Theoretical Economics Letters, 2022, 12, 742-760
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

# An Improved Combining-Model of Financial Analysts' Forecasts and CAPM-Generated Forecasts of Firm-Earnings Growth

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**How to cite this paper:** Terregrossa, S. J. (2022). An Improved Combining-Model of Financial Analysts' Forecasts and CAPM-Generated Forecasts of Firm-Earnings Growth. *Theoretical Economics Letters, 12,* 742-760.
https://doi.org/10.4236/tel.2022.123041

**Received:** April 8, 2022
**Accepted:** June 13, 2022
**Published:** June 16, 2022



## Abstract

The present analysis seeks to develop an improved combining-model to enhance forecast-accuracy of firm-earnings growth. There are two components of the combining-model in this study: An expected-return model in the form of the CAPM, and a structural model underlying financial analysts' forecasts of earnings growth. In the present study, the path to an improved combining-model lies in constructing a more forward-looking CAPM by making an adjustment in the measurement of firm-beta that incorporates the *dispersion of financial analysts' forecasts*. Our aim is to infuse an additional layer of *independent information content* into the CAPM-generated forecasts; which in turn would make them more useful for combining with the financial analysts' consensus forecasts of earnings growth. The existence of *independent information* is ascertained by *in-sample* OLS regressions of realized values against predicted values of the forecast variable by each of the component forecast models. The estimated regression coefficients of the *in-sample* tests of *independent information* then further serve as forecast weights for *out-of-sample* combination forecasts. Mean absolute forecast errors are calculated for each forecasting method, ranging from the component models to the combination models; and comparisons are made. The OLS regression results and the forecast error comparisons collaboratively indicate that incorporating the *dispersion of analysts' forecasts* into the estimation of beta adds an additional *independent information content* in the CAPM-generated forecasts of earnings growth; which generally leads to better CAPM-generated forecasts of earnings-growth, and in turn, improved weighted-average combinations of analysts' consensus forecasts and CAPM-generated forecasts; which prove superior to either component model forecast.

## Keywords

CAPM, Beta, Dispersion of Financial Analysts' Forecasts, Earnings Growth,

Combination Forecasting

## 1. Introduction

A previous study concerning the Capital Asset Pricing Model (CAPM)[1] has demonstrated two things: 1) The existence of *independent-information content* in the CAPM that financial analysts appear not to be fully utilizing when forecasting firm-earnings growth; 2) Combining CAPM-generated forecasts with financial analysts' consensus-forecasts of firm-earnings growth results in superior forecast-accuracy[2]. The objective of the present study is twofold: 1) To increase the *information content*, and thus the accuracy of CAPM-generated forecasts of firm-earnings growth, and in turn, 2) To improve the accuracy of the combined CAPM-generated and financial analysts' consensus-forecasts of firm-earnings growth. This dual objective is achieved by modifying the index of systematic risk (beta) in the CAPM, to construct a more forward-looking model. When estimating the CAPM, the traditional (or conventional) approach in the measurement of beta has been to use historical security- and market-return information, to estimate a security's future level of covariance-of-return with the market portfolio. Thus, an obvious criticism of the CAPM is that it is backward-looking, since practical application of the CAPM requires the use of historical data to estimate expectations of current and future levels of systematic risk. The present study modifies the CAPM to make it more forward-looking with an adjustment in the measurement of a firm's beta that incorporates the dispersion (standard deviation) of financial analysts' forecasts (Carvell and Strebel, 1984), which has been found over time to be a highly significant and most important explanatory risk-variable, with respect to security returns and prices[3]. Our aim is to infuse an additional layer of *independent information content* into the CAPM-generated forecasts; which in turn would make them more useful for combining with the financial analysts' consensus forecasts of earnings growth. The existence (and degree) of *independent information content* may be ascertained by *in-sample* regressions of realized values against predicted values of the forecast-variable by each of the component forecast models. If the respective regression coefficients (with regard to the respective component forecasting models) are non zero and separately identified [and statistically significant], then the existence of an *independent information content* is confirmed for a given model or models. The estimated regression coefficients of the *in-sample* tests of *independent information* can then further serve as forecast weights for *out-of-sample* combination fore-

[1]The Capital Asset Pricing Model (CAPM) was jointly developed by Markowitz (1959), Sharpe (1964) and Lintner (1965), who also jointly shared the 1990 Nobel Prize in Economics for their work in developing the model.

[2]See Terregrossa (1999).

[3]See Conroy and Harris (1987), Harris (1986), Malkiel and Cragg (1982) and Friend, Westerfield and Granito (1978).

casts. The current study implements an ordinary-least-squares (OLS) regression analysis, and a construction and comparison of mean-absolute-forecast-error (MABE) to collaboratively determine if incorporating the *dispersion of analysts' forecasts* into the estimation of firm beta leads to greater *independent information content* in CAPM-generated forecasts, and in turn, more accurate (and superior) combinations of CAPM-generated and financial analysts' consensus-forecasts of firm-earnings growth. The study is organized into four main sections. Following the **Section 1** ***introduction*** above, the **Section 2** ***background*** presents a brief but essential review of related studies, providing context and perspective; and serving as a backdrop from which the empirical analysis springs. **Section 3** presents the ***methodology***; while **Section 4** presents and discusses the ***empirical results***. Lastly, **Section 5** offers a summary of the ***findings***, and ***conclusions*** generated by the analysis.

