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<u>Statistical Insights Into The Performance of EVA</u>

by

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A research paper submitted in fulfillment of the requirements for 3 credits, UNDERGRADUATE INDEPENDENT RESEARCH PROJECT Fall Term 1997, Professor Damien, Faculty Supervisor.

BBA CHEN

Faculty Comments

The research paper, STATISTICAL INSIGHTS INTO THE PERFORMANCE OF EVA, by the three students, Ting-Chun Chen, Eddie Magnus and Ashley Marks is a very important and original contribution to applied corporate finance. In recent years, following the pioneer work of Stern Stewart Company, EVA is being recognized as a valuable indicator of the performance of a company. However, the statistical aspects to this concept have not been explored in depth.

The three students have examined in detail current practice and research in this context. They have proposed a new theoretical framework to evaluate EVA, and using actual data from 14 banks have validated their theory using formal statistical analyses.

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Statistical Insights Into The Performance of EVA

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ABSTRACT

This research focuses on three issues. First, understanding Economic Value Added (EVA) by examining the components that define this well-known financial measure. Second, it is argued that if statistical methods are used to validate EVA as a financial metric, then the appropriate mathematical models should attempt to explain variation in the Market Capitalization (MC) of firms based on their EVA. This is a radical departure from the norm that advocates correlating EVA to Market Value Added (MVA) of a firm. Third, the theoretical arguments developed in this paper are empirically validated using data from 14 banking institutions.

MVA vs. MC

Most Economic Value Added (EVA) models are applied to industries other than financial firms. Due to a financial institution's unique capital structure and use of liabilities in generating income, a modified EVA model is needed. This task of constructing an EVA model for financial institutions was tackled and accomplished by the University of Michigan Business School Multidisciplinary Action Project (MAP) team; Black et al. (1997 a, b).

The MAP team's research laid a solid foundation for the evaluation of banks using the EVA model. Certain evaluation techniques (i.e. Discount Cash Flow) currently being used to measure the performance of banks may be inaccurate. The MAP team developed and validated an EVA model that better predicts Market Capitalization (MC). The rationale underlying predicting MC is that such a statistical model "self-adjusts" by basing the future stock price on EVA, and modeling the error term in an appropriate manner.

Stern & Stewart advocate the use of EVA in conjunction with Market Value Added (MVA) as a way of determining the value added of a firm; see, for example, Stewart (1994). By forecasting MC, we are in no way moving away from the (correct) view that "MVA is a significant summary assessment of corporate performance." MVA is an *inferred* metric. Consider the following example entirely removed from the current discussion.

Example (Damien and Mueller, 1998). Suppose the *time* to inception of a microscopic defect in a material, and the subsequent *time* to failure of the material are observed. This phenomenon is called *electrical treeing* in the engineering literature. A practical application of electrical treeing is in the context of aircraft safety and reliability. The critical notion of interest is the reliability function, which answers the question: "how reliable is the material in withstanding stress over time and at varying pressures?" The observed data (the two "times") is modeled via appropriate statistical distributions; for example, the bivariate Gumbel or Pareto distributions. The answer to the above question is then *inferred* from the resulting model; i.e., the reliability function is a *consequence* of the structure underlying the distributions of time to inception, and the subsequent time to failure. The *uncertainty* in this process is in the *observed* inception/failure times, not the *inferred* reliability function. Any attempt to model the reliability function directly with the observed inception/failure times could lead to a misleading understanding of the reliability of the system.

Reverting back to the present context, consider the well-known identity,

$$MVA = MC - TC.$$

TC (Total Capital) is the amount investors have committed to a firm. It is clear from the identity that the underlying *uncertainty* in the above formulation is in the MC component, defined as the product of the number of outstanding shares and the share price; MVA is *inferred* therefrom. Therefore, it seems natural to use EVA to explain the *variation* in the appropriate *observable,* which, from above, is clearly MC. The "reliability" of a firm assessed by its MVA can be readily obtained subsequently, and will be consistent with the theoretical arguments in favor of MVA put forth by Stewart (1994). Such an approach is particularly appealing given the explosion of sophisticated mathematical models that have been developed in this context in recent years; see, for example, Damien et al. (1998).

The use of an EVA model can help banks better assess its competitors and evaluate possible mergers and acquisitions. It will also present a useful tool for investors who are looking for profitable investments. Such a tool can be used by a bank for its client banks in strategic partnerships as well as for outside investors who want to diversify against interest rates by investing in financial institutions.

In the rest of this paper, several arguments in favor of using EVA as the appropriate metric in assessing a bank's performance relative to other measures are validated using statistical methods. The insights obtained by considering new ways of studying such performance measures should further enhance the use of MVA and related metrics in assessing the performance of financial institutions.

EVA: The Equity Approach

Traditionally, the entity approach is used when calculating EVA, but this method of measuring cash flow generated by the entire entity is not compatible with the unique structure of banks. Using the MAP team's theoretical reasoning as well as their methodology, the equity approach to calculating EVA will be adopted in this paper; see, Black et al. (1997 a, b).

The equity approach evaluates the cash flows available to common equity holders and offset these cash flows by a capital charge based upon the cost of equity and adjusted equity. It considers liability management as a component of operations rather than financial element. By considering interest expense as a cost of goods sold rather than a financing activity, this approach allows for value creation on the liability side of balance sheet when determining "value added." The equity approach is able to capture this "value added" while the entity approach does not consider the liability side of the operating component of the balance sheet.

