An Improved Methodology to Assess Value-relevance of Earnings and Book Values on Corporate Equity Securities

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This paper advances Minimum Sum (MS) nonlinear iterative regression to model price as a function of earnings and book values per share. The MS methodology improves upon OLS methodology in three ways. First, MS allows for nonlinear estimation of price to eps and bvps. Second, MS allows for modeling Minimum Absolute Percentage Error (MAPE) as the objective function instead of Minimum Sum of Squared Errors. Third, MAPE mutes the negative effects of outlying observations and non-normal data compared to OLS. Better price estimates are provided which will aid participants in the primary and secondary markets, or financial services in general.

INTRODUCTION

Valuation of corporate equity securities has been a subject of extensive theoretical, statistical and analytical research over the years. Early theoretical research focused on discounted earnings or discounted dividend models to value securities. More contemporary research incorporates optionality into valuation models considering equity as options with an infinite life.

Statistical modeling generally assumes a linear relationship between price and earnings and book value, and uses Ordinary Least Squares (OLS) to estimate equity valuation models using fundamental balance sheet data. For example, Eqns. 1 and 2 are a functional specification and linear regression model, respectively, for equity price valuation:

$$P = f(\overset{+}{EPS}, \overset{+}{BVPS}) \tag{1}$$

$$P = a + beps *EPS + bbvps*BVPS \tag{2}$$

Predicted values generated there-from, are used in the investment banking and investment management businesses in many contexts. Successes in these contexts are contingent upon both accurate price estimates which, unfortunately, OLS does not provide. Following are three limitations confronted by participants in their pursuit of modeling equity share prices. This research resolves all three of these.

Problem 1 Non-Normal Data

Pricing and balance sheet data tend to be highly skewed, usually to the right, often highly leptokurtic and often with very severe outliers. Figs. 1-3, belose, display histograms of price, eps and bvps for constituents of the SP1500 as of 12/31/2014. A few *very* severe outliers are deleted from each histogram. Histograms for all years follow the same distribution.

FIGURE 1
HIST. OF PRICE

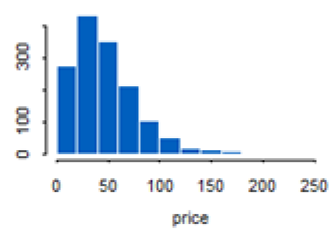


FIGURE 2
HIST. OF EPS

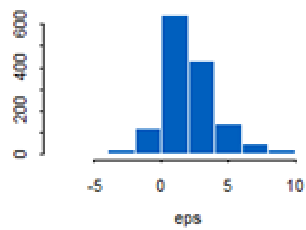
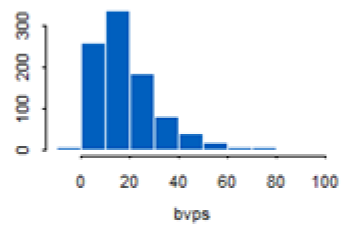


FIGURE 3
HIST. OF BVPS



Parameter estimates and inferences from OLS regression under such skewed and outlying data circumstances are unreliable.

Problem 2 Nonlinearity

Discounted earnings or earnings per share models presume a *linear* relationship between price, and earnings per share and book value per share with no intercept. The true relationship, owing to behavioral factors and/or optionality, might be *nonlinear* with an intercept.

Scatterplots of price with eps and bvps for 12/31/2014 are presented in Figs. 4 and 5, below, with very severe outliers deleted. Notice that, as shown by the curved (solid) regression overlay plots, the relationship of price with eps and bvps are non-linear. Scatterplots for all years generally follow the same configuration.

FIGURE 4
PRICE VS EPS

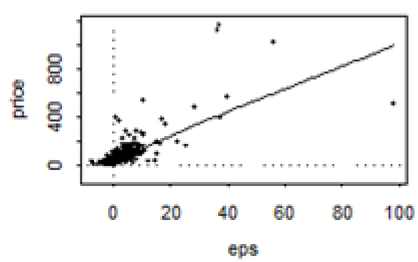
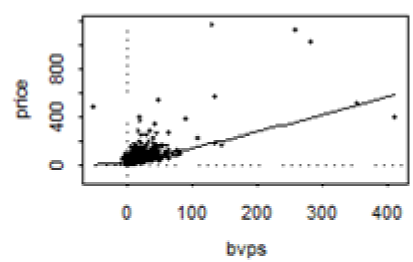


FIGURE 5
PRICE VS BVPS



Use of OLS in the presence of these nonlinear relationships will result in biased predicted values of price generally, and unrealistic, and perhaps negative, predicted values with low or negative eps or bvps values. Logarithmic transformations of price are often used, but are too elementary to model the complexity of the nonlinear relationship.

