001) and Knight (2005). In other words, we use the VaR as the investors' risk measure and evaluate the performance of portfolio based on the given benchmark.

PORTFOLIO SELECTION MODEL

The portfolio optimization in the modern portfolio theory is to allocate the assets by maximizing the expected value of a given utility function or minimizing the expected risk level of the portfolio. We assume that the institutional investors we analyze try to optimize their portfolio by maximizing the following utility function of over performed value between the portfolio and benchmark under VaR constraint:

$$\max \; E(U) = E\left[U(W_{PT} - W_{BT})\right] = E\left[U\left(W_0 \cdot \sum_{i=1}^{n}(w_i - b_i)\cdot R_i\right)\right] \tag{1}$$

subject to $\sum_{i=1}^{n} w_i = \sum_{i=1}^{n} b_i = 1$

$$w_i > 0\,,\; b_i > 0$$

$$\Pr\left\{\sum_{i=1}^{n} w_i \cdot R_i < -VaR^*\right\} \le 1 - c$$

where W_{PT} is the expected wealth of the Portfolio p at period T; W_{BT} is the expected wealth of the Benchmark b at period T, if the "portfolio" Benchmark b has the same initial wealth as the Portfolio p at period 0; w_i, b_i are the asset i weight of Portfolio p and Benchmark b respectively during the period from time 0 to time T; R_i is the gross return of asset i during the period T; VaR^* is the desired level of VaR value set by the institutional investors; c is the expected level of confidence.

Following Freund (1956), we assume that the institutional investors are "conservative entrepreneurs" and they have the same negative exponential utility function, $U(r) = 1 - e^{-\lambda r}$ where λ indicates the investors' aversion to risk. That is, the higher the value of λ, the more "conservative" the investors. Under the assumption that the returns follow a normal distribution, Freund (1956) shows that the maximization of expected utility

$$E(U) = \int_{-\infty}^{+\infty}(1 - e^{-\lambda r}) \cdot e^{-(r-\mu)^2/2\sigma^2}\, dr \tag{2}$$

is easily shown to be accomplished if we maximize the function

$$E(U^*) = \mu - \frac{\lambda}{2}\sigma^2 \tag{3}$$

Using matrix notation we maximize the following:

$$E(U^*) = \mu' w - \frac{\lambda}{2} w'\Omega w \tag{4}$$

Therefore, similar to Knight (2005), the maximization of expected utility for the institutional investors can be rewritten as follows.

$$\max \ E(U) = \mu'(w-b) - \frac{\alpha}{2}(w-b)'\Omega(w-b) \tag{5}$$

$$\text{subject to } \ w'i = b'i = 1$$

$$\Pr\left\{\sum_{i=1}^{n} w_i \cdot R_i < -VaR^*\right\} \le 1-c$$

Let r_p be $\sum_{i=1}^{n} w_i \cdot R_i$, and we assume here that the returns are normally distributed.

Then, $r_p \sim N(E(r_p),\sigma_p^2)$.

Therefore, from $\Pr\{r_p < -VaR^*\} \le 1-c$, we can get

$$\Pr\left\{\frac{r_p - E(r_p)}{\sigma_p} < \frac{-VaR^* - E(r_p)}{\sigma_p}\right\} \le 1-c \tag{6}$$

Sequentially,

$$1 - N\left(\frac{VaR^* + E(r_p)}{\sigma_p}\right) \le 1-c \tag{7}$$

Obviously, under the assumption of normally distributed returns, the VaR constraint could be simply changed as follows.

$$VaR^* \ge -(E(r_p) - N^{-1}(c)\sigma_p) \tag{8}$$

where $N(\cdot)$ is the distribution function of the standard normal distribution.

$$N(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}} \tag{9}$$

It will be a better way to calculate the VaR of portfolio if we use the Monte Carlo simulation to estimate the $E(r_p)$ land σ_p. To simplify the calculation we will assume normality and we simply use $E(r_p) = \mu' w$

and $\sigma_p^2 = w'\Omega w$ to describe the VaR constraint. If we use Lagrange method, we get the following equation:

$$L = \mu'(w-b) - \frac{\alpha}{2}(w-b)'\Omega(w-b) + \lambda_1(w'i-1) + \lambda_2(VaR^* + \mu'w - N^{-1}(c)\sqrt{w'\Omega w}) \tag{10}$$

and find a relative maximum of L with respect to w and a relative minimum with respect to λ_2.
The Kuhn-Tucker conditions are a complete taxonomy of the first-order necessary conditions for obtaining a saddle point for L. These Kuhn-Tucker conditions are given by:
1) w is feasible

2) $$\frac{\partial L}{\partial w} = \mu - \alpha\Omega(w-b) + \lambda_1 i + \lambda_2\mu - \frac{\lambda_2}{2}N^{-1}(c)\frac{\Omega w}{\sqrt{w'\Omega w}}) = 0 \tag{11}$$

$\lambda_2 \geq 0$ and λ_1 unrestricted sign

3) $$VaR^* + \mu'w - N^{-1}(c)\sqrt{w'\Omega w} \geq 0 \tag{12}$$

4) $$w'i - 1 = 0 \tag{13}$$

5) $$\lambda_2(VaR^* + \mu'w - N^{-1}(c)\sqrt{w'\Omega w}) = 0 \tag{14}$$

and $\lambda_2 \geq 0$

The Lagrange Multipliers λ_1 and λ_2 represent the sensitivities of the objective function to the first and second constraints, respectively. The key idea of Kuhn-Tucher theorem is that if the inequality constraint of VaR is not precisely satisfied, then the corresponding Lagrange Multiplier λ_2 should have to be zero, relaxing a non-binding constraint.

The first possibility is $\lambda_2 = 0$. In this case, the VaR constraint will be loosed and the optimization question will be quite similar to the one Knight (2005) faced and solved. Following the method presented in Knight (2005), we re-solve this question here. The first order condition is:

$$\frac{\partial L}{\partial w} = \mu - \alpha\Omega(w-b) + \lambda_1 i = 0 \tag{15}$$

We get $w = b + \frac{1}{\alpha}\Omega^{-1}(\mu + \lambda_1 i)$ (16)

Using $w'i = b'i = 1$, that is, $i'w = i'b = 1$ we can see that,

$$i'w = i'b + \frac{1}{\alpha}i'\Omega^{-1}(\mu + \lambda_1 i) \Rightarrow i'\Omega^{-1}(\mu + \lambda_1 i) = 0 \Rightarrow \lambda_1^* = -\frac{i'\Omega^{-1}\mu}{i'\Omega^{-1}i} \tag{17}$$

So, we finally get the optimized weights $w^* = b + \frac{1}{\alpha}\Omega^{-1}(\mu - \frac{i'\Omega^{-1}\mu}{i'\Omega^{-1}i}i)$. (18)

However, the difference between Knight (2005) and this paper is that the solved optimized weights should satisfy the VaR constraint. In the case $\lambda_2 = 0$, if $VaR^* + \mu' w^* - N^{-1}(c)\sqrt{w^{*'}\Omega w^*} \geq 0$, then we can say we find a best weights of portfolio, which make the objective function have its maximum value:

$$E(U_1^*) = \mu'(w_1^* - b) - \frac{\alpha}{2}(w_1^* - b)'\Omega(w_1^* - b) \tag{19}$$

here ($w_1^* = w^*$).

If we find $VaR^* + \mu' w^* - N^{-1}(c)\sqrt{w^{*'}\Omega w^*} < 0$, which means that the optimized weights w^* violates the VaR constraint, then we can't solve for a potential maximum point by using the Lagrangian and the Lagrange Multiplier conditions for the optimal point. In other words, the VaR constraint may be such a strict one that it is impossible for us to find out any optimal point for the problem with this inequality constraint.

The only other possibility to solve this maximum utility problem is when $\lambda_2 > 0$. From the Kuhn-Tucker constraint 5, we can see that the VaR constraint is changed to $VaR^* + \mu' w - N^{-1}(c)\sqrt{w'\Omega w} = 0$ in this case. Let β be $N^{-1}(c)$ and substitute $w'\Omega w = \left(\frac{VaR^* + \mu' w}{\beta}\right)^2 = \frac{VaR^{*2} + 2VaR^* \mu' w + (\mu' w)^2}{\beta^2}$

into the institutional investors' utility function. The objective optimization problem is changed to:

$$\max \ E(U) = \mu'(w-b) - \frac{\alpha}{2}(w-b)'\Omega(w-b) \tag{20}$$

$$\Rightarrow E(U) = \mu'(w-b) - \frac{\alpha}{2}(w'\Omega w - 2w'\Omega b + b'\Omega b) \tag{21}$$

$$\Rightarrow E(U) = \mu'(w-b) - \frac{\alpha}{2}(\frac{VaR^{*2} + 2VaR^* \mu' w + (\mu' w)^2}{\beta^2} - 2w'\Omega b + b'\Omega b) \tag{22}$$

subject to $w'i = b'i = 1$

Let us use the Lagrange Multiplier method to solve it. The Lagrange function is:

$$L = \mu'(w-b) - \frac{\alpha}{2}(\frac{VaR^{*2} + 2VaR^* \mu' w + (\mu' w)^2}{\beta^2} - 2w'\Omega b + b'\Omega b) + \lambda_1(w'i - 1) \tag{23}$$

The First Order Conditions are:

$$\frac{\partial L}{\partial w} = \mu - \frac{\alpha}{\beta^2}VaR^* \mu - \frac{\alpha}{\beta^2}\mu\mu' w + \alpha\Omega b + \lambda_1 i = 0 \tag{24}$$

$$\frac{\partial L}{\partial \lambda_1} = w' i - 1 = 0 \tag{25}$$

Let $(N \times 1)$ matrix Ψ be $\mu - \frac{\alpha}{\beta^2} VaR^* \mu + \alpha \Omega b$, then from equation (24) we can get:

$$w = \frac{\beta^2}{\alpha} (\mu\mu')^{-1} (\Psi + \lambda_1 i). \tag{26}$$

Combining it with the equation (25), we have $i' \frac{\beta^2}{\alpha} (\mu\mu')^{-1} (\Psi + \lambda_1 i) = i' w = 1$. Finally, we get

$$\lambda_1^* = \frac{\frac{\alpha}{\beta^2} - i'(\mu\mu')^{-1}\Psi}{i' i}. \tag{27}$$

We know that $i' i = N$, so $\lambda_1^* = \frac{\alpha}{N \cdot \beta^2} - \frac{i'(\mu\mu')^{-1}\Psi}{N}$ land $w^* = \frac{\beta^2}{\alpha} (\mu\mu')^{-1} (\Psi + \lambda_1^* i)$. Similarly, we can calculate the maximum utility function based on the optimized w^* as follows.

$$E(U_2^*) = \mu'(w_2^* - b) - \frac{\alpha}{2} (w_2^* - b)' \Omega (w_2^* - b) \tag{28}$$

where ($w_1^* = w^*$).

We choose the maximum one between $E(U_1^*)$ based on w_1^* and $E(U_2^*)$ calculated by w_2^* as the final potential maximum value of the institutional investors' utility function and its best portfolio selection. In summary, the mathematical solution of this class of optimization utility function is shown as follows. One of the possible optimal asset allocation solutions is

$$w_1^* = b + \frac{1}{\alpha} \Omega^{-1} \left(\mu - \frac{i'\Omega^{-1}\mu}{i'\Omega^{-1} i} i\right) \text{ if } VaR^* + \mu' w_1^* - N^{-1}(c)\sqrt{w_1^{*\prime} \Omega w_1^*} \geq 0 \tag{29}$$

The other possibility is

$$w_2^* = \frac{\beta^2}{\alpha} (\mu\mu')^{-1} (\Psi + \lambda_1^* i) \tag{30}$$

where $\lambda_1^* = \frac{\alpha}{N \cdot \beta^2} - \frac{i'(\mu\mu')^{-1}\Psi}{N}$, $\Psi = \mu - \frac{\alpha}{\beta^2} VaR^* \mu + \alpha \Omega b$ and $\beta = N^{-1}(c)$

The optimized asset weight w^* which could make the utility function $E(U^*)$ bigger is the solution we are looking for. Next section gives information about the stock exchanges in China and explains why we decided to apply our model to Chinese market.

CHINA'S CAPITAL MARKET AND DATA

In order to put more pressure on the State Own Enterprises (SOE) to increase their accountability, reduce the SOEs' debt, liquidate the government's state assets, and enable the non-SOEs have access to capital, two stock exchanges were set up in Shenzhen and Shanghai in 1990 respectively. Over the past sixteen years, China stock market has facilitated the development of China's economic growth and market oriented reform, but it is still a young and immature market. At the end of 2005, there were 1378 listed companies in Chinese stock exchanges, which included 834 listed companies in Shanghai Stock Exchange and 544 listed companies in Shenzhen Stock Exchange.

A share market is for Chinese investors while the international investors can only invest in B share market because Chinese currency RMB is a domestic currency and the Chinese people can't exchange foreign currency freely. In both stock exchanges, there are A shares, B shares, T-notes, and some corporate bonds available for investors to trade. Although the stock markets in China have developed rapidly, China's stock markets remain relatively small in proportion to GDP, only 23.76% shown in the table above.

On its road to join the international market and finally become a well-developed market, Chinese stock market has been opening more and more to overseas institutional investors. Due to the promise made to World Trade Organization (WTO), China now allows the establishment of Sino-foreign joint venture securities firms and fund management companies and the Qualified Foreign Institutional Investors (QFII) have begun to participate in securities investment in Chinese stock market. We have reasons to believe that the gradual opening up of China's stock market will provide foreign institutional investors with excellent opportunities to invest in China. The potential opportunity of investing in Chinese stock market is the main reason why we choose it as the object of our empirical research.

On the other hand, Chinese stock market is an emerging market as mentioned above. Because the economic and political circumstances are different from those of the developed capitalist countries, emerging markets, including Chinese market, are usually considered to be much more risky. The severity of the Asian financial crisis in the late 1990's has stressed the importance of identifying the market risk and credit risk, especially in the emerging economies. Value at Risk which is a mathematical measurement of market risk is primarily concerned with the maximum loss in portfolio value over a given holding period to be experienced under a specific probability level. The VaR approach encourages the institutional investors to think of the portfolio as a set of assets exposed to, in theory, all sources of market risk. Therefore, adding VaR constraint will efficiently help our institutional investors to manage the high risk of investing in emerging markets and to pursue a higher risk-adjusted return of their portfolio to some extent.

Table 1: Summary Statistics of China Stock Market

Stock Exchange	Listed Companies	A Stock Shares	B Stock Shares	Market Cap. (C$,bn)	Market Cap. to GDP	Investor Accounts (mn)	Turnover in Value (C$,bn)	Average P/E
Shanghai	834	827	54	329.94	16.92%	38.56	711.08	16.33
Shenzhen	544	531	55	133.35	6.84%	35.37	189.65	16.36
Total	1378	1358	109	463.29	23.76%	73.93	900.73	16.35

This table shows basic information about two main stock exchanges in China.

Data

In order to show how the model works, we use the data obtained from DataStream database which is one of familiar international financial information providers. We try to find out the optimal portfolio from 25 listed companies that have the biggest market values from Shanghai Stock Exchange and 20 listed companies that have the biggest market values from Shenzhen Stock Exchange such that a VaR constraint over various time horizons is met. The reason why we use the market value as the stock selection criteria is that most institutional investors in Chinese market prefer to invest their funds in the big market value stocks. We employ daily data from these stocks from January 1996 or the date when the stocks were listed in the boards until June 2006.

We first calculate the number of observation, average return, standard deviation, median return, minimum return, maximum return, skewness, kurtosis and ratio of skewness to kurtosis for each stock we analyzed. Then we summarize their average values in the Table 2. A normal distribution has a skewness equal to zero and a kurtosis of 3. The negative or positive skewness implies that the distribution has a higher probability of a large loss or gain than the normal one. A kurtosis greater than 3 indicates that the distribution has longer tails than the normal distribution. One less than 3, on the other hand, means that the values of the distribution are bunched up near the mean. The further the skewness/kurtosis ratio from zero, the more likely it is that the returns are not normally distributed. If we take a look at the skewness and kurtosis of the monthly returns and daily returns, we can find that the stock returns do not conform well to a normal distribution. However, the skewness/kurtosis ratio shows us that the distribution of the daily returns is much closer to the normal distribution due to its larger observations.

Table 2: Summary Statistics of the Analyzed Data (Statistics Period: 01/01/1996 – 30/06/2006)

	Monthly			Daily		
Market	**Shanghai**	**Shenzhen**	**All Market**	**Shanghai**	**Shenzhen**	**All Market**
Observations	126	126	126	2533	2533	2533
Avg. Return	0.91%	1.45%	1.15%	0.05%	0.07%	0.06%
Avg. Standard Deviation	11.05%	13.69%	12.22%	2.61%	2.82%	2.70%
Avg. Median Return	0.20%	0.17%	0.19%	0.00%	0.00%	0.00%
Avg. Minimum Return	-27.37%	-35.32%	-30.90%	-16.67%	-16.65%	-16.66%
Avg. Maximum Return	46.74%	62.68%	53.83%	18.38%	19.82%	19.02%
Avg. Skewness	0.8486	0.9994	0.9156	0.2767	0.3112	0.2920
Avg. Kurtosis	3.3493	4.9012	4.0390	6.5199	6.6568	6.5807
Skewness/Kurtosis	0.2534	0.2039	0.2267	0.0424	0.0467	0.0444

This table shows the risk and return information of 45 stocks we pick. The skewness and kurtosis of the monthly returns and daily returns indicate that the time series data has longer tails than the normal distribution while the distribution of the daily returns is closer to the normal distribution.

Since Fama (1965), it has been well known and accepted by academic researchers and real investors that the asset returns do not always follow a normal distribution. In spite of this fact, the normality assumption is still working as a popular assumption in mainstream finance, as we do it in this paper. The only reason, why we use the assumption of normal distribution even when we know it is not true in the real world, is that it helps us to simplify the question and to clean the technical impediments in our research way. Also, as the number of observations increase, distribution approach would be normal.

Benchmark

The seemingly simple construction and rebalancing rules for price weighted index cause it to be the most popular index in the markets all over the world. As a basic benchmark, we use a price weighted index that includes all the stocks we chose from Chinese stock market. It means that each stock in the benchmark is weighted by its stock price as a proportion of the total price of all stocks in the index. Apparently, the price weighted index is a passive benchmark and it represents the buy and hold strategy. If at inception each stock in the index is weighted by its share of the index's total price and no new stock is introduced into the index after then, no adjustments to the index are necessary for it to keep its construction strategy. In other words, the performance of the price weighted index is the most easily replicate with a very low degree of tracking error.

We know that the index requires keeping rebalanced as soon as any price of the stock in the index changes after the index is constructed. That means that the equally weighted index is a good choice to be a benchmark because of its easy calculation, but its performance is nearly impossible to replicate with a low degree of tracking error. Because of its easy calculation and few rebalancing, we decided to construct a price weighted index which includes all analyzed stocks and used it as our benchmark. The rebalancing of this benchmark portfolio only takes place at the first trading day for each year in order to keep consistency between the benchmark and the real invested portfolio. On the other hand, we also choose the average monthly and daily return of the Shanghai A share stock index and Shenzhen A share stock index as another benchmark. Comparing the performance of our optimized portfolio with the performance of the whole markets will help us find out the extent to which the portfolio get the extra return compared to the average return of the market.

In this paper, what we investigate whether or not the optimized method is able to lead to outperformed portfolios for institutional investors. The statistics of Table 3 show that the average and the standard deviation of the monthly return of the equally weighted benchmark are 1.1478% and 8.0826%, respectively. It also tells us that the average daily return of the benchmark is much lower, 0.0571%, while its standard deviation is also lower, 1.7753%. Both the monthly and daily average returns of the whole market are less than those of benchmark, while their standard deviations are also much lower. The data shows us that the performances of the stocks whose market values are the greatest in the market are more outstanding. On the other hand, the average returns and standard deviations of the Shanghai A share stock index and the Shenzhen A share stock index present the similar risk and return tradeoff as shown in the following table. Monthly return and daily return of average stock index are 0.9789% and 0.0487% respectively, while the standard deviations are 7.9938% and 1.7136%. Again, the skewness, kurtosis and the ratio of skewness to kurtosis in Table 3 show us that neither the monthly return of the benchmark nor daily return is normally distributed. The average returns and standard deviations of both monthly and daily data from the 45 sample stocks are shown at Table 4.

Table 3: Summary Statistics of Equally Weighted Benchmark and Stock Index (Statistics Period: 01/01/1996 – 30/06/2006)

Statistics	Monthly Benchmark	Daily Benchmark	Monthly Stock Index	Daily Stock Index
Observations	126	2533	126	2533
Average Return	1.1478%	0.0571%	0.9789%	0.0487%
Standard Deviation	8.0826%	1.7753%	7.9938%	1.7136%
Median Return	0.8030%	0.0671%	0.3271%	0.0824%
Minimum Return	-19.4571%	-10.5963%	-19.6695%	-10.4900%
Maximum Return	29.7135%	10.4923%	29.3151%	9.6624%
Skewness	0.7520	-0.1993	0.8142	-0.2885
Kurtosis	1.7350	4.9774	1.8383	5.6070
Skewness/Kurtosis	0.4334	-0.0400	0.4429	-0.0514

This table shows statistical information about equally weighted benchmarks and main stock indices. The data in the table tells that the higher the risk, the better the returns. It also indicates that neither the monthly return series nor the daily return series is normally distributed.

Table 4: Summary Statistics of Sample Stocks (Statistics Period: 01/01/1996 – 30/06/2006)

	Daily Data		Monthly Data	
DataStream Code	**Average Return**	**Standard deviation**	**Average Return**	**Standard deviation**
CN:SPO	0.0391%	2.4845%	0.7861%	11.6670%
CN:SOP	0.0548%	2.7451%	1.1010%	12.0407%
CN:MIS	0.0155%	2.5676%	0.3108%	11.4078%
CN:SNN	0.0465%	2.6391%	0.9351%	12.2281%
CN:TTB	0.0484%	2.4355%	0.9737%	8.7942%
CN:SLF	0.0034%	2.4190%	0.0678%	10.3415%
CN:KGI	0.0107%	2.9167%	0.2143%	11.4095%
CN:DDS	0.1025%	2.4453%	2.0612%	9.3762%
CN:SSW	0.0499%	2.5426%	1.0027%	10.9729%
CN:SEA	0.0578%	3.0565%	1.1627%	12.2818%
CN:SDS	0.0291%	2.5489%	0.5855%	10.8973%
CN:HPC	0.0856%	2.6170%	1.7212%	11.2390%
CN:DEM	0.0346%	2.8638%	0.6962%	11.6314%
CN:SXX	0.0548%	2.8243%	1.1025%	9.8836%
CN:FY	0.0729%	2.8232%	1.4662%	11.4489%
CN:WCC	0.1106%	2.8147%	2.2225%	13.3332%
CN:BWJ	0.0572%	2.4063%	1.1502%	9.7123%
CN:SJF	-0.0015%	2.5995%	-0.0307%	10.0041%
CN:SCE	0.0270%	2.5563%	0.5435%	13.1500%
CN:QHR	0.0594%	2.3003%	1.1937%	10.1749%
CN:SSA	0.0337%	2.7256%	0.6772%	11.8141%
CN:CES	0.0299%	2.4241%	0.6019%	10.1069%
CN:IMM	0.0300%	2.6291%	0.6030%	11.0491%
CN:DNG	0.0583%	2.6181%	1.1717%	12.3640%
CN:SYT	0.0205%	2.2943%	0.4127%	9.0258%
CN:VAN	0.1036%	2.6170%	2.0819%	13.1405%
CN:CMA	0.0984%	2.5682%	1.9787%	10.7359%
CN:DEV	0.0551%	2.4209%	1.1087%	12.7659%
CN:LUZ	0.0709%	2.5557%	1.4247%	12.2338%
CN:GEP	0.0528%	2.4052%	1.0619%	10.6844%
CN:HPR	0.1193%	2.6545%	2.3984%	10.7195%
CN:CMP	0.0524%	2.6832%	1.0539%	13.3794%
CN:CHI	0.0687%	2.6187%	1.3811%	11.9969%
CN:ENI	0.0895%	2.6504%	1.7996%	12.5634%
CN:JAU	0.0440%	2.9861%	0.8850%	13.8560%
CN:KAF	0.0890%	3.1511%	1.7886%	20.8097%
CN:CSG	0.0655%	3.1265%	1.3163%	16.6308%

	Daily Data		Monthly Data	
DataStream Code	**Average Return**	**Standard deviation**	**Average Return**	**Standard deviation**
CN:BAH	0.0678%	3.0826%	1.3620%	14.5882%
CN:HSR	0.0988%	3.4348%	1.9856%	19.3540%
CN:GMH	0.0657%	2.4890%	1.3213%	10.9921%
CN:XHT	0.0715%	3.2398%	1.4382%	14.1822%
CN:ZHH	0.1018%	2.8659%	2.0460%	15.7506%
CN:SRA	0.0124%	3.2227%	0.2498%	15.0756%
CN:WAN	0.0575%	2.6082%	1.1556%	11.0887%
CN:GLM	0.0538%	2.9202%	1.0809%	13.1573%
Average	0.0571%	2.7022%	1.1478%	12.2235%

This tab le shows the return and risk information of all stock we select from two Chinese stock exchanges.

Apparently, there is a positive relationship between the expected reward measured by average return and the risk level estimated by the standard deviation. In order to examine the empirical support for this risk-return tradeoff, which is the most important assumption in Markowitz's mean variance model and accordingly our model, we use the following regression equation to identify the relationship between the average return and the standard deviation.

$$\mu_d = \alpha + \beta\sigma_d \tag{31}$$

where μ_d = Expected (Average) return of the daily return of the stock σ_d = Standard deviation of the daily return of the stock. The Ordinary Least Squares (OLS) estimates were obtained. The results are presented in Table 5.

Table 5: Regression between Each Year's Average Returns and Standard Deviations

Data	Variable	Coefficients	Standard Error	t Stat
Daily Data	Intercept α	-0.000018	0.000449	-0.040493
	Slope β	0.021801	0.016530	1.318863
Monthly Data	Intercept α	0.001695	0.004421	0.383436
	Slope β	0.080032	0.035491	2.255012

This table shows the regression estimates of the equation: $\mu = \alpha + \beta\sigma$. The first two rows show the estimated results using daily data while other two rows show the results for monthly data. The regression coefficients are shown in the third column. The fourth column shows standard error values of the time series data and the figure in each cell under last column is the t-statistic at the 5 percent level.

The estimated regression line based on daily data is:

$$\mu_d = -0.000018 + 0.021801\sigma_d + \varepsilon \tag{32}$$

where μ_d = Expected (Average) return of the daily return of the stock σ_d = Standard deviation of the daily return of the stock. The estimated regression line based on monthly data is:

$$\mu_m = 0.001695 + 0.080032\sigma_m + \varepsilon \tag{33}$$

where μ_m = Expected (Average) return of the monthly return of the stock, σ_m = Standard deviation of the monthly return of the stock.

T-stat test and p value in Table 5 show us that the estimated coefficient of standard deviation in monthly regression model is statistically significant at the 5% level, while the one in daily regression model is statistically significant at the 20% level. In other words, all these stocks have the identical characteristic: the greater the risk, the higher the return investors demand as compensation on them. That makes them relatively suitable to our institutional investors' utility model.

EMPIRICAL RESULTS

The investment period is from January 1, 1997 to June 30, 2006. The computation steps of the invested weights of the portfolio are presented as follows: We choose the first day of each year as the rebalancing date for the portfolio. At each rebalancing date, we calculate the optimized weights of the portfolio by using the model mentioned above and the data of previous year. For example, at the first trading day in 1997, we analyze the data between the first trading day and the last trade day in 1996 and use the utility maximum function subject to VaR constraint to generate the optimized weights for each stock in the invested portfolio. We allocate the actual weights of the portfolio by using the optimized weights calculated previously and keep the proportion in the whole year. Therefore, during the whole year in 1997, we adopt the hold strategy in the portfolio investment after the asset allocation at the beginning of 1997. At next rebalancing date, we repeat the process. In other words, at the first trading day of 1998, we use the optimized weights calculated by using the data in 1997 to allocate the assets for1998.