Initially, we considered capitalizing operating leases and depreciating them. However, the difference between depreciation expense versus operating expense was not substantial enough to make an adjustment. With that caveat, we now explain Exhibit 1, which forms the basis for the underlying assumptions used in calculating a bank's EVA; we note here that the details in Exhibit 1 is finding increased acceptance among academicians as well as practitioners.

From Exhibit 1, interest expense is considered as a cost of goods sold, matching interest revenue as operating revenue. Other revenues must be added, and gains and amortization on securities must be adjusted. One must subtract operating expenses (including leases), reverse goodwill amortization and adjust for net credit recoveries (losses). After taking out the GAAP tax expenses, the deferred tax asset (cash tax effect), and adding back the cash effect of the deferred tax liability, we obtain the Net Operating Profit After Taxes: NOPAT is defined as Net Operating Profits after Taxes available to Common Shareholders.

The effect to equity after adjustment is not substantial, but is conceptually needed to advocate a theoretically satisfactory position. Starting with stockholder's equity, and following the steps in Exhibit 1, an adjusted equity number is computed. A bank's EVA is then given by:

$$EVA = NOPAT - (ADJUSTED\ EQUITY * COST\ OF\ EQUITY).$$

To find EVA, the cost of equity must be computed. Using the Capital Asset Pricing Model (CAPM), the beta for a company must be estimated for each year, as well as the risk-free rate for that year. Therefore, one of the assumptions made in calculating EVA is that the beta accurately assigns the company's risk compared to the market. This has come under debate because beta is computed using past data and no future considerations about the company are taken into account. Be that as it may, in this paper, we use the CAPM to assess a company's beta, and take it to be the best measure of risk for a specific company.

What is EVA?

What does EVA really mean? Stewart (1994) offers a comprehensive discussion in answering this question. From the above formula, one can see that EVA is no more than the abnormal returns of the company for any specific year. Denoting Return on Equity as ROE, the equation for abnormal returns is given by:

ABNORMAL RETURNS = ROE - COST OF EQUITY.

Simply dividing the EVA equation by the adjusted equity (assuming that NOPAT is the return and adjusted equity is the equity base used to compute ROE) results in:

ABNORMAL RETURNS = EVA/ADJUSTED EQUITY.

This formula indicates that analysts who predict abnormal returns into the future are also predicting EVA. This is consistent with Stewart's (1994) statement: "For this reason, it [EVA] automatically accounts for any premium over or discount under the capital employed..." Thus, if markets are efficient, EVA is already in the stock price and therefore included in the MC; hence the link to MVA. It is in this sense that MVA as a measure of a firm's performance becomes valuable. From a validation perspective, this implies that by correlating EVA to MVA *directly*, one might actually *understate* the usefulness of these two measures in assessing a company's performance.

EVA as a predictor of MC

Using 14 banks' data, Black et al. (1997 b) consider a regression model with MC and EVA as the dependent and independent variables, respectively. The R-squared, a measure of fit, from their model, which adjusts for bank-to-bank differences, is approximately 97%; i.e., 97% of the *variation* in MC can be explained by a linear regression with EVA as the independent variable. The first reaction to this high linear relationship between EVA and MC is that it must be a result of the "size effect", i.e., larger banks will likely have a higher EVA as well as a higher MC. This is not quite accurate. Black et al. (1997 b) argue that the reason why EVA is able to better explain the variation in MC is the inherent structural relationship between the two variables. This structure varies from bank-to-bank, and is also correlated over time. Hence, a simple linear regression would be a gross misspecification of the true underlying structure in the data. By appropriately modeling the error term in the regression model, the association between EVA and MC (and whence MVA) is enhanced; see Appendix for details.

In the following discussion of the remaining exhibits, the phrase, "adjusted for bank to bank differences" that appears in the figure headings alludes to the mathematical adjustments made to the regression model detailed in the Appendix.

A plot of the actual versus predicted values for MC, using EVA as the independent variable, appears in Exhibit 2. Also provided in this Exhibit are the adjusted R-squared (approximately 97%), the value of the intercept and slope coefficients and their standard errors; from the latter it is clear that the EVA parameter estimate is significant. Consider Exhibit 3. Prior to accounting for bank-to-bank differences, the adjusted R-squared is approximately 1%. Note also that the EVA parameter estimate is not significant. The adjustments made to the banks (see Appendix) essentially are another way to account for the size of each bank without using size as an independent variable. We have here not reported the regression using MVA as the dependent variable. We simply note that even *after* adjusting for bank-to-bank differences the proportion *of variation* in MVA explained by EVA was less than 25%.

So what are the implications of the above? As noted previously, an analyst considers EVA either directly or indirectly when computing a value for a stock price. However, he or she must consider other variables, mainly the growth rate in book value which is directly correlated to sales, assuming that turnover remains constant. So while EVA should already be in the stock price, it is one of two *unsystematic* variables. Clearly, projections of these *stochastic* variables will be imprecise. Among others, reasons for an imprecise forecast could be the result of analysts using poor evaluation methods by focusing on discounted cash flows; working with faulty assumptions; and the market may not realize the actual value creation or value destruction until after the fact. In other words, when the market is making its predictions, it is not considering companies' EVA. However, when analysts look back on the fundamentals of what drives stock price, EVA inherently guides them to a better assessment of a company's future as measured by the future value of its stock. Of course this is an iterative and ongoing process. Any current stock price has both future predictions as well as fundamentals built in to its stock. Each year that passes, the ending value of EVA gets "added" to the stock price while it should have been included if EVA had been valued correctly at the outset. More weight is placed on the current EVA, which explains the positive correlation with MC. In addition to a single year's EVA, book value growth for one year (or the terminal value growth) is also critical to one's valuation of the stock price. It is easy to become blinded by the fact that growth is considered positive by the market when in reality high book value growth with a negative EVA actually increases the *rate* of *decreasing* value.