Problem 3 Price Scale

The OLS objective function is as follows:

$$\text{Min } \Sigma(\text{price-predicted})^2 \tag{3}$$

Publicly traded equities have prices ranging from very low single digits to high prices in the hundreds of dollars. OLS will give higher priced securities greater "weight" in achieving its objective function. For example, consider 2 companies with the same market values and with actual and OLS generated predicted equity prices, as follows:

Security	MV	Actual Price	OLS Predicted Price	Deviation	Deviation^2	%Error
A	1B	200	190	-10	100	-5%
B	1B	10	20	10	100	100%

Both predicted prices deviate from actual prices by 10 dollars, per the objective function, but have a hugely different %Error. But as *both companies have the same market value*, it is reasonable that the deviations should have the *same percentage* deviation, e.g. 10% or 15%, not the same absolute deviation. This problem is referred to by Ohlson (1995) as a scale problem. In the presence of this scale problem, minimizing squared deviations is not the correct objective function. The ideal objective function is Minimum Absolute Percentage Error (MAPE), as follows:

$$\text{Min } \Sigma(\text{abs}(\ln(\text{price}/\text{predicted}))) \tag{4}$$

This research proposes Minimum Sum Regression (MS) as an alternative to Ordinary Least Squares (OLS) which corrects for the three limitations and better models equity prices as a function of fundamental balance sheet data. Specifically:

1. MS allows for *any functional parametric relationship* between one response variable and one or more independent variables. The relationship could be exponential, logistic, negative binomial, growth, Weibull, Erlang, gamma, beta, Unit Normal Loss Integral (UNLI), or any other. In this research, MS is used to model equity price as a nonlinear UNLI function of earnings per share and book value per share. The UNLI function mimics the nonlinear relationship portrayed in Figs. 3 and 4. Importantly, the model will provide better price estimates in the presence of low (or negative) eps or bvps which OLS is not capable of achieving. UNLI mimics a call option model and eliminates the possibility of negative estimated prices.
2. MAPE minimization as the objective function eliminates the problem of bias due to price scale. Low price equities are directly modeled to be given the same weight in the regression algorithm as high prices, also allowing for more accurate price estimates.
3. Minimizing MAPE, instead of $\Sigma(\text{price-predicted})^2$ mitigates the problem of skewed data or outlying error terms, and reduces to a robust regression methodology allowing for more accurate price estimates.

Better models and algorithms will produce better price estimates which makes for better decision making in investment banking, investment management, and other pursuits.

METHODOLOGY

Cross-section SP1500 constituent data for price, earnings per share and book-value per share for the years 2000-2014 was drawn from FactSet[1]. Thus the dataset is pooled time series and cross section. The functional specification is given in Eqn. 1, below.

$$\text{price} = f(\overset{+}{\text{eps}}, \overset{+}{\text{bvps}}) \tag{5}$$

where,

price	- equity price per share
eps	- earnings per share
bvps	- book value per share

Support for the notion of price being a positive function of both earnings and book value per share is given in Ohlson [2]. Collins, et. al. [1] provide theoretical detail noting that book value per share is especially important when earnings per share is low or negative, or contains non-recurring items, transitory components.

Ordinary Least Squares (OLS) and Minimum Sum Regression (MS) will be used to estimate, evaluate and compare cross-section regressions from 2000 to 2014 for all companies included in the SP1500 for which all data was present for that year. The serious deficiencies and biases inherent in OLS and the improvements to the estimating prices due to MS will be highlighted.

Eqns. 6 and 7 display the OLS and MS models to be estimated:

$$\text{OLS:} \quad price = a + b_{eps}*eps + b_{bvps}*bvps \tag{6}$$

$$\text{MS:} \quad price = a + b_{eps}*UNLI(eps) + b_{bvps}*UNLI(bvps) \tag{7}$$

where UNLI in Eqn. 7 is the Unit Normal Loss integral as computed in Eqn. 8, below.

$$\text{UNLI(z)}=\int_z^{\infty}(X-z)\varphi(z)dz \tag{8}$$

A closed form expression for UNLI is given in Eqn. 9, below.