According to Chinese stock market policy, the investors are prohibited from short selling stocks in both Shanghai and Shenzhen Stock Exchange by the China Securities Regulatory Commission. Therefore, in the following scenario analysis, we also add non-short selling restrictions in the model, which is different from the academic one. Another important assumption in the calculation process is how to estimate the annual return and standard deviation by using the daily and monthly returns in order to calculate the VaR. We estimate the annual return by simply timing the daily or monthly average returns by the number of trading days or months in a year, while we calculate the annual standard deviation by multiplying the daily or monthly standard deviation by the square root of the number of trading days or months in a year. In this paper, we use the formulas as follows.

$$E(r_{annual}) = E(r_{daily}) * 250; \quad (34) \quad \sigma_{annual} = \sigma_{daily} \cdot \sqrt{250}; \quad (35)$$

$$E(r_{annual}) = E(r_{monthly}) * 12; \quad (36) \quad \sigma_{annual} = \sigma_{monthly} \cdot \sqrt{12} \quad (37)$$

where 250 is the number of the trading days in a year and 12 is the number of the trading months in one year. Let us assume the investor's risk aversion score $\alpha = 1$ and the utility function will be $E(U) = \mu'(w-b) - \frac{1}{2}(w-b)'\Omega(w-b)$ (38). We also suppose that $VaR^* = 2\%$ and the confidence level c = 95%. That is, the institutional portfolio managers are 95% confident the loss will be no greater than 2% of the initial investment of the initial or rebalancing date during the same year. Based on these assumptions, we solve this optimization problem with the initial \$1,000 thousand investment.

Finally, we get the result as shown in Table 6. From it, we can find that both monthly and daily returns are higher than the return of the equally weighted benchmark and the average return of the whole market. Both monthly data and daily data show us that the benchmark has the risk and return similar to those of the market. Once again, the skewness, kurtosis and the ratio of the skewness to kurtosis show that the return distribution of our investment portfolio is a little far away from the assumption of the normal distributed return.

Table 6: Summary Statistics of Optimized Portfolio, Equally Weighted Benchmark and Stock Index (Statistics Period: 01/01/1997 – 30/06/2006)

Statistics	Monthly Data			Daily Data		
	Portfolio	Benchmark	Market	Portfolio	Benchmark	Market
Observations	114	114	114	2286	2286	2286
Average Return	0.69%	0.58%	0.39%	0.07%	0.03%	0.02%
Standard Deviation	10.48%	7.13%	7.03%	1.95%	1.63%	1.56%
Median Return	0.39%	0.67%	-0.36%	-0.01%	0.04%	0.05%
Minimum Return	-28.47%	-14.82%	-14.30%	-10.06%	-9.72%	-9.84%
Maximum Return	36.93%	29.34%	29.32%	9.54%	9.42%	9.32%
Skewness	0.60	0.59	0.70	0.41	-0.12	-0.15
Kurtosis	2.03	1.43	1.64	4.03	4.88	5.75
Skewness/Kurtosis	0.29	0.41	0.43	0.10	-0.02	-0.03

This table indicates that both monthly and daily returns of our optimized portfolio are higher than those of the equally weighted benchmark and the market's returns while the portfolio has slightly higher risk than benchmarks and market main indices. The skewness and kurtosis show that the return distribution of our optimized portfolio unlikely satisfies the assumption of the normal distributed return.

When we use the daily data to do our optimization, the returns of our optimized portfolio, the equally weighted benchmark and the stock index are shown in Graph I. It tells us that the total return, average return and standard deviation of the optimized portfolio are the highest. The risk and return properties of the benchmark and the stock index are similar and both of them follow the rule of risk-return tradeoff. In our case, the equally weighted benchmark has a similar risk-return behavior to the whole market.

Using the daily data gives us the similar result in the relationship among the total returns of our portfolio, equally weighted benchmark and stock index. On this angle, we can make a conclusion that the performance of our optimized portfolio is much better than the normal performance of the whole market, and exceeds the equally weighted benchmark as well.

These results from both monthly data and daily data show us that our portfolio outperforms the equally weighted benchmark and has a better performance than the market. However, the relative return of our portfolio to the equally weighted benchmark and the stock index is much higher than the result shown by the daily data. In other words, the weights optimized from daily data can improve the performance of our portfolio more than those calculated by using monthly data. On the other hand, the return distribution of daily data is much closer to a normal one comparative to that of monthly data. We know that the normal distribution is one of the most important assumptions in our model. Therefore, we can say that the result is somewhat close to our expectation of the paper.

As shown in Table 7, stocks listed on Shenzhen exchange in our optimized portfolios are riskier than those listed on Shanghai exchange, but they have much more return contributions to our optimized portfolio.

Table 8 gives us another chance to take a closer look at stock return contributions of our optimized portfolios. Over years, the sector Construction & Materials has the biggest return contribution to our portfolio with the highest standard deviation. The sectors Autombiles & Parts, Beverages, and Technology Hardware & Equip. have also played very important roles in the nearly 10 year return of our optimized portfolio.

Table 7: Contribution Statistics of Optimized Portfolio by Stock Exchanges (Statistics Period: 01/01/1997 – 30/06/2006)

Statistics	Monthly Data		Daily Data	
	Shanghai	Shenzhen	Portfolio	Benchmark
Observations	114	114	2286	2286
Average Return	1.83%	6.20%	0.09%	0.31%
Standard Deviation	5.62%	15.27%	0.98%	2.21%
Median Return	0.02%	2.07%	0.00%	0.00%
Minimum Return	-12.35%	-21.07%	-7.13%	-10.02%
Maximum Return	30.47%	102.83%	9.96%	10.18%
Skewness	2.13	3.06	1.91	1.14
Kurtosis	8.78	14.76	20.59	6.44
Skewness/Kurtosis	0.24	0.21	0.09	0.18

Besides Table 6, this table gives us a closer look at the performance of our optimized portfolio by stock exchanges. The data tells a similar story as Table 6 does.

Table 8: Contribution Statistics of Optimized Portfolio by Sectors (Statistics Period: 01/01/1997 – 30/06/2006)

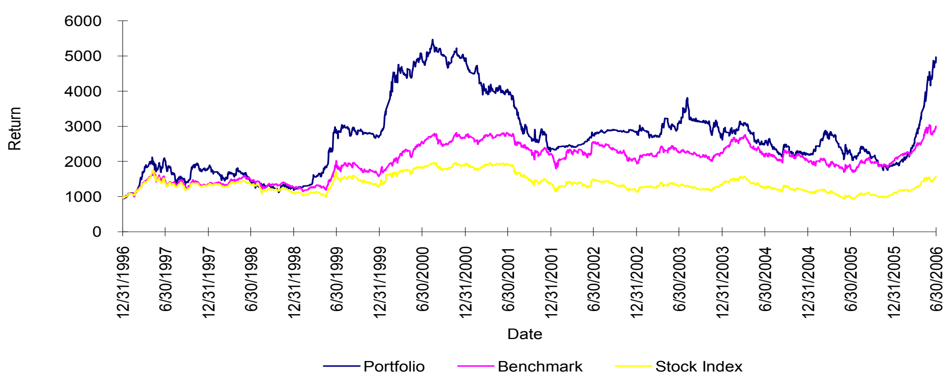
Statistics	Monthly Data				Daily Data			
	Average Return	Standard Deviation	Skewness	Kurtosis	Average Return	Standard Deviation	Skewness	Kurtosis
Aerospace & Defense	0.33%	3.20%	7.39	71.33	0.02%	0.41%	2.72	39.89
Automobiles & Parts	1.49%	4.47%	3.15	12.92	0.07%	0.89%	2.86	26.05
Banks	0.00%	0.00%	0.54	34.62	0.00%	0.00%	-2.65	66.17
Beverages	1.25%	5.69%	5.10	27.05	0.06%	0.91%	5.47	71.81
Chemicals	0.16%	1.08%	5.94	40.71	0.01%	0.19%	5.12	65.90
Construction & Materials	1.52%	11.23%	7.35	61.84	0.08%	1.29%	3.04	34.95
Electricity	0.13%	0.74%	3.64	17.89	0.01%	0.12%	4.92	66.63
Electronic, Electrical Equip.	0.00%	0.00%	2.08	14.34	0.00%	0.00%	1.32	40.60
Gas, Water & Multiutilities	0.00%	0.00%	-2.69	14.41	0.00%	0.00%	0.27	29.88
General Financial	0.00%	0.00%	-1.68	30.92	0.00%	0.00%	-0.44	41.14
General Industrials	0.17%	1.15%	3.18	15.52	0.01%	0.23%	1.76	23.70
General Retailers	0.29%	1.30%	0.59	10.77	0.01%	0.31%	1.02	29.86
Household Goods	0.00%	0.00%	-1.24	15.22	0.00%	0.00%	2.07	49.29
Industrial Engineering	0.34%	1.49%	3.66	20.26	0.02%	0.32%	2.01	26.55
Industrial Metals	0.02%	0.15%	3.08	21.23	0.00%	0.04%	4.62	64.32
Industrial Transportation	0.21%	0.97%	3.19	20.85	0.01%	0.20%	1.94	29.65
Leisure Goods	0.10%	0.47%	4.07	20.08	0.00%	0.09%	2.74	46.16
Pharmaceuticals, Biotechnology	0.73%	4.08%	2.95	16.56	0.04%	0.75%	3.68	58.24
Real Estate	0.05%	0.45%	1.05	16.46	0.00%	0.09%	2.19	43.97
Support Services	0.00%	0.00%	1.42	11.97	0.00%	0.00%	0.89	17.45
Technology Hardware & Equip.	1.23%	8.55%	4.24	24.20	0.06%	1.16%	1.69	31.43
Travel & Leisure	0.00%	0.00%	-4.40	31.76	0.00%	0.00%	-1.67	31.32

This table provides us another view of the return and risk of all sectors in our optimized portfolio.

However, before we decide to use this optimization model in our real investment world, we should pay attention to the followings in advance: 1.The greater the number of stocks in the portfolio, the more complicated the calculation of the model. 2. One of the most important requirements for the model is that the stocks in the portfolio should have the similar risk-return characteristics. The stock which has a high risk is supposed to have a high expected return. Although most stocks in our case seems to have this type of the risk-return tradeoff, other stocks in the market may not satisfy this requirement. 3. The deterministic optimization approach typically uses historical data to forecast the weights of portfolio in the coming year and expect the trends of stocks similar to those in the past year. The premise of this type of forecasting is that all current market information has always been reflected in the price movement of the stocks.

In summary, there are some potential problems which are needed to be researched further, although we can use this mathematical model in the real world to provide the suggestion on portfolio allocation to decision-makers.

Figure 1: The Daily Returns of Our Portfolio, Equally Weighted Benchmark and Stock Index



This figure uses the daily time series data to compare the historical performance among our optimized portfolio, equally weighted benchmark and market stock index.

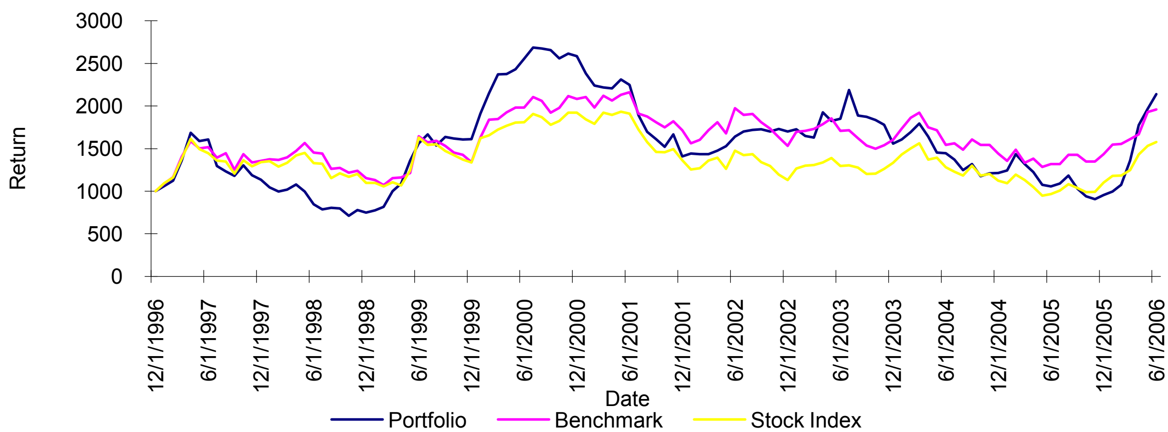
CONCLUSIONS

One of the main contributions of our paper is to provide a theoretical solution to our institutional investors' portfolio optimization problem. Solving this optimal investment in the mathematical way helps us to develop a framework for portfolio allocation under Value-at-Risk constraint. The measure for the risk of our portfolio depends not only on the variance or standard deviation, as normal mean variance analysis theories do, but also on the portfolio's potential loss, which is measured by Value at Risk in the paper. Introducing VaR into the institutional investors' optimal utility function has the benefit of allowing the risk-return tradeoff analyzed through focusing on the control of our portfolio's maximum potential loss. The mathematical solution provides a practical way for our institutional investors to carry out the investment decisions in the well-know mean-variance allocation framework, which also satisfy the common Value at Risk restrictions imposed by the internal and/or external regulators.

On the other hand, in order to study the feasibility of our solution, we collect the data from Chinese stock markets to do the empirical analysis and examine how our model works. China has been becoming a hotter and hotter investment zone with the more and more advanced opening of her financial market coming along with WTO. The analysis based on about 10-year monthly and daily data from Chinese markets shows us that our optimized portfolio can be expected to do slightly better than the market return and outperforms than the equally weighted benchmark. Consistent with the risk-return tradeoff, the result also shows us that the higher the return among our portfolio, benchmark index, and market index, the greater the risk.

During the period we analyze in this paper, Chinese stock markets were still relatively small and mainly domestic because they didn't allow any foreign players. Because of this, some global financial events such as global financial crisis have very limit effect on this emerging market. However, it will be interesting and meaningful to see how our model will perform when exposed to global financial events. This will be one of areas in our future research.

Figure 2: The Monthly Returns of Our Portfolio, Equally Weighted Benchmark and Stock Index



This figure uses the monthly time series data to compare the historical performance among our optimized portfolio, equally weighted benchmark and market stock index.

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BIOGRAPHY

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A SIMULATION OF THE U.S. ECONOMY TO DETERMINE THE EFFECT OF MANDATORY EXPENSES AND INTEREST ON THE U.S. DEBT

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ABSTRACT

Cost for the three major mandatory social programs; Social Security, Medicare and Medicaid have increased at a rate much higher than the Gross Domestic Product (GDP), and thus revenue. As a result, these programs account for a larger portion of the U.S. budget. As projections continue to rise relative to available revenue, a lower level of funds will be available for other programs or the U.S. debt will continue to increase further exacerbating the problem. As the total U.S. debt approaches the yearly GDP (in 2010 the total U.S. debt is projected to be 97% of the GDP), the risk of rising interest rates becomes a larger concern. This paper shows that even a small increase in the interest rate has a big impact on the overall budget. This paper shows that the practice of continuing to increase the U.S. debt at a rate higher than the GDP/revenue increases is simply unsustainable.

JEL: H51, H55, H68

KEYWORDS: Projections, Interest on U.S. Debt, Social Security, Medicare, Medicaid

INTRODUCTION

Over the last several decades mandatory spending, primarily Social Security, Medicare and Medicaid have been consuming a larger portion of Federal spending. In 1966, Social Security, Medicare and Medicaid accounted for 16% of Federal spending. In 1986 and 2006, these same programs accounted for 30% and 40% of Federal spending, respectively. With 80 million baby boomers hitting retirement age beginning in 2008, projections indicate that these mandatory programs will see even bigger demands.

This paper looks at Social Security in detail and displays surplus/deficit projections under intermediate and high assumptions as reported in the 2009 Social Security Trustees Report. Social Security is projected to begin running a deficit in 2016, under intermediate assumptions, but with unemployment at 10% and an increased number of claims; Social Security will most likely see a deficit much sooner. In Walker's *Comeback America*, Social Security expects to have a negative cash flow in 2010/2011. This paper also looks at the effect increasing revenue and/or decreasing cost has on the long-term Social Security surplus/deficit projections.

As described in Friedman, Medicare spending has grown by 2.4% points faster than GDP over the past thirty years more than tripling as a share of GDP since 1960. If costs continue to grow at current rates relative to GDP, then Medicare alone will account for 8% of the GDP and 44% of the revenue in 2030. According to the Congressional Budget Office, rising health cost is the biggest contributor to cost growth contributing even more than that due to the ageing population. In this paper, the author calculates budget surplus/deficit projections for Medicare Health Insurance (HI). Medicare Hospital Insurance (HI) currently operates in a deficit and that deficit projects to grow with each passing year.

The deficit is the gap between expenditures and revenue in any given year ($1.4 trillion in the U.S. in 2009), whereas debt accumulates past deficits (total, public plus private, U.S. debt at the end of 2009 is $12.4 trillion). As described in Chernew, Baicker and Hsu, having such a large total debt relative to the

GDP is a concern for many reasons. First, interest payments consume and increasing share of income (9% of spending in 2009 was used to pay the interest on the total U.S. debt); Second, growing debt can lead to higher interest rates for all borrowers (government, businesses, and individuals) thus impeding economic growth. Finally, high debt reduces our capacity to respond to economic shocks and magnifies the detrimental effects of any deficit. The author performs an analysis to determine the effect rising interest will have on future available revenue under a various assumptions.

Finally, the author makes projections showing the percentage of U.S. revenue spent on mandatory programs and interest on the U.S. debt for the years 2018 and 2035. In 2018, projections in the 2009 U.S. Budget indicate that spending on mandatory expenses and interest will account for 85% of the U.S. revenue. Results presented at the end of this report show the need for reform of mandatory programs, debt control, and increase in revenue.

LITERATURE REVIEW

All historical data, prior to 2008, was taken directly from the 2010 U.S. Budget Historical Tables. Unless otherwise noted, projection data for years 2009 through 2018 was taken directly from the 2010 U.S. Budget Updates Summary Tables (May 2009). The 2010 U.S. Budget assumes an average annual GDP increase of 4.92% from 2010 through 2019 with the increase tapering down to 4.45 % from 2014- 2019. For the last 30 years, the annual U.S. revenue has averaged 18.0 % of the Gross Domestic Product (GDP). For the last 40-years, the U.S. debt has increased an average of 9 % per year. In the 2009 U.S. Budget, the U.S. debt projects to increase an average of 8.7% per year for years 2009-2018. During that same 10-year period, revenue projects to increase an average of 5.3% per year. Mandatory programs as a percentage of Federal spending, provided in the Introduction, was calculated from the 2010 U.S. Budget historical tables and is consistent with the data provide in the 2008 U.S. Financial Condition and Fiscal Future Briefing.

All Social Security data comes from the 2009 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds hereafter referred to as the 2009 Social Security Annual Report. Total Social Security benefits paid in 2008 were $615 billion. Total income was $805 billion, and assets held in special issue U.S. Treasury securities grew to $2.4 trillion. Social Security currently operates on a yearly surplus and that yearly surplus pays the current U.S. obligations in exchange for special issue Treasury Securities. Since the Social Security Administration has loaned the surplus funds to the Treasury Department, only IOU's are in the $2.4 trillion Social Security trust fund.

All Medicare data comes from the 2009 Annual Report of the Board of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. In 2008, total Medicare expenditures were $468 billion and future expenditures will increase at a faster pace than the overall U.S. economy. Medicare Hospital Insurance (HI), Part A, is currently operating in a deficit and that deficit will grow with each passing year with the Medicare trust fund exhausted in 2017 under intermediate assumptions. The Medicare HI trust fund is similar to the Social Security trust fund because Medicare loans surplus funds to the Treasury Department in exchange for special issue securities (IOU's). For the last 10-years, income has increase an average of 4.2% while expenses have increased an average 6.4% per year. Under intermediate assumptions, this deficit trend expects to continue and increase in the out years. The Supplementary Medical Insurance (SMI), Part B, trust fund is adequately financed over the next 10-years because general revenues are reset every year to match cost. Under current law, Medicare requires an average annual growth rate of 5.5% for the next 5-years. As described in the Annual Report, this is unrealistically constrained and requires physician fee reductions (21.5% for 2010) to be continually overridden by Congress (2003-2009). If Congress continues to override these physician fee reductions, the part B average annual growth rate will be 8.5% to 9.0%. The average annual Part D growth rate is 11.1% through 2018. The U.S. Economy, as described in the Medicare Trustees Report, projects to grow 4.5% during the same period.

All Medicaid data comes from the 2008 Actuarial Report on the Financial Outlook for Medicaid. Medicaid spending in 2007 was 333.2 billion; $190.6 billion represents Federal spending and $142.6 billion represents State spending. Medicaid expects to grow about 7.9% per year on average and reach $673.7 billion by 2017. The U.S. budget projects revenue to grow an average of 4.9% per year during the same timeframe.

Projected cost for "Other Mandatory Programs" comes directly from the 2010 U.S. Budget for years 2009 through 2019. Other Mandatory Programs projects to increase 4.26% per year after 2019, which is the average projected increase from 2008 through 2019.

In 2008, the U.S. debt was $9.986 trillion and interest paid on the U.S. debt was $253 billion accounting for 10% of the 2008 revenue. The interest rate paid on the total U.S. debt in 2008, as reported in the Updated 2010 U.S. Budget Summary Tables, was 2.53%. The current U.S. debt is $12.04 trillion (Nov. 2009). The debt in the 2010 U.S. Budget projects to be $23.29 trillion in 2019. The average interest rate paid on the U.S. debt for years 2009-2019 in the U.S. Budget is 2.5%.

DATA AND METHODOLOGY

In the short term, Social Security is projected to begin running a yearly growing deficit. In the long term, under intermediate assumptions, Social Security projects to continue to account for a larger portion of the yearly U.S. revenue thereby increasing the total U.S. debt. The Social Security Surplus/Deficit Projections (Figures 1 and 2) were determined from data provided in the 2009 Social Security Annual Report and calculated by subtracting income from cost that were determined by multiplying the OASDI Income and Cost Rates (Table IV.B1) by the Taxable Payroll (Table VI.F6) for years 2010 – 2035 under Intermediate and High assumptions. Results under intermediate assumptions are consistent with that reported by Allan Sloan (2010) in "*The next great bailout: Social Security*" which utilized the same methodology (high projections were not provided by Mr. Sloan). Potential solutions discussed in the Social Security Trustees Report include increasing the payroll tax from its current level of 12.4 percent (for employees and employers combined) to 14.41 percent. This tax increase, excluding reaction effects, results in a theoretical 16.2% increase in income [16.2% = (14.1/12.4) -1]. Alternatively, Social Security can reduce current and future costs by 13.3 percent. Alternatively, there could be a combination of the two. A first order analysis of these options looks at the effect on Social Security itself and not the impact to the growth of the U.S. economy or impact on beneficiaries. Results shown in the next section (Figures 3-6) were determined as described in this paragraph and by increasing the income or decreasing the cost by the percentages suggested in the Social Security Annual Report under intermediate assumptions.

The Medicare Hospital Insurance surplus/deficit deficit (Figure 7) was determined from data provided in the 2009 Federal Hospital Insurance and Federal Supplementary Medical Insurance Annual Report and calculated by subtracting income from cost that was determined by multiplying the HI Income and Cost Rates (Table III.B7) by the Taxable Payroll for years 2010 – 2035 under intermediate assumptions. This data is similar but worse than that presented in David M. Walkers GAO U.S. Financial Condition and Fiscal Future Briefing however his data was based on the 2007 Medicare Annual Report.

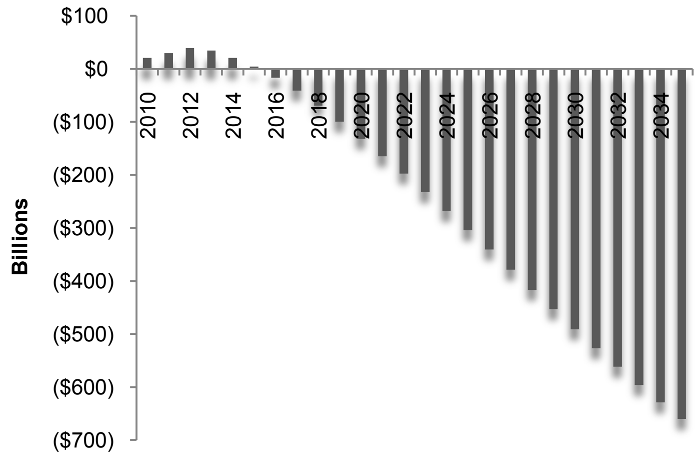
A Monte Carlo simulation, utilizing Oracle Crystal Ball©, was performed to look at the effect GDP growth, yearly U.S. debt increases, and varying interest rates have on the available revenue and future U.S. debt. Oracle Crystal Ball© is the leading spreadsheet based application suite for predictive modeling, forecasting, simulation, and optimization. Simulation A, B, and C, assume the following; (1) The U.S. debt continues increasing at an average rate of 7% per year. Debt increases with a normal distribution with 7.06% as the mean. Since this is an average increase over a number of years, the standard deviation was set at .005%. (2) The average annual GDP growth rate modeled with a normal distribution with the mean set at 4.6%. Since this is an average increase over a number of years, the standard deviation was set at .002%. For simulation A (low assumption), the interest rate paid on the Total U.S. debt for a given year was modeled with a normal distribution with the mean set at 2.5%. The standard deviation was set at .005 with the interest rate truncated at 1.2%. The interest rate paid on the U.S. debt listed in the 2010 U.S. Budget for 2011 is 1.2% and represents the minimum. For simulation B (moderate assumption), the interest rate paid on the Total U.S. debt for a given year was modeled with a normal distribution with the mean set at 2.5%. The standard deviation was set at .02 with the interest rate truncated at 1.2%. For simulation C (high assumption), the interest rate paid on the Total U.S. debt for a given year was modeled with a triangular distribution with the likeliest set at 2.5%, the minimum set at 1.2%, and the maximum set at 9.4%. Table 1 displays the results from this analysis.

Finally, we look at the effect that mandatory programs and interest on the U.S. debt have on available revenue for 2008, 2018 and 2035. GDP, total U.S. debt and revenue for 2008 and projections for 2018 come directly from the 2010 U.S. Budget. GDP was projected to increase 4.6 % per year from 2019-2035, consistent with GDP increase contained in the Social Security Annual Report. The U.S. debt projects to increase 7% per year from 2019- 2035. All Social Security expense data comes from the 2009 Social Security Annual Report. Medicare expenses for 2008 and 2018 come directly from the 2009 Medicare Annual Report (Table V.E4). Medicare expenses were estimated to continue increasing 6.9% per year for 2019-2035 which is the average annual increase from 2008 – 2018 reported in the 2009 Medicare Annual Report. Medicaid expenses for 2008 and 2018 come from the 2010 U.S. Budget. Medicaid expenses were estimated to increase 7.9% per year from 2019-2035 consistent with the projected yearly increases described in the 2009 Medicaid Annual Report. Other Mandatory Expenses for 2008 and projections for 2018 come directly from the 2010 U.S. Budget. Projections for 2035 assume an average 4.26% per year increase, consistent with the increases from 2008 – 2018. Interest on U.S. debt comes directly from the 2010 U.S. Budget for 2008 and 2018. For this analysis, interest on the total U.S. debt in 2035 is 2.5%. Table 2 and Figure 8 display the results.

RESULTS

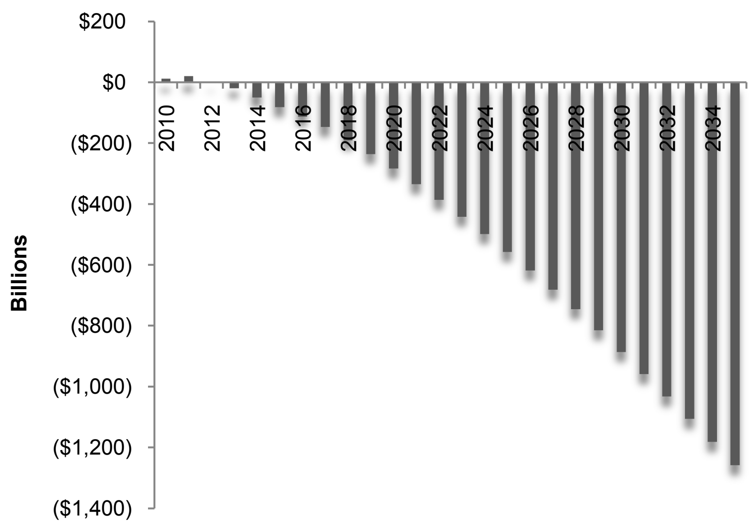
Under intermediate assumptions (Unemployment rate of 8.2%, 8.8%, and 7.9% in calendar years 2009, 2010, and 2011 respectively and tapering down to 5.5% in 2016), Social Security will continue to operate with a yearly surplus until 2016 at which time it will begin operating on a yearly deficit that is projected to grow with each passing year (see Figure 1). Under high-cost assumptions (Unemployment rate of 8.5%, 9.3%, and 8.3% in calendar years 2009, 2010, and 2011 respectively and tapering down to 6.5% in 2018), Social Security will begin operating on a yearly deficit in 2013 (see Figure 2). Since the U.S. unemployment rate is currently at 10.2% (Nov. 2009), Social Security is expected to run a deficit before 2013 and possibly as early as 2010. When Social Security runs a yearly deficit, Social Security will sell the Treasury Securities that the U.S. government owes itself to investors. The bond market will react to this debt shift especially as it grows. Under the intermediate assumptions, the Social Security Trust fund will remain solvent until 2036 at which time the annual Social Security deficit will be $690 Billion per year and growing (See Figure 1). Social Security reform is required and expects to be a hot topic in Washington, DC after the Health Care debate.