One can see from Exhibits 1 and 2 that the larger the bank, the more volatile its EVA, resulting in more inaccurate forecasts of its MC. A way out of this ostensible difficulty is to develop Bayesian models; see, for example, Qin et al. (1998) who develop a hierarchical model to assess the unsystematic risk of a bank based on factors such as its capital structure, foreign exposure, etc. An alternative and approximate way is described in Black et al. (1997 b).

What are the drawbacks of using EVA as a predictor of MC, and why not forecast stock price rather than MC? This is easily answered by noting that the most obvious drawback to EVA as a predictor of MC is that MC can increase with the issuance of shares, while value might be destroyed rather than created. A firm has control over the number of outstanding shares in any given year through a variety of options at its disposal, which in turn can influence the value of its share price. MC, defined as the product of the number of outstanding shares and share price, is thus influenced by two related sources of variation; hence it is more appropriate to use MC as the dependent variable. The empirical findings in this paper adds credence to this position. Growth in book value or adjusted equity is simply a magnifier of either positive or negative EVA. Therefore growth in outstanding shares will actually decrease EVA if a firm has a negative abnormal return. In addition, the issuance of shares would also be captured in the regression that *explicitly* accounts for bank-to-bank variability over time.

The possibilities of this model and type of thinking are numerous. To be able to predict a company's MC down the line is an incredible advantage, not only for the company itself that can adjust its strategy if need be, but also to possible investors and/or take-over artists.

What about MVA?

MVA is given by:

$$MVA = MC - Adjusted\ Equity$$

MVA makes perfect sense as a measure of a firm's value. It's the value added to the company after the capital invested. In the case of banking firms, adjusted equity is the capital invested or the discounted future EVA. It is important to note that the value of MVA is meaningful in a *conditional* sense; MVA itself needs MC; i.e., it is an *inferred* metric. If we're able to explain variations in MC using EVA, we need not concern ourselves with the intermediate steps of finding the MVA and then computing MC. In any case, as noted earlier in the paper, the latter approach is counterintuitive because the *uncertainty* is in the forces that influence MC; hence the latter can be modeled statistically.

In order to better understand the use of EVA in forecasting MC, we performed several regressions using a combination of variables. A key variable in this context is TOPS that stands for True Overall Profit for Shareholders; see, for example, Baciadore et al. (1997). Mathematically, at any given time, t, TOPS is defined by:

$$TOPS_t = NOPAT_t - Re*MC_{(t-1)}$$

In this equation, Re is the cost of equity for the banks after the necessary adjustments are made (Exhibit 1). The purpose of TOPS is to measure the value creation for shareholders. Therefore its purpose serves much the same as MVA. TOPS is supposed to be able to predict abnormal returns, which as we have already discussed is EVA/Adjusted Equity. Baciadore et al. point out that TOPS must be used more in the spirit of an organizational behavioral tool than a financial performance metric such as EVA. We calculated TOPS for the 14 banks, and performed a regression using abnormal returns and TOPS as the dependent and independent variables, respectively; this is consistent with the regression model presented in Baciadore et al. The adjusted R-squared is 2.86% (Exhibit 4); i.e., approximately three percent of the variation in abnormal returns can be explained by TOPS. Note also in this Exhibit that the TOPS parameter estimate is negative; i.e., as TOPS increases, abnormal return declines. This poor and counterintuitive correlation doesn't come as a surprise. By definition, TOPS at any given time is a function of MC from the *previous* time period. The latter quantity, however, is needed to calculate abnormal returns at the *current* time, which, of course, is correlated to the *current* MC. The circularity amounts to the following: a specification error will likely result if the variable you are trying to explain appears also as a modified independent variable in the model. Stated differently, MC should be treated as a dependent, not an independent variable. This is impossible given the definition of TOPS.

A third model using both TOPS and EVA as independent variables was entertained. The purpose was to assess the nature of interaction between these two metrics in explaining the variation in MC (not abnormal returns). From Exhibit 6, it is clear that TOPS must not be used to assess variations in MC; note the negative parameter estimate. Also note that the adjusted R-squared has actually declined from 97% (Exhibit 1) to 95% (Exhibit 6).

Conclusions

The main purpose of this paper is to show that EVA is a better performance metric relative to linear combinations of related financial measures for banking institutions. We also argued that predicting MC and not MVA is more appealing from a theoretical perspective. The statistical analysis supports this contention within the context of banking institutions.

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References

(1) Baciadore, J., Boquist, John A., Milbourn, Todd T., and Thakor, Anjan V. (1996). A Search for the Best Financial Performance Measure. *Journal of Applied Corporate Finance.* To appear.

(2) Bennett Stewart III, (1994). EVA: Fact And Fantasy. *Journal of Applied Corporate Finance*, 7, 2, 71-84.