## 2. Background

Forecast accuracy of a given forecast variable is, in part, a function of the information set from which the forecasts are derived. For example, with regard to firm earnings, Liu (2020) analyses the impact of industrial agglomeration on analysts' earnings forecasts and finds that clustering fosters greater information transmission to analysts, which leads to significantly improved accuracy of their earnings-forecasts. One reason is that companies in industrial clusters often have similar fundamentals (Engelberg et al., 2018), which allows analysts to discern information about one firm from other firms in the cluster. Another reason is that firms in a cluster tend to pool and share information about one another (Liang and Qian, 2007) which leads to a broader information set made available to analysts. Similarly, Du and Li (2015) find a greater degree of cross-firm management communication in an industrial cluster, which also facilitates a broader conveyance of information to analysts regarding the firms in the cluster.

Another way to broaden the information set from which earnings forecasts are derived is by forming weighted-average combinations of forecasts generated by different models. If there exists *independent information content* in the component models, then a weighted-average combination formed of the component model forecasts may lead to superior forecast accuracy (over the individual component models). One or more models may contribute *independent information* (toward forecasting the target variable) if they process different data; or if they process the same data differently. The technique of combination forecasting has been successfully applied over a wide range of forecast variables, from economic and financial variables [such as GDP growth (Bischoff, 1989) and housing values (Torres-Pruñonosa et al., 2022) to environmental variables [such as rainfall and flooding (Wu et al., 2015)]. The present analysis seeks to develop an improved combining-model to enhance forecast-accuracy of firm-earnings growth. There are two components of the combining model in this study: An expected-return model in the form of the CAPM, and a structural model underlying financial analysts' forecasts of earnings growth[4]. In the present study, the path to an improved combining model lies in constructing a more forward-looking CAPM by making an adjustment in the measurement of firm-beta that incorporates the dispersion of financial analysts' forecasts (Carvell and Strebel, 1984). The conventional form of the Capital Asset Pricing Model (CAPM) relates an asset's expected return to its beta, an index of systematic, market-related risk. This positive, linear function is stated in *ex ante* format as follows:

$$E(r_{it}) = \beta_i \left[ E(r_{Mt}) \right] \tag{1}$$

where $r_{it} = R_{it} - R_{ft}$ = the excess return on security *i*, $r_{Mt} = R_{Mt} - R_{ft}$ = the excess return on the market portfolio, $R_{it}$ = the return on security *i*, $R_{Mt}$ = the return on the market portfolio, $R_{ft}$ = the risk-free rate of return, all at time *t*, $E(*)$ is the expectation operator. And where $\beta_i$ is the security's beta (an index of systematic, market related risk), and is equal to: $cov(R_{it}, R_{Mt})/var(R_{Mt}) = (\rho_{i,M})(\sigma_{it})(\sigma_{Mt})/(\sigma_{Mt})^2$, where $(\sigma_{it})$ is the standard deviation (SD) of return for security *i*, $(\sigma_{Mt})$ is the SD of return for the market portfolio, $(\sigma_{Mt})^2$ is the variance of return for the market portfolio, $(\rho_{i,M})$ is the correlation-coefficient between the return for security *i* and the corresponding return for the market portfolio, all at time *t*.

Conventionally, practical application of the CAPM requires the use of historical data to estimate expectations of current and future levels of systematic risk ($\beta_i$). Fama and French (1992) famously challenged this empirical convention and found no positive, systematic relation between beta and realized asset-return[5]. However, an empirical study (made around the same time as the Fama and French (1992) analysis) generated the seemingly anomalous finding of useful *independent information content* in the CAPM that financial analysts appear to not be fully utilizing in their forecast generating mechanism; useful to such an extent that forming combinations of CAPM-generated forecasts and financial analysts' consensus forecasts (IBES) of earnings growth led to forecasts superior to either component model forecast [CAPM and IBES] (Terregrossa, 1999). However, the specific form of the *independent information content* of the CAPM was not identified. A subsequent study (Bollen, 2010) may have provided identification of the specific form of this *independent information content* of the CAPM, with its finding that it is not beta by itself but instead an *interaction effect* between beta and market return (as captured by the cross-product term $\hat{\beta}_{it} r_{Mt}$) that drives asset return; where $r_{Mt}$ = the observed excess return on the market-portfolio, $\hat{\beta}_{it}$ is the estimated historical beta of portfolio *i*, and $r_{it}$ = the observed excess return on portfolio *i*, all at time *t*; $\gamma_0$, $\gamma_1$ are fixed parameters and

[4]Financial analysts' consensus-forecasts of firm-earnings growth are provided by International Brokers' Estimate System [IBES] Inc. In the following passages of this paper we will use the acronym IBES to refer to the structural model underlying financial analysts' forecasts of earnings growth.

[5]Other, subsequent empirical studies, employing data from different equity markets and across different time periods, have each generated a similar finding of no systematic relation between beta and realized asset return, in an unconditional sense (see for example Pettengill, Sundaram and Mathur, 1995 [US]; Bollen, 2010 [Australia]; Terregrossa and Eraslan, 2016, 2020 [Türkiye]).

$E[\varepsilon_{it}] = 0$:

$$r_{it} = \gamma_0 + \gamma_1\left(\hat{\beta}_{it} r_{Mt}\right) + \varepsilon_{it} \tag{2}$$[6]

The Bollen (2010) study generates a highly significant, and very close-to-one in value, estimated regression coefficient ($\gamma_1$) of the interactive product-term of beta and excess market-return ($\hat{\beta}_{it} r_{Mt}$), with a regression of realized excess portfolio returns ($r_{it}$) against the interactive cross-product term $\left[\hat{\beta}_{it} r_{Mt}\right]$ and thus concludes that, "…to a very large extent, the interaction term ($\hat{\beta}_{it} r_{Mt}$) models the level of portfolio returns well and offers good evidence in support of the CAPM" (p. 1237)[7].