Figure 1: Social Security Yearly Surplus/Deficit (Intermediate Projections)



This figure shows the yearly Social Security surplus/deficit projections under intermediate assumptions for years 2010 – 2035. Data comes from the 2009 Social Security Annual Report by subtracting expenses from income.

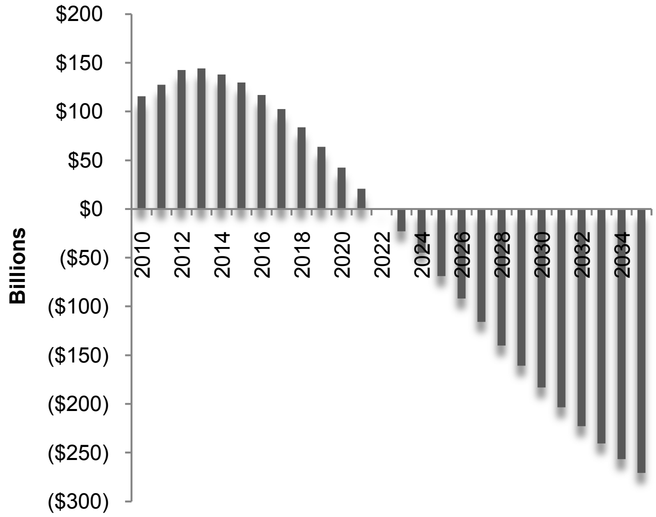
Figure 2: Social Security Yearly Surplus/Deficit (High Projections)



This figure shows the Social Security yearly surplus/deficit projections under high assumptions for years 2010 – 2035. Data comes from the 2009 Social Security Annual Report by subtracting expenses from income.

Figures 3 through 6 show the results of reducing cost, increasing income or a combination thereof as described in the 2009 Social Security Annual Report. Figure 3 displays the Social Security surplus/deficit projection assuming a 13.3% reduction in costs as reported in the 2009 Social Security Annual Report under nominal assumptions.

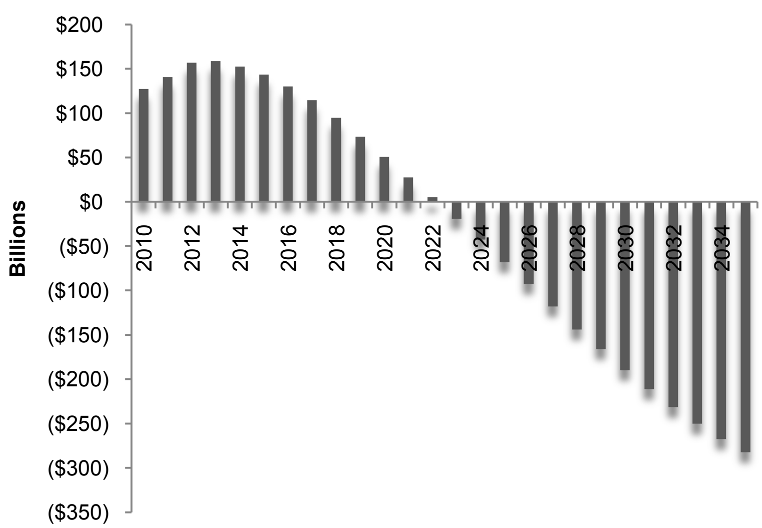
Figure 3: Social Security Yearly Surplus/Deficit Projections (Intermediate) with 13.3% Reduction in Cost



This figure shows the Social Security yearly surplus/deficit projections under intermediate assumptions with a 13.3% reduction in cost for years 2010 – 2035. Results come from the 2009 Social Security Annual Report by subtracting expenses x 86.7% from income.

With a 13.3% reduction in cost, Social Security will begin operating in a yearly growing deficit in 2023. The Social Security Trust Fund will have more years to grow and therefore will take longer to deplete. Keep in mind that the intermediate projections are optimistic since Social Security under-predicted unemployment rates. Figure 4 displays the Social Security surplus/deficit projection assuming a 16.2% increase in revenue, as reported in the 2009 Social Security Trustees Report under nominal assumptions. With a 16.2% increase in revenue, Social Security will begin operating in a yearly growing deficit in 2023. The Social Security Trust Fund will have more years to grow and therefore will take longer to deplete.

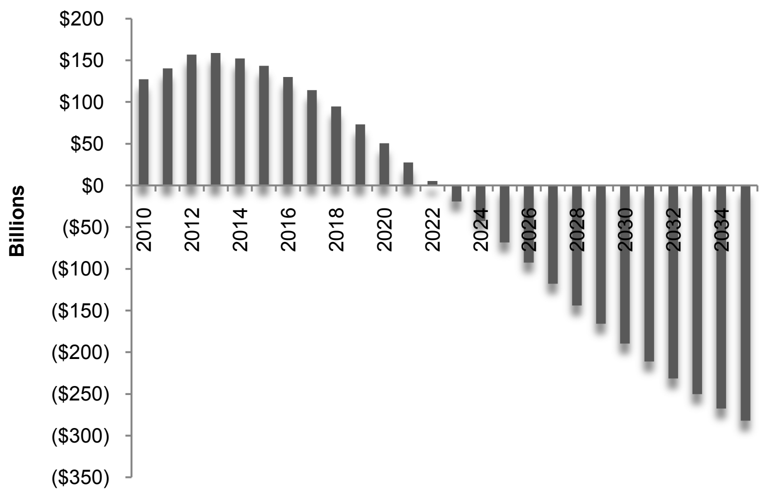
Figure 4: Social Security Yearly Surplus/Deficit Projections (Intermediate) with 16.2% Increase in Revenue



This figure shows the Social Security yearly surplus/deficit projections under intermediate assumptions with a 16.2% increase in revenue for years 2010 – 2035. Results come from the 2009 Social Security Annual Report by subtracting expenses from income x 16.2%.

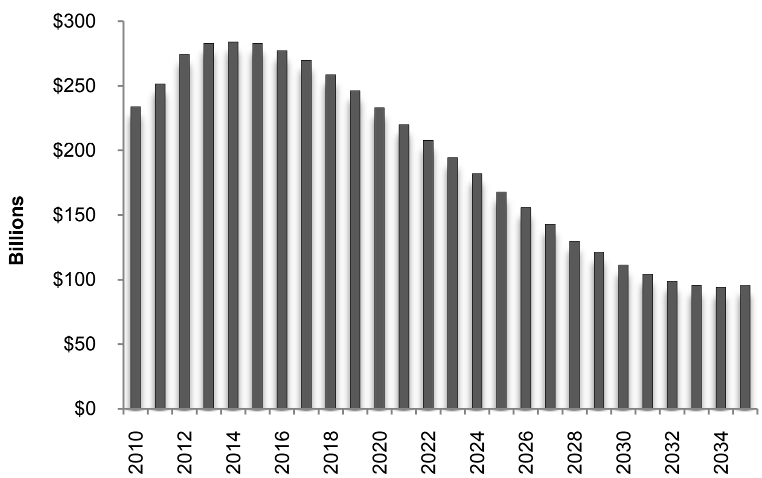
Figure 5 displays the Social Security surplus/deficit projection assuming a combination of 6.65% reduction in costs and an 8.1% increase in revenue. Also for this case, Social Security will begin operating in a yearly growing deficit in 2023. The Social Security Trust Fund will have more years to grow and therefore will take longer to deplete.

Figure 5: Social Security Yearly Surplus/Deficit (Intermediate Projections) with 6.65% Reduction in Cost and 8.1% Increase in Revenue



This figure shows the Social Security yearly surplus/deficit projections under intermediate assumptions with a combined 6.65% reduction in cost and 8.1% increase in revenue for years 2010 – 2035. Results come from the 2009 Social Security Annual Report by subtracting expenses x 93.35% from income x 8.1%.

Figure 6: Social Security Yearly Surplus/Deficit Projections (Intermediate) with Full 13.3% Reduction in Cost and 16.2% Increase in Revenue



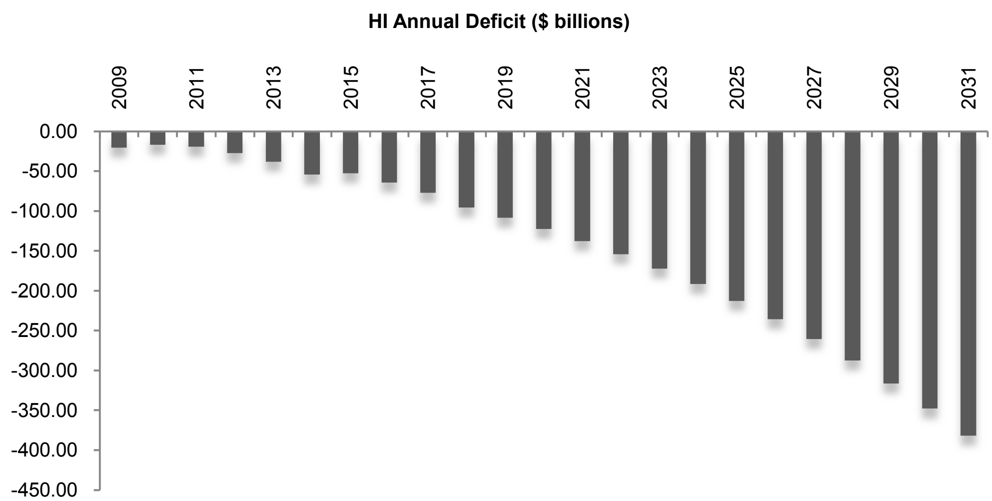
This figure shows the Social Security yearly surplus/deficit projections under intermediate assumptions with a combined 13.3% reduction in cost and 16.2% increase in revenue for years 2010 – 2035. Results come from the 2009 Social Security Annual Report by subtracting expenses x 86.7% from income x 16.2%.

A final projection of the Social Security surplus/deficit assumes a full combination of 13.3% reduction in costs and 16.2% increase in revenue. Clearly, a full 13.3% reduction in benefits and 16.2% increase in

Social Security payroll taxes would have a larger impact on beneficiaries and economic growth. As shown in Figure 6, for a combined effort less than a 13.3% reduction in benefits and less than 16.2% increase in payroll taxes could keep Social Security operating in the black.

Figure 7 displays the Medicare Hospital Insurance (HI) surplus/deficit curve for 2010 – 2035. Medicare HI is currently operating with a yearly deficit and that yearly deficit projects to grow with each passing year. In addition, the Medicare HI surplus/deficit deficit keeps getting worse with each Annual Report. Clearly, Medicare HI costs need to be controlled.

Figure 7: Medicare HI Yearly Surplus/Deficit Projections (Intermediate)



This figure shows the annual Medicare Health Insurance (HI) deficit in billions of dollars. Results come from the 2009 Medicare Annual Report by subtracting expenses from income.

Next, the Monte Carlo simulation results are presented that predict the probability of what percentage of yearly revenue will be required to pay the interest on the U.S. debt for 2018 and 2035. Results from simulation A (low assumption), show a 50% probability that in 2018, the interest on U.S. debt will account for between 12% - 16% of the revenue for that year with the full range of probabilities between 6% - 22%. In 2035, for simulation A there is a 50% probability that the interest on the U.S. debt will account for 17% - 23% of the revenue for that year with the full range of probabilities between 8% - 33%. Presented in Table 1 are the results for Simulations B and C in addition to Simulation A.

Table 1: Probability of Percent of U.S. Revenue Paid Towards Interest on U.S. Debt (2018 and 2035)

	Year	50% Probability Range	Complete Probability Range
Simulation A	2018	12% - 16%	6% - 22%
(low)	2035	17% - 23%	8% - 33%
Simulation B	2018	8% - 19%	6% - 42%
(moderate)	2035	13% - 28%	8% - 61%
Simulation C	2018	13% - 27%	7% - 53%
(high)	2035	17% - 37%	9% - 76%

This table shows the probability distribution of the percentage of revenue required to pay the interest on the U.S. debt for 2018 and 2035 under Low (Simulation A), Moderate (Simulation B), and High (Simulation C) interest rate assumptions. For all simulations the U.S. Debt was modeled to increase 7.06% per year with a normal distribution with a standard deviation of .005, GDP was modeled to increase 4.6% per year with a normal distribution with a standard deviation of .002. For Simulation A, the interest rate was model with a normal distribution with the mean set at 2.5% and a standard deviation of .005. For Simulation B, the interest rate was model with a normal distribution with the mean set at 2.5% and a standard deviation of .02 and the minimum truncated at 1.2%. For Simulation C, the interest rate was model with a triangular distribution with the most likely value of 2.5%, a minimum of 1.2% and a maximum of 9.4%.

Based on the results above, it is clear that rising interest rates are a threat to available resources in the coming years. It is clear that the U.S. cannot continue to increase the U.S. Debt at an average of 9% per year while GDP, and thus revenue, increase at an average rate of 4.6%. The Federal Reserve must make efforts to keep interest rates relatively low while at the same time controlling inflation. At the same time, after the U.S. economy improves, the Government must then focus its efforts to reduce the yearly deficit and thus debt. To keep this problem from getting worse, at a minimum, the average annual debt increase should be lower than the average annual revenue increase. Below are projections of mandatory expenses and interest on the U.S. debt for 2008, 2018, and 2035.

Table 2: Mandatory Outlays and Interest on U.S. Debt for Years 2008, 2018 and 2035

U.S. Dollars in Billions	2008 (% of revenue)	2018 (% of revenue)	2035 (% of revenue)
GDP	$ 14,222	$ 21,884	$ 46,940
U.S. Debt (EOY)	$ 9,986	$ 22,248	$ 68,756
Revenue	$ 2,524	$ 4,218	$ 8,778
Social Security Outlay	$ 625 (24.8%)	$ 1,148 (27.2%)	$ 2,923 (33.3%)
Medicare Outlay (Fed.)	$ 386 (15.3%)	$ 780 (18.5%)	$ 2,775 (31.6%)
Medicaid Outlay	$ 201 (8.0%)	$ 438 (10.4%)	$ 1,590 (18.1%)
Other Mandatory Expenses	$ 411 (16.3%)	$ 506 (12.0%)	$ 1,064 (12.1%)
Interest on U.S. Debt	$ 253 (10.0%)	$ 708 (16.8%)	$ 1,719 (19.6%)

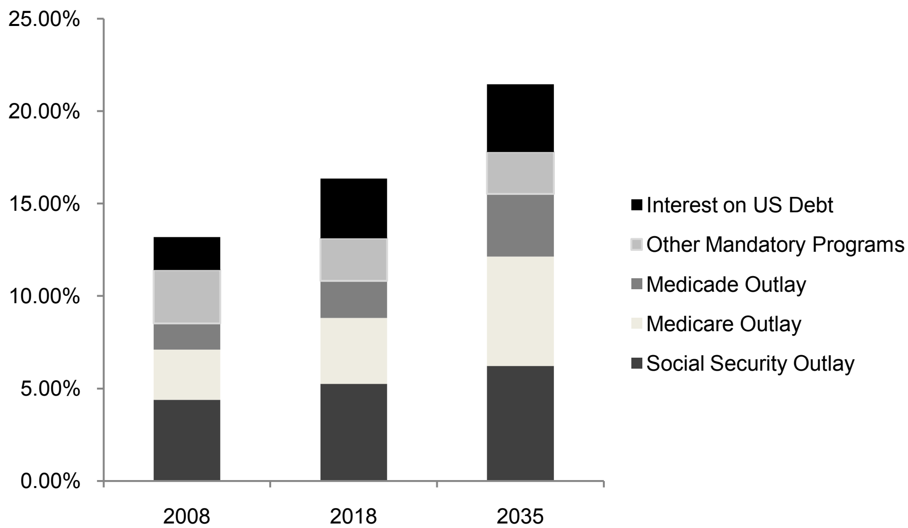
This table shows GDP, U.S. Debt, revenue, mandatory expenses, and interest on U.S. debt for 2008, 2018, and 2035. Also shown in parentheses is the percentage of yearly revenue for each of the mandatory programs under intermediate assumptions.

In 2018, using projections in the 2010 U.S. Budget, the interest paid on the U.S. debt will account for 16.8 % of the revenue for that year. Based on the assumptions mentioned above, in 2035 the interest paid on the U.S. debt will account for 19.6 % of the revenue for that year. An interesting side note, for every 1% increase in the interest rate on the U.S. debt, in 2018 and 2035, an additional 4.9% and 7.8 %, respectively, of the revenue for that year is required.

As shown in Table 2 and Figure 8, mandatory programs and interest on U.S. debt accounted for 74% of the available revenue in 2008. Under intermediate assumptions, Mandatory Programs and interest payment on the U.S. debt projects to account for 85% of the revenue in 2018 and 115% of the revenue in 2035. This analysis does not account for any military, State Department, FBI, IRS, EPA, unemployment compensation, veteran's benefits, food assistance programs or any other discretionary spending. From this first order analysis, with most of the data taken directly from Government reports, it is clear that a major shift in U.S. policy is required with a focus on fiscal responsibility.

According to the analysis performed by Kogan, Cox, and Horney, the "fiscal gap" or the average amount of program reductions or revenue increases required over the next forty years to stabilize the debt to its 2009 levels, as a share of the U.S. economy- equals 4.2% of the GDP. Eliminating the gap would require the equivalent, immediate and permanent 24 percent increase in tax revenues or 20 percent reduction in expenditures for all federal programs. Given the size of the gap, some combination of revenue increases and program cuts is required.

Figure 8: Mandatory Outlays and Interest on U.S. Debt as a Percentage of GDP



This figure shows the percentage of U.S. revenue spent on mandatory programs and the interest on total U.S. debt relative to GDP for years 2008, 2018 and 2035. It is a graphical presentation of the results presented in Table 2. Revenue is a constant 18.7% of GDP.

CONCLUDING COMMENTS

There are serious concerns for Social Security, Medicare and Medicaid. Projected growth, as reported in their respective annual reports, for all three programs outpaces projected revenue growth. With unemployment currently higher than the estimated high projections, one can expect less near-term revenue for all three programs further taxing these strained programs. Major reform is required for all three programs and the sooner we enact solutions, the more flexible and gradual they can be.

With the total U.S. debt approaching the annual GDP, yearly debt payments project to further strain the economy. As shown through the Monte Carlo simulation and through basic math equations, with even a small increase in the interest rate, the interest payments go up a lot due to the large size of the current and increasing U.S. debt. With interest rates currently at historic lows and debt currently at historic highs, the combination makes us especially vulnerable to rising interest rates. After the U.S. economy improves, we must make a focused effort to control the growing U.S. debt while the problem is still manageable.

The combination of mandatory programs and interest on U.S. debt, as reported in their respective annual reports, account for 85% of the U.S. revenue in 2018. If current trends continue, in 2035 115% of revenue will be required for mandatory programs and interest on the U.S. debt. Clearly, major reform is required. It will likely require both an increase in revenue and a reduction in cost requiring Congress and the President to overcome a political quagmire.

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USING FINANCIAL RATIOS AND LENDER RELATIONSHIP THEORY TO ASSESS FARM CREDITWORTHINESS

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ABSTRACT

This study examines the determinants of farm loan delinquencies, and in particular, the influence of multiple loans and multiple lenders on delinquency. The number of lenders used by a borrower, the number of loans outstanding, and the interaction of the two factors are all positively related to loan delinquency rates. In fact, these factors are at least as significant as standard financial ratios in explaining farm loan delinquency. The most consistent finding is that borrowers who have been denied credit in the past five years are more likely to be delinquent. Furthermore, borrowers using multiple lenders appear to be able to bargain for lower interest rates.

JEL: G2; M1; M4

KEYWORDS: Credit scoring, lending relationships, farm credit

INTRODUCTION

The current financial crisis in general and the problems associated with CTI, a major small businesses lender, demonstrates the importance of a prosperous small business sector in terms of supporting economic growth and employment. Small businesses in the US are responsible for approximately half the economic activity and more than 50% of the job growth. At the same time, small business generally do not have the same direct access to the money markets that larger firms have and hence are more reliant on their local bank for funding. Using a unique data set this paper focuses on a frequently neglected small business sector, namely small farms. While agricultural commodity prices rose dramatically from 2003-2007, the financial crises ultimately caught up to this sector in the guise of falling land and crop prices and increasingly tight credit conditions. The focus of this paper is to examine the factors that influence the creditworthiness of small farm borrowers. While small farms are similar in many respects to other small businesses, the farm owner-operator often resides on the farm and the distinction between personal and corporate assets may blur. For example, farmland may serve as collateral for loans to both the farm operation and to secure a mortgage on the residence. Alternatively, the residence and other personal assets may serve as collateral for farm operating loans. Thus, researchers often make a distinction between the farm-household and the farm-firm.

LITERATURE

A few authors have examined the determinants of bank loans to agricultural firms. Zech and Pederson (2003) found that the debt-to-asset ratio is a strong predictor of the farm borrower's ability to repay the loan. They further found that asset turnover and family living expenses are good predictors of farm performance. Durguner and Katchova (2007) find that the prior year's working capital to gross farm return, debt-to-asset ratio, and return on farm assets are the most pertinent factors explaining creditworthiness. In earlier work, Splett, Barry, Dixon, and Ellinger (1994) developed a five-factor credit-scoring model. The five factors measure liquidity (current ratio), solvency (equity-asset ratio), profitability (ROE), repayment capacity (capital debt-repayment margin), and efficiency (net income from operations ratio). Weights are applied to each factor to arrive at an overall credit score. Some authors estimate separate credit scoring models for different types of farms (e.g., livestock vs. crop farms) and for unique regions of country.

The Farm Financial Standards Council (FFSC), a cooperative of agricultural producers, lenders, academics, and other interested parties has developed a standardized set of 16 financial ratios for use in financial reporting and analysis of the farm-firm. They are grouped in five categories: liquidity, solvency, profitability, repayment capacity, and efficiency. These groups are consistent with those used by Splett, et al (1994) as mentioned above.

Alternatively, Moody's Investor Services, provides credit rating for both firms and the individual securities they issue. In addition to their public firm credit ratings, Moody's has developed a credit-scoring model for private companies. Most farms are small privately owned businesses and would fall under the general category of business for which Moody's private sector credit model would apply. A detailed description of the model is provided by Falkenstein, et. al. (2000), although pertinent details of the specific variable transformations employed are not publicly available. Financial ratios are selected based on their univariate relationship with the likelihood of default. Moody further transforms each variable to achieve better explanatory power in the model. The ratios included in their model are similar, but not identical to those recommended by the FFSC. A comparison of the ratios used by the two organizations is provided in the Table 1. As noted, both have measures of liquidity, solvency/capital structure, profitability, and repayment capacity. Moody's model includes two other categories relating to trading accounts and growth, but does not include distinct efficiency measures.

Much of the prior research is conducted with farm level data from a single geographic region. An exception is provided by Walraven and Barry (2004) who use loan level data from the national Survey of Terms of Bank Lending to Farms conducted by the Federal Reserve Board. The focus of their research is to examine the factors that determine the interest rate applied to farms loans. In addition, to macro factor which impact all interest rates, several loan-specific risk rating categories were included to identify whether farm loan rates are set on a risk-adjusted basis. Included among the explanatory variables are five risk rating categories. They show that the risk rating levels, along with other non-price loan characteristics, and certain bank characteristics affect interest rates.

There is also a body of research addressing transition rates found in risk migration tables which indicate the probability of a borrower moving from one risk category to another (e.g., Aaa to Aa). In addition to using Moody's or Standard and Poor's (S&P) ratings to construct the matrix for publicly traded firms, credit scores may be used to estimate the risk ratings in the matrix for non-publicly traded firms. A credit score is assigned based upon the data taken from loan applications and various financial statements. Presumably loan risk will affect both the priced and non-price terms of the loans. Consistent with Basle II, lenders may then use a credit migration matrix to estimate capital requirements. As reported in Walraven & Barry (2004), approximately 20% of lenders did not credit score their farm loans, while an additional 25% did not show any variation in their assigned risk categories. The purpose of this research is to determine which financial performance variables are associated with farm-firms that become delinquent on their loans. A delinquent borrower, as distinct from a defaulted borrower, is identified in the survey when the borrower self-reports paying less than the amount required by their lender(s) during the year. Credit scoring ratios as recommended by both the FFSC and Moody's will be used in the analysis, although the primary focus will be on the Moody data. The reminder of this paper is organized as follows. Section 2 reviews the prior literature. Section 3 discusses the methodology and the empirical model. Section 4 presents the empirical findings, while Section 5 presents the conclusion.

METHODOLOGY AND DATA

The data, described in the next section, provides considerable detailed information about small farms and their financial condition. Included in the data are important lending relationship variables that indicate the amount of debt outstanding at year end, the number of loans outstanding, the number of lenders used for those loans, and whether any loans were delinquent at the time of survey. There is also information about whether a borrower has been denied credit in the past five years, or whether a borrower reported no new loans because credit is denied in the current year. Based on this information, it is possible to segregate farm businesses into two broad categories: 1) borrowers which are: a) current on all loans, b) delinquent on at least one loan, and c) those that have had trouble obtaining credit in the past, and 2) non-borrowers which: a) don't currently require external financing, b) those who are currently unable to obtain credit, and c) those where the terms of credit are unacceptable due to high interest rates and/or collateral requirements, and d) those borrowers who have had trouble obtaining credit in the past. Based on these categories of borrowers and non-borrowers, the followings research questions are addressed:

1) How are farm borrowers different than non-borrowers? That is, what operating characteristics determine when a farm requires external bank financing?
2) When a farm does require external funds, what factors determine the number of loans outstanding and the number of unique banks a borrower uses to obtain credit? Furthermore, what influence does the number of lenders a borrower has have on the borrowing relationship?
3) How are delinquent borrowers different from non-delinquent borrowers? In particular, is the number of loans outstanding from various lenders a significant factor in explaining the differences?

Testable Hypotheses

Weak liquidity, low profitability, and high leverage are likely indicators of financial distress for farms. Furthermore, it is possible that financial difficulties, which contributed to the denial of credit in the past, may be an indication of continued financial distress or financial mismanagement. This might be called the "persistence hypothesis". However, it can also be argued that borrowers who have been denied credit have an incentive to reform their financial management practices to enable them to borrow in the future. This might be called the "reformation" hypothesis. Furthermore, the existence of multiple outstanding loans is potentially another contributor toward default. This is analogous to individual borrowers with numerous credit cards issued by multiple lenders who become overextended. On the other hand, farm borrowers using multiple lenders can possibly negotiate more favorable terms and may possibly be more readily assured of obtaining credit during periods of banking distress. On the negative side it is also possible that using multiple lenders may diminish the value of the borrower's primary banking relationship. These propositions will be formally tested as follows:

H1: The standard set of financial ratios proposed by both Moody's and FFSC to measure a borrower's creditworthiness should be effective in predicting farm loan delinquencies.

H2: Borrowers who have had difficulty getting credit in the past are more likely to be delinquent on their current loan(s).

H3: Delinquent borrowers are more likely to have a larger number of outstanding loans and deal with a greater number of lenders than non-delinquent borrowers.

H4: Borrowers using multiple lenders should be able to negotiate more favorable lending terms such as lower effective interest rates, longer maturity loans, lower collateral requirements, and have access to a larger and more stable flow of credit.

Data

The data used for this study is the ARMS (Agricultural Resource Management Survey) data, developed by the United States Department of Agriculture (USDA) and provided through the Economic Research Service (ERS). This is a large annual survey of farms, which includes data on farming practices as well as other operational and financial information. The most recent surveys conducted in 2006 and 2007 include more information about farm debt and borrowing practices than have past surveys. This study will focus on the 2007 survey data since certain key information is only available in the 2007 survey. The 2007 survey contains data on 18,709 farms.

In addition to the loan relationship variables, numerous financial ratios variables are included in the analysis. As mentioned above, various financial metrics suggested by Moody's and FFSC to predict creditworthiness are computed. Other variables are created to test each specific research hypotheses. Several control variables were included such as farm type, legal form of organization, age and education of the primary business operator, as well as variables representing each of the nine geographic survey regions. A detailed description of these variables is presented in Table 1.