(3) Black, F., Martinez, S., Ou, C, Reinhard, S., Rodriguez, A., Savage, T., and Wilton, T. (1997 a). Economic Value Added Model For Banks. *The University of Michigan MAP Team Report.*

(4) Black, F., Martinez, S., Ou, C, Reinhard, S., Rodriguez, A., Savage, T., Wilton, T., and Damien, P. (1997 b). Economic Value Added Model To Assess Bank Performance. *Submitted for Publication.*

(5) Damien, P. and Mueller, P.M. (1998). A Bayesian Bivariate Failure Time Regression Model. *Computational Statistics and Data Analysis.*. To appear.

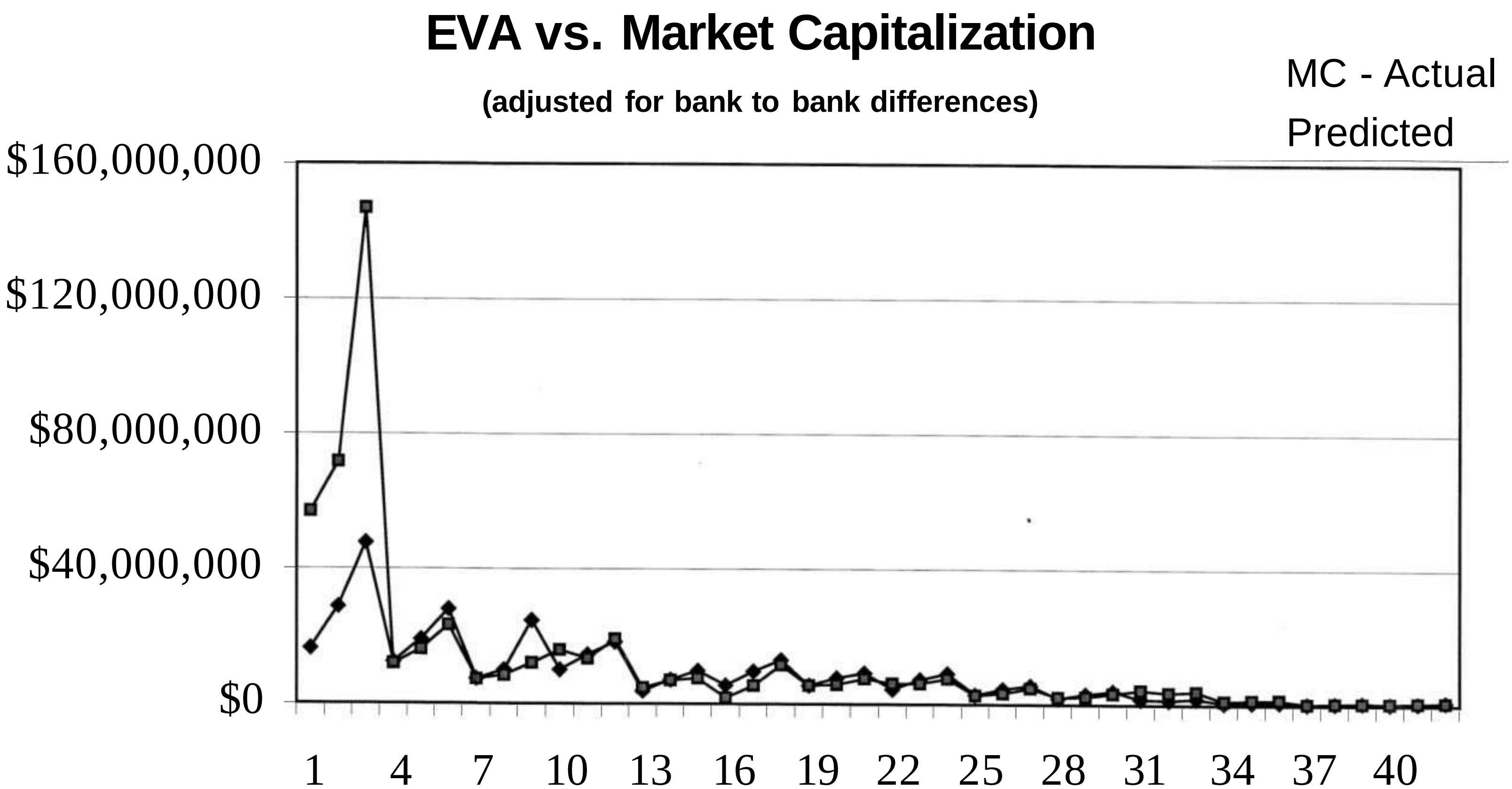
(6) Damien, P., Wakefield, J.C. and Walker, S.G. (1998). Gibbs Sampling For Bayesian Nonconjugate Models Using Auxiliary Variables. *Journal of the Royal Statistical Society* - *B.* To appear.