$$\text{UNLI(X)} = .399*\exp(-0.5*z*z)- z*(1\text{-CDF }(-z)) \tag{9}$$

where $z=(X- \mathbf{x_o})/ \mathbf{x_d})$

Substituting z to UNLI we get:

$$\text{UNLI(X)} = .399*\exp(-0.5 *((X-\mathbf{x_o})/\mathbf{x_d})*((X- \mathbf{x_o})/ \mathbf{x_d}))-(-((X- \mathbf{x_o})/ \mathbf{x_d}))*(1\text{-CDF }(-((X- \mathbf{x_o})/ \mathbf{x_d}))) \tag{10}$$

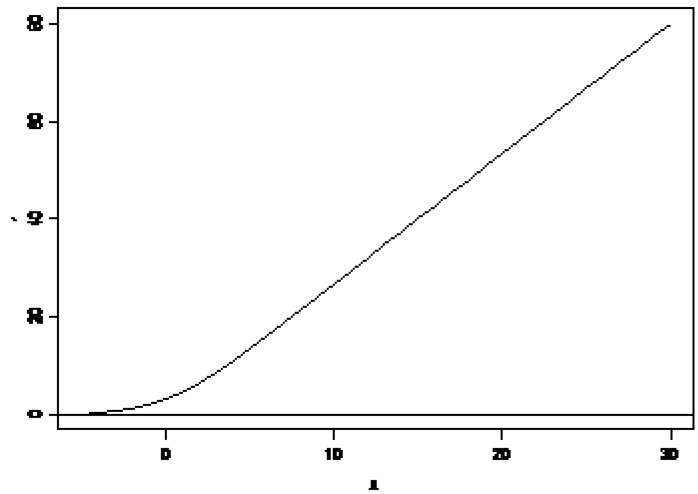
where bold-faced items are parameters to be estimated and CDF is the cumulative normal distribution.

A Digression on UNLI

UNLI models the expected value of a normal variable weighted by its associated gain or loss beyond $\mathbf{x_o}$, where $\mathbf{x_o}$ is a location of the bend in UNLI, i.e. a shift parameter, and $\mathbf{x_d}$ is a dispersion parameter akin to the standard deviation and reduces to a convexity parameter. See Figure 6.

Importantly, UNLI is appropriate to model price as a function of eps and bvps, as it is asymptotic to the x axis for very low values of either, but is positive *and linear* for high values of x. The location of the bend depends upon $\mathbf{x_o}$ and the severity of the bend depends upon $\mathbf{x_d}$. The function effectively mimics the payoff of a call option. Often, nonlinear functions are modeled using exponential or parabolic functions. This is incorrect, as both of these are *nonlinear* for increasing values of each of eps or bvps. UNLI is the correct function, as it is *linear* for high values of eps or bvps.

FIGURE 6
y = f(unli(x))



The reduced form model of combining Eqns. 7 and 10 is given in Eqn. 11, below,

$$\begin{aligned}
&\text{price} = \\
&\mathbf{b_{eps}}*\mathbf{eps_d}*(.399*\exp((-.5*((eps-\mathbf{eps_o})/\mathbf{eps_d})*((eps-\mathbf{eps_o})/\mathbf{eps_d}))- \\
&(-((eps-\mathbf{eps_o})/\mathbf{eps_d}))*(1-CDF(-((eps-\mathbf{eps_o})/\mathbf{eps_d})))) \\
&+\mathbf{b_{bvps}}*\mathbf{bvps_d}*(.399*\exp((-.5*((bvps-\mathbf{bvps_o})/\mathbf{bvps_d})*((bvps-\mathbf{bvps_o})/\mathbf{bvps_d}))- \\
&(-((bvps-\mathbf{bvps_o})/\mathbf{bvps_d}))*(1-CDF(-((bvps-\mathbf{bvps_o})/\mathbf{bvps_d})))
\end{aligned} \tag{11}$$

where bold-faced terms are parameters to be estimated and CDF is the cumulative normal distribution. Parameters to be estimated are as follows:

$\mathbf{b_{eps}}$, $\mathbf{b_{bvps}}$ change in price for $1 change in eps or bvps for high values of eps and bvps
$\mathbf{eps_o}$, $\mathbf{bvps_o}$ discontinuity point in price to eps or bvps
$\mathbf{eps_d}$, $\mathbf{bvps_d}$ dispersion in eps or bvps