Table 2 provides descriptive statistics for each variable. Average total assets are approximately $2.6 million. Furthermore, the delinquent variable (DELINQYN) is an indicator variable and equals one if any loans outstanding at year end are delinquent. There were 121 farms with delinquent loans in 2007. Furthermore, there are a total of 7,708 loans made to farms (LOANSTOT#) and a total of 4,580 lenders identified in the survey (LEANDERNO). The weighted average interest rate (RATEWTAVG) is 6.7%. The weighted average term of the outstanding loans is 127.4 months (TERMWTAVG). Most of the farms are not limited liability organizations but are typically partnerships or sole proprietorships. A total of 2,704 farms are limited liability C or S corporations. This represents 12.9% of the farms surveyed. The majority of the farms are categorized as crop farms (58.4%) with the remaining being livestock farms (FTYPE; 1=livestock). In general the farms appear to be highly liquid with the current ratios averaging almost 60, and the quick ratio of over 34. However, it does not appear that current assets include large cash reserves as the cash/asset ratio has a mean value of only three percent. The average debt to asset ratio equals 20.2%. The total number of farms denied credit over the past five years is 183 (DENIED5YR).

An analysis of the difference between borrowers and non-borrowers reveals the following statistically significant differences: 1) The number of non-borrowers greatly exceeds the number of borrowers (14,540 vs. 4,169), 2) Borrowers are larger in terms of total assets, hold more cash (scaled by assets), turn their inventories more slowly, grow net income more rapidly, have higher levels of working capital but lower operating margins, 3) Borrowers report greater net income, higher capital replacement margins, and greater levels of interest expense, 4) Livestock farms and farms organized as limited liability organizations have a higher proportion of borrowers versus non-borrowers, and 5) Comparing personal characteristics, borrowers are younger and have a higher proportion of college education.

Many of the Moody's ratios have low correlation coefficients with one another and they tend to be below 5%, with two exceptions. ROA is correlated with liabilities over assets (65.6%) and net income over assets (97%). The binary variable DELINQYN is not highly correlated with any of the ratio variables, and none of the correlations are significant. There are three hypothesis variables that capture loan/lender characteristics: 1) the number of different lenders per farm (LENDERNO), 2) the total number of loans per farm (LOANSTOT#), and 3) LOANS*LENDERS, which is the product of the previous two variables.

LENDERNO and LOANSTOT# are significantly correlated with a coefficient of 67%. Because of high correlation, the model will include only one of these two variables at the same time. The weighted average interest rate (RATEWTAVG) has a negative and significant correlation with the number of lenders, but the correlation with the number of loans (LOANSTOT#) is positive, but not significant.

As is true of the Moody's data mentioned above, correlations among the FFSC ratios are generally low or not significant, with a few exceptions. Many of the significant correlations are size related. For example, working capital, net income, and the capital replacement margin are dollar amounts and are therefore jointly affected by the size of the farm. Other significant correlations are operating margin, operating expense ratio, and depreciation expense ratio. The issue of multicollinearity will be examined detail in the results section (Both correlation matrices and the analysis of borrower vs. non-borrower characteristics are available from the authors upon request).

The ARMS database includes a variable for each loan indicating whether the borrower paid the amount due, paid more than the amount due, or paid less than the amount due during the year. This variable can either specified as a binary variable DELINQYN (1=delinquent) or as a continuous variable, such as, the percent of the total dollar amount of loans outstanding, which are delinquent per borrower (i.e., $ of loans delinquent/ $ total loans). The two forms of the delinquency variable will then be used as the dependent variable in logistic and multiple regression models, where the appropriate lending relationship, financial ratios, and control variables are included as explanatory variables. As mentioned before, there are a total of 121 farms with delinquent loans in the 2007 survey. This represents 0.65% of the total farms in the survey and 1.83% of the loans outstanding. The rate of delinquency is consistent with that reported in the Federal Reserve Board's Agricultural Finance Databook.

The following model (equation 1) will be estimated using a binary variable (DELINQYN) as the dependent variable. In this case, a logistics procedure will be used.

$$\text{DELINQ} = \alpha + \gamma_m \text{HYPOTHESIS}_m + \beta_n \text{RATIO}_n + \delta_p \text{CONTROL}_p + \varepsilon \qquad (1)$$

where, HYPOTHESIS is a vector of 'm' lending relationship variables, RATIO is a vector of 'n' financial ratios, and CONTROL is a vector of 'p' control variables for farm type, location, and farmer characteristics, such as, age and experience.

For each dependent variable, two regression models were estimate for each year: one using the FFSC recommended ratios and the other using Moody's. Given the large number of tables generate the paper focuses on the Mood's variables (The FFSC results are available upon request). Because there are multiple loan/lender variables that are correlated, several versions of each equation will be estimated to reduce the effects of multi-collinearity. To test hypothesis H3, two additional models will be analyzed. These are as follows:

$$\text{RATEWTAVG} = \alpha + \gamma_m \text{HYPOTHESIS}_m + \beta_n \text{RATIO}_n + \delta_p \text{CONTROL}_p + \varepsilon \qquad (2)$$

where, RATEWTAVG is the weighted average of the interest rate on the loans, HYPOTHESIS is a vector of hypothesis variables, which are primarily the number of lenders and the number of loans; RATIO is a vector of financial ratios and metrics, and CONTROL is a vector of control variables.

$$\text{TERMWTAVG} = \alpha + \gamma_m \text{HYPOTHESIS}_m + \beta_n \text{RATIO}_n + \delta_p \text{CONTROL}_p + \varepsilon \qquad (3)$$

where, TERMWTAVG is the weighted average original loan maturity, HYPOTHESIS is a vector of hypothesis variables, which are primarily the number of lenders and the number of loans, RATIO is a vector of financial ratios and metrics, and CONTROL is a vector of control variables.

For the estimation of both equations 2 and 3, only the population borrowers will be included.

EMPIRICAL RESULTS

Parsimonious Model

Because some of the ratio variables are correlated (especially among the FFSC ratios) a parsimonious model with fewer independent variables is developed as follows. One variable from each of five broad financial performance categories (liquidity, solvency, repayment capacity, efficiency/productivity, and profitability) is selected. The selection is based upon which variable has the highest level of statistical significance from either of the two equations estimated using the Moody's and FFSC data. The results of this parsimonious model are provided in Table 3. Each of the three lending relationship variables: the number of lenders (LENDERNO), the number of loans (LOANSTOT#), and the interaction of the two variables (LOANS*LENDERS) are entered one at time in the logistic regression model to evaluate the potential impact of multicollinearity. The following discussion relates to Model 4, which includes all three relationship variables.

The regression coefficient on number of lenders (LENDERNO) is positive and statistically significant, suggesting that borrowers who "shop" for a lender are more likely to be delinquent. On the other hand, the number of outstanding loans (LOANSTOT#) is not significant and neither is the interaction term (LOANS*LENDERS). The size of coefficient on LENDERNO in Model 4 is roughly the same size as the coefficient in Model 1 (0.359 vs.0.365), all though the level of statistical significant declines from 1% to 5%. The coefficient on the previous credit denial variable (DENIED5YR) is positive and highly significant in all three models. Among the six financial ratios, four are statistically significant: 1) the debt to asset ratio (DEBTASSET), 2) return on equity (ROE), 3) fixed payment coverage ratio (TERMDEBTCOV), and 4) the asset turn over ratio (ASSETTURNOVER). Both DEBTASSET and ASSETTURNOVER have the expected positive coefficient. The length of the loan (TERMWTAVG) has a negative coefficient possibly due to the fact that mortgage loans are included in the sample and that mortgage loans, prior to recent financial crisis, have historically had a low delinquency rate. The level of education attained by the principal farm operator (COLLEGE) has a weak but statistically significant impact, as a college education appears to reduce the likelihood of default. The firm type (FTYPE) is negative and statistically significant suggesting that livestock farms are less risky than crop farms. The pseudo R-square for the logistic regression is 0.099 and the model produced a 69.7% concordant ratio.

To address hypothesis H3, which states that borrowers with multiple lenders will obtain lower interest rates and longer loan terms, two different regression models are used. As discussed below, one uses the weighted average loan interest rate (RATEWTAVG) as the dependent variable, and the other uses weighted average term or maturity of the loan (TERMWTAVG) as the dependent variable.

Interest Rate Model

Looking at Model 4 in Table 4, where the dependent variable is the weighted average loan rate (RATEWTAVG), of the three lending relationship variables only the number of lenders (LENDERNO) is statistically significant and negatively related to the average loan rate. This suggests that the borrowers who deal with multiple lenders can negotiate lower interest rates. It should be noted that the absolute size of the regression coefficient increases substantially when the both the number of loans (LOANSTOT#) and the interaction term (LOANS*LENDERS) are included into the model.

Table 1: Variable Definitions

Source and Type	Definitions	
Moody's Ratios:	TOTASSETS	Total assets/1000000
	QUICKRATIO	Quick ratio
	LIABOVRASSETS	Liabilities divided by total assets
	CASHOVRASSETS	Cash divided by total assets
	NIOVRASSETS	Net Income divided by total assets
	DEBTSVCCOV	Debt Service coverage ratio
	INVTURNS	Inventory Turns
	NIGROWTH	Net Income growth (1 year)
	ROA	Net Income divided by total assets
FFSC Ratios:	CURRENT	Current assets divided by current liabilities
	WORKCAP	Current assets less current liabilities / 1000000
	DEBTASSET	Total debt divided by total assets
	EQUITYASSET	Book equity divided by total assets
	DEBTEQUITY	Total debt divided by book equity
	ROE	Net Income divided by book equity
	OPMARGIN	Operating income divided by sales
	NETINC	Before tax income / 1000000
	TERMDEBTCOV	Annual after-tax cash flow divided by annual debt and least payment obligations
	CAPREPLACE	Dollar amount, cash flow after all debt and least payments / 1000000
	ASSETTURNOVER	Gross revenue divided by total assets
	OPEXPRATIO	Operating expenses less depreciation/amortization divided by revenue
	DEPREXPRATIO	Depreciation/amortization divided by revenue
	INTEXPRATIO	Total interest expense divided by revenue
	NETFARMINCRATIO	Net farm income divided by revenue
Hypothesis Variables:	DELINQYN	Binary - 1 if any loan is delinquent, otherwise 0
	DELTOT	Total number of delinquent loans
	DELINQAMT	Dollar amount of delinquent loans
	DELINQPCT	Delinquent divided by total debt
	LENDERNO	Number of different lenders used
	LOANNBR	Number of loans detailed (4 or 5 max, depending on survey year)
	LOANNBRTOT	Total number of loans
	FIXEDPCT	Weighted average (by dollar amount) of fixed rate loans
	BORROWER10	Binary - 1 if farm has debt, 0 otherwise
	BORROWER123	Discrete: 1 for good borrower; 2 for delinquent borrower; 3 if denied in year
	NONBORROWER	Binary - 1 if farm is a non-borrower, 0 otherwise
	RATEWTAVG	Weighted average (by dollar amount) of interest rate
	TERMWTAVG	Weighted average (by dollar amount) of original maturity or term of debt (in months)
	DENIED5YR	Binary - 1 if farm has been denied credit in past 5 years, otherwise 0
Control Variables:	AGE	Age of principal in farm, in years
	COLLEGE	Binary - 1 if principal in farm has attended college
	LIMLIAB	Binary - 1 if farm is a limited liability legal form (e.g. S or C corp)
	FTYPE	Binary - Farm type, 1=livestock, 0 = agricultural

List of variable definitions and their source Moody's or Farm Financial Standards Council (FFSC); grouped by type of variable

The coefficient on the previous credit denial variable (DENIED5YR) is consistently positive and averages approximately 0.45 across all four model specifications. Thus, borrowers that have been denied credit over the past five years pay approximate 45 basis points higher interest rates. Larger borrowers, as measured by total assets, (TOTASSETS) pay lower interest rates suggesting that they have more bargaining power and that lending institutions can charge a lower interest as they spread the fixed costs of making a loan across a larger loan. Of the traditional financial ratios only the rate of inventory turnover (INVTURNS) is statistically significant and surprisingly carries a positive coefficient. Perhaps this high turnover ratio is simply an indication of lower levels of inventory which provide less collateral for loans. Somewhat surprisingly, borrowers that are currently delinquent are charged similar rates compared to non-delinquent borrowers since DELINQYN is not statistically significant.

Table 2: Descriptive Statistics

Variable	N	Mean	Std Dev
Totassets	18709	2.586	6.290
Quickratio	18573	34.183	764.0
liabovrassets	18697	0.202	8.057
cashovrassets	18697	0.030	0.117
NIovrassets	18697	0.174	6.862
DebtSvcCov	11771	32.813	1,183
Invturns	18706	0.626	7.846
Nigrowth	5132	6.183	82.825
ROA	18697	0.101	6.233
Delinqyn	18709	0.006	0.080
Deltot	18709	56.398	36.518
Delinqamt	18709	3,814	92,634
Delinqpct	18573	0.005	0.080
lenderno	18709	0.245	0.590
loannbrtot	6614	1.165	1.972
loansxlenders	6614	1.891	4.223
fixedpct	3307	0.667	0.434
borrower10	18709	0.223	0.416
nonborrower	2571	1.270	0.823
ratewtavg	3307	6.699	1.625
termwtavg	3307	127.400	103.114
denied5yr	18709	0.010	0.098
age	18709	55.722	12.201
college	18709	0.539	0.498
limliab	18709	0.129	0.335
ftype	18709	0.416	0.493
Current	18573	59.561	913.387
workcap	18709	0.244	1.185
debtasset	18697	0.202	8.057
equityasset	18697	0.798	8.057
debtequity	18705	0.146	8.825
ROE	18705	-0.412	59.023
OpMargin	18597	-1.259	46.160
NetInc	18709	0.165	1.047
Termdebtcov	10916	22.490	354.652
capreplace	18709	0.186	1.104
Assetturnover	18697	0.820	27.693
Opexpratio	18597	1.279	23.921
Deprexpratio	18597	0.095	1.768
intexpratio	18597	0.079	1.236
Netfarmincratio	18597	-1.339	46.267

Basic statistics for each of the variables included in the study. Note: the provider of the data prohibits the publication of minimum or maximum values as they may reveal proprietary information

This suggests that the delinquency was entirely unexpected as the lender failed to properly price the risk of default. The proportion of fixed rate debt (FIXEDPCT) carries a statistically significant negative coefficient, suggesting that as the proportion of fixed rate debt increases, the interest rate is lower. As mentioned before, this may reflect the fact that mortgage debt is often fixed rate and lower than other rates on less well collateralized loans. Also reported in this table are variance inflation factors (VIF) for Model 4. The financial variables are not highly correlated so there is little variance inflation among those variables. However, the number of lenders (LENDERNO), number of loans (LOANSTOT#) and their interaction (LOANS*LENDERS) are highly correlated and when included together, show evidence of substantial variance inflation (VIF = 2.4 to 8.7). This suggests that it is most appropriate to use these variables individually in a regression model. The R-square for the model is 0.036 and the F-value is 5.05.

Table 3: Logistic Regression Results for Parsimonious Model

		Model 1			**Model 2**			**Model 3**			**Model 4**		
Parameter	Exp. sign	Estimate	Std Error		Estimate	Std Error		Estimate	Std Error		Estimate	Std Error	
Intercept		-3.09	-0.756	***	-2.729	-0.74	***	-2.732	-0.737	***	-3.106	-0.785	***
Lenderno	+	0.365	-0.132	***							0.359	-0.196	**
loantot#	+				0.045	-0.035					0.013	-0.102	
loans*lenders	+							0.023	-0.012	*	-0.002	-0.045	
denied5yr	+	1.142	-0.277	***	1.18	-0.277	***	1.177	-0.277	***	1.14	-0.278	***
Quickratio	-	-0.044	-0.032		-0.047	-0.032		-0.046	-0.032		-0.044	-0.032	
Debtasset	+	0.861	-0.329	***	0.849	-0.328	***	0.848	-0.328	***	0.854	-0.332	***
ROE	-	0.039	-0.016	**	0.038	-0.016	**	0.039	-0.016	**	0.039	-0.016	**
termtebtcov	-	0.0004	-0.0001	***	0.0004	-0.0001	***	0.0004	-0.0001	***	0.0004	-0.0001	***
assetturnover	-	-0.797	-0.274	***	-0.771	-0.269	***	-0.772	-0.27	***	-0.796	-0.274	***
invturns	-	-0.227	-0.202		-0.179	-0.195		-0.184	-0.197		-0.225	-0.202	
ratewtavg	-	0.042	-0.059		0.037	-0.059		0.038	-0.059		0.042	-0.059	
termwtavg	?	-0.003	-0.001	***	-0.003	-0.001	***	-0.003	-0.001	***	-0.003	-0.001	***
fixedpct	?	-0.363	-0.224		-0.312	-0.221		-0.316	-0.221		-0.363	-0.224	
age	-	-0.001	-0.008		-0.001	-0.008		-0.001	-0.008		-0.001	-0.008	
limliab	+	0.219	-0.256		0.205	-0.255		0.213	-0.256		0.218	-0.256	
college	-	-0.352	-0.198	*	-0.337	-0.197	*	-0.337	-0.197	*	-0.353	-0.198	*
ftype	?	-0.525	-0.208	***	-0.566	-0.207	***	-0.554	-0.208	***	-0.527	-0.209	***
totassets	?	-0.04	-0.027		-0.041	-0.0275		-0.043	-0.0278		-0.041	-0.0275	
R square		0.027			0.025			0.025			0.027		
Likelihood Ratio		89.039	***		83.339	***		84.844	***		89.084	***	
Concordant		69.7			69.6			69.9			69.9		
Discordant		28.1			28.2			27.9			28		

Logistic regression of DELINQ = α + γmHYPOTHESISm + βnRATIOn +δpCONTROLp + ε where Delinq is a binary variable (1 = one or more delinquent loans) and HYPOTHESIS is a vector of 'm' lending relationship variables, RATIO is a vector of 'n' financial ratios, and CONTROL is a vector of 'p' control variables for farm type, location, and farmer characteristics, such as, age and experience. The 4 models include the loan/lender variables individually and in model 4 are all included. Eight regional dummies included but not reported .

<u>Term to Maturity Model</u>

In Table 5 a regression model is estimated where the dependent variables is the weighted average loan term to maturity (TERMWTAVG). Once again, among the three loan relationship variables, the number of lenders (LENDERNO) is positive and statistically significant. This suggests that borrowers that deal with multiple lenders are able to negotiate longer-term loans. It is somewhat surprising that maturity is not influenced by prior delinquencies as the coefficient on DENIED5YR is insignificant. Among the traditional financial ratios, the coefficient on the variable liabilities divided by total assets

Table 4: OLS Regression Results for Interest Rate Model Using Moody's Ratios

		Model 1			**Model 2**			**Model 3**			**Model 4**			
Parameter	Exp. sign	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	Sig.	VIF
intercept		7.300	(0.193)	***	7.022	(0.187)	***	7.061	(0.185)	***	7.337	(0.203)	***	
lenderno	-	-0.198	(0.046)	***							-0.294	(0.069)	***	2.4
loantot#	-				0.009	(0.014)					0.013	(0.032)		6.0
loans*lenders	-							-0.004	(0.006)		0.015	(0.016)		8.7
denied5yr	+	0.476	(0.139)	***	0.439	(0.139)	***	0.450	(0.139)	***	0.466	(0.139)	***	1.0
totassets	-	-0.032	(0.006)	***	-0.034	(0.007)	***	-0.033	(0.007)	***	-0.035	(0.007)	***	1.2
quickratio	-	-0.004	(0.003)		-0.003	(0.003)		-0.004	(0.003)		-0.004	(0.003)		1.1
liabovrassets	+	0.211	(0.121)	*	0.169	(0.122)		0.192	(0.122)		0.172	(0.122)		1.2
cashovrassets	-	-0.179	(0.27)		-0.192	(0.271)		-0.188	(0.271)		-0.184	(0.269)		1.3
debtsvccov	+	0.000	(0.0002)		0.000	(0.0002)		0.000	(0.0002)		0.000	(0.0002)		1.1
invturns	+	0.105	(0.043)	**	0.096	(0.044)	**	0.097	(0.044)	**	0.107	(0.043)	**	1.3
nigrowth	+	0.000	(0.0003)		0.000	(0.0003)		0.000	(0.0003)		0.000	(0.0003)	*	1.0
ROA	-	0.161	0.110		0.133	0.111		0.139	0.111		0.160	0.110		1.1
delinqyn	+	0.1090	(0.173)		0.0720	(0.173)		0.0790	(0.173)		0.1050	(0.172)		
termwtavg	+	0.000	(0.0003)		0.000	(0.00003)	**	0.000	(0.001)		0.000	(0.0003)		
fixedpct	?	-0.259	(0.071)	***	-0.011	(0.008)		-0.276	(0.071)	***	-0.258	(0.07)	***	
age	-	-0.004	(0.002)		0.000	(0.0003)		-0.004	(0.003)		-0.004	(0.003)		
limliab	?	0.022	(0.083)		0.008	(0.009)		0.034	(0.083)		0.025	(0.083)		
college	-	-0.070	(0.061)		-0.009	(0.007)		-0.079	(0.062)		-0.072	(0.061)		
ftype	?	0.074	(0.064)		-0.020	(0.007)	***	0.081	(0.064)		0.071	(0.064)		
F statistic		5.050***			4.310***			4.310***			4.970***			
Adjusted R-square		0.036			0.030			0.030			0.038			

This table presents the results of an OLS regresion of the form $RATEWTAVG = \alpha + \gamma_m HYPOTHESIS_m + \beta_n RATIO_n + \delta_p CONTROL_p + \varepsilon$ Where, RATEWTAVG is the weighted average of the interest rate on the loans, HYPOTHESIS is a vector of hypothesis variables, which are primarily the number of lenders and the number of loans; RATIO is a vector of financial ratios and metrics, and CONTROL is a vector of control variables. The 4 models include the loan/lender variables individually and then are all included in Model 4. VIF values are reported for Model 4. Eight region dummies were included but not reported

(LIABOVRASSETS) is positive and significant, suggesting that as total debt increases the loan maturity also increases. The variable cash divided by assets (CASHOVRASSETS) has a negative and significant relationship with maturity, suggesting that borrowers with more cash receive shorter-term loans. This seems logical since farms with greater liquidity can pursue a more aggressive funding strategy by borrower shorter term at lower rates. For the same reasons the coefficient on the debt service coverage ratio (DEBTSVCCOV) is also negative and statistically significant. It is also not surprising that delinquent borrowers (DELINQYN) have shorter-term debt, by an average of approximately 21 months, since one way to ration credit to risky borrowers is to reduce maturity. The proportion of debt that is fixed rate (FIXEDPCT) is significant and positively related to maturity, which likely shows the influence of mortgage debt as discussed above. The coefficient on the limited liability variable (LIMLIAB) is negative and significant indicating that corporate borrowers generally receive shorter-term debt. The coefficient on type of farm (FTYPE) is positively indicating that livestock farms receive long-term debt, consistent with the finding in Table 3 that livestock farms appear to be less risky than crop farms. The R-square of the equation is 0.06 with an F-value of 7.9.

Table 5: OLS Regression Results for Maturity Model Using Moody's Ratios

		Model 1			Model 2			Model 3		
Parameter	Exp.	Estimate	(Std. Error)		Estimate	(Std. Error)		Estimate	(Std.	
intercept		85.969	(15.253)	***	98.539	(14.667)	***	98.816	(14.629)	***
lenderno	+	9.720	(2.971)	***						
loantot#	+				1.244	(0.873)				
loans*lenders	+							0.552	(0.361)	
denied5yr	?	6.790	(8.93)		7.868	(8.941)		7.769	(8.941)	
totassets	?	0.328	(0.419)		0.289	(0.424)		0.309	(0.422)	
quickratio	-	-0.006	(0.2)		-0.024	(0.201)		-0.023	(0.201)	
liabovrassets	+	43.470	(7.73)	***	43.366	(7.815)	***	43.620	(7.781)	***
cashovrassets	-	-51.784	(17.289)	***	-51.727	(17.318)	***	-51.777	(17.317)	***
debtsvccov	-	-0.027	(0.012)	**	-0.027	(0.012)	**	-0.028	(0.012)	**
invturns	?	0.073	(2.808)		0.529	(2.809)		0.464	(2.809)	
nigrowth	-	-0.002	(0.017)		-0.002	(0.018)		-0.002	(0.018)	
ROA	-	-11.543	(7.07)		-10.647	(7.075)		-10.659	(7.074)	
delinqyn	?	-21.6260	(11.06)	*	-20.3440	(11.07)	*	-20.6060	(11.074)	*
ratewtavg	+	-1.506	(1.243)		-1.873	(1.24)		-1.821	(1.24)	
fixedpct	?	27.306	(4.52)	***	28.006	(4.519)	***	28.014	(4.518)	***
age	?	0.181	(0.173)		0.179	(0.173)		0.179	(0.173)	
limliab	?	-18.682	(5.309)		-19.262	(5.315)	***	-19.138	(5.317)	***
college	?	-1.194	(3.938)		-0.884	(3.944)		-0.909	(3.944)	
ftype	?	8.845	(4.084)	**	8.435	(4.089)	**	8.569	(4.089)	**
F statistic		7.880***			7.510***			7.520***		
Adj. R-squared		0.060			0.057			0.057		

This *table presents the results of an OLS regresion of the form TERMWTAVG = α + γmHYPOTHESISm + βnRATIOn +δpCONTROLp + ε where, TERMWTAVG is the weighted average of the interest rate on the loans, HYPOTHESIS is a vector of hypothesis variables, which are primarily the number of lenders and the number of loans, RATIO is a vector of financial ratios and metrics, and CONTROL is a vector of control variables. The 3 models include one of the loan/lender variables each. Eight region dummies were included but not reported.*

CONCLUSION

The focus of this research is on the factors associated with farm loan delinquency, the use of two sets of financial ratios as determinants of those delinquencies, the effect of multiple lenders and multiple loans on delinquencies and other terms of lending. The results of this study find that one or more measures in each of the five categories are associated with loan delinquencies. Measures of liquidity, solvency, repayment capacity, and profitability are typically significant. Measures of efficiency are generally not significant. Fro example, the number of inventory turns is never significant. In terms of lending relationship variables, the number of lenders influences both loan delinquencies and loan interest rates. As the number of lenders increases the likelihood of delinquency increases and the loan rate declines. The number of loans is consistently insignificant.

Credit denial in the past five years is the most consistent predictor of current loan delinquencies. A priori, it was not clear whether this variable would have a positive or negative sign. One explanation is that borrowers that have had difficulty getting credit in the past are more likely to continue to struggle financially, so the sign should be positive. However, it is also possible that borrowers that have had prior credit difficulties may reform their behavior in order to get credit in the future. The results suggest that strongly suggests that prior credit denial is an important predictor of future loan delinquency. In this case, the analyses indicate that past credit difficulties tend to "persistent" rather than "reformative".

The number of lenders plays a role in interest rate determination. Farms using more lenders have a significantly lower average interest rate. This finding supports the hypothesis that borrowers are able to use competition among lenders to negotiate lower rates. On the other hand, the number of loans and the loan/lender interaction variable are never significant when the weighted average interest rate is the dependent variable. Prior credit denial is not a factor in the weighted average term of the loan. The size of the farm is also not significant. Limited liability organizations have shorter-term debt. Farms with higher liabilities relative to assets have longer-term debt, perhaps because of higher level of liabilities. The liquidity position of the farm does not explain the term of its debt.

Overall, either set of financial ratios is helpful in explaining farm borrower delinquencies, but many of the factors are not always significant. There are eleven financial measures that are significant at least once. At least one measure in each of five major categories is significant one or more times. When multiple measures in each category are used, multi-collinearity can confound the results, so simple models are more effective. Thus, five categories representing some mix of liquidity, solvency, repayment capacity, efficiency/productivity and profitability seem appropriate. Difficulty with getting credit seems to be persist as the most consistent explanation for loan delinquency is prior credit denial.

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DO FUNDAMENTALLY-ADJUSTED VALUATION MULTIPLES IMPROVE VALUATION ACCURACY? THE CASE OF THE POLISH STOCK MARKET

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ABSTRACT

A series of popular stock investment strategies are based on buying stocks with low valuation multiples. These strategies assume that low multiples signal undervaluation. However, the low multiples can be justified by fundamentals. In such cases even stocks with very low multiples can be overvalued. In this paper regression analysis is used to identify the impact of fundamentals on multiples. The multiples are the dependent variable and the accounting ratios are the explanatory variables. Such a regression enables the estimation of the fundamentally-adjusted multiple. The regression residuals measure the scope of undervaluation / overvaluation. Using this approach, the most undervalued (overvalued) stocks are those with the most negative (positive) residuals (and not the stocks with the lowest actual multiples). We compared the profitability of strategies based on low actual multiples with the profitability of strategies based on actual and fundamentally-adjusted multiples. Data from the Polish stock market from 1998-2010 are examined. The research found that allowing for the impact of accounting fundamentals on multiples can increase the accuracy of valuation in the case of P/S multiple but not in the case of P/E and P/BV multiples.