(7) Qin, Z. Damien, P. and Walker, S.G. (1998). Bayesian Analysis of Banking Institutions. *Submitted for Publication.*

Exhibit 1

Economic Value Added of Equity (EVA)	
Banks	
	Year
Interest Revenue	+
Interest Expense	-
Net Interest Revenue	**Total**
Fees, Commissions, Securities Gains and other Revenue	**+**
Reverse: Securities Gains (Losses)	**+** or-
Amortized Gains or Losses on Sales of Securities	**+** or-
Adjusted Other Revenue	**Total**
Operating expense (including Depreciation, Operating Lease Expense, and Goodwill Amortization Expense)	**-**
Reverse: Goodwill Amortization Expense	**+**
Net Credit Recoveries (Losses)	**+** or-
Adjusted Operating Expense	**Total**
GAAP Income Tax Expense	**-**
Deferred Tax Asset: Cash Tax Effect	**-**
Deferred Tax Liability: Cash Tax Effect	**+**
Adjusted Tax Expense	**Total**
Preferred Stock Dividend	**-**
Minority Interest	**-**
NOPAT (Net Operating Profits After Tax	**Total**
Stockholders' Equity	**+**
Preferred Stock	-
Reverse: Unrealized Gains (Losses) on AFS Securi	+ or-
Allowance for Credit Losses (Net of Tax effect of Deferred Tax Assets)	+
Deferred Tax Liabilities	+ or -
Deferred Tax Assets (Net of Allowance for Credit Losses Adjustment)	+ or-
Cumulative Amortized Goodwill	+
Equity Effect of Operating Leases	
Adjusted Equity	Total
Cost of Equity	%

Exhibit: 2

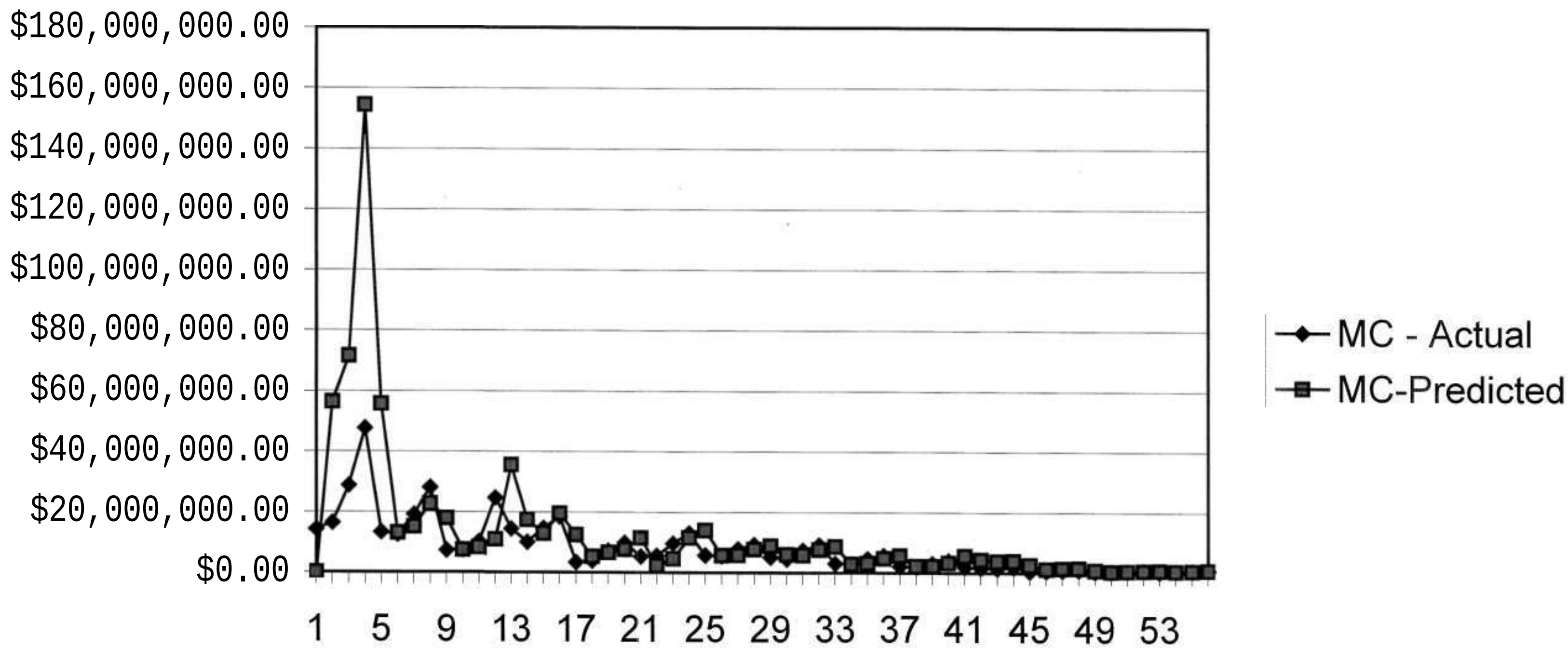


every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	EVA
0.9672353	**Coefficient:**	7845348.9	3.4210014
	Standard Deviation:	(174610.15)	(.6965627)