Utilizing and building upon previous analyses, the present empirical analysis begins by modifying the CAPM to make it more forward-looking, by making an adjustment in the measurement of a firm's beta that incorporates the dispersion (standard deviation) of financial analysts' forecasts. In fact, some researchers maintain that dispersion of analysts' forecasts may be a more reliable and accurate index of a security's systematic risk, than the traditional beta measure itself (Carvell and Strebel, 1984; Harris, 1986; Conroy and Harris, 1987). The [consensus] reasoning is that dispersion of analysts' forecasts may indirectly measure the sensitivity of securities to underlying macroeconomic factors (such as movements in the general stock markets, in economic activity [GDP], in the inflation rate and in the exchange rate). Thus, standard deviation of analysts' forecasts may serve as an effective (and more forward-looking) proxy for systematic [market-related] risk. In this way, with this modification of beta in the estimation of the CAPM, we are attempting to infuse an additional layer of *independent information content* into the CAPM (over and above the *information content* generated by *interaction effect* between beta and market return, as captured by the cross-product term $\hat{\beta}_{it} r_{Mt}$). An additional *information content* provided by the *modified beta* may then be reflected in the *earnings growth forecasts* generated from the thus modified CAPM.

We then form weighted-average combinations of the modified CAPM-generated forecasts and the financial analysts' consensus forecasts [IBES] of firm-earnings growth (using estimated regression coefficients from OLS tests of *independent information* as forecast weights), attempting to generate a superior forecasting model. Testing is then conducted by calculating and comparing *mean absolute forecast error* (MABE) to determine which (if any) of the different forecasting methods examined in the present analysis proves superior (with regard to the component forecasting models [traditional-CAPM; modified-CAPM; IBES] and the various combining models of the present study, respectively). Ultimately, we

[6]For the full derivation of the empirical Security Market Plane (SMP) model from the SLB market model (Black, Jenson, and Scholes, 1972), see Bollen, 2010: p. 1233.

[7]Other, subsequent empirical studies employing data from a different equity market and across different time periods, have provided confirmation and further elaboration of the interaction effect between beta and excess market-return and its impact on asset return (See Terregrossa and Eraslan, 2016, 2020).

want to determine if a weighted-average combination forecast proves superior to the financial analysts' consensus forecasts [IBES] of earnings growth.

## 3. Methodology

An implicit forecast of the five-year average, annual growth rate of earnings-per-share (EPS), for each firm in a given sample, is obtained from the CAPM, using a technique introduced by Rozeff (1983), and modified in a later study[8].

Combinations of financial analysts' consensus forecasts (IBES) and implicit CAPM-generated forecasts of five-year average, annual earnings-growth (for each firm in a given sample) are then formed, which can be expressed as:

$$F_{ci} = W_A\left(\text{IBES }[\text{Model A}]\text{ forecast}_i\right) + W_B\left(\text{CAPM }[\text{Model B}]\text{ forecast}_i\right)$$

$$F_{ci} = W_A\left(\text{IBES }[\text{Model A}]\text{ forecast}_i\right) + W_C\left(\text{CAPM }[\text{Model C}]\text{ forecast}_i\right)$$

Combination weights ($W_A$, $W_B$ *and* $W_C$) are generated using cross-sectional regressions, thus incorporating information from all firms in a given sample. Actual values are regressed on predicted values in the following manner:

$$\begin{aligned} & g_{it}\left(\text{in sample}\right) \\ & = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iBt(t-5)}\left[\text{CAPM}\left(\text{Model B}\right)\right]\right) + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} & g_{it}\left(\text{in sample}\right) \\ & = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iCt(t-5)}\left[\text{CAPM}\left(\text{Model C}\right)\right]\right) + \varepsilon_{it} \end{aligned} \tag{4}$$

where,

$g_{it}$ = actual five-year average, annual growth-rate of EPS of firm $i$ over the 60 months preceding time $t$;

$\hat{g}_{iAt(t-5)}\left[\text{IBES}\left(\text{Model A}\right)\right]$ = consensus forecast of the five-year average, annual EPS growth rate of firm $i$, made by financial analysts (Model A) in period $t$ – 5, taken from the IBES data-source;

$\hat{g}_{iBt(t-5)}\left[\text{CAPM}\left(\text{Model B}\right)\right]$ = forecast of the five-year average, annual EPS growth rate of firm $i$, generated from the CAPM-based forecasting-mechanism that employs the *traditional beta* (Model B), using only information available at time $t-5$, and using the model's estimation-procedure and forecasting-method each period;

$\hat{g}_{iCt(t-5)}\left[\text{CAPM}\left(\text{Model C}\right)\right]$ = forecast of the five-year average, annual EPS growth rate of firm $i$, generated from the CAPM-based forecasting-mechanism that employs the *modified beta* (Model C), using only information available at time $t$-5, and using the model's estimation-procedure and forecasting-method each period;

$\varepsilon_{it}$ = error term;

[8]See Terregrossa (1999) for a detailed description and explanation of the CAPM based forecasting-method that is employed in the present study to generate the statistical component-forecast of EPS growth.

$\alpha$ = constant term.

Using constrained [the sum-of-the-coefficients constrained to sum-to-one] ordinary-least-squares (OLS)[9], the regression model is estimated four ways:

1) With a constant, and employing the CAPM-based forecasts that reflect the traditional-beta (Model B);

2) With a constant, and employing the CAPM-based forecasts that reflect the modified-beta (Model C);

3) With the constant suppressed, and employing the CAPM-based forecasts that reflect the traditional-beta (Model B);

4) With the constant suppressed, and employing the CAPM-based forecasts that reflect the modified-beta (Model C).