JEL: G11, C21

KEYWORDS: corporate valuation, relative valuation, investment strategies, valuation multiples

INTRODUCTION

The efficient market theory argues that "the market takes into account all information that is relevant to the valuation of assets when setting the price (such as earnings estimates, management team skill, industry conditions, estimated demand, etc.), and thus it is nothing but a big waste of time and money to try to outsmart the market" (Jones, 2008). However, this theory is in sharp contrast with abundant research indicating that using simple stock market investment strategies such as buying stocks with low values of valuation multiples can in the medium- and long-run generate returns significantly exceeding returns of the market as a whole as well as returns of more sophisticated (allowing for much more data) strategies (Fama, French, 1998).

These investment approaches assume that low valuation multiples signal a relative undervaluation. However, in many cases, the low values of multiples are justified by fundamental factors. In such cases even stocks with very low valuation multiples can be considerably overvalued (Damodaran, 2004; Goedhart, Koller, Wessels, 2005). The tool that enables at least partial allowance for the impact of the fundamentals on multiples is linear regression in which the actual multiples of individual stocks constitute the dependent variable and the selected historical or forecasted accounting ratios are the explanatory variables. The residuals of the regression measure the scope of relative undervaluation / overvaluation of the individual stocks. In this approach, the most undervalued (overvalued) are the stocks with the most negative (positive) regression residuals (and not the stocks with the lowest actual valuation multiples).

In the paper we compared the profitability of investment strategies based on actual valuation multiples with the profitability of the strategies based on comparison of the actual and fundamentally-adjusted valuation multiples on the Polish stock market in 1998-2010 years. The analysis embraced price-to-net-earnings, price-to-book-value and price-to-sales multiples (referred further as P/E, P/BV and P/S, respectively).

The remainder of the paper is organized as follows. In the next section we discuss the relevant literature. Next the data and methodology used in the study are described. Then the section that presents the empirical results follows. The paper closes with concluding comments.

LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

The comprehensive research conducted by Schreiner (2007) states that "multiples generally approximate market values reasonably well". However, choosing the universally best multiple is not viable. Schreiner (2007) found that different industries are associated with different best multiples. Other research states that "the accuracy and bias of value estimates, as well as the relative performance of the multiples, vary greatly by company size, company profitability, and the extent of intangible value in the company" (Lie, Lie, 2002). Others found that "contrary to the results in the extant studies valuation errors for multiples based on sales are often lowest", as compared to book-value-based multiples and earnings-based multiples (Deng, Easton, Yeo, 2010). Another research states that contrary to the theory, valuations based on earnings multiples are much more accurate than valuations based on cash flow multiples (Liu, Nissim, Thomas, 2006). Penman (2010) found that combining valuations obtained from different multiples reduce the valuation errors (as compared to valuations based on the individual multiples). Other research found that using multiples based on earnings averaged over the last several years (instead of only previous year's earnings) significantly increases accuracy of valuation (Anderson, Brooks, 2006; Sommer, Wöhrmann, Wömpener, 2009). Hence the application of relative valuation requires choosing between the types of multiples used.

The theoretical foundations of the multiples can be derived from the concept of valuing stocks on the basis of discounted cash flows. The P/E multiple, which is the most frequently used valuation multiple (Fernandez, 2002), is derived from the dividend discount model (Jones, 1998). However, given the findings of the empirical research, indicating that discounting accrual earnings instead of cash flows results in improvement of valuation accuracy (Penman, Sougiannis, 1997), let's substitute net earnings for dividends and let's consider the case of constant growth. In this case the price of the stock is determined by the equation:

$$P_t = \frac{E_t(1+g)}{r-g} \tag{1}$$

where:

P_t - price of the common stock at the end of period t;

E_t - net earnings per share in period t,

r - appropriate discount rate,

g - constant growth rate of earnings in the future.

Dividing both sides of equation (1) by net earnings per share or book value of equity per share or net sales per share gives the theoretical foundation for P/E, P/BV and P/S multiple, respectively.

As can be seen in Table 1, the multiples are related to company's expected growth of earnings, its cost of capital and its profitability. Hence the expected values of these factors can be used in evaluating whether the current valuation multiples of individual stocks are justified on the grounds of fundamentals. But in practice, when applying these concepts of valuation, one must choose the extent to which the inputs are based on historical vs. expected (forecasted) data. Theoretically, all the inputs should have predicted values. But forecasting (especially long-run) is difficult and time-consuming and the abundant research points to the rather disappointing accuracy of long-run earnings forecasts, both made by analysts as well as mechanical methods. (O'Brien, 1988; Brown, 1996; Dreman, 1998; Malkiel, 2007; Rothovius, 2008). Some practitioners therefore prefer to base relative valuation only on historical accounting data, arguing that these data are much more solid and credible as compared to any forecasts. However, the empirical research confirms that forward (i.e. based on expected data) valuation multiples, although burdened with complexity and high level of forecast uncertainty, result in more accurate valuations than in the case of valuations based on historical data (Moonchul, Ritter, 1999; Schreiner, 2007; Liu, Nissim, Thomas, 2002). In practice it implies a significant trade-off between the valuation accuracy (which is generally higher when one uses forecasted data) and valuation timeliness and simplicity.

Table 1: Theoretical Derivation of Selected Valuation Multiples

Derivation of P/E multiple	**Derivation of P/BV multiple**	**Derivation of P/S multiple**
$P_t / E_t = \frac{1+g}{r-g}$, **where:** P_t / E_t **- price-to-earnings multiple at the end of period *t*, other denotations as in equation (1).**	$P_t / BV_t = \frac{E_t}{BV_t}\frac{1+g}{r-g}$, where: P_t / BV_t - price-to-book-value multiple at the end of period *t*, BV_t - book value of equity per share at the end of period *t*, other denotations as in equation (1).	$P_t / S_t = \frac{E_t}{S_t}\frac{1+g}{r-g}$, where: P_t / S_t - price-to-sales multiple at the end of period *t*, S_t - net sales per share in period *t*, other denotations as in equation (1).

This table shows the theoretical derivation of P/E, P/BV and P/S valuation multiples, by dividing both sides of equation (1) by net earnings per share, book value of equity per share and net sales per share, respectively.

On the developed capital markets expected fundamentals can be approximated by consensus analysts' forecasts. On these markets the application of valuation tools based on expected fundamentals is not very troublesome (even for someone lacking forecasting skills) if only there are consensus forecasts available for a significant number of companies. However, the task is much more difficult in the case of many emerging markets because the consensus forecasts are available only for a small number of the biggest companies and in the case of most stocks there are not even single regular analysts' forecasts produced. In these cases one has to choose between forecasting each valued company' fundamentals on herself or basing the valuation solely on the historical data. Therefore, despite the generally higher valuation accuracy of forward-looking multiples, using this future-based approach is not always viable. As a result, many investors on emerging markets ignore any relationships between multiples and fundamentals (on the ground that analyzing relationships between valuation multiples and historical data makes no sense because there are not such relationships and analyzing the relationships between expectations and the multiples is not practically viable).

To summarize the discussion so far, the valuation multiples are consistent with finance theory because they can be derived from the discounted cash flow models. However, their use is not as simple as it may seem on the face of it. This is so because the accuracy of valuation is dependent on the availability of financial forecasts and these forecasts are not always obtainable and/or are very uncertain. Hence in many situations (especially in the case of emerging markets) constructing stock portfolios on the basis of valuation multiples implies the necessity of using only historical data (which probably limits the valuation accuracy). Therefore many emerging markets investors limit their relative valuation techniques to just comparing the raw multiples without any reference to the relationships between those multiples and fundamentals. However, one of the potential ways of allowing for these relationships is the use of the regressions between the multiples and the accounting ratios (with the assumption that these historical data can at least partially approximate the expectations). This approach is not new in the literature. The previous research (related to capital markets more developed then the Polish one) generally confirms its usefulness (Bhojraj, Lee, 2002; Hermann, Richter, 2003; Dittmann, Weiner, 2005). In the context of the

Polish market the previous research (based on shorter periods than in this paper) initially corroborated the usefulness of regression-based fundamental adjustment in the case of P/S multiple (Welc, 2009), but the research concerning other multiples has been lacking to date.

DATA AND METHODOLOGY

In order to evaluate the impact of valuation multiples' fundamental adjustment on the portfolios' profitability we compared the nominal returns of strategies based on regressions of the multiples (enabling the estimation of fundamentally-adjusted multiples) with the nominal returns generated by alternative strategies based on actual multiples. The analysis comprised the period between the end of February 1998 and the end of February 2010 (the earlier periods were omitted due to quite a small number of then listed companies). Because multiples show long-term tendency of reverting toward the mean (White, Sondhi, Fried, 2003) we assumed annual rebalancing of all the alternative portfolios under investigation.

In order to evaluate the profitability of strategies based on fundamentally-adjusted multiples we applied the regressions of companies' multiples with several accounting ratios as explanatory variables. At the end of February of each year we classified stocks on the basis of three cross-section regressions, in which the dependent variables were P/E, P/BV and P/S multiples of companies listed on the Warsaw Stock Exchange. We estimated the regressions for P/E and P/BV for every year in the period under investigation and in the case of P/S multiple we used the regressions presented in the work of Welc (2009) for the period between 1999 and 2008 and we estimated the missing regressions. The regressions estimated at the end of February of each year enabled the calculation (for all the companies listed at that time, excluding those for which the calculation of multiple is nonsensical) of fundamentally-adjusted multiples (as the fitted values of the regressions' observations). The comparisons of the fundamentally-adjusted and actual values of the multiples enabled the evaluation of the scope of overvaluation / undervaluation of every stock at a given date.

In every regression the dependent variable is a given multiple, computed as follows:

$$VM = \frac{P_t}{VD_t / n} \tag{2}$$

where:

VM - a given valuation multiple (P/E, P/BV or P/S) at the end of February,

P_t - common stock price at the end of February,

VD_t - the company' value driver (net earnings in the previous calendar year in the case of P/E multiple, book value of equity at the end of the previous calendar year in the case of P/BV multiple and net sales in the previous calendar year in the case of P/S multiple),

n - the number of company' common shares at the end of February.

We computed the multiples at the end of February in order to allow for the time lag between the end of the previous year and the time when all the quarterly reports concerning that year are available. The stock prices data were obtained from *money.pl* database, and historical financial results were obtained from *parkiet.com.pl* database. We computed the multiples for all the companies for which all the necessary data were available and for which the calculation of a given multiple makes economic sense. Due to significant accounting differences we omitted all the financial companies as well as The National Investment Funds. The summary statistics of the multiples are presented in Tables 2, 3 and 4.

Table 2: Summary Statistics Computed for P/S Multiple in the Analyzed Samples

Multiples at the end of:	Arithmetic average	Median	Standard deviation	Coefficient of variation
February 1998	0.78	0.50	0.88	111.9%
February 1999	0.48	0.30	0.61	125.8%
February 2000	0.68	0.36	1.25	182.6%
February 2001	0.56	0.25	1.03	184.3%
February 2002	0.39	0.20	0.54	139.2%
February 2003	0.40	0.23	0.52	129.5%
February 2004	0.83	0.49	0.92	110.1%
February 2005	1.04	0.64	1.28	123.6%
February 2006	1.45	0.79	1.89	130.2%
February 2007	2.30	1.28	3.30	143.6%
February 2008	2.33	1.09	5.00	214.6%
February 2009	0.79	0.42	1.19	151.5%

This table shows the summary statistics computed for P/S multiple on the Polish stock market.
Source: money.pl; parkiet.com.pl; author's calculations.

Table 3: Summary Statistics Computed for P/E Multiple in the Analyzed Samples

Multiples	Arithmetic	Median	Standard	Coefficient
February 1998	14.96	12.75	8.66	57.9%
February 1999	13.30	8.05	20.05	150.8%
February 2000	24.78	11.22	56.80	229.2%
February 2001	22.88	9.45	54.16	236.7%
February 2002	95.00	15.21	458.52	482.6%
February 2003	28.07	11.37	84.71	301.8%
February 2004	42.33	18.62	126.26	298.3%
February 2005	32.66	14.05	84.04	257.3%
February 2006	55.36	18.71	197.88	357.4%
February 2007	64.48	23.65	171.32	265.7%
February 2008	92.39	17.84	925.52	1001.7%
February 2009	16.18	9.49	23.44	144.8%

This table shows the summary statistics computed for P/E multiple on the Polish stock market.
Source: money.pl; parkiet.com.pl; author's calculations.

Table 4: Summary Statistics Computed for P/BV Multiple in the Analyzed Samples

Multiples at the end of:	Arithmetic average	Median	Standard deviation	Coefficient of variation
February 1998	1.61	1.37	1.06	65.8%
February 1999	1.02	0.70	1.00	97.8%
February 2000	1.66	0.92	2.54	152.7%
February 2001	1.15	0.74	1.49	129.6%
February 2002	0.99	0.74	0.85	86.4%
February 2003	0.90	0.67	0.79	88.0%
February 2004	1.88	1.45	1.98	104.8%
February 2005	2.23	1.65	1.98	88.9%
February 2006	2.93	1.99	2.64	90.3%
February 2007	3.79	2.87	3.56	94.1%
February 2008	2.67	2.04	2.23	83.7%
February 2009	1.37	0.70	3.63	265.5%

This table shows the summary statistics computed for P/BV multiple on the Polish stock market.
Source: money.pl; parkiet.com.pl; author's calculations.

In the case of every regression the identification of outliers was carried out after completing the data. To this end we applied the method based on the analysis of the significance of regression' coefficients obtained for dummy variables constructed for potential outliers (Evans, 2003). We started with an estimation of a given regression based on all the potential explanatory variables and all the available observations at a given date. In order to identify potential outliers we computed the residuals of the regression and found the residual with the highest absolute value. Then we constructed a dummy variable with the value of unity in the case of primary regression' highest residual and zero values for all the remaining observations. This variable was added to the regression and the coefficients were re-estimated. If the dummy variable turned out to be statistically significant we assumed this observation to be an outlier and removed it from the sample. Next, we re-estimated the primary regression and again found the residual with the highest absolute value, for which we again constructed a dummy variable with the value of unity in the case of identified highest residual and zero values for all the remaining observations. This dummy variable was added to the regression and the coefficients of this regression were re-estimated and tested for statistical significance. The procedure of outliers' elimination was repeated until the dummy variable for another potential outlier turned out to be statistically insignificant.

In the case of every regression we tested several accounting ratios as potential explanatory variables. In selecting explanatory variables we used the following procedure (Nilsson, Nilsson, 1994):

1) we estimated *i* simple regressions of the form:

$$VM = \alpha_0 + \alpha_1 EV_i + \varepsilon \tag{3}$$

where:

VM - the dependent variable, being the respective valuation multiple (P/E, P/BV or P/S),
α_0, α_1 - regression' coefficients,
EV_i - *i*-th potential explanatory variable,
i – the number of potential explanatory variables under investigation in stage 1,
ε – random factor,
and chose the potential variable EV_1 with the highest value of adjusted R-squared statistic.

2) then we estimated *i*-1 regressions of the form:

$$VM = \alpha_0 + \alpha_1 EV_1 + \alpha_2 EV_n + \varepsilon \tag{4}$$

where:

EV_1 - the explanatory variable selected in stage 1,
n – the number of potential explanatory variables under investigation in stage 2 (*n*=*i*-1),
and chose the potential variable EV_2 with the highest value of adjusted R-squared statistic.

3) we reiterated the procedure, adding more variables, until the number of variables in the regression reached the point at which the adjusted R-squared had the maximum value.

Apart from the adjusted R-squared, the analysis of the significance of explanatory variables was conducted on 5% significance level (*t*-statistics were used). In order to mitigate the distorting impact of potential heteroscedasticity on the significance tests the procedure of weighted least squares estimation was applied in all the regressions (Nowak, 1994).

We used only ratios based on historical (and not forecasted) data, as potential explanatory variables. This is due to the fact, that (as was stated earlier) on the Polish stock market the consensus earnings forecasts are available only for several companies and in the case of most companies there are not even single regular analysts' forecasts produced. For the same reason we considered as the dependent variables only trailing (and not forward) multiples. As was demonstrated, the valuation multiples are related to companies' growth, profitability and cost of capital. Therefore we used the ratios of sales growth (as the proxy for growth), return on equity, sales margin and assets turnover (as the proxies for profitability) and the leverage ratio (as the proxy for financial risk), as explanatory variables. This set of ratios is generally consistent with other studies (Henschke, Homburg, 2009). We also used two dummy variables as the additional proxies for risk and profitability. The accounting ratios used in the regressions were defined as follows:

$$Growth_t = S_t / S_{t-1} \tag{5}$$

where:

$Growth_t$ - sales growth in year *t*,

S_t - net sales in year *t*.

$$ROE_t = E_t / SE_t \tag{6}$$

where:

ROE_t - return on equity in year *t*,

E_t - net earnings in year *t*,

SE_t - book value of shareholders' equity at the end of year *t*.

$$Margin_t = OP_t / S_t \tag{7}$$

where:

$Margin_t$ - sales margin in year *t*,

OP_t - operating profit in year *t*.

$$Turnover_t = S_t / A_t \tag{8}$$

where:

$Turnover_t$ - assets turnover in year *t*,

A_t - total assets at the end of year *t*.

$$Leverage_t = TL_t / A_t \tag{9}$$

where:

$Leverage_t$ - leverage ratio in year *t*,

TL_t - total liabilities and provisions at the end of year *t*.

The additional dummy explanatory variables were defined as follows:

$DummyProfit_t$ - equaling 1 in the case of positive net earnings in year *t* and 0 otherwise,

$DummyProfitChange_t$ - equaling 1 in the case of net earnings' growth in year *t* and 0 in the case of net earnings' decline in year *t* (as compared to year *t-1*).

On the basis of the estimated regressions we computed the fundamentally-adjusted multiples for all the companies (also these that were eliminated as outliers during process of regression' estimation) listed at the end of February of each analyzed year, excluding these for which the calculation of a given multiple was nonsensical. We did this by introducing appropriate values of the explanatory variables into regressions. Next, we computed the residuals that measure the scope of relative overvaluation or undervaluation of individual stock at a given date. The positive residuals imply overvaluation and the negative residuals imply undervaluation. In the case of every multiple, at the end of February of each analyzed year all the (then listed) stocks, excluding those with nonsensical (i.e. negative) values of a given multiple, were sorted in order of decreasing values of the residuals and divided into five portfolios in such a way that the first portfolio consisted of 20% most overvalued stocks (the 20% stocks with the highest positive residuals) and the fifth portfolio consisted of 20% most undervalued stocks (the 20% stocks with the highest negative residuals). Because in most cases the whole sample didn't divide equally by five we adjusted the number of stocks in the last portfolio.

In order to verify the effectiveness of the estimated regressions in detection of overvalued and undervalued stocks we treated all portfolios as alternative investment strategies. Hence, we assumed that buying stocks from the first portfolio is equivalent to strategy of investing in 20% most overvalued stocks and buying stocks from the fifth portfolio is equivalent to strategy of investing in about 20% most undervalued stocks. Within all the alternative portfolios the equal weights for all the stocks were applied.

For all the portfolios we computed annual nominal returns (for the periods between the end of February of a given year and the end of February of the next year). Next**,** we calculated the geometric average nominal annual returns in the period between the end of February 1998 and the end of February 2010. We applied geometric average because it represents the constant return an investor must earn every year to arrive at the same final value that would be produced by a series of variable returns (Cornell, 1999). The dividends and transaction costs were disregarded in all our calculations, due to the lack of any database regarding them.

In order to evaluate the relative profitability of individual strategies we compared the average nominal annual returns of the portfolios constructed on the basis of estimated P/E, P/BV and P/S regressions with the average nominal annual returns obtained from simple strategies based on actual multiples as well as with the nominal annual returns of indexing strategy (based on the Warsaw Stock Exchange WIG Index). In the case of simple strategies all the stocks were sorted in order of decreasing actual values of a given multiple in such a way that the first portfolio consisted of 20% stocks with the highest values of a given multiple (at a given date) and the fifth portfolio consisted of about 20% stocks with the lowest values of a given multiple. Because in most cases the whole sample didn't divide equally by five we adjusted the number of stocks in the last portfolio.

RESULTS

Table 5, 6 and 7 show the results of the regressions' estimations. The regressions are characterized by relatively good fit to the empirical data in the case of P/S multiple (with adjusted R-squared statistics usually above 0.45), but not in the case of P/E and P/BV multiples. Also F statistics point out to considerably higher statistical significance of P/S regressions. Furthermore, the P/S regressions are much more consistent as regards the structure of explanatory variables as well as the signs of the parameters (it suggests the presence of some spurious regressions in the case of P/E and P/BV multiples). This is probably mainly due to relatively high share of outliers remaining in the samples in the case of P/E and P/BV regressions as well as the distorting impact of inter-company differences in accounting policies (that are distorting P/E and P/BV multiples to a greater extent than P/S multiple). One of the reasons causing poor quality of P/E and P/BV regressions could also be the introduction of IFRS (instead of Polish accounting standards) in 2005 (after joining the European Union) by the companies publishing consolidated financial statements (companies publishing only separate statements are still allowed to prepare them in accordance to Polish accounting laws). This further limited the inter-company comparability of earnings and book value numbers (with much lower distorting effect in the case of net sales data).

Table 5: The Results of Estimation of the P/E Regressions

Regression at the end of:	Dependent variable: P/E multiple	Additional statistics		
	Regression' explanatory variables (signs of parameters in parentheses)	Sample 1 / Sampie 2 [1)]	Adjusted R-squared	F statistic [2)]
February 1998	ROE(-), Leverage(+), Growth(-)	64 / 73	0.116	3.75**
February 1999	ROE(-)	88 / 104	0.096	10.21***
February 2000	ROE(-), Growth(+), DummyProfit(-)	85 / 94	0.332	14.92***
February 2001	ROE(-), DummyProfitChange(-)	75 / 84	0.100	5.15***
February 2002	ROE(+), DummyProfitChange(-)	53 / 65	0.250	9.66***
February 2003	Turnover(-), DummyProfitChange(-)	61 / 76	0.268	11.98***
February 2004	ROE(-), Turnover(-), Growth(+), DummyProfitChange(-)	59 / 95	0.342	8.54***
February 2005	ROE(-), DummyProfitChange(-)	74 / 117	0.570	49.40***
February 2006	ROE(-), Leverage(+)	97 / 141	0.308	22.36***
February 2007	ROE(-)	122 / 155	0.129	18.97***
February 2008	ROE(-), Turnover(+), DummyProfitChange(-)	192 / 230	0.208	17.69***
February 2009	ROE(-), Turnover(+), Growth(+)	170 / 210	0.267	21.47***

This table shows the results of the regressions estimated for P/E multiple on the Polish stock market.
[1)] Sample 1 consists of all the observations used in regression' estimation; Sample 2 consists of all the observations used in portfolios' construction at a given date (including outliers removed from Sample 1 in the process of regression' estimation)
*[2)] *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively*
Source: money.pl; parkiet.com.pl; author's calculations.

Table 6: The Results of Estimation of the P/BV Regressions

Regression at the end of:	Dependent variable: P/BV multiple	Additional statistics		
	Regression' explanatory variables (signs of parameters in parentheses)	Sample 1 / Sampie 2 [1)]	Adjusted R-squared	F statistic [2)]
February 1998	ROE(+), Turnover(-), Leverage(+)	61 / 83	0.452	17.51***
February 1999	ROE(-), Leverage(+), Turnover(+), Growth(+),	111 / 126	0.466	20.23***
February 2000	Growth(+), DummyProfitChange(+)	117 / 138	0.390	38.14***
February 2001	ROE(-), Leverage(+), DummyProfitChange(+)	117 / 133	0.067	3.78**
February 2002	ROE(-)	78 / 122	0.129	12.44***
February 2003	ROE(-), Growth(+)	85 / 120	0.402	29.20***
February 2004	ROE(+), Leverage(+), Turnover(-), Growth(+)	85 / 128	0.142	4.48***
February 2005	ROE(+), Leverage(+)	91 / 135	0.432	35.26***
February 2006	ROE(-), Growth(+), DummyProfitChange(+)	129 / 172	0.506	44.72***
February 2007	ROE(+), Growth(+), DummyProfitChange(+)	149 / 179	0.192	12.74***
February 2008	ROE(+), Turnover(+)	188 / 256	0.343	49.81***
February 2009	ROE(+), Turnover(+), DummyProfit(+)	247 / 294	0.239	26.82***

This table shows the results of the regressions estimated for P/BV multiple on the Polish stock market.
[1)] Sample 1 consists of all the observations used in regression' estimation; Sample 2 consists of all the observations used in portfolios' construction at a given date (including outliers removed from Sample 1 in the process of regression' estimation)
*[2)] *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively*
Source: money.pl; parkiet.com.pl; author's calculations.

Table 7: The Results of Estimation of the P/S Regressions

Regression at the end of:	*Dependent variable: P/S multiple*	**Additional statistics**		
	Regression' explanatory variables (signs of parameters in parentheses)	**Sample 1 / Sampie 2 [1]**	**Adjusted R-squared**	**F statistic [2]**
February 1998	Margin(+), Turnover(-), Leverage(-)	76 / 84	0.521	28.22***
February 1999	Margin(+), Turnover(-), Leverage(-)	97 / 128	0.454	27.62***
February 2000	Margin(+), Turnover(-), Leverage(-)	118 / 141	0.499	39.89***
February 2001	Margin(+), Turnover(-), Leverage(-)	120 / 136	0.481	37.80***
February 2002	Margin(+), Turnover(-), Leverage(-)	112 / 130	0.527	42.21***
February 2003	Margin(+), Turnover(-), Leverage(-)	92 / 145	0.505	31.90***
February 2004	Margin(+), Turnover(-), Leverage(-)	86 / 131	0.564	37.63***
February 2005	Margin(+), Turnover(-), Leverage(-)	125 / 139	0.529	47.38***
February 2006	Margin(+), Turnover(-), Leverage(-)	121 / 183	0.570	53.93***
February 2007	Margin(+), Turnover(-), Leverage(-)	109 / 179	0.674	75.34***
February 2008	Margin(+), Turnover(-), Leverage(-)	242 / 259	0.540	95.30***
February 2009	Margin(+), Turnover(-), Leverage(-)	231 / 294	0.473	69.90***

This table shows the results of the regressions estimated for P/BV multiple on the Polish stock market.
[1] Sample 1 consists of all the observations used in regression' estimation; Sample 2 consists of all the observations used in portfolios' construction at a given date (including outliers removed from Sample 1 in the process of regression' estimation)
*[2] *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively*
Source: Welc (2009); money.pl; parkiet.com.pl; author's calculations.

On the basis of the regressions we classified (at the end of February of each year) the companies in order of their over- or undervaluation. Next, we sorted all the stocks in order of decreasing residuals. The stocks sorted in this way were divided into five portfolios. Then the profitability of the most overvalued and the most undervalued portfolios based on the three multiples' regressions were compared with the returns of strategies using actual P/E, P/BV and P/S multiples as well as with the indexing strategy. The returns are shown in Table 8.

Table 8: The Average Returns of the Alternative Portfolios

Strategy based on:	*Fundamentally-adjusted multiples*		**Actual multiples**	
	Most overvalued portfolio*	**Most undervalued portfolio***	**Most overvalued portfolio****	**Most undervalued portfolio****
Price-to-earnings multiple	1.2%	16.0%	1.0%	19.2%
Price-to-book-value multiple	2.0%	18.4%	1.5%	20.8%
Price-to-sales multiple	-4.1%	21.7%	-3.0%	19.1%
WIG Index	6.8%			

This table shows the geometric average nominal annual returns of portfolios constructed on the basis of fundamentally-adjusted multiples, actual multiples and indexing strategy (between the end of February 1998 and the end of February 2010).
** most overvalued portfolio comprised 20% of stocks with the highest difference between actual and implied (from the regression) multiple (the most overvalued stocks); most undervalued portfolio comprised 20% of stocks with the lowest difference between actual and implied (from the regression) multiple (the most undervalued stocks).*
*** most overvalued portfolio comprised 20% of stocks with the highest value of the multiple (the most overvalued stocks); most undervalued portfolio comprised 20% of stocks with the lowest value of the multiple (the most undervalued stocks).*
Source: money.pl; parkiet.com.pl; author's calculations.

The data confirm the supremacy of all strategies focused on the most undervalued stocks over the strategies based on buying the most expensive stocks. In the analyzed twelve-year period the highest average returns were generated by the strategy of buying 20% of companies with the highest differences between actual and implied (from the regressions) P/S multiples. It confirms the previous research (Welc, 2009), conducted on the shorter period data, that selecting stocks on the basis of fundamentally-adjusted P/S multiples on the Polish stock exchange can constitute a profitable strategy with high potential of generating above-average returns. The results obtained for strategies based on P/E and P/BV regressions are much less encouraging. In both cases the average returns of strategies focused on most undervalued stocks as indicated by actual multiples were significantly greater than the returns from regression-based strategies. This could be expected given the poor quality of most regressions estimated for P/E and P/BV multiples, resulting in producing more noise rather than explaining the true relationships between the multiples and fundamentals.