Exhibit: 3

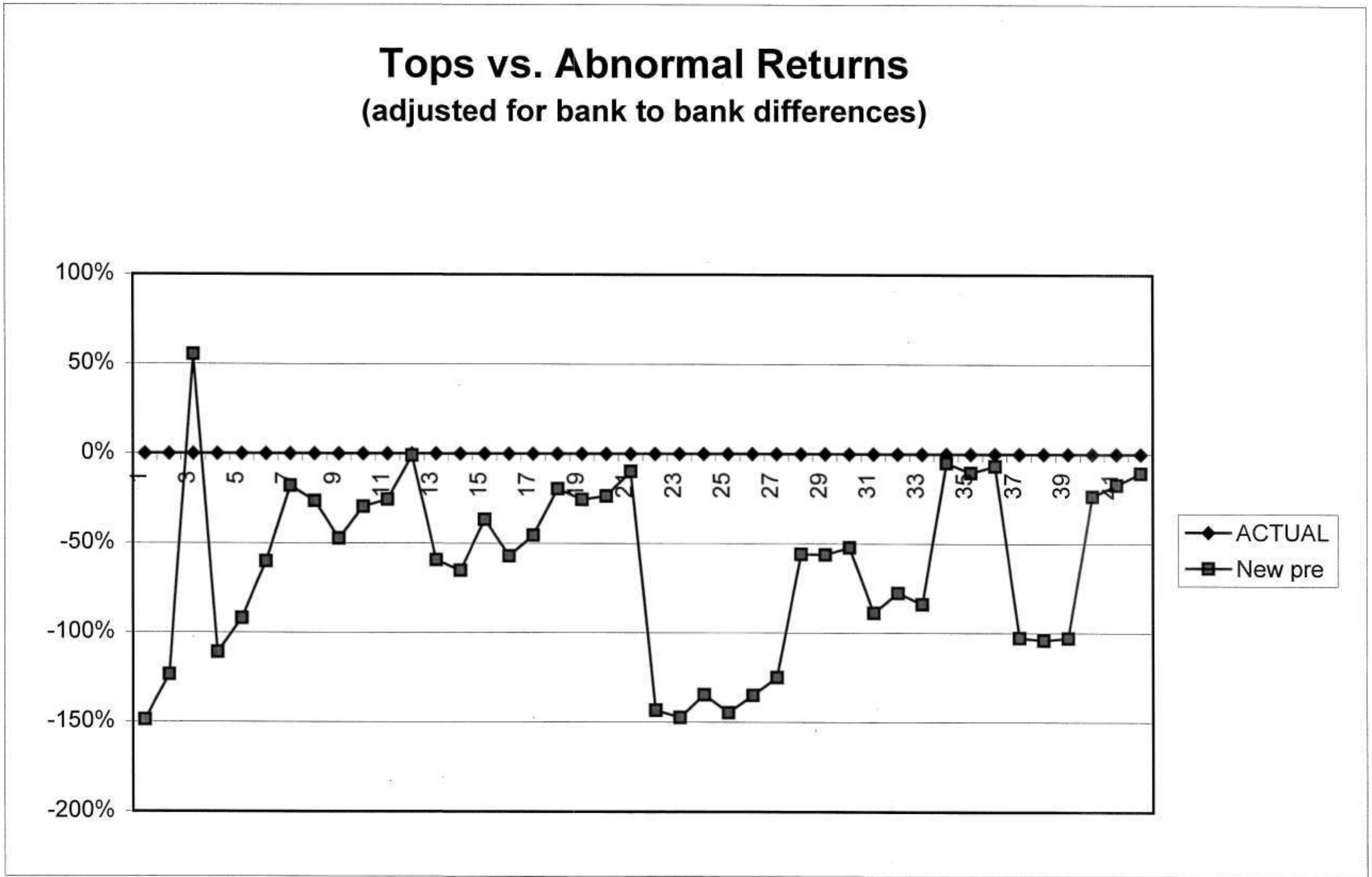
EVA vs. Market Capitalization
(not adjusted for bank to bank differences)



* every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	EVA
0.0068763	**Coefficient:**	7886612.3	2.0076411
	Standard Deviation	(1186247.2)	(3.2833149)

Exhibit: 4



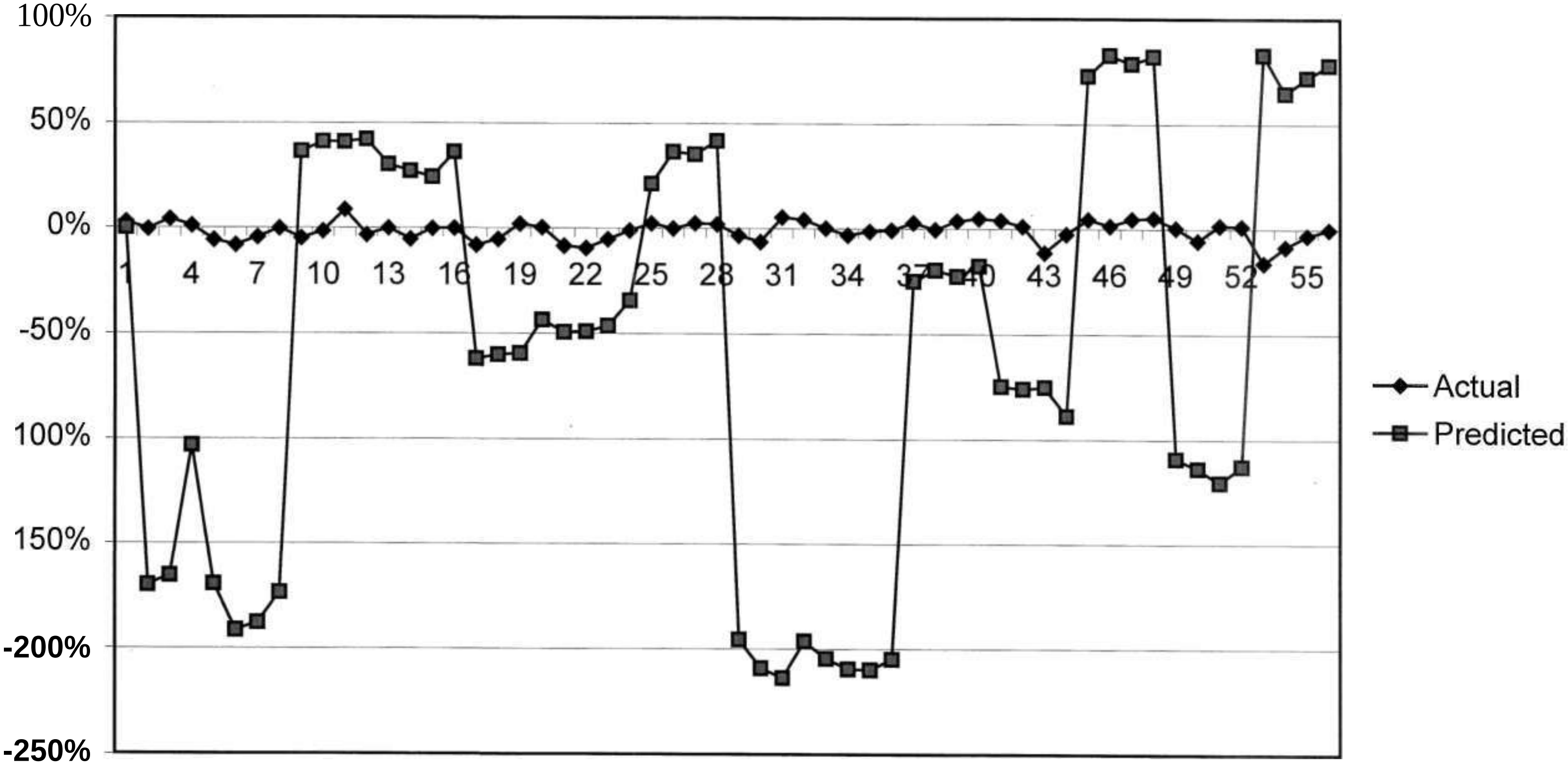
* every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	TOPS
0.0285573	**Coefficients:**	-1.048139	-5.45E-07
	Standard Deviation:	(.708083)	(9.3787E-7)