The Minimum Sum model to be executed given in Eqn. 12, below:

$$\begin{aligned}
&\min(\text{abs}(\ln(\text{price} / (\mathbf{b_{eps}}*\mathbf{eps_d}*(.399*\exp((-.5*((eps-\mathbf{eps_o})/\mathbf{eps_d})*((eps-\mathbf{eps_o})/\mathbf{eps_d}))- \\
&(-((eps-\mathbf{eps_o})/\mathbf{eps_d}))*(1-CDF(-((eps-\mathbf{eps_o})/\mathbf{eps_d})))) \\
&+\mathbf{b_{bvps}}*\mathbf{bvps_d}*(.399*\exp((-.5*((bvps-\mathbf{bvps_o})/\mathbf{bvps_d})*((bvps-\mathbf{bvps_o})/\mathbf{bvps_d}))- \\
&(-((bvps-\mathbf{bvps_o})/\mathbf{bvps_d}))*(1-CDF(-((bvps-\mathbf{bvps_o})/\mathbf{bvps_d}))))))
\end{aligned} \tag{12}$$

Notice that Eqn. 12 addresses issues of interest in this research:

1. Use of UNLI models a non-linear function of price to both eps and bvps and will eliminate negative predicted prices for low eps and bvps.
2. Since there will be no negative prices, MAPE *can* be computed and MAPE minimization *is* the objective function. Minimizing MAPE gives equal weight to low and high priced securities.
3. Minimizing absolute percentage values instead of residuals squared give much less weight to outlier observations, and reduces to a robust methodology.

Use of *ln* in the objective function ensures invariant results between using price/predicted vs. predicted/price.

OLS and MS will be used to estimate Eqns. 6 and 12, respectively, for the years 2000-2014. The OLS prediction biases instigated by nonlinearities, negative earnings per share and outlier observations will be identified. MS, which eliminates these biases, will illustrate the superiority of this methodology. Specifically, comparing the MS model to the OLS model for a time series of 15 years of cross-section regressions shows higher explanatory power as measured by r^2, lower sums of absolute residuals, no negative predicted prices, and parameter estimates which are more stable over time. MS is available in almost all advanced-level statistical packages.

RESULTS

Descriptive statistics for 2014 are presented in Table 1, below. The severe skewness and kurtosis detailed in the table confirm the skewness and kurtosis noted in the histograms displayed in Fig. 1, 2 and 3. The skewness and kurtosis parameters will be problematic when using OLS. Descriptive statistics for 2000-2013 largely mimic 2014.

TABLE 1
SP1500 DESCRIPTIVE STATISTICS-2014

	n	Mean	median	st dev	skew	kurt	min	Max
price	495	51.34	40.31	56.95	5.71	42.88	2.34	645.90
eps	495	3.09	2.52	3.25	3.43	20.96	(8.61)	29.75
bvps	495	21.73	16.48	24.04	6.46	71.75	(31.27)	342.76

A correlation matrix between price, eps and bvps is presented in Table 2 for 2014. Correlations of price with eps and bvps are positive, as hypothesized, with eps having the higher linear correlation compared to bvps. The moderate inter-correlation between eps and bvps of .57 suggests that multi-collinearity will not be a problem. Correlation matrices for years 2000 to 2013 are largely the same as for 2014. It should be noted that the correlations are Pearson's linear correlations. Given, as seen in Figs. 4 and 5, that the scatterplots are highly non-linear, heteroscedastistic and with outliers, the magnitudes of the correlations are suspect. In spite of this, they do indicate that price is more highly correlated with eps than with bvps.

TABLE 2
SP1500 CORRELATION MATRIX – 2014

	price	eps	bvps
price	1.000	0.780	0.523
eps	0.780	1.000	0.547
bvps	0.523	0.547	1.000

The OLS regression results for 2014, which are presented in Table 3 are problematic.

TABLE 3
ORDINARY LEAST SQUARES REGRESSION RESULTS - 2014

price = 21.28 + 17.86*eps + 1.16*bvps
t-stat (19.61)* (20.88)*

r2 = .517 adj-r2=.717 F=800.5* p=0 se = 49.66 df=1492

Number of negative price estimates: 25
MAPE: NA

* - Significant at the 1% level of significance.

Explanatory power is moderate, indicating that 51.7% of the variation in price can be explained by or attributed to variation in eps and bvps. The F-statistic for the entire model is significant at the 1% level of significance. Both coefficients have t-statistics significant at the 1% level of significance and indicate the change in price for a $1 increase in eps or bvps.

There are a number of concerns, however. The intercept of $21.28, which indicates the average share price if eps and bvps were equal to zero, is unrealistic and suggestive of a model mis-specification or statistical issue. Furthermore, the 25 negative predicted price estimates negate the applicability or usefulness of MAPE.