The above analysis does not allow for the risk associated with the alternative strategies. The high returns of some strategies can entail above-average risk. The table below shows Betas of the portfolios under investigation. The Betas were computed as the slope coefficients of the linear regressions with the given portfolio' annual returns as dependent variable and the Warsaw Stock Exchange WIG Index' annual returns as an explanatory variable.

Table 9: Beta Coefficients of the Alternative Portfolios

Strategy based on:	**Fundamentally-adjusted multiples**		**Actual multiples**	
	Most overvalued portfolio*	**Most undervalued portfolio***	**Most overvalued portfolio***	**Most undervalued portfolio***
Price-to-earnings multiple	0.89	1.73	0.96	2.01
Price-to-book-value multiple	0.93	1.67	0.97	1.84
Price-to-sales multiple	1.03	1.83	1.08	1.95

This table shows the Beta coefficients of portfolios constructed on the basis of fundamentally-adjusted multiples and actual multiples (between the end of February 1998 and the end of February 2010).
** portfolios constructed in the same way as in Table 8*
Source: money.pl; parkiet.com.pl; author's calculations.

All the strategies focused on most undervalued stocks, although bringing above-average returns, are also associated with the above-average risk. However, this positive risk-return relationship does not hold when comparing the individual portfolios composed of 20% most undervalued stocks, because the portfolio built on the basis of fundamentally-adjusted P/S multiples (having the highest average annual return) is characterized by Beta coefficient lower than in the case of all three strategies focused on the most undervalued stocks as indicated by actual multiples.

CONCLUDING COMMENTS

We attempted to evaluate the effectiveness of relative valuation with the use of simple linear regressions of valuation multiples. The analysis of the average returns in the period between the end of February 1998 and the end of February 2010 showed that in the case of the Warsaw Stock Exchange the strategy of buying 20% most undervalued stocks as indicated by the regressions of P/S multiples generated the average returns exceeding returns of strategies based on actual P/E, P/BV and P/S multiples as well as the average return of the market as a whole. It confirmed the previous research stating that on the Warsaw Stock Exchange allowing for the relationships between P/S multiples and accounting ratios increases the accuracy of valuation. These results are promising given the fact that P/S regressions under investigation are based solely on the historical accounting data. However, the results obtained for P/E and P/BV multiples are much less encouraging, because in these cases the simplest strategies of buying stocks with the lowest actual multiples generated returns beating those obtained with the use of the regressions.

In the case of all the strategies based on buying 20% most undervalued stocks relatively high returns are associated with relatively high risk (as measured by Beta coefficient) when compared to the strategies based on higher values of multiples. Therefore**,** investors following these strategies must face the necessity of tolerating relatively high risk. However, the positive risk-return relationship does not hold when comparing the individual portfolios composed of 20% most undervalued stocks, because the portfolio built on the basis of fundamentally-adjusted P/S multiples is characterized by Beta lower than in the case of all three strategies focused on the most undervalued stocks as indicated by actual multiples.

These results, corroborating relatively high accuracy of valuation with the use of fundamentally-adjusted P/S multiple, are encouraging given the usefulness of this multiple in the periods characterized by significant deterioration of companies' results. This is so because net sales are always positive, regardless of current phase of business cycle. Thanks to it this approach enables valuation of almost all listed companies (excluding small number of companies with no sales), opposite to the multiples based on earnings and book values.

However, among the significant limitations of the proposed approach are the lack of allowance for many potentially important factors (especially with the qualitative nature) influencing companies' market values (e.g. corporate strategies, growth potential, competitive advantages, etc.) as well as for potential non-linearity of the relationship between valuation multiples and the fundamentals.

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DO CHANGES IN PENSION PLAN ACCOUNTING STANDARDS RESULT IN BETTER MARKET VALUATION?

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ABSTRACT

This study investigates if changes in U.S. accounting standards result in a better assessment of firms' pension commitments as reflected in stock prices. Fama and French three factor (1993) model results reveal that the market inefficiently incorporates defined benefit pension plan information for the three accounting standard related periods. In contrast to Franzoni and Marín (2006), and Fama and French (1993), the returns were estimated starting the fourth month after the end of fiscal year t. The results suggest that investors are not paying enough attention to the implications of the underfunding for future earnings and cash flows. Apparently, the changes in accounting standards do not alter the way investors evaluate this type of obligation. Hedge-portfolio tests are performed to verify if there is an opportunity to outperform the market by identifying weaknesses in the incorporation of information. Tests' results corroborate that the market overprices firms that have severely negative funding status.

JEL: G14; G23; M48

KEYWORDS: Pension plans, accounting standards, information content

INTRODUCTION

Pension plan systems have been growing fast after the post World War II period. As a result, pension plan obligations have become a major concern for management, regulators, and the government. Through the years, the Financial Accounting Standards Board (FASB) has demonstrated preoccupation with respect to pension plan information disclosures, as demonstrated by the changes in disclosure requirements in the last decades. Efforts to enhance the relevance and understandability of reported pension information also include the enactment of ERISA (Employee Retirement Income System Act of 1974) and the "Pension Protection Act of 2006", the issuance of Statement of Financial Accounting Standards (SFAS) No. 36, SFAS No. 87, SFAS No.132, and most recently, the SFAS No. 158. SFAS No. 158, effective for fiscal years ending after December 15, 2008, provides new pension disclosure requirements intended to address previous shortcomings. Before the issuance of SFAS No. 158, pension plan information concerning the pension plan status was reported in the notes to the financial statements. One of the most important changes of this statement is the presentation of pension plan status in the balance sheet.

A severely underfunded pension plan has future implications in cash flows and earnings. As a result, it is important for investors to assess the pension plan status before making investment decisions. By moving this information from the notes to the financial statements to the balance sheet, the intention of the FASB is to improve and create awareness of the importance of pension plan status information. Evidence from various studies suggests that the information content of selected items included in the financial statements is relevant or has impact on stock prices. Studies about pension plan information suggest different results as to markets evaluation or incorporation of this information. This study examines the incorporation of defined benefit (DB) pension plan information for three different accounting standard related periods between 1980 and 2005. For these accounting standard related periods pension information was presented in the notes to the financial statements.

The work in this article proceeds as follows: first, there is a presentation of the relevant literature regarding this topic. Second, after the literature review, there is a description of the sample selection procedure, data analysis and methodology. Finally, a summary of the empirical findings is presented followed by some concluding remarks.

LITERATURE REVIEW

As formally stated by the efficient market hypothesis (EMH), asset prices in financial markets should reflect all available information. Fama, Fisher, Jensen and Roll (1969) introduced the term "efficient market" into the economics literature and defined it as a market that "adjusts rapidly to new information". While approaching the twenty-first century the arguments about market efficiency were challenged and its dominance started to be less universal. Becheey, Gruen and Vickery (2000) argue that evidence suggests, that the EMH cannot explain some important and worrying features of asset market behavior.

As for pension plan information, a review of the literature suggests that the market may be inefficient incorporating this information. Apparently, the market overvalues firms with severely underfunded pension plans. Franzoni and Marín (2006) argue that investors do not anticipate the impact of the pension liability on future earnings, and that they are surprised when the negative implications of underfunding ultimately materialize. Godwin and Key (1998) assess market reaction to the Pension Benefit Guarantee Corporation (PBGC) list of the 50 firms with the largest underfunding by calculating abnormal returns around PBGC press release dates using standard event study methodology. Their results suggest that maybe the market had access to the information before the announcement or that investors inefficiently incorporate this news information.

Phillips and Moody (2003) examine the relationship between pension plan funding levels and capital structure and provide statistically significant empirical support for the pecking order theory of capital structure. Results suggest that more highly levered firms experience lower profitability and are constrained by a larger dividend payout. In addition, these firms have exhausted their internal resources of financing by underfunding their pension plans, most likely to the extent legally possible. The study demonstrates that underfunding occurs principally due to a firms' incapacity to fully fund.

Livnat (1984), examines whether unfunded vested benefits and unfunded past service costs possess any information content. The author argues that these findings suggest that neither of the disclosures tested was sufficiently informative but they improved the information content of the earnings disclosure. Feldstein and Seligman (1981) examine empirically the effect of unfunded pension liabilities on corporate share prices and discuss the implications of these estimates for national saving, the decline of the stock market for periods preceding the study, and the rationality of corporate financial behavior. The authors state that it would be more accurate to say that the data is consistent with the conclusion that shareholders accept the conventional measure as the best available information and adjust prices accordingly.

DATA AND METHODOLOGY

In order to test these predictions a sample comprised of all the firm-years with available data on the Compustat Annual Industrial and Research files for NYSE, AMEX, and NASDAQ firms is used. The sample period is the end of fiscal year 1980 to end of fiscal year 2005. The study only includes firms that sponsor DB pension plans. Firms' monthly returns were obtained from the Center for Research and Security Prices (CRSP), Monthly Stock database.

The variables of interest correspond to different accounting items over the years. Consequently, this accounting data is constructed differently for different periods in the time span that is studied. There are two breaks in the way Compustat informs the data related to pension plans. These breaks result from changes in accounting standards. The first break is caused by the accounting standard SFAS 87. It affects the way pension data is presented starting fiscal years beginning after December 15, 1986. The second break, effective for fiscal years beginning after December 15, 1997, is caused by SFAS 132.

In order to measure the funding status of the pension plans, the procedure used by Franzoni and Marín (2006) is used. To solve the problem of the impact that the same dollar amount of underfunding has depending on the size of the firm, the funding status needs to be appropriately normalized. Funding status is defined as the difference between the fair value of pension assets (*FVPA*) and the pension benefit obligation (*PBO*). They choose to divide the funding status by market capitalization (*Mkt Cap*) at the end of the fiscal year when the pension items are measured. As them, this variable is labeled funding ratio (*FR*). This variable is computed as follows:

$$FR_{t-1} = FVPA_{t-1} - PBO_{t-1} / Mkt\ Cap_{t-1} \tag{1}$$

After calculating the *FR*, firms-years are classified by accounting standard period. Then, firms are sorted into three sets of portfolios by period and by *FR*. Firms sponsoring DB pension plans are classified as underfunded and overfunded. Eleven portfolios were formed for each accounting standard period. The first ten portfolios include only underfunded firms ($FR<0$) in a given year. The eleventh portfolio includes overfunded firms ($FR\geq0$).

Monthly portfolio return series are created in each group starting the four month after the end of fiscal year $t - 1$ to the third after the end of fiscal year t. The Fama and French (1993) three-factor model is used to calculate each portfolio's excess return. Portfolios are tested for risk-adjusted returns by running time-series regressions of portfolio returns on the returns on different factors, including the market. Discrepancies in returns among portfolios could be explained by different factor loadings. In formula, the time-series regression (Fama-French three-factor model) for the portfolios is expressed:

$$R_{it} = \alpha_i + b_i\,EXM_t + h_i\,HML_t + s_i\,SMB_t + \varepsilon_{it} \tag{2}$$

where R_{it} is the portfolio excess return. The EXM, HML and SMB factors are constructed as in Fama and French (1993). EXM is the factor that represents the market portfolio minus the risk free rate. The HML factor represents a portfolio long in high book to market (B/M) and short in low B/M firms. The last factor, SMB represents a portfolio long in small and short in large companies. The factor data was retrieved from the Kenneth French Data Library.

Finally, statistical tests are performed to verify if there are statistically significant differences between the risk-adjusted returns of the different portfolios. As in Sloan (1996) and Xie (2001), hedge-portfolio tests are performed to verify if there is an opportunity to outperform the market by creating investment strategies that focus in exploiting the market failure to incorporate pension plan information.

Aggregate Funding Status Historical Trends

It is important to look at the historical evolution of the DB pension plan elements to observe any trends that can help in the analysis. Figure 1 reports the time series of the aggregate funding level for all the companies in Compustat with available pension items. The funding level is the difference between the aggregate *FVPA* and *PBO*.

As can be observed from Figure 1, an aggregate underfunding appears, for the first time in our sample, in 1994. Starting in 1996 the funding status of DB pension plans started to improve and in 1997, concurring with the bull market of the second half of the 1990's, pension plan assets grew more than benefits, and peaked in 1999 at about $163 billion. On March of 2000, the Internet bubble exploded causing stock prices to decrease and as a result, the fair value of pension assets dropped. In 2001, the gap between the *PBO* and the *FVPA* appears reaching almost $85 million. Major economic events effects arose from September 11, 2001 attacks, with initial impact causing global markets to drop sharply. Then, on 2002, a surplus appears, reaching about $754 million in aggregate overfunding. However, the volatility in the markets is reflected in years to come. In 2003, another aggregate underfunding appears. This is in contrast to an aggregate overfunding of $1.3 billion in 2004. This is the highest aggregate overfunding for the whole sample period. For 2005, the last year in the sample, another aggregate underfunding appears. It represents the biggest change in funding status. It reaches almost $1.5 billion dollars in deficit on a year-to-year basis.

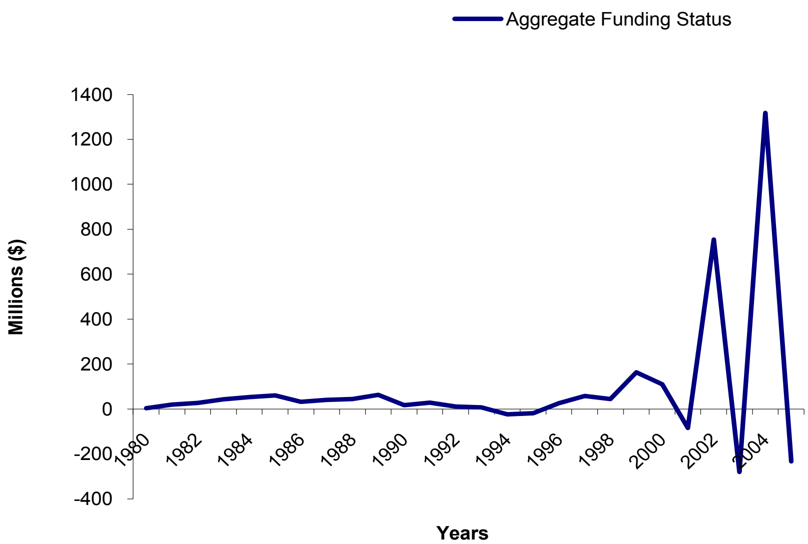

Figure 1. Aggregate Pension Plan Status. The graph reports the difference between aggregate assets (FVPA) and aggregate benefits (PBO) for the companies in the sample.

<u>Descriptive Statistics per Period</u>

Table 1 reports descriptive statistics of the eleven portfolios created according to accounting standard period and *FR*. The characteristics are measured at the end of fiscal year $t - 1$ relative to portfolio formation. The difference in the level of average *FR* between the most underfunded portfolio and the least underfunded is noticeable in each period. Panel A shows that for the most underfunded firms (portfolio one) in this period the average *FR* is about -131%. In contrast, for the least underfunded firms (portfolio 10) the average level of *FR* is about -0.1%. The average *FR* for the portfolio that contains overfunded firms (portfolio eleven) is about 9%. The most underfunded firms have higher levels of long-term debt ratio (*LTDR)*. A consistent decrease in *LTDR* is observed through portfolio ten. The average size of the firms increases almost consistently, where smaller firms are concentrated in the most underfunded portfolio. Interestingly, firms in portfolio eleven have the second smallest average size of all the portfolios. As for B/M, value firms are concentrated in the most underfunded portfolio. Portfolio 11 also has value firms but to a lesser degree.

Panel B shows the results for the period between 1987 and 1997. For the most underfunded firms (portfolio one) the average *FR* is about -117%. In contrast, for the least underfunded firms (portfolio 10) the average level of *FR* is about -0.1%. The average *FR* for the portfolio that contains overfunded firms (portfolio eleven) is about 7.3%. The most underfunded firms have high levels of *LTDR*. An almost consistent decrease in *LTDR* is observed through portfolio ten. The second most underfunded portfolio has on average the smallest firms. In contrast, the overfunded firms are the biggest. As for B/M, value firms are concentrated in the most underfunded portfolio. Portfolio 11 also has value firms but to a lesser degree.

Panel C shows the results for the period between 1998 and 2005. For the most underfunded firms (portfolio one) the average *FR* is about -945%. In contrast, for the least underfunded firms (portfolio 10) the average level of *FR* is about -0.1%. The average *FR* for the portfolio that contains overfunded firms (portfolio eleven) is about 12%. The most underfunded firms have the highest levels of *LTDR* among portfolios. The most underfunded portfolio has on average the smallest firms. In contrast, the least underfunded firms are the biggest. As for B/M, value firms are concentrated in the most underfunded portfolio. Portfolio 11 also has value firms but to a lesser degree.

Table 1: Descriptive Statistics per Accounting Standard Period

	Most									**Least**	**Over**
	1	2	3	4	5	6	7	8	9	10	11
					Panel A: Period 1980-1986						
FR	-1.31	-0.20	-0.10	-0.05	-0.03	-0.02	-0.01	-0.007	-0.003	-0.001	0.09
LTDR	2.08	1.42	0.94	0.87	0.78	0.71	0.62	0.70	0.52	0.37	1.24
Size	133.38	318.16	311.14	239.62	337.84	261.50	290.22	392.72	397.02	310.64	812.93
B/M	1.49	1.43	1.33	1.45	1.21	1.13	0.98	0.86	0.82	0.69	1.16
Firms	156	156	176	183	183	196	189	197	188	184	8511
					Panel B: Period 1987-1997						
FR	-1.17	-0.09	-0.05	-0.03	-0.02	-0.01	-0.01	-0.006	-0.003	-0.001	0.073
LTDR	103.15	1.07	0.85	0.74	0.56	0.49	0.46	0.41	0.39	0.38	2.15
Size	2,013	1,803	2,087	1,998	2,395	1,981	2,061	2,424	2,580	3,735	2,593
B/M	23.37	0.81	0.79	0.79	0.72	0.68	0.63	0.63	0.57	0.50	0.90
Firms	707	817	829	845	848	865	881	877	872	855	9,496
					Panel C: Period 1998-2005						
FR	-9.45	-0.13	-0.07	-0.04	-0.03	-0.02	-0.01	-0.007	-0.004	-0.001	0.12
LTDR	41.24	1.13	0.91	0.64	0.56	0.44	0.38	0.40	0.44	0.41	2.71
Size	3,420	5,023	5,007	5,135	8,299	7,174	7,909	8,846	8,460	13,014	9,093
B/M	23.02	0.75	0.69	0.70	0.64	0.58	0.54	0.54	0.51	0.47	6.21
Firms	800	1,023	1,047	1,042	1,066	1,058	1,055	1,066	1,049	1,039	4,190

In the fourth month after the end of fiscal year t, firms with available data at the end of fiscal year t-1 are assigned to a set of ten portfolios according to the deciles of the distribution of FR. The stocks in portfolios one through ten have underfunded DB pension plans. Firms in portfolio eleven contain firms with overfunded pension plans. FR is the difference between the fair value of plan assets (FVPA) and the projected benefit obligation (PBO) in fiscal year ending in year t – 1, divided by the market capitalization at the end of fiscal year t – 1. Presented are the average of the annual averages of the FR of the companies in each portfolio; the average of the annual averages of the LTDR of the companies in each portfolio (long-term debt in fiscal year ending in year t – 1, divided by the market capitalization at the end of fiscal year t – 1); the average of the annual averages of the market capitalization (in millions of dollars) of the companies in each portfolio at the end of fiscal year t - 1; the average of the annual averages of the book-to-market ratio (B/M) of the companies in each portfolio at the end of fiscal year t – 1; and the average of the annual number of firms in each portfolio. The sample covers formation periods from April 1981 to April 2006.

EMPIRICAL RESULTS

Risk-Adjusted Returns

Table 2 reports the alphas for the sets of portfolios of firms that sponsor DB pension plans for the three accounting standard periods. Panel A shows the results of portfolios for the period between 1980 and 1986. Portfolios four, seven and nine through eleven have positive and significant alphas. This may indicate undervaluation because the market is inefficiently incorporating this information. This evidence suggests that the market tends to undervalue firms with relatively lower levels of underfunding. Undervaluation is also observed for overfunded firms.

Table 2: Three Factor Model Results for the Three Accounting Standard Periods

	Most under									**Least under**	**Over**
	1	2	3	4	5	6	7	8	9	10	11
Panel A: Period 1980-86											
Alphas											
Alphas	0.00	0.026	-0.001	0.010*	0.005	0.006	0.008*	0.005	0.014*	0.014*	0.010*
	(-0.03)	(1.20)	(-0.34)	(2.50)	(1.30)	(1.21)	(2.91)	(0.76)	(5.45)	(3.69)	(11.31)
Factor Loadings and R^2											
EXM	0.012	-0.002	0.012	0.006	0.009	0.011	0.008	0.01	0.009	0.014	0.009
	(4.84)	(-0.27)	(7.27)	(3.65)	(6.70)	(7.53)	(11.60)	(10.01)	(8.25)	(5.92)	(37.72)
HML	0.002	0.003	0.008	0.001	-0.002	0.004	0.001	0.005	-0.002	0.002	0.001
	(0.38)	(0.58)	(3.42)	(0.33)	(-0.97)	(1.72)	(0.32)	(1.78)	(-1.05)	(1.19)	(2.13)
SMB	0.01	0.024	0.01	0.011	0.01	0.01	0.009	0.011	0.01	0.013	0.007
	(1.30)	(1.73)	(5.33)	(6.52)	(8.07)	(4.24)	(5.56)	(3.61)	(5.34)	(5.99)	(13.73)
R2	0.22	0.07	0.45	0.47	0.56	0.52	0.64	0.42	0.68	0.58	0.95
Firm-years	525	553	546	553	560	560	560	560	560	560	560
Panel B: Period 1987-97											
Alphas											
Alphas	-0.015*	-0.004	0.001	0.002	0.006*	0.005*	0.006*	0.007*	0.008*	0.012*	0.005*
	(-4.42)	(-1.45)	(0.41)	(0.89)	(2.85)	(4.04)	(4.65)	(6.87)	(6.10)	(5.90)	(7.56)
Factor Loadings and R^2											
EXM	0.01	0.01	0.011	0.01	0.011	0.01	0.01	0.007	0.01	0.01	0.009
	(8.86)	(26.67)	(19.64)	(21.70)	(22.03)	(17.13)	(23.47)	(29.50)	(19.82)	(20.06)	(43.29)
HML	0.008	0.005	0.001	0.003	0.004	0.002	0.002	0.002	0.002	0.003	0.003
	(6.23)	(4.69)	(3.75)	(3.49)	(4.88)	(2.93)	(3.28)	(2.47)	(1.91)	(3.75)	(7.97)
SMB	0.011	0.009	0.01	0.008	0.007	0.006	0.006	0.006	0.005	0.007	0.005
	(8.59)	(9.11)	(11.07)	(0.00)	(7.25)	(7.55)	(9.85)	(12.68)	(7.06)	(5.06)	(20.05)
R2	0.6	0.79	0.85	0.81	0.83	0.79	0.88	0.88	0.88	0.83	0.96
Firm-years	1573	1562	1573	1562	1573	1562	1551	1573	1573	1573	1573
Panel C: Period 1998-2005											
Alphas											
Alphas	-0.020*	-0.003	0.001	0.003	0.004	0.006*	0.009*	0.012*	0.014*	0.016*	0.007*
	(-5.35)	(-1.36)	(0.40)	(1.57)	(1.77)	(2.69)	(5.39)	(4.79)	(6.19)	(7.36)	(3.82)
Factor Loadings and R^2											
EXM	0.01	0.009	0.008	0.008	0.008	0.007	0.008	0.008	0.008	0.009	0.007
	(15.27)	(14.08)	(13.77)	(13.76)	(11.90)	(9.34)	(11.22)	(4.79)	(8.33)	(15.43)	(10.48)
HML	0.009	0.007	0.005	0.004	0.004	0.005	0.003	0.008	0.002	0.002	0.004
	(15.27)	(11.23)	(5.59)	(6.31)	(6.87)	(6.70)	(5.09)	(7.87)	(2.40)	(5.17)	(9.11)
SMB	0.011	0.007	0.006	0.006	0.005	0.005	0.004	0.003	0.002	0.004	0.003
	(10.04)	(11.05)	(6.34)	(8.80)	(8.67)	(6.70)	(5.22)	(3.31)	(1.95)	(6.16)	(5.85)
R2	0.77	0.83	0.82	0.85	0.83	0.75	0.79	0.69	0.71	0.84	0.81
Firm-years	888	888	888	888	888	888	888	888	888	888	888

*In the fourth month after the end of fiscal year t, firms with available data at the end of fiscal year t-1 are divided in deciles according to FR. The stocks in the first portfolio are the most underfunded and the stocks in the tenth portfolio are the least underfunded. In addition, in the fourth month after the end of fiscal year t, stocks with positive FR at the end of fiscal year t – 1 are assigned to portfolio eleven. FR is the difference between the fair value of plan assets (FVPA) and the projected benefit obligation (PBO) in fiscal year ending in year t – 1, divided by the market capitalization at the end of fiscal year t – 1. Panel A reports the results for the portfolios formed for the accounting standard period from 1980-1986. Panel B reports the results for the portfolios formed for the accounting standard period from 1987-1997. Panel C reports the results for the portfolios formed for the accounting standard period from 1998-2005. The constant (alpha) from a time-series regression of portfolio excess returns on the three Fama and French factors is presented for each set of portfolios. The factors are the market excess return (EXM), the return on HML portfolio, and the return on the SMB portfolio. The slopes and the R^2 from these regressions are also presented. The sample period is from the fourth month after the end of fiscal year 1980 to 2006. T-statistics are presented in parentheses. * denotes significance at the 0.05 level, based on a two-tailed t-test for the time-series (26 years) of annual average returns.*

This may indicate undervaluation because the market is inefficiently incorporating this information. In addition, portfolio eleven, the portfolio of overfunded firms, portrays undervaluation. Evidence suggests that the market inefficiently overvalues firms with relatively higher levels of underfunding and tends to undervalue firms with relatively lower levels of underfunding. The most underfunded portfolio has the higher loadings for HML and SMB. This is expected since firms in this portfolio have high B/M and are small.

Panel C shows the results of portfolios for the period between 1998 and 2005. The results show that portfolio one has a significantly negative intercept; an indication of overvaluation for firms that have severely underfunded pension plans. Portfolios six through ten have positive and significant alphas. Apparently, the market undervalues these firms because the market inefficiently incorporates pension information. For portfolio eleven, the portfolio for overfunded firms, reveals undervaluation. Evidence suggests that the market inefficiently overvalues firms with relatively higher levels of underfunding and tends to undervalue firms with relatively lower levels of underfunding. Not surprisingly, the most underfunded portfolio has the higher loadings for HML and SMB. This is expected since firms in this portfolio have high B/M and smaller than the firms in other portfolios are.

Hedge-Portfolio Tests

The risk-adjusted returns estimated using the Fama and French (1993) three-factor and four-factor models indicate that investors may be overpricing firms with severely underfunded pension plans. In addition, the results indicate that investors may be underpricing stocks with relatively lower levels of underfunding. In order to verify if there are statistically significant differences between diverse sets of portfolios, hedge portfolio tests were performed.

Table 3 reports the results for the hedge portfolio tests for the three sets of portfolios. For the period between 1980 and 1986 a portfolio hedge that is long in least underfunded firms (portfolio ten) and short in the most underfunded firms (portfolio one) was formed. The strategy may be profitable for the next year after portfolio formation. For the second and third period, results are not significant. These results are consistent with the market overpricing severely underfunded firms in the portfolio formation year (year t). The second comparison is between portfolios one and eleven. This comparison is between the portfolio that contains firms with severely underfunded pension plans and firms that are adequately funded. For this strategy, results are not significant in each of the three years after portfolio formation. The last comparison for these portfolios is between portfolios ten (least underfunded firms) and eleven (overfunded firms). For this strategy, results are not significant in each of the three years after portfolio formation. These results may indicate that this type of strategy may not be efficient.

For the period between 1987 and 1997, the same strategies are used. A portfolio hedge that is long in the least underfunded firms (portfolio ten) and short in the most underfunded firms (portfolio one) was formed. The strategy may be profitable for the next year after portfolio formation. For the second and third period, results are not significant. The results are consistent with the market overpricing severely undefunded firms in the portfolio formation year (year t). The second comparison is between portfolios one and eleven. The strategy may be profitable only for the next year after portfolio formation and not for the other years. The last comparison is between portfolios ten (least underfunded firms) and eleven (overfunded firms). For this strategy, results indicate that this type of strategy may not be efficient.