Each of the four sets of estimated regression-coefficients are then alternately used as forecast-weights for out-of-sample combination-forecasts of five-year average, annual EPS growth, for each firm in a cross-sectional sample, for a given time period.

Combinations are also formed using five different, simple weighted-averages: equally-weighted (0.50/0.50); and asymmetrically-weighted (0.75/0.25); (0.80/0.20); (0.85/0.15); (0.90/0.10). The financial analysts' forecasts are ***a priori*** assigned the greater weights in the *asymmetric averages*, since these forecasts can reasonably be expected to embody a greater information-content than the CAPM-generated forecasts. One set of these simple-average combinations uses the CAPM-based forecasts that employ the traditional-beta (Model B), in conjunction with the analysts' consensus forecasts (IBES); and the other set combines the IBES forecasts with the CAPM-based forecasts that are based on the modified-beta (Model C).

Thus overall, fourteen different combination-forecasts are formed for each firm in a given sample, for a given time period.

### 3.1. Estimating the *Traditional Beta* $\beta_{Ti}$ and Expected Security Return $E(R_{it})$

The Capital Asset Pricing Model states that, in equilibrium, an individual security's expected return is a linear function of it covariance of return with the market portfolio. This relationship (as detailed above in Section 2) is depicted in ex-ante form by the equation:

$$E(R_{it}) = \beta_i \left[ E(R_{Mt}) - R_{ft} \right] \tag{5}$$

A firm's expected return, $E(R_{it})$, is calculated by the CAPM in the following

[9]Constrained-OLS (with the sum-of-the-coefficients constrained to sum to one; and with the constant supressed) is employed in the present study to generate forecast-weights, as this technique has been shown to generate more accurate out-of-sample combination-forecasts, than by using unconstrained-OLS. The explanation is that constrained OLS generates more efficient estimators (lower dispersion around the mean) but at the expense of induced bias. The trade-off has proved effective in improving forecast accuracy. For a more detailed explanation of the merits of this approach and supportive empirical evidence, see Terregrossa (2005); Terregrossa and Ibadi (2021); Torres-Pruñonosa et al. (2022).

manner:

First, a characteristic-line is generated to manufacture a conventional (traditional) estimate of a firm's index of systematic risk [beta] ( $\hat{\beta}_{Ti}$ ): Actual, monthly security-returns, ($R_{it}$) [thirty-day geometric mean] are regressed against actual, monthly market-returns ($R_{Mt}$) [thirty-day geometric mean] over the 60-month period prior to a forecast-horizon. This regression in equation form is:

$$R_{it} = \beta_{Ti}\left(R_{Mt}\right) \tag{6}$$

The monthly market-return ($R_{Mt}$) is a value-weighted measure of the returns of all stocks on the Centre for Research of Security Prices (CRSP). All returns (firm and market) include both dividends and price-changes.

Once a firm's traditional-beta ($\beta_{Ti}$) is estimated by Equation (6), it is then inserted into Equation (5) (in place of $\beta_i$), to solve for a firm's expected rate of return [$E(R_{it})$]. (In Equation (5) the risk-free rate ($R_{ft}$) is taken as the yield-to-maturity on a five-year U.S. government security prevailing at the beginning of a forecast-horizon[10]. The data source is Moody's Municipal and Government Manual. The mean market return [$E(R_{Mt})$] is estimated as the average of the monthly market-returns over the 60-month period prior to a forecast-horizon. This measure is a value-weighted index of all stocks on the CRSP tape.) An earnings-growth forecast for firm $i$ is then generated by the CAPM forecasting-mechanism, employing the traditional-beta.

### 3.2. Estimating the *Modified Beta* $\beta_{Mi}$ and Expected Security Return $E(R_{it})$

The traditional-beta ($\beta_{Ti}$) estimate is then modified with the dispersion (standard-deviation) of analysts' earnings-growth forecasts to form a more forward-looking index of a firm's systematic risk ($\beta_{Mi}$), as follows[11]:

$$\beta_{Mi} = \left(\beta_{Ti}^2 + \beta_{Ei}^2\right)^{0.5} \tag{7}$$

where:

$\beta_{Ti}$ = traditional (or conventional) beta estimated from a characteristic-line, based on historical information (as shown in Equation (6) above);

$$\beta_{Ei} = \sigma_{im}\left(\sigma_a / \sigma_m\right);$$

$\sigma_{im}$ = historical correlation-coefficient between the return of security i and the return of the market-portfolio;

$\sigma_a$ = standard deviation in analysts' forecasts;

$\sigma_m$ = historical standard-deviation in the return of the market-portfolio;

$\sigma_i$ = historical standard-deviation in the return of security $i$;

$\sigma_{im}$, $\sigma_i$, and $\sigma_m$ values are obtained from the conventional-beta ($\beta_T$) regressions (Equation (6));

[10]A five-year government bond-yield is used as the risk-free rate in the CAPM forecasting-mechanism, to correspond with the desired five-year forecast-horizon, following Rozeff (1983).

[11]See Carvell and Strebel (1984) for the derivation, and further explanation of the modified-beta used in the present study.

$\sigma_a$ values are obtained from the IBES data source.

This more forward-looking index of ex-ante systematic risk ($\beta_{Mi}$) is then inserted (in place of $\beta_i$) into Equation (5) to solve for the firm's expected rate of return [$E(R_{it})$].

An earnings-growth forecast for firm $i$ is then generated by the more forward-looking CAPM forecasting-mechanism, employing the modified-beta.