Problems are also evident in the OLS residual graphs presented in Figs. 7-10. The histogram of the residuals in Fig. 7 is slightly skewed to the right, indicating that regression coefficients and t-statistics might be biased upward. Fig. 8, which displays a scatterplot of the actual vs. predicted price, is problematic. The graph is not linear, indicating a model specification bias, the residuals are heteroscedastistic, and there are many outliers. The specific variables which are the source biases are identified in the individual plots of residuals vs. eps and bvps. The curvilinear pattern of the residuals indicated by the spline curve indicates that price is non-linear to *both* eps and bvps. Given the nonlinear bias in the model, it should not be surprising that 25 negative price estimates are generated by this OLS model for firms with low or negative eps or bvps. The mis-specification of the model as linear, when the evidence points to a non-linear relationship, will bias all the predicted values.

FIGURE 7
HIST. OF RESIDUALS

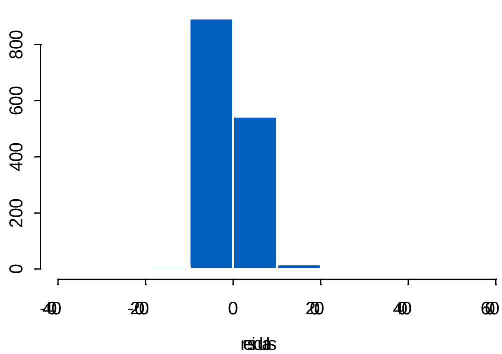


FIGURE 8
PLOT OF ACTUAL VS PREDICTED PRICES

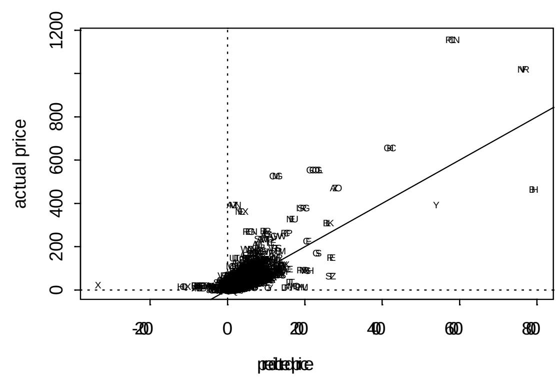


FIGURE 9
PLOT OF RESIDUALS VS EPS

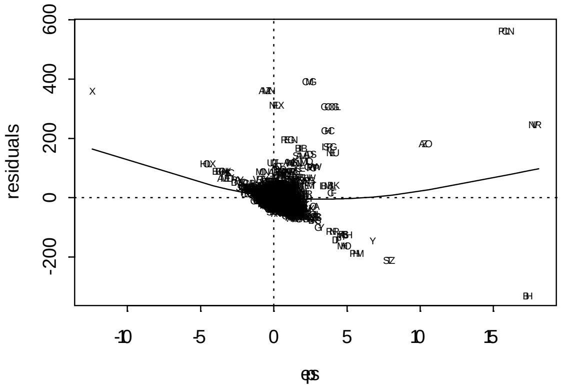


FIGURE 10
PLOT OF RESIDUALS VS BVPS

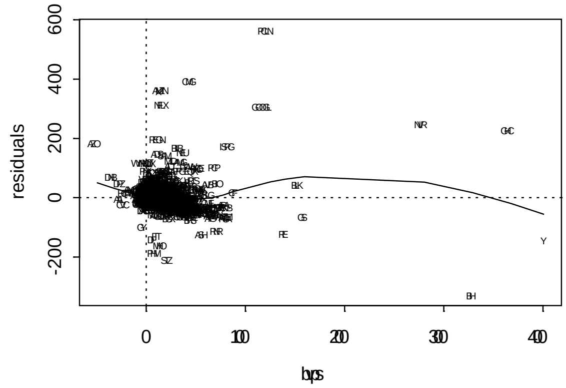


Table 4, displays a time series of OLS SP1500 cross-section regression results are presented for the 2000 to 2014. The results, and problems, are the same for the time series as for the single year.