Exhibit: 5

Tops vs. Abnormal Returns

(not adjusted for bank to bank differences)



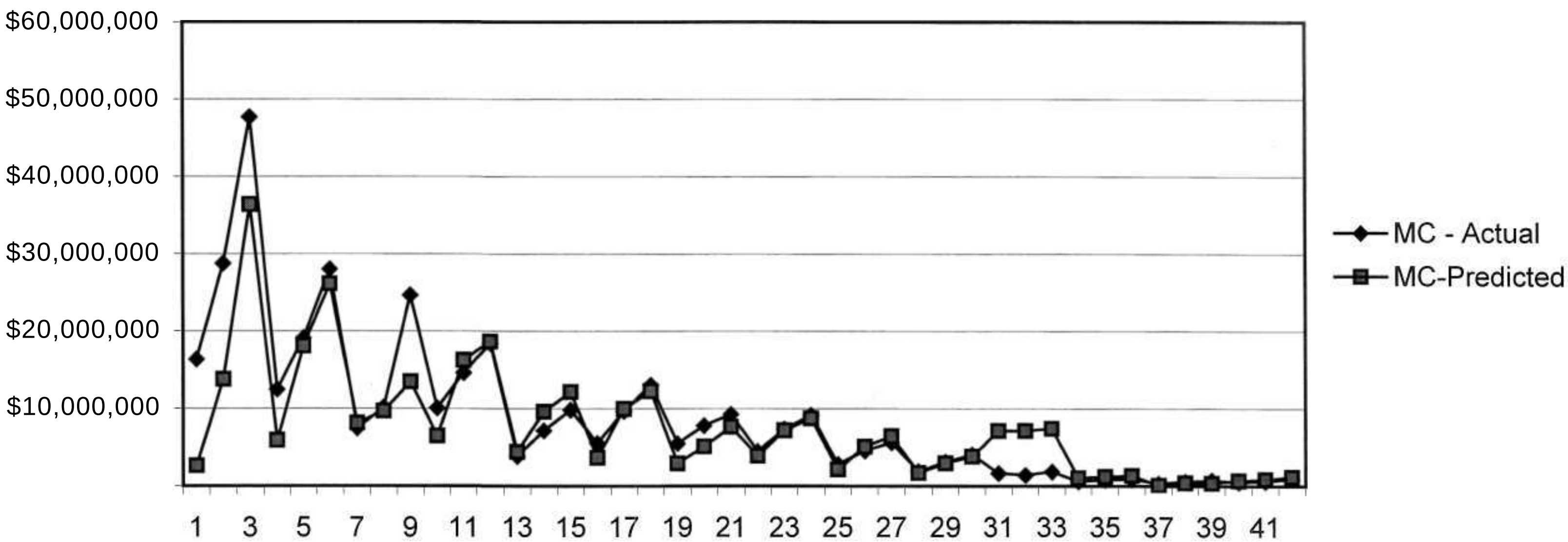
every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	TOPS
0.0003615	**Coefficients:**	-1.173042	-1.74E-07
	Standard Deviation:	(0.7513995)	(0.00000125)

Exhibit: 6

EVA and TOPS vs. Market Capitalization

(adjusted for bank to bank differences)