Finally, for the set of portfolios for the period between 1998 and 2005, a portfolio hedge that is long in the least underfunded firms (portfolio ten) and short in the most underfunded firms (portfolio one) is formed. The hedge portfolio yields positive returns for each of the three years. These results are consistent with the market overpricing severely underfunded firms in the portfolio formation year (year t). The second comparison is between portfolios one and eleven. The results suggest this strategy may not be efficient. The last comparison for this set of portfolios is between portfolios ten (least underfunded firms) and eleven (overfunded firms). For this strategy, results are significant in each of the three years after portfolio formation but results indicate that this strategy may not be efficient.

Table 3: Hedge Portfolio Tests for *FR* Portfolios per Accounting Standard Period

	Average Returns Per Portfolio								
Portfolio Ranking	Panel A: FR Period 1980-86			Panel B: FR Period 1987-97			Panel C: FR Period 1998-2005		
	Year t+1	Year t+2	Year t+3	Year t+1	Year t+2	Year t+3	Year t+1	Year t+2	Year t+3
1	0.000	-0.001	0.000	-0.002	-0.002	0.000	-0.003	-0.002	0.001
	(-0.02)	(-0.08)	(0.06)	(-0.01)	(-0.04)	(0.25)	(-0.01)	(0.17)	(0.40)
2	0.008	0.008	0.007	0.007	0.006	0.006	0.007	0.007	0.008
	(0.06)	(0.03)	(-0.06)	(-0.14)	(-0.10)	(-0.03)	(-0.19)	(-0.01)	(0.25)
3	0.009	0.007	0.009	0.009	0.007	0.008	0.009	0.008	0.009
	(0.06)	(-0.17)	(0.17)	(0.01)	(-0.40)	(0.26)	(-0.26)	(-0.17)	(0.15)
4	0.013	0.130	0.140	0.009	0.007	0.008	0.010	0.009	0.009
	(0.10)	(0.02)	(0.10)	(-0.04)	(-0.42)	(0.17)	(-0.21)	(-0.21)	(-0.01)
5	0.010	0.010	0.011	0.012	0.011	0.010	0.012	0.011	0.012
	(-0.14)	(0.06)	(0.05)	(-0.17)	(-0.26)	(-0.10)	(-0.01)	(-0.17)	(0.08)
6	0.110	0.120	0.120	0.012	0.011	0.011	0.012	0.011	0.011
	(-0.20)	(0.02)	(0.07)	(-0.20)	(-0.28)	(0.05)	(-0.27)	(-0.23)	(0.07)
7	0.012	0.010	0.011	0.014	0.012	0.013	0.014	0.013	0.012
	(-0.14)	(-0.20)	-0.060	(-0.28)	(-0.39)	-0.190	(-0.27)	(-0.25)	(-0.19)
8	0.140	0.013	0.012	0.014	0.011	0.011	0.016	0.015	0.015
	(-0.24)	(-0.08)	(-0.06)	(-0.21)	(-0.61)	-0.040	(-0.14)	(-0.32)	(-0.04)
9	0.017	0.016	0.016	0.016	0.014	0.014	0.016	0.015	0.014
	(-0.06)	(-0.07)	(-0.03)	(-0.24)	(-0.39)	(-0.08)	(-0.29)	(-0.06)	(-0.25)
10	0.150	0.013	0.012	0.017	0.014	0.014	0.019	0.016	0.016
	(-0.35)	(-0.15)	(-0.06)	(-0.44)	(-0.59)	(-0.02)	(-0.41)	(-0.46)	(-0.04)
11	0.014	0.013	0.014	0.012	0.011	0.011	0.006	0.005	0.005
	(-0.80)	(-0.47)	(0.16)	(-0.69)	(-1.02)	(-0.08)	(-0.74)	(-0.51)	(-0.17)
	Panel D: Portfolio Hedge								
Comparison	*Period 1980-86*			*Period 1987-97*			*Period 1998-2005*		
1 and 10	0.15*	0.01	0.01	0.019*	0.02	0.01	0.02*	0.02*	0.02*
	(11.48)	(1.03)	(0.84)	(2.90)	(1.17)	(0.98)	(3.77)	(2.91)	(2.25)
1 and 11	0.014	0.01	0.01	0.014*	0.01	0.01	0.01	0.01	0.01
	(1.43)	(1.36)	(1.29)	(2.49)	(1.26)	(1.02)	(1.79)	(1.31)	(0.69)
10 and 11	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01*	-0.01*	-0.01*
	(0.23)	(0.00)	(0.21)	(-1.37)	(-0.33)	(-0.32)	(-3.43)	(-2.73)	(-2.56)

*Time-series means (t-statistics) of the average monthly returns for each accounting standard period FR portfolio in three years after portfolio formation are calculated. Panel A shows the returns for portfolios formed for the period 1980-86. Panel B shows the returns for portfolios formed for the period 1987-97. Panel C shows the returns for portfolios formed for the period 1998-2005. The stocks in portfolio one (ten) have higher (lower) levels of underfunding. Firms with overfunded plans are assigned to portfolio eleven. Panel D presents the hedge between portfolios one and ten, one and eleven, and ten and eleven. * denotes significance at the 0.05 level, based on a two-tailed t-test for the time-series (26 years) of annual average returns.*

CONCLUSIONS

This study investigates if changes in accounting standards result in a better assessment of firms' pension commitments as reflected in stock prices. This study contributes to the recent discussion by the FASB

and the release of SFAS No. 158 about the incorporation and importance of more DB pension plan information in the financial statements.
The results suggest, the changes in accounting standards, as required for DB pension plan information, do not reflect or result in a better assessment by investors of firms' valuation as reflected in stock prices by accounting standard period. To the contrary, evidence suggests that as the disclosures, availability of information increase, the opportunities to exploit markets inefficiencies become greater. This may signify that the efforts made by regulators do not result in a better assessment of a firms' value or that the efforts to better present this information may have failed. This may be due to investors having problems in understanding the complex pension accounting calculations and disclosures or the inability to incorporate timely and efficiently the information.

The results are consistent with Franzoni and Marín (2006). Their results suggest that investors are not paying enough attention to the implications of the current underfunding for future earnings and cash flows. In addition, Godwin and Key (1998) find that stock prices do not react to additional publications that point out severely underfunded pension plans. Particular to this study is the integration of hedge portfolio tests. The investment strategies suggest that for the three accounting standard related periods strategies to benefit from market inefficiencies may be profitable in some cases. The identified inefficiencies may result from market's inability to integrate information and to identify future consequences related to these long-term commitments. Alternatively, as Sloan (1996) argues, investors appear to be "fixating" just on earnings figures.

Investors, regulatory bodies, accounting standard setters, analysts and researchers may benefit from this study. However, some limitations are pointed out. First, the results of this study are based on the Fama and French (1993) factor model, therefore, are affected by the measurement error introduced by the estimation model. Matching methods may outperform factor models because they match firms based on characteristics that are more specific.

Results suggest that the market is inefficient incorporating pension plan information. The Fama and French model (1993) may have affected the results because of the measurement error introduced by the estimation model. Instead, other methodologies, like matching methods, may give more insight to this respect. This study concentrates on accounting periods in which firms were required to present pension plan status information in the notes to the financial statements. Starting on December of 2006 (after SFAS No. 158), publicly traded firms are required to present information related to pension plan status in the financial statements. Future studies can examine if the changes in disclosure requisites imply information that investors incorporate in stock prices.

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BIOGRAPHY

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THE SENSITIVITY OF COMMON HORIZONTAL EQUITY MEASURES TO VARIATIONS IN OMITTED INCOME

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ABSTRACT

This paper examines the sensitivity of horizontal equity measures (coefficient of variation (CV) and coefficient of residual variation (CRV)) to a common assumption in horizontal equity studies – that changes in level of omitted income do not change horizontal equity experienced by taxpayers in similarly situated income groups. It have been assumed in many prior studies that certain income exclusions or deductions allowed from taxable income have no effect on the resulting horizontal equity measurements. This paper examines whether the CV and CRV remain low within each income group when the mortgage interest deduction and the charitable contribution deduction are disallowed. In general, the omission of certain income does create a wider variation of effective tax rates within income groups. The results of this study indicate that future horizontal equity studies should consider that omitted income, either through income exclusions or deductions allowed, may affect horizontal equity measures. In addition, for policy makers, taking steps to decrease the tax gap also increases horizontal equity.

JEL: M41

KEYWORDS: taxation, horizontal equity, coefficient of variation, coefficient of residual variation

INTRODUCTION

Horizontal equity refers to the idea that taxpayers with the same economic income should have the same tax burden (Musgrave 1959). The "tax gap" refers to the differences between what the US government should be collecting from its taxpayers versus actual collections. The tax gap is reportedly over $300 billion per year (IRS 2005). This gap hurts the economy in two ways. First, to make up for the difference, the tax rates must increase, or debt must increase (along with interest rates). Second, the public perception that, in a self-reporting tax system, that some taxpayers are "getting away with cheating" lessens the ability of the government to collect from everyone. As this paper shows, the "tax gap" also effects horizontal equity – which is another important point of public perception of the tax fairness and hence tax collectability. Prior to this study, tax equity studies often made the assumption that the amount of omitted income has no substantive effect on the outcome of horizontal equity measures calculated. This study examines whether varying levels of income through disallowance of the deductions for home mortgage interest and charitable contribution affects the horizontal equity measures. The purpose of this study is to provide guidance to future tax equity researchers in understanding the capabilities as well as the limitations of currently existing horizontal equity measures. It also points out that decreases in the tax gap will strength horizontal equity. This paper is outlined as follows. Section two describes some of the motivation for the study and provides a literature review. Section three introduces the research design and the hypotheses. Section four presents the results and section five concludes.

LITERATURE REVIEW

The study of equity and tax distribution is one of the broad paradigms which comprise the accounting literature in taxation. Studies in this paradigm compare the relative tax burdens borne by individual taxpayers or groups of taxpayers. Generally, these studies focus on vertical equity (ability to pay), horizontal equity (similarly situated taxpayers being tax equally), or both.

The optimal level of vertical equity has been a controversial issue over the years. Horizontal equity, however, has been described as the "most universally accepted of all principles of tax policy", (White and White 1965, 225).

Legislators have used concerns for "improved horizontal equity" or "improved vertical equity" and results of equity studies as a means of gaining approval for tax policy changes. Given the important and influence of equity studies, it is clear that tax equity needs to be measured in an accurate, reliable and consistent manner to ensure that tax policymakers are informed.

The measure of dispersion is considered the measure of horizontal equity. Horizontal studies use archival data, sorting it in groups of "equal economic circumstance," and then computing the coefficient of variation (CV) or the coefficient of residual variation (CRV) for each income group in what is considered to be the measure of horizontal equity.

In most of the studies common assumptions are made, whether or not explicitedly stated, that variations in certain factors have no substantive effect on equity measures calculated in the study. One of these factors is the amount of income omitted in the databases used in the study. Expanded income is assumed to be an appropriate surrogate for economic income. Thus the implicit assumption is made that income not reported, whether omitted intentionally or not, has an immaterial effect on horizontal equity.

For example, White and White (1965) examined horizontal inequity arising from the homeowners' understatement of income due to the mortgage interest deduction, the property tax deduction and the "imputed net rental return on the homeowner's equity." The taxpayers were first divided into four family status groupings, and then thirteen "equal-circumstance" groups. To statistically measure horizontal inequity, the coefficient of variation (the standard deviation divided by the mean) was used to determine "the relative dispersion in tax liability or disposable income among members of equal-circumstance groups" (White and White, 1965, 226). There was no adjustment made for any possibility of omitted income

Studies which also used the coefficient of variation to measure the dispersion within income groups, but made no adjustment for the consideration of omitted income include Brennan (1971), Fields and Fei (1978), Madeo and Madeo (1981), Anderson (1985), Pierce (1989), Ricketts (1990) and Enis and Craig (1990).

This study moves beyond those studies by considering the possibility of omitted income. Such income would include transfer payments from social security, worker's compensation, excluded capital gains not required to be reported on tax returns as well as reportable income that taxpayers either willfully (i.e., through the "black economy") or by mistake fail to include in their return.

With regard to legally omitted income, Bakija and Steuerle (1991) estimated that, for 1988, 15/2 percent of personal income was excluded from adjusted gross icome according to the following categories: 1) Net nontaxable government transfers – 6.4 percent; 2) Net nontaxable labor-related income – 3.8 percent; 3) Other statutory exclusions – 1.6 percent; and 4) Other net differences (i.e., imputed rent on owner-occupied home, etc.) – 3.4 percent.

After subtracting 1.7 percent for Social Security and Railroad Retirement, -.5 percent for pension and profit sharing, and 1.6 percent for statutory exclusions (which are all available in the IRS Tax File), an average of 12.4 percent of personal income excluded from 1988 taxable income was not included in the IRS Tax File. For this study, 12.5 percent was the assumed average.

The "black economy" is a term used to describe tax evasion of illegally omitted income. While it is not easy to measure an activity that is by nature covert, estimates between 2 and 10 percent of the GNP in Western industrialized countries have been made (Cowell 1990). Pyle (1989) reported figures as high as 14.2 percent of the GNP for the United States in 1980. Also, the Subcommittee on Oversight of the Committee on Ways and Means (2004) noted that self-employed taxpayers represented the group with the greatest compliance problem, and they reported that taxpayers providing services for a "fee rather than wages, report 97 percent of the income they report on information returns, but only 83 percent of income which is not on information returns…whereas wage earners report 99 percent of their wages on Forms W-2 and subject to withholding." Furthermore, Graetz and Wilde (1985) reported that 10-15 percent of taxable income in the United States went unreported. For the purpose of this study, it is assumed that the average illegally omitted income is 15 percent.

Based on these estimates of the black economy in conjunction with the estimates of legally omitted income, it is assumed that the IRS Tax File data used in this study includes an average combined omitted income of 27.5 percent, with a range of zero to 55.5 percent.

HYPOTHESES AND RESEARCH DESIGN

This study investigates the validity of the assumption that omitted income has no effect on horizontal equity by examining the effect of two horizontal equity measures, the coefficient of variation (CV), and the coefficient of residual variation (CRV), on changing two tax laws. The first tax law change is the disallowance of the mortgage interest deduction, and the second is the disallowance of the charitable contributions deduction. To test the validity of this omitted income assumption, the following two hypotheses are proposed:

H1: For each horizontal equity measure studied, the percentage of omitted income has no effect on the weighted average percentage change in the horizontal equity measure when the mortgage interest deduction is disallowed.

H2: For each horizontal equity measure studied, the percentage of omitted income has no effect on the weighted average percentage change in the horizontal equity measure when the charitable contributions deduction is disallowed.

The Internal Revenue Service 1989 Tax File (ITF) for individuals was used to examine the sensitivity of the equity measures to variations in the number of income groups. The ITF is a machine-readable data source including a stratified sample if 96,588 individual returns selected from a population of 112.2 million returns. The ITF for 1989 was selected for two reasons: 1) the last year for the ITF in this format was 1992 and 2) the years after 1989 would have seen significant distortion from income and expense shifting due to the Omnibus Budget Reconciliation Act of 1990.

For each return the Internal Revenue Service provides a corresponding weighting factor that indicates how many population returns the single sample represents. Of the 96,588 sample of returns in the ITF, 59,870 Form1040 returns classified as married filing jointly for the calendar year 1989 were selected for this study. This study only used married filing jointly returns in to make the equal circumstance groups as homogenous as possible.

Before horizontal equity can be measured, taxpayers must be classified into equal circumstance groups according to ability-to-pay. To operationalize ability-to-pay, adjusted expanded income ("AEI") as used by Ricketts (1990) and similar to expanded income used in numerous studies (Anderson 1985; Pierce 1989; Enis and Craig 1990; and Grasso and Frischmann 1992), was the income measure incorporated in this study because it is a broader income measure that better approximates income. Therefore, for each sample return, AEI was calculated by adding to the taxpayer's AGI tax-exempt interest, allowable IRA, Keogh and SEP contribution deductions, allowed passive losses, nontaxable security benefits, nontaxable pensions, and tax preferences items (assumed to be passive activity related) in excess of the absolute value of losses allowed for passive activities. After calculating AEI for each taxpayer, the taxpayers were grouped from the least to the greatest AEI.

To explore whether a variation in the percentage of omitted income has an effect on the percentage change in the coefficient of variation or the coefficient of residual variation, horizontal equity measures were calculated using eleven alternative combinations of omitted income shown in Table 1.

Table 1: Research Design Matrix Used to Create Categories of Income Differences Between Taxpayers

Factor Studied	Mortgage Interest Deduction Disallowed	Charitable Contributions Deduction Disallowed
Percentage of Omitted Income – Mortgage Deduction	I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11	none
Percentage of Omitted Income – Charitable Contribution Deduction	none	I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11

I i = Percentage of omitted income simulations. Groupings by income deciles has been the most commonly used number of income groups when grouping equal numbers of taxpayers in each group. Also, it is not known whether omitted income is constant across income groups, higher for the upper income groups, or higher for the lower income groups. Therefore, there are eleven alternative combinations of omitted income which represent each of these possibilities while maintaining the same midpoint percent of omitted income for each alternative simulation.

As discussed previously, the use of adjusted expanded income as the income measure implicitly assumes that omitted income has no material effect on calculated changes in horizontal equity measures. The assumed average omitted income from the ITF was 27.5 percent; however, whether income is constant across income groups, higher for the upper income groups, or higher for the lower income groups is not known. Therefore, this study examined eleven alternative combinations of omitted income which represent each of these possibilities while maintaining a midpoint of 27.5 percent for each scenario. Grouping by income deciles has been the most commonly used number of income groups when grouping equal numbers of taxpayers in each group. This study used eleven groups because it was close to ten, and it allowed 27.5 percent to be the omitted income percentage for the sixth income group with five groups above and below. Table 2 outlines the assumed omitted income percentage for each income group in the eleven alternative simulations.

Table 2: Omitted Income Simulation Alternatives between Equally Situated Income Groups

INCOME GROUP		Omitted Income Simulations										
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
	1	0.0	5.5	11.0	16.5	22.0	27.5	33.0	38.5	44.0	49.5	55.0
	2	5.5	9.9	14.3	18.7	23.1	27.5	31.9	36.3	40.7	45.1	49.5
	3	11.0	14.3	17.6	20.9	24.2	27.5	30.8	34.1	37.4	40.7	44.0
	4	16.5	18.7	20.9	23.1	25.3	27.5	29.7	31.9	34.1	36.3	38.5
	5	22.0	23.1	24.2	25.3	26.4	27.5	28.6	29.7	30.8	31.9	33.0
	6	27.5	27.5	27.5	27.5	27.5	27.5	27.5	27.5	27.5	27.5	27.5
	7	33.0	31.9	30.8	29.7	28.6	27.5	26.4	25.3	24.2	23.1	22.0
	8	38.5	36.3	34.1	31.9	29.7	27.5	25.3	23.1	20.9	18.7	16.5
	9	44.0	40.7	37.4	34.1	30.8	27.5	24.2	20.9	17.6	14.3	11.0
	10	49.5	45.1	40.7	36.3	31.9	27.5	23.1	18.7	14.3	9.9	5.5
	11	55.0	49.5	44.0	38.5	33.0	27.5	22.0	16.5	11.0	5.5	0.0

Note: Cell entries represent the percentage increase in income applied to each taxpayer within that income group. The assumed average omitted income was 27.5 percent. Thus the 27.5 amount was applied consistently to all eleven income groups in simulation I6. The same midpoint percent of 27.5 was applied to income group 6 in all eleven simulations with omitted income percentages increasing in the upper income groups at different rates for alternative simulations I1 – I5, and decreasing at different rates in the lower income groups for alternative simulations I7 - I1.

To test the omitted income assumption, the sample taxpayers' incomes were ordered from the least to the greatest AEI and classified into eleven equal groups of taxpayers. Then each taxpayer's taxable income was increased by the product of the appropriate percentage from the table above multiplied by each taxpayer's AEI. Tax liabilities were recalculated using a 20 percent proportional tax and each taxpayer's effective tax rate was determined for the pre-tax law change scenario. Two of the larger deductions used by married couples who file joint tax returns are the home mortgage interest deduction and the charitable contributions deduction. Each of these deductions was disallowed separately, and the tax liabilities were also recalculated and each taxpayer's effective tax rate determined for each of the post tax-law change scenarios. For each of these deductions and the corresponding simulations, horizontal equity was measured using the CV and the CRV by allowing the deduction (pre-tax law change) and then by disallowing the deduction (post-tax law change).

Coefficient of Variation

In earlier studies the coefficient of variation was calculated by either using taxpayers' actual tax liabilities (White and White 1965; Anderson 1985; and Enis and Craig 1990) or effective tax rates (Pierce 1989; and Ricketts 1990). Pierce and Ricketts both note that by using effective tax rates comparability should be improved by lessening dispersion within a group that results from the range of incomes. The coefficient of variation formula used in this study is as follows (adapted from Ricketts 1990, 41)

If CVj is the coefficient of variation for group j, SD, is the standard deviation of the effective tax rate for group j and ETRj is the mean effective tax rate for group j, then the coefficient of variation can be stated as follows:

$$CV_j = \frac{SD_j}{ETR_j} \times 100$$

Coefficient of Residual Variation

In an attempt to reduce an overstatement of the coefficient of variation due to the progressivity of income within equal circumstance groups, Grasso and Frischmann (1992) proposed a new approach to measuring horizontal equity called the coefficient of residual variation. The first step involves regressing the effective tax rate on AEI for each equal circumstance group. The following regression equation was used to predict the effective tax rate for each tax payer within each equal circumstance group (adapted from Grasso and Frischmann 1992, 128):

IF ETR is the tax liability divided by the AEI, LnAEI is the natural logarithm of the AEI and I is either 1 if AEI is less than zero or zero if the AEI is greater than or equaled to zero, then the CRV for group j is (adapted by Grasso and Frischmann 1992):

$$CRV_j = \frac{\sqrt{\sum_{i=1}^{n_j} (ETR_{ij} - \overbrace{ETR_j})^2 / (n_j - 2)}}{\overline{ETR_j}} * 100$$

Where:

ETR_{ij} = the effective tax rate (tax liability/AEI) for the ith taxpayer on group j

$\widehat{ETR}_j$ = the predicted effective tax rate for the ith taxpayer in group j

$\overline{ETR}_j$ = the mean effective tax rate for group j

n_j = the number of taxpayer in group j

Percentage Change in HE

As discussed earlier, the horizontal equity measures were tested for their sensitivity of variations in the percentage of omitted income. Therefore, percentage changes in horizontal equity measures were computed for both tax law change scenarios under each alternative simulation (similar to Anderson 1985; Pierce 1989; and Ricketts 1990). The formula for the percentage change in the coefficient of variation is as follows for the PCHE for income group i:

$$PCHE_i = \frac{HE_{pre} - HE_{post}}{HE_{pre}} x100$$

Where:

$PCHE_i$ = Percentage change in horizontal equity measure for income group i

HE_{pre} = Horizontal equity measure for the pre-tax law change simulation

HE_{post} = Horizontal equity measure for the post-tax law change simulation

i = Percentage change in omitted income

A positive change indicates improved horizontal equity

Weighted Average Percentage Change in CV

Next, the overall weighted average percentage change in the horizontal equity measures from the pre- to the post-law change for each of the percentage of omitted income group alternative simulations. The equation is as follows:

$$WAHE = \frac{\sum (N_j * PCHE_j)}{\sum N_j}$$

Where:

WAHE = weighted average percentage change in horizontal equity measures for each alternative simulation

N_j = Number of taxpayers in income group j

PCHE = Percentage change in horizontal equity measure for income group j

j = Number of income groups

Since there were eleven simulations, there were eleven WAHE for each of the two hypothetical tax law changes. To test the hypotheses, WAHE measures were tested for a trend using the Cox and Stuart Trend test (Conover 1971).

RESULTS

Coefficient of Variation and Coefficient of Residual Variation Pre- and Post-Tax Law Change

By comparing the pre-tax law change CV and CRV to the post-tax law change CV and CRV for the individual income AEI groups, it can be observed that in each case the post-tax law change CV and CRV is always less than the pre-tax law change CV and CRV. A decrease in the CV and CRV represents an increase in horizontal equity. This, for all percentage of omitted income alternatives, the disallowance of the mortgage interest deduction and, alternatively, the charitable contributions deduction resulted in an improvement in horizontal equity.

Sensitivity Analysis

To measure the improvement in the horizontal equity, the percentage change in each horizontal equity measure (PCHE) and for each hypothetical law change was calculated. A positive percentage change in the HE indicates an improvement in the horizontal equity while the negative percentage change indicates a decline in horizontal equity. Consistently, the PCHE was positive for all the alternative simulations. Therefore, disallowance of either the mortgage interest deduction or the charitable contributions deduction resulted in improved horizontal equity for all income groups using either the CV or the CRV.

Finally, an overall weighted average of the percentage change in the CV and CRV (WAHE) was calculated for each alternative simulation of the percentage of omitted income.
To apply the trend test, the overall WAHE in the CV for each simulation were grouped in Table 3. In each scenario, for all five pairs the second measurement was higher than the first. The resulting WAHE gradually increased as the higher omitted income percentages gradually switched from the higher AEI groups to the lower AEI groups. Thus, H1 and H2 are rejected as the omitted income percentage apparently does have an effect on the resulting CV.

Table 3: H1 and H2 Cox and Stuart Trend Test – Coefficient of Variation

Omitted Income Paired	**WAHE – Tax Law Change Scenario**	
Simulations	Mortgage Interest (pre-tax law change, post-tax law change)	Charitable Contributions (pre-tax law change, post-tax law change)
(I1, I7)	(8.98 , 9.32) *	(2.34 , 2.45) *
(I2, I8)	(9.01 , 9.46) *	(2.35 , 2.49) *
(I3, I9)	(9.05 , 9.56) *	(2.35 , 2.52) *
(I4, I10)	(9.10 , 9.67) *	(2.37 , 2.53) *
(I5, I11)	(9.18 , 9.72) *	(2.40 , 2.52) *
	T = 5	T = 5

Note: This table shows the results of the Cox and Stuart trend test for the coefficient of variation. The middle simulation I6 was deleted, and the first half of the omitted income simulations (I1 – I5) was paired with the other half (i7-I11). Each simulation indicates that the second paired WAHE was higher than the first. The test statistic T (total number of pairs) was used in a two-tailed trend test.
** The acceptance region for the hypotheses H1 and H2 that the percentage of omitted income has no effect on the WAHE for each of the tax law changes was 0<T<5. For both tax law change scenarios, H1 and H2 are rejected because T equals 5. Therefore, there is support that the omitted income percentage does affect the coefficient of variation at the .05 level.*

Table 4 shows the trend test results for the CRV. Table 4 illustrates that the WAHE in the CRV increased for both tax law changes as the omitted income percentage adjustment decreased for the upper income groups and increased for the lower income groups. In both cases, H1 and H2 are rejected. Therefore, there is support that the omitted income percentage does affect the CRV.

As the omitted income percentages for the lower AEI groups increased and the omitted income percentage for the upper AEI groups decreased, the WAHE for the CV and CRV increased. However, while there is a statistically significant trend in the WAHE for the CV and the CRV for both hypothetical tax law changes, one may argue it does not result in a material difference.

Table 4: H1 and H2 Cox and Stuart Trend Test – Coefficient of Residual Variation

Omitted Income Paired Simulations	WAHE – Tax Law Change Scenario	
	Mortgage Interest (pre-tax law change, post-tax law change)	Charitable Contributions (pre-tax law change, post-tax law change)
(I1, I7)	(9.10 , 9.43) *	(2.37 , 2.47) *
(I2, I8)	(9.13 , 9.56) *	(2.37 , 2.51) *
(I3, I9)	(9.17 , 9.66) *	(2.38 , 2.54) *
(I4, I10)	(9.22 , 9.76) *	(2.40 , 2.55) *
(I5, I11)	(9.30 , 9.81) *	(2.43 , 2.53) *
	T = 5	T = 5

*Note: This table shows the results of the Cox and Stuart trend test for the coefficient of residual variation. The middle simulation I6 was deleted, and the first half of the omitted income simulations (I1 – I5) was paired with the other half (I7-I11). Each simulation indicates that the second paired WAHE was higher than the first. The test statistic T (total number of pairs) was used in a two-tailed trend test. *The acceptance region for the hypotheses H1 and H2 that the percentage of omitted income has no effect on the WAHE for each of the tax law changes was 0<T<5. For both tax law changes H1 and H2 are rejected because T equals 5. Therefore, there is support that the omitted income percentage does affect the coefficient of residual variation at the .05 level.*

CONCLUDING COMMENTS

This study examines the changes in horizontal equity (as measured by the coefficient of variation and the coefficient of residual variation) when considered omitted income, as varied between zero and 55 percent, within each "equal economic circumstance groupings." While the omission of income (or overstatement of deductions) in the US tax system can be considered widespread, most horizontal equity studies assume that omitted income is not important when measuring the variations of tax liabilities within income groups.