TABLE 4
ORDINARY LEAST SQUARES REGRESSION RESULTS - 2000-2014

	year	r-sq	mape resid	sum abs resid	n	#neg	intcpt	beps	bbvps	t-int	t-eps	t-bvps
1	2000	0.59	NA	18,208	1109	97	-4.21	7.22	2.96	-2.73	8.82	38.85
2	2001	0.8	NA	14,307	1166	8	8.92	3.11	1.56	8.24	5.85	67.37
3	2002	0.74	NA	12,300	1202	26	0.04	3.78	1.95	0.05	8.5	52.68
4	2003	0.85	NA	20,743	1225	14	2.07	3.35	2.3	3.08	5.3	63.62
5	2004	0.84	NA	14,468	1253	16	5.76	13.2	1.77	7.4	19.33	51.43
6	2005	0.89	NA	15,068	1287	8	7.87	9.24	1.7	13.21	20.95	76.6
7	2006	0.89	NA	17,657	1322	4	11.07	10.79	1.45	18.25	15.74	44.72
8	2007	0.75	NA	20,336	1364	9	16.09	13.23	0.98	20.53	16.53	33.36
9	2008	0.54	NA	14,800	1385	11	9.2	3.43	0.83	15.74	10.14	38.32
10	2009	0.6	NA	17,549	1404	12	10	8.21	1.15	13.89	17.05	38.54
11	2010	0.45	NA	21,581	1417	3	17.44	1.87	1.07	19.19	4.6	30.92
12	2011	0.46	NA	22,238	1441	13	12.33	9.82	1.05	12.35	15.25	27.14
13	2012	0.49	NA	25,103	1461	12	14.32	14.93	0.95	12.84	18.14	22.4
14	2013	0.58	NA	31,597	1472	21	19.35	29.37	0.8	13.94	26.4	14.42
15	2014	0.52	NA	38,588	1496	8	20.81	17.85	1.16	12.58	19.42	20.88

As measured by r^2, the explanatory power of each regression is moderate but not stable with r^2 ranging between 41% and 82%. The F-statistic of each model (not displayed) easily exceeds the critical F-statistic indicating each regression to be significant at the 1% level. All eps and bvps coefficients are positive, highly significant as measured by the t-statistic, and have their conventional interpretations.

Note that the intercept is positive for all years and that the coefficients for eps and bvps are highly volatile. For example, the eps coefficients range from .14 to 12.36 and the bvps coefficients range from .30 to 3.41. *Worst of all, note that the OLS algorithms generate between 4 and 96 negative predicted* *prices for the cross-section regressions.* Therefore MAPE is not able to be computed. Graphical residual plots were generated with the same problematic results seen in Figs. 6-9.

Clearly, OLS is an incorrect algorithm to model and assess the effect of eps and bvps on price. The frequently used analyst convention of eliminating low eps or bvps companies or taking logarithms is a low-level solution to the problem.

MS regression results are displayed in Table 5, below, and illustrate the superiority of the MS methodology.

TABLE 5
MINIMUM SUM REGRESSION RESULTS - 2014

beps	epsOpt	epsVar	bbv	bvOpt	bvVar
41.06	-0.24	.17	.60	-.66	6.36

Eqn. 6 price =
+ 41.06 * .17 *(.399*exp((-.5* ((eps- -.24)/.17)*((eps- -.24)/ .17))-
(-((eps- -.24)/.17))*(1-CDF (-((eps- .24)/ .17))))
+ .60 * 6.36 *(.399*exp((-.5*((bvps- -.66)/ 6.36)*((bvps- -.66)/6.36))-
(-((bvps- -.66)/ 6.36))*(1-CDF (-((bvps- -.66)/6.36)))

r^2=0.70 mape=0.43 n=1496
n negative predicted values - 0

Unlike OLS which is based on Gaussian metrics, MS does not produce t-statistics or F-statistics. Parameter and model significance is determined casually by the increase in r-squared or decrease in the sum of absolute (or absolute percent) residuals. Note that r^2 is higher than in OLS.

Residual graphs for MS are presented in Figs. 11-14 and indicate MS to be a much more robust methodology than OLS. The histogram of the percent residuals closely approximates a normal distribution, much more-so than the OLS histogram. The graph of the actual vs. predicted values in Fig. 12 is linear indicating that the UNLI model specification is correct. The heteroskedasticity has been eliminated and there are no outliers. This compares to the OLS graph which *did* display a non-linear bias *with* heteroskedastistic residuals *and with* many outliers. The plots of percent residuals vs. eps and bvps in Figs. 13 and 14 confirm that nonlinearity has been removed by the UNLI transformation. Thus, it should not be surprising that no negative predicted values were produced by the estimating equation. And, as there are no negative predicted values, MAPE is a relevant measure of fit.