### 3.3. Samples and Test Procedures

#### 3.3.1. Samples[12]

The first in-sample coefficient-estimation period is the five-year period from January 1982 to January 1987. Using only information available prior to January 1982, and employing the CAPM-based forecasting-mechanism, a simulated ex-ante forecast of the average, annual earnings-per-share (EPS) growth-rate over the January 1982-January 1987 period is made, for each firm in the sample. The actual, average annual EPS growth-rates over this period are then regressed against financial analysts' (IBES) consensus-forecasts and CAPM-generated forecasts for this period, to generate the four sets of regression-coefficients to be used as forecast-weights for the out-of-sample combination-forecasts, for each firm in a given sample (as explained above).

The first out-of-sample forecast horizon is the adjacent five-year period from January 1983 to January 1988. For each firm in the sample, employing the CAPM (Model B; Model C) based forecasting-method, a simulated ex-ante forecast for the January 1983-January 1988 period is then made. For each firm in the sample, combinations of CAPM-generated (Model B; Model C) forecasts and financial analysts' consensus-forecasts for this period are then formed, using in turn the four different sets of regression-coefficients (generated from the January 1982-January 1987 in-sample coefficient-estimation period) as weights for the combination-forecasts.

The four sets of (1982-1987) estimated regression-coefficients are also used to manufacture out-of-sample combination-forecasts for the five-year period from January 1984 to January 1989; and also for the five-year period from January 1985 to January 1990. Thus, the temporal stability of a given set of forecast-weights is tested.

The experiment is replicated twice more: The second coefficient-estimation period is from January 1983 to January 1988, generating four sets of forecast-weights for out-of-sample combination-forecasts for the adjacent five-year period from January 1984 to January 1989; and also for the five-year period from January 1985 to January 1990.

The third coefficient-estimation period is from January 1984 to January 1989,

[12]For a detailed list and explanation of the criteria each firm must satisfy to be included in a given sample of firms, chosen from the Centre for Research of Security Prices (CRSP) data source, for each forecast horizon of the present analysis, see Terregrossa, 1999: p 149. The present analysis utilizes the same, exact data set; which allows direct and true comparisons with regard to previous analyses.

leading to out-of-sample combination-forecasts for the adjacent five-year period from January 1985 to January 1990[13].

As explained above, the present study also forms combinations using simple averages (equally- and asymmetrically-weighted), for each of the three forecast-horizons (1983-1988, 1984-1989, and 1985-1990)[14].

#### 3.3.2. Test Procedures

Let

$a_i$ = actual five-year average, annual growth rate of earnings-per-share (EPS) for firm *i*;

$g_{ij}$ = forecasted five-year average, annual growth rate of EPS for firm *i* by method *j* (where method *j* ranges from one to seventeen)[15].

In each test period a vector of forecast errors is calculated for each method *j*:

$$\left|a_i - g_{ij}\right| = e_{ij} \tag{8}$$

$e_{ij}$ is the absolute value of the difference between the forecasted and realised growth-rates. The mean absolute forecast error (MABE), defined as the sample average of $|a_i - g_{ij}|$, is then computed. This measure best reflects the overall forecasting-performance of a given forecasting-method since it takes into account the average error size.

## 4. Empirical Results and Discussion

### 4.1. Results Summary

First, with regard to the constrained OLS regression tests of *independent information* (Equations (3) and (4)), Table 1 indicates that for each of the three sets of *in sample* estimation periods and corresponding regressions, the estimated coefficients of the forecasts generated by the financial analysts' structural model [IBES (Model A)] are significantly positive, each with a *t-stat* > 2.00. And the estimated coefficients of the forecasts generated by each of the two forms of the CAPM forecasting method (Models B and C) are likewise significantly positive: For the regressions over the first two estimation periods, these estimated CAPM-method coefficients also each have a *t-stat* > 2.00. For the third estimation period, the estimated CAPM-method (Models B and C) coefficients each have a *t-stat* approximately equal to 1.00, which implies a statistical significance by way of the Theil (1957, 1966) test.

[13]The combinations of the present study formed with in-sample regression-coefficients as weights, may be considered out-of-sample in the sense that some portion of a combination-forecast horizon is outside the in-sample estimation period.

[14]The combinations formed of asymmetric proportions, with the analysts' forecasts assigned the greater weight, may be considered to be simulated ex-ante forecasts in the sense that, *a priori*, an earnings forecaster could reasonably be expected to assign the analysts' forecast a larger weight on the grounds that the analysts' forecast embodies a broader information set.

[15]For each firm, in a given sample and in a given test period, there is a financial analysts' consensus forecast, a CAPM-generated ex-ante simulated forecast using the traditional-beta, a CAPM-generated ex-ante simulated forecast using the modified-beta, and fourteen ex-ante simulated combination-forecasts.

**Table 1.** (a) *In sample* OLS regression results (Equation (3) and Equation (4)): $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iBt(t-5)}[\text{CAPM}(\text{Model B})]\right) + \varepsilon_{it}$; $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[IBES]\right) + \gamma\left(\hat{g}_{iCt(t-5)}[\text{CAPM}(\text{Model C})]\right) + \varepsilon_{it}$. 1982-1987 estimation-period. (b) *In sample* OLS regression results (Equation (3) and Equation (4)): $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iBt(t-5)}[\text{CAPM}(\text{Model B})]\right) + \varepsilon_{it}$; $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iCt(t-5)}[\text{CAPM}(\text{Model C})]\right) + \varepsilon_{it}$. 1983-1988 estimation-period. (c) *In sample* OLS regression results (Equation (3) and Equation (4)): $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iBt(t-5)}[\text{CAPM}(\text{Model B})]\right) + \varepsilon_{it}$; $g_{it}(\text{in sample}) = \alpha + \beta\left(\hat{g}_{iAt(t-5)}[\text{IBES}]\right) + \gamma\left(\hat{g}_{iCt(t-5)}[\text{CAPM}(\text{Model C})]\right) + \varepsilon_{it}$. 1984-1989 estimation-period.