Using the Internal Revenue Service Tax File database for roughly 60,000 married filing joint returns we measure the sensitivity of equity indicators, coefficient of variation and coefficient of residual variation, to two hypothetical changes in the tax laws – the disallowance of the mortgage interest deduction and the charitable contribution deduction. We found the disallowance of either deduction increases horizontal equity using the CV and the CRV. The results of this study should prove useful to tax policy analysts, legislators, and the general public. This research predicts that increase compliance with the tax code increases the horizontal equity within income groups, leading to a stronger belief in the overall fairness of the tax system. This study should provide guidance to policy analysts, legislators and other government officials that reliance should be placed on equity measures in equity studies that consider this exception.

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FINANCIAL ACCOUNTING REGULATION AND EXECUTIVE COMPENSATION DESIGN

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ABSTRACT

We examine the economic consequences of the recent adoption of SFAS 123(R) in the United States. Consistent with the conjectures of prior research, our results show that the removal of favorable accounting treatment for stock options post SFAS 123(R) results in a switch from stock options to restricted stock. Further analysis shows that this shift is more prominent for high-volatility firms than for low-volatility firms and for low-growth firms than for high-growth firms, a pattern consistent with the implications of the agency theory. This study extends the literature on the economic consequences of financial reporting standards by providing evidence that the leveling of accounting treatment for different forms of equity compensation causes the design of executive compensation to converge to the economically optimal form. By empirically examining the actual consequences of a heavily debated accounting standard change, this study also provides important policy implications that can be helpful in the consideration of future regulatory accounting changes in the United States as well in other accounting jurisdictions.

JEL: J33, M41, M43, M44, M52

KEYWORDS: Executive compensation, financial reporting, SFAS 123(R)

INTRODUCTION

This study investigates the economic consequences of the recent change in the financial reporting standard for employee stock options in the United States. Specifically, we empirically test whether the removal of favorable accounting treatment for stock options post SFAS 123(R) induces firms to alter the relative weight of restricted stock and stock options. Using this accounting regulatory change as a quasi experiment setting, we examine whether the leveling of accounting treatment for different forms of equity compensation causes the design of executive compensation to converge to the economically optimal form as prescribed by the agency theory.

Previous studies on executive compensation have cited favorable accounting treatment of stock options as an important explanation for the deviation of executive compensation from the predictions of the principal agent model. For example, Hall and Liebman (1998) cite accounting rules as an explanation for the virtual non-existence of relative pay (e.g. indexed stock options). Hall and Murphy (2003) suggest that discriminatory accounting treatments may suppress the use of restricted stock in favor of stock options although restricted stock provides economically more efficient incentive instruments under certain circumstances. They argue that the accounting treatment of stock options leads to low perceived cost and thus contributes to the widespread adoption of stock options and hefty pay packages. Consistent with this hypothesis, Carter et al. (2007) find a positive association between financial reporting concerns and the use of stock options and a negative association between financial reporting concerns and the use of restricted stock during the period of 1995 to 2001. Carter et al. (2007) corroborate these findings by examining a sample of firms that began voluntarily expensing stock options in 2002 or 2003, with the conclusion that these firms increased their use of restricted stock and decreased their use of stock options following the voluntary expensing decision. However, the voluntary nature of the expensing decision makes it difficult to draw direct inferences regarding the role of accounting in compensation design due to the existence of self-selection bias.

In this study, we use the mandatory adoption of SFAS 123(R) to create a cleaner setting to test whether the 'veil of accounting' has artificially caused executive compensation design to diverge from the economically optimal form. Moreover, the mandatory expensing rule allows us to empirically test propositions of the analytical studies modeling the choice between restricted stock and stock options by observing whether the pattern of convergence following the removal of the potentially biasing factor is consistent with the theoretical implications. Consistent with the conjectures of prior research, our results show that the removal of favorable accounting treatment for stock options post SFAS 123(R) results in a switch from stock options to restricted stock. Further analysis shows that this shift is more prominent for high-volatility firms than for low-volatility firms and for low-growth firms than for high-growth firms, a pattern consistent with the implications of the agency theory.

This study makes three contributions. First, this study adds to the evidence in support of the view that accounting impacts 'real' economic decisions by showing that financial reporting standards play a role in the design of executive compensation. Second, the results of this study provide empirical support to previous studies modeling the optimal choice between restricted stock and stock options. Finally, the findings of this study provide important policy implications. The potential costs and benefits induced by mandatory stock option expensing have been heavily debated among policy makers, practitioners, and academics. By empirically examining the actual consequences of SFAS 123(R), the study can provide evidence regarding the validity of these *ex ante* perspectives and shed light on the potential economic impacts of similar regulatory accounting changes in the future or in other accounting jurisdictions.

The remainder of the paper is organized as follows. Section 2 briefly discusses the relevant literature. Section 3 develops the research hypotheses. Section 4 describes the sample and analysis methods. Section 5 discusses the results from the empirical analyses. Section 6 concludes the paper.

LITERATURE REVIEW

Executive compensation has been extensively studied by researchers in a variety of disciplines including accounting, finance, economics, management, and sociology. The purpose of this section is to provide a brief review of the related literature that covers the basic issues in this area.
Most of the economics-based research on executive compensation centers on the principal-agent relationship derived from the agency theory first proposed by Jensen and Meckling (1976). According to the agency theory, the objective of executive compensation scheme is to achieve optimal incentive and risk sharing. On one hand, high-level incentive is desirable because it helps align manager's goals with those of the shareholders and thus mitigate the moral hazard problem. On the other hand, compensation scheme designed to tie managers' pay to outcomes can lead to suboptimal risk sharing. In particular, managers tend to be more risk averse than shareholders because of the difficulty in diversifying human capital investment. As such, managers will demand a premium for accepting performance-based pay in lieu of fixed pay to compensate for increased uncertainty. This premium represents the discrepancy between the 'executive value' and 'company cost' of executive compensation and results in a deadweight loss from the efficiency perspective (Hall and Murphy, 2002). Therefore, the efficient executive compensation scheme needs to achieve the optimal tradeoff between incentive and risk sharing, that is, when the marginal benefit of increasing incentive equals the marginal increase in the deadweight loss due to suboptimal risk sharing.

Consistent with the agency theory's focus on the principal-agent relationship, a large volume of research has examined the role of executive compensation as a control mechanism to mitigate the conflict of interest between shareholders (the principle) and managers (the manager). One major stream of research in this context focuses on pay performance sensitivity based on the assumption that executive compensation should be highly correlated with firm performance when the compensation contract efficiently aligns the interests of shareholders and managers. Despite the existence of the large volume of empirical work on this topic, however, the findings are mixed regarding the association between executive pay and firm performance. For example, Jensen and Murphy (1990) find that the pay-performance sensitivity for executives is "small" at approximately $3.25 change in executive pay per $1,000 change in shareholder wealth. Similarly, Miller report very low and statistically insignificant correlation between executive pay and two proxies for firm performance: sales and net profits. By contrast, Belliveau et al. (1996) report the ROE-CEO pay correlation to be statistically and economically significant at 0.410. Boschen and Smith (1995) also provide evidence supporting the positive linkage between executive compensation and firm performance by showing that pay-performance sensitivity is dramatically higher when measured under a longer time frame.

The theory-based explanation for the mixed evidence on pay-performance sensitivity is that the relation between incentive alignment and agency costs is non-linear (Gomez-Mejia and Wiseman, 1997). This explanation is consistent with the agency theory's prediction regarding the tradeoff relation between incentive alignment and risk sharing. According to this view, linking pay and performance initially reduces agency costs by aligning the interests of managers with those of shareholders. After a certain inflection point, however, linking pay to performance would shift excessive amount of risk to the more risk avert manager and thus increase agency costs as the manager becomes overly conservative in decision making and sacrifices returns for higher level of certainty. There is some evidence in support of this notion. For example, Cannella and Gray (1992) document that executive pay is closely related to firm performance under conditions of low risk but not under conditions of high risk. As pointed out by Gomez-Mejia and Wiseman (1997), however, considerably more theoretical development and empirical work has to be done before the shape of the pay-performance relation can be clarified.

In the context of incentive-risk tradeoff relation under the agency theory, previous research has examined the implications of the design of executive compensation. One issue of interest concerns the effects of different performance measures on pay at risk, a key concept in the incentive-risk tradeoff. For example, Baysinger and Hoskisson (1990) argue that quantitative performance measures are associated with higher pay risk than qualitative performance measures because managers have limited control over objective firm performance outcomes. By contrast, Dyl (1989) argues that pay risk is greater when executive compensation is linked to market-based performance measures rather than accounting-based performance measures.

Another related issue along this line is the modeling of optimal pay practices. In particular, within the category of equity-based compensation, restricted stock and employee stock options also have different payment structures and thus different implications to both incentive and risk sharing. Previous studies have modeled the choice between restricted stock and stock options from the efficiency perspective. For example, Hall and Murphy (2002) and Jenter (2000) demonstrate that restricted stock generally dominate stock options from the efficiency perspective. In contrast, Feltham and Wu (2001) show that restricted stock are the preferred form of equity compensation only when the agent's action has little impact on the variance of the outcome.

Despite the theoretical arguments for the relative advantage of restricted stock under certain conditions, empirical evidence has shown that restricted stock are rarely used in practice (Carter et al., 2007). One explanation for this puzzling observation is the perceived cost hypothesis proposed by Hall and Murphy (2003). They argue that the favorable accounting treatment of stock options creates a gap between the perceived and economic costs of options grants, which leads to excessive use of stock options at the expense of restricted stock because stock options are considered a 'bargain' since there is an accounting charge for restricted stock grants but not for option grants. That is, costs associated with restricted stock grants had to be recognized in the income statement even when the costs associated with stock option grants were allowed not to be included in the body of financial statements. However, the adoption of

SFAS 133 levels the accounting treatment of stock options and restricted stock by requiring the expensing of employee stock options in the income statement based on the fair value. The purpose of this study is to empirically test whether the removal of favorable accounting treatment for stock options post SFAS 123(R) induces firms to alter the relative weight of restricted stock and stock options.

HYPOTHESES DEVELOPMENT

As discussed in the previous section, favorable accounting treatment for stock options over restricted stock prior to the adoption of SFAS 133 may have caused executive compensation design to deviate from its economically optimal form. As such, we hypothesize that the adoption of SFAS 123(R) will increase the weight of restricted stock and decrease the weight of stock options in executive compensation packages as SFAS 133 levels the accounting treatment for the two forms of equity compensation.

H1: The weight of restricted stock in total compensation is greater after the adoption of SFAS 123(R) than before the adoption of SFAS 123(R). The weight of stock options in total compensation is smaller after the adoption of SFAS 123(R) than before the adoption of SFAS 123(R).

One important objective of this study is to use the adoption of SFAS 123(R) as a setting to test the theoretical propositions regarding the optimal choice between restricted stock and stock options. Accordingly, we also test whether the switch from stock options to restricted stock is more concentrated among the subpopulation of firms for which restricted stock is more likely to dominate stock options as the more efficient form of equity compensation. In particular, we identify two conditioning firm characteristics from previous literature to capture the differential effect of SFAS 123(R): volatility and growth.

Volatility affects both the incentive and risk sharing features of stock options. Higher volatility implies that the value of the underlying stocks are more likely to fall into the tail of the distribution, that is, stock options are more likely to be either deep in the money or deep out of the money. Due to options' asymmetric value structure, stock option loses its incentive power when the stock price is well below the exercise price. Moreover, using stock options as incentive instruments can also induce excessive risk-taking when the stock options are out of money because the agents can benefit from the upside potential but the downside risk is entirely borne by shareholders. Therefore, we expect more high-volatility firms to switch from stock options to restricted stock after SFAS 123(R) removed the favorable accounting treatment for stock options.

H2: The switch from stock options to restricted stocks following the adoption of SFAS 123(R) is more prominent for firms with high return volatility than for firms with low return volatility.

Feltham and Wu (2001) model the choice between restricted stock and stock options and conclude that restricted stock are the preferred form of equity compensation when the manager's action has little impact on the firm's operating risk while stock options are the preferred form when the manager's action significantly affects the operating risk. As pointed out by Feltham and Wu (2001), the former scenario is represented by mature firms while the latter setting is represented by high-growth firms. As such, we expect to observe that the switch from stock options to restricted stock following the adoption of SFAS 123(R) are more prevalent among low-growth firms than among high-growth firms.

H3: The switch from stock options to restricted stocks following the adoption of SFAS 123(R) is more prominent for low-growth firms than for high-growth firms.

DATA AND METHODOLOGY

Sample

The analysis in this study is based on executive compensation and financial statement data obtained through ExecuComp and COMPUSTAT North America, two integrated databases provided by Standard & Poor's containing information for publicly traded companies in the United States. Since our focus is to examine the effect of accounting regulatory change, we choose the sample period between fiscal year 1996 through fiscal year 2007 to have a clean test of the consequences of the mandatory expensing of stock options. Before the adoption of SFAS 123(R), accounting treatment for stock options is governed by SFAS 123, which came into effect for fiscal years beginning after Dec 15, 1995. SFAS 123 requires the disclosure but not the recognition of stock option expenses, while SFAS 123(R) mandates the expensing of stock option costs. Choosing a sample period after SFAS 123 came into effect helps ensure that the change observed after the adoption of SFAS 123(R) are due to the mandatory expensing of stock option costs rather than other accounting changes (e.g. the disclosure of the fair value of the stock options).

Model Specification

We estimate the effect of SFAS 123 (R) on the design of executive compensation based on the following pooled regressions models:

$$Restrict\ stock\ percentage\ = \alpha 0 + \alpha 1(After) + \alpha 2(Volatility) + \alpha 3(Growth) + \alpha 4(After * Volatility) + \alpha 5(After * Growth) + (Control\ Vars) \quad (1)$$

$$Stock\ option\ percentage\ = \beta 0 + \beta 1(After) + \beta 2(Volatility) + \beta 3(Growth) + \beta 4(After * Volatility) + \beta 5(After * Growth) + (Control\ Vars) \quad (2)$$

Since we are interested in the relative composition rather than the absolute level of executive compensation, we use the weight of restricted stock and the weight of stock options in the total compensation as the dependent variables in the regression analysis to examine how the weight of each component changes following the adoption of SFAS 123(R). *After* is a dummy variable coded as 0 if the observation is from the pre-SFAS 123 (R) period and coded as 1 if the observation is from the post-SFAS 123(R) period. As we hypothesize that the adoption of SFAS 123(R) will increase the weight of restricted stock and decrease the weight of stock options in executive compensation packages, we hypothesize α1 to be significantly positive in equation (1) and β1 to be significantly negative in equation (2).

We include two interaction terms, *After*Volatility* and *After*Growth*, in equation (1) and (2) to test H2 and H3. Since all the main effects are controlled for in the regression models, the coefficients on the interaction terms capture the differential effects of SFAS 123(R) for different subpopulations of firms as hypothesize in H2 and H3. As hypothesized in H2, the increase in the weight of restricted stock and the decrease in the weight of stock options following the adoption of SFAS 123(R) should be more prominent for high-volatility firms than for low-volatility firms. Accordingly, we expect α4 to be significantly positive in equation (1) and β4 to be significantly negative in equation (2). As hypothesized in H3, the increase in the weight of restricted stock and the decrease in the weight of stock options should be more prominent for low-growth firms than for high-growth firms. Therefore, we expect α5 to be significantly negative in equation (1) and β5 to be significantly positive in equation (2).

Volatility is measured as the volatility input used in the Black-Scholes model in the valuation of the firm's stock options. We choose this volatility measure because Black-Scholes model is the most widely used model to determine the fair value of stock options. Companies are required to disclose all the inputs to the model, and these measures must be examined and approved by auditors. As such, the volatility measure reported in ExecuComp should be sufficiently reliable for data analyses. Consistent with the corporate finance literature, we use Tobin's q (the ratio of the market value of equity to the book value of equity) as the proxy for growth opportunity. We also include control variables that represent important dimensions of firm characteristics. Specifically, we include log of total assets, debt to asset ratio, and ROA to capture the size effect, the leverage effect, and the performance effect respectively.

Sub-period Analysis

We perform sensitivity analysis to confirm the validity of our inferences. In particular, our pre-SFAS 123(R) period includes the late 1990's, a period in which the dot-com boom skyrocketed the use of stock options and questionable accounting practices were more likely to be considered acceptable. In order to rule out the possibility that our results are driven by these macro factors, we estimate equation (1) and (2) using the sample period from 2002 to 2007, which only covers fiscal years after the dot-com bust and major accounting scandals. As discussed earlier, a number of public companies had opted to voluntarily expense stock options before SFAS 123(R) came into effect. Including these companies in the pre-and-post SFAS 123(R) comparison will create noises that bias against finding significant results, and using the shorter sample period from 2002 to 2007 will amplify this bias. Therefore, the sensitivity analysis represents the more conservative test of our research hypotheses.

Additional Analysis

We conduct additional analysis to examine whether the hypothesized change in executive compensation design have implications for important firm characteristics such as performance and capital structure. The rationale for such analysis is that, if the adoption of SFAS 123 (R) helps restore the design of executive compensation to the economically optimal form as we hypothesize, the improvement in executive compensation design could lead to changes in performance indicators and capital structure. Specifically, we estimate the following pooled regressions:

$$ROA = \gamma 0 + \gamma 1(After) + \gamma 2(Volatility) + \gamma 3(Growth) + \gamma 4(Size) \qquad (3)$$
$$Debt = \delta 0 + \delta 1(After) + \delta 2(Volatility) + \delta 3(Growth) + \delta 4(Size) \qquad (4)$$

The dependent variable in equation (3) is return on asset (measured as net profit scaled by total asset at the beginning of the period), and the dependent variable in equation (4) is debt level (measured as debt scaled by total assets at the beginning of the period). *After*, *Volatility*, and *Growth* are measured the same way as in equation (1) and (2). I also include *Size* (measured as natural log of total assets) as a control variable.

RESULTS

Table 1 reports descriptive statistics. The mean of total assets is $13, 256 million while the median of total assets is $1,544 million, suggesting that the distribution of firms' total assets in the sample is highly right skewed. Similarly, the mean of total compensation is $3,176 while the median of total compensation is $1,219, suggesting a positive skewed distribution. The mean (median) of the weight of stock options in total compensation is 0.3741 (0.3496). By contrast, the weight of restricted stock is strikingly lower with a mean value of 0.0528 and a median value of 0.

Table 1: Descriptive Statistics

Variable	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
Total ASSETS (in million $)	159617	13,256	63,754	486	1,544	5,981
Debt	160342	0.5879	0.3761	0.4023	0.5825	0.7470
ROA	159547	0.0135	0.5960	0.0010	0.0382	0.0785
Total Compensation (in thousand $)	140861	3,176	10,835	588	1,219	2,781
Restricted stock weight	133257	0.0582	0.1303	0.0000	0.0000	0.0192
Stock options weight	133257	0.3701	0.2903	0.1021	0.3496	0.6013

Table 2 reports the regression results for the weight of restricted stock in total compensation. Panel A reports results based on the full sample, and Panel B reports results of the sub-period analysis. Consistent with H1, the coefficients on *After* are significantly positive in both panels, suggesting that firms use more restricted stock following the adoption of SFAS 123(R). Consistent with H2, the coefficients on the interaction term *After*Volatility* are significantly positive in both panels, suggesting that the switch to restricted stock following the adoption of SFAS 123(R) is more concentrated among high volatility firms. The coefficients on the interaction term *After*Growth* are negative as reported in both panels as H3 predicts, although they are not statistically significant at conventional level. In addition, it is clear that there is no substantial difference between Panel A and B, indicating that the results are not driven by other macro factors discussed earlier.

Table 2: Weight of Restrict Stock in Total Compensation

Panel A: Full Sample		
Independent variable	Parameter estimate	Hypothesized sign
Intercept	-0.043 (-2.43)***	NA
After	0.046 (8.89)***	+
Volatility	-0.014 (-9.59)***	NA
Growth (Tobin's Q)	-0.00001 (-1.29)	NA
After*Volatility	0.044 (4.56)***	+
After*Growth	-0.0002 (-0.28)	-
Size	0.014 (5.82)***	NA
Debt ratio	0.009 (7.20)***	NA
ROA	0.00004 (2.64)***	NA
R^2	0.1739	
Adjusted R^2	0.1728	
F value	507.57***	
Panel B: Sub-period Analysis		
Independent variable	Parameter estimate	Hypothesized sign
Intercept	-0.032 (-2.47)***	NA
After	0.012 (1.98)*	+
Volatility	-0.028 (-2.15)***	NA
Growth (Tobin's Q)	-0.00001 (-0.70)	NA
After*Volatility	0.063 (5.49)***	+
After*Growth	-0.0002 (-0.26)	-
Size	0.016 (3.68)***	NA
Debt ratio	0.010 (5.58)***	NA
ROA	0.00007 (2.11)**	NA
R^2	0.1675	
Adjusted R^2	0.1618	
F value	496.37***	

*Table 2 reports regression results on the weight of restricted stock in total compensation. Panel A reports results based on the full sample of 122,554 observations from fiscal year 1996 through fiscal year 2007. Panel B reports results based on the subsample of 48,571 observations from fiscal year 2002 through fiscal year 2007. ***, **, and * indicate statistically significant at 0.01, 0.05 and 0.1 level respected based on two-tailed t tests (t statistics reported in parentheses).*

Table 3 reports the regression results for the weight of stock options in total compensation. Panel A reports results based on the full sample, and Panel B reports results of the sub-period analysis. Consistent with H1, the coefficients on *After* are significantly negative in both panels, suggesting that firms use less stock options following the adoption of SFAS 123(R). Consistent with H2 and H3, the coefficients on the interaction term of *After*Volatility* and *After*Growth* in both panels are significantly negative and positive respectively, suggesting that the switch away from stock options following the adoption of SFAS 123(R) is more concentrated among high volatility firms and among low growth firms. Again, there is no substantial difference between Panel A and B.

Table 3: Weight of Stock Options in Total Compensation

Panel A: Full Sample		
Independent variable	Parameter estimate	Hypothesized sign
Intercept	0.172 (3.98)***	NA
After	-0.073 (-6.51)***	-
Volatility	0.230 (3.76)***	NA
Growth (Tobin's Q)	0.0002 (2.97)***	NA
After*Volatility	-0.175 (-8.57)***	-
After*Growth	0.007 (5.92)***	+
Size	0.025 (5.36)***	NA
Debt ratio	-0.140 (-4.25)***	NA
ROA	-0.0008 (-2.91)***	NA
R^2	0.2326	
Adjusted R^2	0.2208	
F value	877.65***	
Panel B: Sub-period Analysis		
Independent variable	Parameter estimate	Hypothesized sign
Intercept	0.236 (3.71)***	NA
After	-0.035 (-3.19)***	-
Volatility	0.143 (3.76)***	NA
Growth (Tobin's Q)	0.00003 (1.32)	NA
After*Volatility	-0.116 (-5.86)***	-
After*Growth	0.007 (6.61)***	+
Size	0.011(2.15)***	NA
Debt ratio	-0.116 (-3.09)***	NA
ROA	-0.001 (-2.51)***	NA
R^2	0.1918	
Adjusted R^2	0.1879	
F value	838.28***	

*Table 3 reports regression results on the weight of stock options in total compensation. Panel A reports results based on the full sample of 122,554 observations from fiscal year 1996 through fiscal year 2007. Panel B reports results based on the subsample of 48,571 observations from fiscal year 2002 through fiscal year 2007. ***, **, and * indicate statistically significant at 0.01, 0.05 and 0.1 level respected based on two-tailed t tests (t statistics reported in parentheses).*

Taken together, the evidence summarized in Table 2 and 3 shows that, following the adoption of SFAS 123(R), the weight of restricted stock in total executive compensation increases while the weight of stock options decreases. Further analysis indicates that this switch from stock options to restricted stock is more prominent for high-volatility firms than for low-volatility firms, and more prominent for low-growth firms than for high-growth firms. These inferences are consistent with the implications of the agency theory, suggesting that the removal of favorable accounting treatment for stock options following the adoption of SFAS 123(R) causes the design of executive compensation to converge to the economically optimal form.

Table 4 reports results of the analysis that examines the change in performance (ROA) following the adoption of SFAS 123(R). Although we make no formal hypothesis regarding the direction of the change in ROA, we expect that firm performance improves following the adoption of SFAs 123(R) as the standard helps restore the design of executive compensation to the economically optimal form. The results reported in Table 4 are consistent with this notion. Specifically, the regression coefficient on *After* is positive and statistically significant at 0.01 level, with a parameter estimate of 0.0195 and a t value of

2.90. More generally, the results suggest a case in which the removal of discriminatory accounting practices can have positive implications for firm performance.

Table 4: Change in ROA Following the Adoption of SFAS 123(R)

Independent variable	Parameter estimate	Predicted sign
Intercept	0.01107(2.90)***	NA
After	0.0195 (4.26)***	+
Volatility	-0.1804 (-6.29)***	NA
Growth (Tobin's Q)	0.0006 (3.74)***	NA
Size	0.0232 (5.41)***	NA
R^2	0.0734	
Adjusted R^2	0.0727	
F value	221.37***	

*Table 4 reports regression results on ROA (return on asset measured as net profit scaled by total assets at the beginning of the period) based on 122,554 observations from fiscal year 1996 through fiscal year 2007. ***, **, and * indicate statistically significant at 0.01, 0.05 and 0.1 level respected based on two-tailed t tests (t statistics reported in parentheses).*

Table 5 reports results of analysis that examines the change in debt level following the adoption of SFAS 123(R). We make no formal hypothesis regarding the direction of the change in debt level due to the lack of sufficient theoretical basis. However, given that the difference in restricted stock versus stock options comes from stock options' asymmetric payoff pattern, it is reasonable to expect that the switch from stock option to restricted stock in executive compensation induces mangers to care more about the downside risk and thus take on less leverage. Our findings are consistent with this notion. In particular, the regression coefficient on *After* is negative and statistically significant at 0.01 level (with a parameter estimate of -0.0173 and a t value of -5.14), suggesting a reduced debt level following the adoption of SFAS 123(R).

Table 5: Change in Debt Level Following the Adoption of SFAS 123(R)

Independent variable	Parameter estimate	Predicted sign
Intercept	0.1559 (3.41)***	NA
After	-0.0173(-5.14)***	-
Volatility	-0.0595(-3.94)***	NA
Growth (Tobin's Q)	0.0001(1.90)*	NA
Size	0.0615(2.45)***	NA
R^2	0.0518	
Adjusted R^2	0.0516	
F value	131.28***	

*Table 5 reports regression results on debt level (total debt scaled by total assets) based on 122,554 observations from fiscal year 1996 through fiscal year 2007. ***, **, and * indicate statistically significant at 0.01, 0.05 and 0.1 level respected based on two-tailed t tests (t statistics reported in parentheses).*

CONCLUDING COMMENTS

We empirically examine the economic consequences of the recent adoption of SFAS 123(R) in the United States and find evidence that the removal of favorable accounting treatment for stock options post SFAS 123(R) result in a switch from stock options to restricted stock. Further analysis shows that this shift is more prominent for high-volatility firms than for low-volatility firms and for low-growth firms than for high-growth firms, a pattern consistent with the implications of the agency theory. These findings add to the evidence in support of the view that accounting impacts 'real' economic decisions by showing that financial reporting standards play a role in the design of executive compensation.

By empirically examining the actual consequences of a heavily debated accounting standard change, this study also provides important policy implications that can be helpful in the consideration of future regulatory accounting changes in the United States as well in other accounting jurisdictions. In particular, the findings highlight the possibility that biasing financial reporting standards will cause firms to deviate from the economically optimal decisions. As such, it is important for standard setters to carefully consider the potentially unintended consequences of both existing and proposed financial reporting standards.

Finally, we recognize that this study is subject to an important caveat. In particular, we examine the design of executive compensation within the framework of agency theory. As a result, we ignore 'non-economic' factors that may have played a key role in shaping executive compensation contract. For example, a large body of literature in the organizational sciences has highlighted the importance of interpersonal/political factors in the design of executive compensation (Gomez-Mejia and Wiseman, 1997). These studies are often premised on organizational behavior theories that view executive compensation as outcome of power struggle rather than of efficient contracting. One promising area of future accounting research is to examine how financial reporting interacts with the political factors that have been shown to impact the design of executive compensation. For instance, researchers could look at whether firms with compensation design that is more favorable to mangers tend to exhibit more opportunistic earnings management behavior that would further increase the level of compensation. Research along this line would deepen our understanding of executive compensation by putting the issue in a broader context.

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