FIGURE 11
HIST. OF RESIDUALS

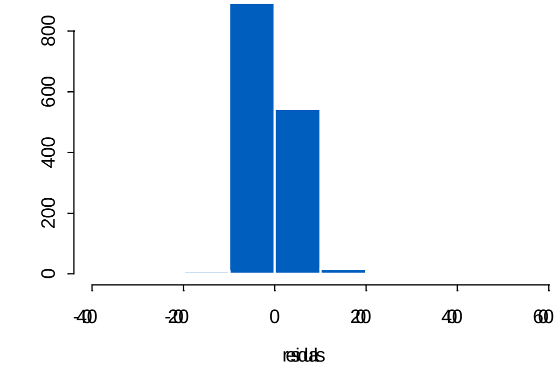


FIGURE 12
PLOT OF ACTUAL VS PREDICTED PRICES

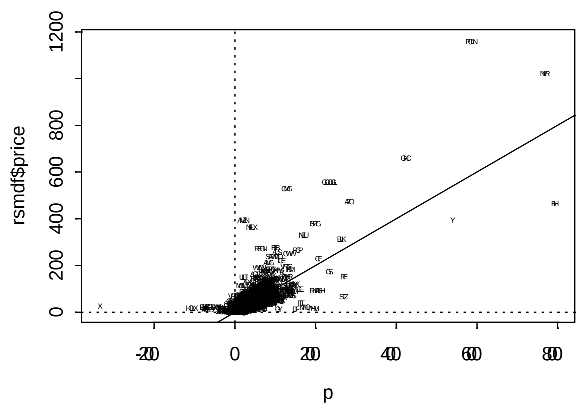


FIGURE 13
PLOT OF RESIDUALS VS EPS

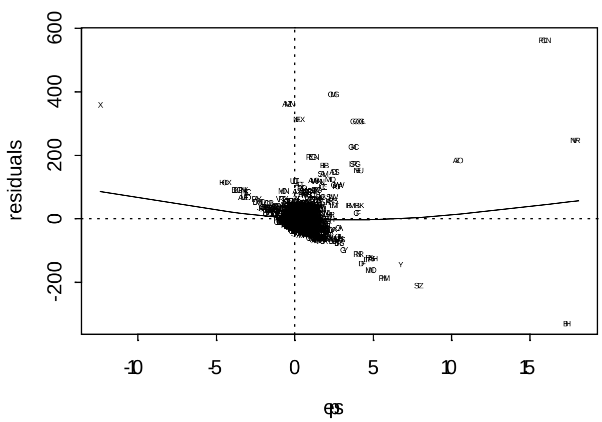
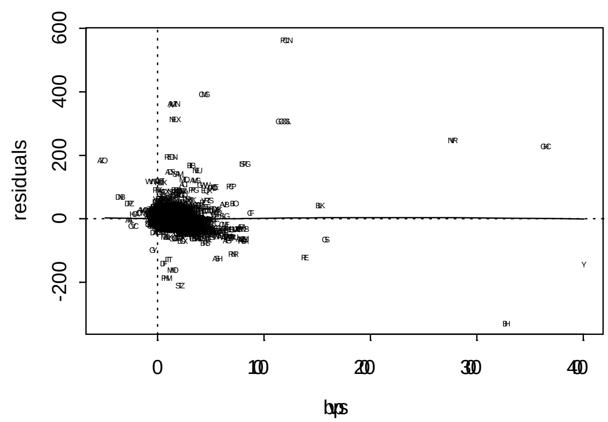


FIGURE 14
PLOT OF RESIDUALS VS BVPS



Comparing 2014 OLS and MS Regression Results

MS SP1500 cross-section regression results for years 2000 to 2014 years are presented in Table 6, below. Note that R^2 is higher and the sum of the residuals lower for each regression.

The MS regression results are superior on every dimension compared to the OLS results. Explanatory power, as measured by a pseudo r^2 is higher and more stable and the sum of the absolute residuals is lower for MS than for OLS for each regression. Also, the eps and bvps coefficients are more stable year to year. *Importantly, there are no negative predicted equity prices for any of the years*. This compares to OLS wherein every year had one or more negative predicted values. In spite of the location parameters for bvps being low for 2011-2013, probably due to outliers the slope, location and dispersion parameters are stable, especially when compared to OLS parameters.