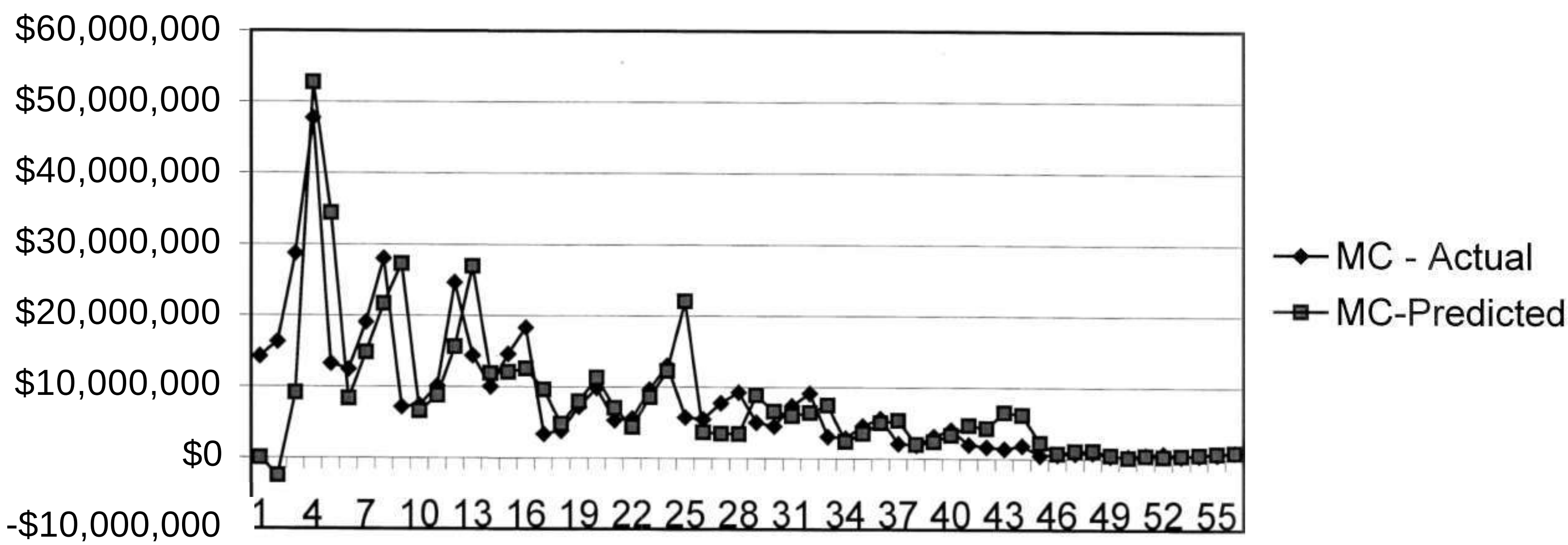
every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	EVA	TOPS
0.9454065	**Coefficient:**	5749178.8	11.015169	-8.22738
	Standard Deviation:	(899001.04)	(1.5065482)	(.8211908)

Exhibit: 7

EVA and TOPS vs. Market Capitalization

(not adjusted for bank to bank differences)



every three data points represents the years '94, '95, and '96 for each bank

R-squared		Y intercept	EVA	TOPS
0.5431924	**Coefficient:**	4186014.6	5.5221268	-12.48572
	Standard Deviation	(937845.82)	(2.2914213	(1.5828212)

Appendix

Upon examining the data for each of the 14 banks in our sample, for the years 1993 through 1996, it was clear that an error component model which allowed for error correlation to decline over time (one year) would be needed. Also there were significant bank-to-bank differences. These suggested that pooling the cross-sectional and time-series data under error assumptions of autocorrelation as well as cross-section heteroscedasticity would be an appropriate model to use in this context (Judge et al., 1980). Consider the following.

$$Y_{it} = \alpha + \beta X_{it} + \epsilon it, \tag{1}$$

where

$$\epsilon_{it} = \rho_i \epsilon_{i,t-1} + u_i t,$$

$i = 1 \cdots 14$ and $t = 1 \cdots 4$. Also, $E(\epsilon_{it}^2) = \sigma^2$ and $u_{it} \sim N(0, \sigma_u^2)$. The errors are assumed uncorrelated with the cross-section disturbances and have constant variance; however the time-series errors are autocorrelated. ρ_i varies from bank-to-bank.

It is well-known that a variant of generalized least squares will yield efficient parameter estimates. To accomplish this, the ρ_is are first estimated using ordinary least squares with the entire pooled sample of 56 data points as follows:

$$\rho_i = \frac{\sum_{t=2}^{4} \hat{\epsilon}_{it} \hat{\epsilon}_{i,t-1}}{\sum_{t=2}^{4} \hat{\epsilon}_{i,t-1}^2}, \; i = 1, \cdots 14,$$

where $\hat{\epsilon}_{it}$ are the estimated residuals obtained after using least squares to estimate (1).

Next we formed the generalized difference equation,

$$Y_{it}^* = \alpha(1 - \rho_i) + \beta X_{it}^* + u_{it}^*, \tag{2}$$

where $Y_{it}^* = Y_{it} - \rho_i Y_{i,t-1}$, $X_{it}^* = X_{it} - \rho_i X_{i,t-1}$, $u_{it}^* = \epsilon_{it} - \rho_i \epsilon_{i,t-1}$.

The model in (2) can now be estimated using ordinary least squares; note that the construction in (2) implies we loose one (time-series) observation for each of the 14 banks. But since there is only one independent variable in the model, the estimates of β and the error variance are based on 42 data points; i.e., the degrees of freedom for the estimation are fairly large.

In the illustration in the main text where we dropped the data relating to two banks ("small" and "large"), note that, in the above formulation, the i index will change to 12, leading to a total sample, in the second stage estimation, of 36 data points.