(a)

| 475 firms: **Equation (3)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 0.30739 | 0.86769 | 0.13230 |
| t-statistic | (0.319) | (18.868) | (2.877) |
| standard error | 0.946 | 0.046 | 0.046 |
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.87708 | 0.12292 |
| t-statistic | NC | (24.857) | (3.484) |
| standard error | | 0.035 | 0.035 |

*Sum-of-the-coefficients constrained to sum-to-one.

| 475 firms: **Equation (4)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 0.30856 | 0.86762 | 0.132377 |
| t-statistic | (0.320) | (18.866) | (2.878) |
| standard error | 0.964 | 0.046 | 0.046 |
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.87705 | 0.12295 |
| t-statistic | NC | (24.857) | (3.485) |
| standard error | | 0.035 | 0.035 |

*Sum-of-the-coefficients constrained to sum-to-one.

(b)

| 478 firms: **Equation (3)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 3.05786 | 0.68738 | 0.31262 |

**Continued**

| | | | |
|---|---|---|---|
| t-statistic | (2.197) | (7.243) | (3.294) |
| standard error | 1.392 | 0.095 | 0.095 |
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.86965 | 0.13035 |
| t-statistic | NC | (18.786) | (2.816) |
| standard error | | 0.046 | 0.046 |

*Sum-of-the-coefficients constrained to sum-to-one.

| 478 firms: **Equation (4)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 3.05992 | 0.68712 | 0.31288 |
| t-statistic | (2.199) | (7.239) | (3.296) |
| | | 0.095 | 0.095 |
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.85956 | 0.13045 |
| t-statistic | NC | (18.778) | (2.817) |
| standard error | | 0.046 | 0.046 |

*Sum-of-the-coefficients constrained to sum-to-one.

(c)

| 484 firms: **Equation (3)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 1.44231 | 0.84193 | 0.15807 |
| t-statistic | (0.591) | (4.923) | (0.924) |
| standard error | 2.441 | 0.171 | 0.171 |
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.93558 | 0.06410 |
| t-statistic | NC | (14.595) | (1.005) |
| standard error | | 0.064 | 0.064 |

*Sum-of-the-coefficients constrained to sum-to-one.

| 484 firms: **Equation (4)** | ***α*** | ***β*** | ***γ*** |
|---|---|---|---|
| | ***Constrained OLS**** | | |
| Estimated coefficients | 1.45974 | 0.84055 | 0.15945 |
| t-statistic | (0.598) | (4.912) | (0.932) |
| standard error | 2.441 | 0.171 | 0.171 |

**Continued**

| | | | |
|---|---|---|---|
| | ***Constrained OLS*, with the constant suppressed*** | | |
| Estimated coefficients | | 0.93538 | 0.06462 |
| t-statistic | NC | (14.585) | (1.008) |
| standard error | | 0.064 | 0.064 |

*Sum-of-the-coefficients constrained to sum-to-one.

Second, with regard to the CAPM-generated forecasts of firm-earnings growth, Tables 2(a)-(c) indicate that in each of the three possible test-periods of our data set, the CAPM forecasting-mechanism employing the modified-beta ($\beta_M$) on average outperformed the CAPM forecasting-mechanism employing the more traditional beta-measure ($\beta_T$) in terms of lower mean absolute forecast error (MABE) (See Tables 2(a)-(c)). The relevant comparisons are between the MABEs of Model B [(CAPM; $B_T$)] and Model C [CAPM; $B_M$)].

Third, Tables 2(a)-(c) also indicate that the structural model underlying the IBES consensus forecasts consistently outperforms both the modified and traditional CAPM in the present study, in terms of lower average forecast error (MABE) (See Tables 2(a)-(c)). The relevant comparisons are between the MABEs of Model A [IBES] and Model B [(CAPM; $B_T$)]; and between Model A [IBES] and Model C [CAPM; $B_M$)].)

Fourth, in each of the three test-periods, a weighted-average combination (with estimated OLS coefficients utilized as forecast weights) formed with financial analysts' consensus forecasts and the modified CAPM-generated (Model C) forecasts generally proved superior, in terms of forecast accuracy, compared to the financial analysts' consensus forecasts [IBES] (See Tables 2(a)-(c)). And in each of three test-periods, regarding the set of combining-models formed with simple-averages of asymmetric-proportions, a combining-model employing the CAPM estimated with the modified-beta again proved superior to the financial analysts' consensus forecasts [IBES], in terms of forecast accuracy (See Table 3)[16].

## 4.2. Discussion of Results

Firstly, overall, the constrained OLS regression analysis indicates the existence of an *independent information content* in each of three component models of the present study (IBES; CAPM estimated with traditional beta; CAPM estimated with modified beta). Further, the constrained OLS regression analysis of our study does indicate an *information content* in each of the CAPM forecasting-mechanisms (Models B and C) that financial analysts appear to be not fully utilizing in their forecast generating mechanism. The implication is that superior forecasting may be achieved by forming weighted average combinations of the respective, component model forecasts (IBES [Model A] and CAPM [Model B]; (IBES [Model A] and CAPM [Model C].

[16]The two combining models formed with equally-weighted simple averages (Model 5 and Model 6) proved inferior to the analysts' forecast mechanism [IBES].