TABLE 6
MINIMUM SUM REGRESSION RESULTS 2000-2014

	year	r-sq	mape	resid	n	#neg	beps	epsOpt	epsVar	bbvps	bvpsOpt	bvpsVar
1	2000	0.68	0.65	14,404	1109	0	21.09	-0.13	0.26	1.21	2	4.97
2	2001	0.8	0.52	12,930	1166	0	3.6	-1.24	1.44	1.36	0.01	6.58
3	2002	0.82	0.47	9,708	1202	0	20.88	-0.11	0.27	1.26	3.24	5.92
4	2003	0.86	0.39	11,442	1225	0	13.59	-0.16	0.09	2.1	7.93	15.16
5	2004	0.84	0.36	13,069	1253	0	20.62	-0.35	0.29	1.36	2.71	6
6	2005	0.89	0.36	13,460	1287	0	16.62	-0.29	0.22	1.2	-1.85	6.15
7	2006	0.9	0.34	16,729	1322	0	2.58	-5.47	1.78	1.55	3.06	5.8
8	2007	0.76	0.42	18,157	1364	0	22.62	-0.5	0.28	0.69	1.77	6.74
9	2008	0.55	0.47	13,859	1385	0	10.71	-0.42	0.2	0.53	-4.8	5.28
10	2009	0.66	0.39	14,952	1404	0	22.45	-0.27	0.42	0.79	1.49	10.12
11	2010	0.46	0.49	19,065	1417	0	19.93	-0.48	0.28	0.77	1.03	5.94
12	2011	0.62	0.41	18,355	1441	0	28.32	0.06	0.04	0.5	-16.74	9.32
13	2012	0.63	0.41	21,978	1461	0	29.32	0	0.12	0.5	-18.52	6.18
14	2013	0.63	0.39	28,385	1472	0	40.95	-0.1	0.25	0.49	-15.63	3.59
15	2014	0.7	0.43	32,827	1496	0	41.06	-0.24	0.17	0.6	-0.66	6.36

Table 7, below, presents a comparison summary of the OLS and MS Regression results.

TABLE 7
COMPARISON OF OLS VS. MS REGRESSION RESULTS

	OLS						Minimum Sum				
	year	r-sq	mape	sum abs resid	N	#neg	r-sq	Mape	sum abs resid	n	#neg
1	2000	0.59	NA	18,208	1109	97	0.68	0.65	14,404	1109	0
2	2001	0.8	NA	14,307	1166	8	0.8	0.52	12,930	1166	0
3	2002	0.74	NA	12,300	1202	26	0.82	0.47	9,708	1202	0
4	2003	0.85	NA	20,743	1225	14	0.86	0.39	11,442	1225	0
5	2004	0.84	NA	14,468	1253	16	0.84	0.36	13,069	1253	0
6	2005	0.89	NA	15,068	1287	8	0.89	0.36	13,460	1287	0
7	2006	0.89	NA	17,657	1322	4	0.9	0.34	16,729	1322	0
8	2007	0.75	NA	20,336	1364	9	0.76	0.42	18,157	1364	0
9	2008	0.54	NA	14,800	1385	11	0.55	0.47	13,859	1385	0
10	2009	0.6	NA	17,549	1404	12	0.66	0.39	14,952	1404	0
11	2010	0.45	NA	21,581	1417	3	0.46	0.49	19,065	1417	0
12	2011	0.46	NA	22,238	1441	13	0.62	0.41	18,355	1441	0
13	2012	0.49	NA	25,103	1461	12	0.63	0.41	21,978	1461	0
14	2013	0.58	NA	31,597	1472	21	0.63	0.39	28,385	1472	0
15	2014	0.52	NA	38,588	1496	8	0.7	0.43	32,827	1496	0

CONCLUSION

This research advanced the use of minimum sum as a superior regression methodology to model equity prices over OLS. The OLS methodology presumes a linear relationship between price and both eps and bvps. Used in the presence of nonlinear relationships between both eps and bvps with price resulted in systematic presence of negative predicted equity prices. OLS parameter estimates are highly biased in presence of non-normal data, outlying observations and non-linear relationships. MS allows for more accurate estimation of complex nonlinear additive or geometric relationships and where there are outliers of varying degrees. Indeed, the nonlinear iterative methodology allows for estimation of equity prices where earnings and/or book value per share negative, clearly an advantage over the OLS algorithm which generated unrealistic negative prices. The explanatory power of the equations using MS is higher with lower standard errors, and the coefficients are more stable.

This research benefits the participants in the primary and the secondary markets. It allows for improved and more efficient estimates of prices in the IPO market and a vehicle to improve the efficiency or pricing in the secondary market. Further research would include other independent variables to better model equity prices to discover investor valuation cognitive precepts. These might include liquidity considerations and debt metrics. Indeed, the methodology hints at the ability to discover implied optimal current and debt ratios as identified by investors in the marketplace.

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