**Table 2.** (a) Mean Absolute Forecast Error (MABE) Summary Table. (In Percentages) (Note: All out-of-sample combination-forecasts are formed with estimated regression-coefficients from the 1982-1987 estimation-period.) (b) Mean Absolute Forecast Error (MABE) Summary Table. (In Percentages) (Note: All out-of-sample combination-forecasts are formed with estimated regression-coefficients from the 1983-1988 estimation-period.) (c) Mean Absolute Forecast Error (MABE) Summary Table. (In Percentages) (Note: All out-of-sample combination-forecasts are formed with estimated regression-coefficients from the 1984-1989 estimation-period).

(a)

| Forecast horizon: | 1983-88 | 1984-89 | 1985-90 |
|---|---|---|---|
| Model A (IBES) | 10.2015 | 10.9918 | 13.03 |
| Model B (CAPM; $B_T$) | 13.4298 | 14.2684 | 17.4012 |
| Model C (CAPM; $B_M$) | 13.4275 | 14.2644 | 17.3989 |
| Model 1 ($B_T$; WC) | 9.9405 | 10.7954 | 12.8764 |
| Model 2 ($B_M$; WC) | 9.9406 | 10.7954 | 12.8763 |
| Model 3 ($B_T$; NC) | 9.9204 | 10.7622 | 12.8736 |
| Model 4 ($B_M$; NC) | 9.9204 | 10.7621 | 12.8735 |

Notes: Model A represents the financial analysts' forecasting-mechanism (IBES). Model B is the CAPM-based forecasting-model employing the traditional-beta, $B_T$. Model C is the CAPM-based forecasting-model employing the modified-beta, $B_M$. Model 1 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 2 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the modified-beta, $B_M$. Model 3 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 4 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the modified-beta, $B_M$.

(b)

| Forecast horizon: | 1984-89 | 1985-90 |
|---|---|---|
| Model A (IBES) | 10.9918 | 13.03 |
| Model B (CAPM; $B_T$) | 14.2684 | 17.4012 |
| Model C (CAPM; $B_M$) | 14.2644 | 17.3989 |
| Model 1 ($B_T$; WC) | 11.001 | 12.9212 |
| Model 2 ($B_M$; WC) | 11.0009 | 12.921 |
| Model 3 ($B_T$; NC) | 10.7541 | 12.871 |
| Model 4 ($B_M$; NC) | 10.754 | 12.8709 |

Notes: Model A represents the financial analysts' forecasting-mechanism (IBES). Model B is the CAPM-based forecasting-model employing the traditional-beta, $B_T$. Model C is the CAPM-based forecasting-model employing the modified-beta, $B_M$. Model 1 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 2 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the modified-beta, $B_M$. Model 3 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 4 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the modified-beta, $B_M$.

(c)

| Forecast horizon: | 1985-90 |
|---|---|
| Model A (IBES) | 13.03 |
| Model B (CAPM; $B_T$) | 17.4012 |
| Model C (CAPM; $B_M$) | 17.3989 |
| Model 1 ($B_T$; WC) | 12.9205 |
| Model 2 ($B_M$; WC) | 12.9012 |
| Model 3 ($B_T$; NC) | 12.9248 |
| Model 4 ($B_M$; NC) | 12.9245 |

Notes: Model A represents the financial analysts' forecasting-mechanism (IBES). Model B is the CAPM-based forecasting-model employing the traditional-beta, $B_T$. Model C is the CAPM-based forecasting-model employing the modified-beta, $B_M$. Model 1 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 2 is the combining-model with weights generated by constrained-OLS with a constant, and employing the CAPM-forecast using the modified-beta, $B_M$. Model 3 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the traditional-beta, $B_T$. Model 4 is the combining-model with weights generated by constrained-OLS with the constant suppressed, and employing the CAPM-forecast using the modified-beta, $B_M$.

**Table 3.** Mean Absolute Forecast Error (MABE) Summary Table (In Percentages). (Note: All combination-forecasts are simple weighted-averages, with the analysts' forecasts assigned the greater weight in the asymmetric averages).

| Forecast horizon: | 1983-88 | 1984-89 | 1985-90 |
|---|---|---|---|
| Model A (IBES) | 10.2015 | 10.9918 | 13.03 |
| Model B (CAPM; $B_T$) | 13.4298 | 14.2684 | 17.4012 |
| Model C (CAPM; $B_M$) | 13.4275 | 14.2644 | 17.3989 |
| Model 5 (0.50/0.50; $B_T$) | 10.3406 | 11.3192 | 13.7952 |
| Model 6 (0.50/0.50; $B_M$) | 10.3399 | 11.3183 | 13.7945 |
| Model 7 (0.75/0.25; $B_T$) | 9.8656 | 10.7321 | 12.9735 |
| Model 8 (0.75/0.25; $B_M$) | 9.8654 | 10.7319 | 12.9732 |
| Model 9 (0.80/0.20; $B_T$) | 9.8565 | 10.7106 | 12.8997 |
| Model 10 (0.80/0.20; $B_M$) | 9.8564 | 10.7105 | 12.8995 |
| Model 11 (0.85/0.15; $B_T$) | 9.8838 | 10.7355 | 12.8704 |
| Model 12 (0.85/0.15; $B_M$) | 9.8838 | 10.7354 | 12.8702 |
| Model 13 (0.90/0.10; $B_T$) | 9.9617 | 10.7901 | 12.8873 |
| Model 14 (0.90/0.10; $B_M$) | 9.9618 | 10.7901 | 12.8872 |

Notes: $B_T$ indicates a combining-model employing the CAPM with the traditional-beta; $B_M$ indicates a combining-model employing the CAPM with the modified-beta.

Additionally, if we compare the estimated coefficients of the respective CAPM forecasting-mechanisms (Models B and C) of equations 3 and 4 (respectively), in each of the three estimation periods, we see that the Equation (4) estimated coefficients corresponding to the CAPM-forecasting method employing the modified beta (Model C) have slightly higher values than those corresponding to the method employing the traditional beta (Model B). (Which of course also means that the Equation (4) estimated regression coefficients of the IBES forecasts have slightly lower respective values than those corresponding to regression Equation (3), since the regression coefficients in each equation are constrained to-equal-one.) Which is all suggestive of an additional layer of *independent information content* in the forecasts generated by the CAPM employing the modified beta, over and above the *information content* generated by the *interaction effect* between beta and market return (as captured by the cross-product term $\hat{\beta}_{it} r_{Mt}$).

Secondly, we see that the adjustment in estimating firm-beta (that incorporates the dispersion [standard deviation] of analysts' forecasts) leads to more accurate CAPM-generated forecasts of firm-earnings growth. Therefore, the present study does find that the modified CAPM consistently generates more accurate forecasts of earnings growth than the more traditional version of the CAPM; which is perhaps even more suggestive of a greater *information content* in the modified CAPM (compared to the evidence provided by the constrained OLS regressions, presented above).

Thirdly, however, the structural model underlying the IBES consensus forecasts consistently outperforms both the modified and traditional CAPM in the present study, in terms of lower average forecast error (MABE). This outcome is not surprising; and, in fact is expected, considering that the financial analysts certainly take into account a much greater information set in forming their growth forecasts. This expectation is verified by the estimated regression coefficients reported in **Table 1**, which are indicative of a much broader information set reflected in the financial analysts' consensus forecasts, in comparison with the respective CAPM-generated forecasts (Models B and C), with an approximate range in magnitude from [0.70 (IBES), 0.30 (CAPM)] to [0.85 (IBES), 0.15 (CAPM)], respectively.

Fourthly, nonetheless and most importantly, in each of the three test-periods, an *out-of-sample* combination forecast (with *in-sample* estimated OLS coefficients serving as forecast weights) formed with financial analysts' consensus forecasts and the modified CAPM-generated (Model C) forecasts generally proved superior, in terms of forecast accuracy, compared to the financial analysts' consensus forecasts [IBES]. Likewise, regarding the set of combining-models formed with simple-averages of asymmetric-proportions, a combining-model employing the CAPM estimated with the modified-beta also proved superior to the financial analysts' consensus forecasts [IBES], in terms of forecast accuracy.

Thus, utilization of the more *forward-looking* beta generally led to more accurate forecasts by the CAPM forecasting-mechanism (Model C); and in turn (and most importantly), superior forecasts by the combining-models of the present study.

## 5. Summary and Conclusions

The present study finds that incorporating the dispersion of analysts' forecasts into the estimation of beta generally leads to better CAPM-generated forecasts of earnings-growth, and in turn, improved weighted-average combinations of financial analysts' consensus-forecasts [IBES] and CAPM-generated forecasts of firm earnings-growth. These combination forecasts prove superior to either component model forecasts (CAPM [Model C] and IBES). Although in some cases the improvement in forecasting performance is slight, small differences in compound earnings-growth can translate into large differences in the absolute level of future earnings. Stock price is of course a direct function of the absolute level of current and future earnings.

The findings of the present study also strongly indicate a temporal-consistency regarding the set of combining-models that use constrained OLS *in-sample* estimated regression-coefficients as forecast-weights: In five out of the six possible test-periods, the combining-model that is formed with estimated regression coefficients from *in sample* constrained OLS with the *constant supressed*, and uses the *modified-beta* in the CAPM forecasting-mechanism (Model 4) had the lowest mean-absolute-forecast-error (MABE). In the remaining test period, the best combination (formed with *in-sample* estimated regression-coefficients as forecast-weights) included a constant term in the constrained OLS regression. In this latter case, the *modified-beta* was again employed in the CAPM forecasting-mechanism. (See Tables 2(a)-(c)) One part of the explanation regarding this particular, demonstrated *temporal-consistency* is that by supressing the constant term in the OLS regression equation, the standard errors of the estimated coefficients are reduced by more than half, approximately; leading to more efficient estimators; which in turn leads to increased forecast accuracy of the combining model. And of course the other part of the explanation, regarding this particular *temporal-consistency*, is the greater *independent informational content* of the CAPM forecasting-mechanism that employs the *modified-beta*.

Regarding the combination-forecasts formed with simple weighted-averages: In all three test periods, each asymmetrically weighted combination that employs the CAPM with the *modified-beta* proved superior to the financial analysts' consensus forecasts [IBES] (See Table 3).

Thus overall, in each possible test-period a combining-model employing the more forward-looking CAPM estimated with the modified-beta had the greatest forecast-accuracy. And in a large majority (about 80%) of matched-pair trials (which directly compare the performance of the various combining-models employing the modified- and traditional-betas, respectively) the most successful combination-forecast technique employed the modified-beta in the CAPM forecasting-mechanism. In conclusion, our analysis indicates that adjusting beta with dispersion of analysts' forecasts leads to greater *informational content* and generally improved forecast accuracy by the CAPM forecasting-mechanism, and in turn (and most importantly), generally more accurate (and superior) weighted-average combinations of CAPM-generated forecasts and financial analysts' consensus-forecasts of firm-earnings growth.

## Conflicts of Interest

There are no conflicts of interest.

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