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The Performance of Alternative methods for Estimating Equity Betas of Jordan Industries

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Abstract
This paper discovers the industry cost of equity for Jordan. Initially, after ranking Jordan industries into five portfolios are based on sorting four variables; beta, size, value and momentum factors. This paper shows that none of the return differences regarding these four factors are significant at the 5% level. Further, the paper also investigates the bias of the standard CAPM approach for each industry separately, and examines the effectiveness of alternative beta estimators. The finding of this work shows that constant betas produce better estimates of cost of equity for particular industries (mostly either 'defensive' or 'high-risk' industries). The paper succeeds in offering a meaningful assessment of the empirical reality of the CAPM, as well as offering guidance concerning the suitable practical application of the CAPM when estimating industry cost of equity.
Keywords: Cost of Equity, Fama and French, Defensive Industries, Constant Beta

1. Introduction

The CAPM model is a one-period model developed by Sharpe (1964) and Lintner (1965) that relates the expected return on an asset or security to its systematic risk. There is a longstanding debate about whether the CAPM is a useful model for estimating the cost of equity. A number of researchers argue that the CAPM does not succeed as a standard for asset pricing explained by Dempsey (2013) or that it does not provide precise results because it depends on the OLS beta which frequently produces biased results examined by Homaifar and Graddy (1991). In a landmark paper, Fama and French (1992) report that the CAPM fails empirically because they observe only a flat relationship between average return and the CAPM beta. Their finding is consistent with most later studies such as Chui and Wei (1998) and Daniel and Titman (1997), although the reasons for the empirical failure of the CAPM remain controversial.

Fama and French's (1993) three-factor model is an empirically-driven alternative to the CAPM. It adds a size factor and a book-to-market factor to the market factor. The three-factor model is designed to capture the size and book-to-market effects which caused problems for the CAPM. The proponents claim that firm size and book-to-market are proxies for distress risk, and that distressed companies are more affected by business cycles than are companies with less distress risk. Fama and French (1993) show that there are five common factors which affect and can explain stock and bond returns. Three aspects are related to stock returns (the market factor, the size factor and book-to-market equity factor) and two factors are related to bond returns (default and maturity factors). They find that average stock returns can be explained by the market, size and book-to-market factors. This finding is consistent with Fama and French's (1992) earlier findings.

Bornholt (2007) argues that there are problems with the Fama-French three-factor model. Firstly, it still lacks a strong academic basis because it is not driven by asset pricing theory. Secondly, it has not been widely adopted by practitioners for CE estimation because it requires the user to estimate the three factor premiums and the three factor sensitivities. Daniel and Titman (1997) argued that the problem with the three-factor model is that it does not take into consideration all the characteristics needed to explain expected returns. In addition, the three-factor model cannot explain various anomalies such as the momentum anomaly (Liu, 2006).

In their UK study of industry cost of equity, Gregory and Michou (2009) comprehensively examine the performances of the capital asset pricing model (CAPM), the Fama-French (1993, 1996) three-factor model, the Cahart (1997) four-factor model, the conditional CAPM, the three-factor model, and simply assuming beta is unity in the CAPM. They conclude that the performances of rolling CAPM estimates are no worse than estimates produced by more-complex models. Similarly, Fama and French's (1997) US study of industry cost of equity does not provide sufficient empirical justification for switching from the CAPM to their three-factor model. Practically, practitioners continue to depend on the CAPM for estimating the cost of equity.

Empirical studies of estimates of the cost of equity need to examine their efficacy over the time frame of interest for capital budgeting (at least 5 years in most cases). In the present paper, cost of equity estimates are assessed by how well they predict the average annual return over the next one and over the next two years, where average annual return is the proxy for the unknown expected annual return. Unlike previous research, this study evaluates the alternative cost of equity estimates separately for each industry. The outcome is that I will be able to advance methods for estimating industry cost of equity that produce economically and statistically significantly better estimates than current CAPM practice, particularly for many defensive and high-risk industries. For the Automobile & Part industry, for example, a constant beta of 1 produces better cost of equity estimates than does the standard CAPM beta estimator. Importantly, this study introduces a methodology for assessing the predictive ability of cost of equity estimates that is more realistic and that is more aligned with how cost of equity estimates are used by practitioners.

This paper investigates the failings of CAPM-derived cost of equity estimates (CEs) on an industry-by-industry basis, and investigates the potential for improving on the standard CAPM approach through the use of alternative beta estimators. The study will focus on estimating the cost of equity of Jordan industries. Specifically, for each industry this paper examines a number of constant betas, at the same time with a Blume-type beta commonly used by commercial data providers. This approach is motivated by the intuition that a constant beta less than unity may be suitable for some low-risk 'defensive' industries and that a constant beta greater than unity may be suitable for some high-risk industries.

The remainder of the paper is arranged as follows. Section 2 locates the sources of the data for the present study and introduces a measure of defensiveness. Section 3 outlines the methodological approaches that are followed. Section 4 presents the results and offers a brief application of the study to the utility industry, while Section 5 concludes the chapter.

2. Data and Classification of Industries

The basic units of observation are the monthly returns for 28 Jordanian industries and for the Amman Stock Exchange market. Annual returns are derived from these by compounding monthly returns. The time frame of the study is from November 2005 until the end of April 2014. In addition, this study employs average firm size and the value-weighted average firm book-to-market ratio for the 28 Jordanian industries for the same period. The monthly returns (denoted R_{mt}^{m}) of the market are the monthly returns of the Amman Stock Exchange (ASE) market of Morgan Stanley Capital International (MSCI) index downloaded from Datastream. Additionally, the study uses the one to twelve-month Treasury bill rates as the risk-free rate (denoted R_{Ft}^{m}) reported at the beginning of each month for the period from November 2005 to April 2014. All data is downloaded from data stream. The study commences from November 2005 because the Datastream has a less comprehensive coverage of ASE stocks prior to November 2005. The final sample is composed of 102 monthly returns on each industry, on the Jordan market index and the risk-free asset, together with observations on the average firm size and value-weighted average firm book-to-market ratio of each industry.

Across the variety of industries, there are a number of industries that investors treat as 'defensive' in the sense that stocks in a defensive industry are not expected to fall as much as the stocks of other industries during market turn down (Reilly & Brown, 2000). While there are a different of ways that the concept of defensiveness could be defined, in this paper I adopt a relatively straightforward approach. The defensiveness of an industry is measured by its average return in down-market months, where down-market months are these specific months for which the excess return of the market index is negative. This average (denoted 'down-market average') is a measure of an industry's downside systematic risk. The larger an industry's down-market average the more defensive it is considered. The 28 industries are ranked on the basis of their down-market averages, and classified into three groups. The 6 industries with the highest down-market averages will be called defensive industries, the 6 industries with the lowest down-market averages will be called high-risk industries, and the remaining 16 industries will be called medium-risk industries. This division is based on making defensive industries represent the extreme 20% of Jordanian industries, while the high-risk industries represent the extreme 20% of Jordanian industries.

$$\overline{R}_i^{down} = \frac{\sum_{t=1}^{N} R_{it}^{m} . \delta_t}{\sum_{t=1}^{N} \delta_t}$$

Where

R_{it}^{m} is the monthly return of industry i in month t;

N is the total number of monthly returns for industry i;

$R_{mt}^{m} - R_{Ft}^{m}$ is the monthly market index excess return in month t; and

$$\delta_t = \begin{cases} 1 & if \ \ R_{mt}^{m} - R_{Ft}^{m} < 0 \\ 0 & otherwise. \end{cases}$$

[Table 1 about here]

Table 1 provides summary statistics for the 28 Jordanian industry portfolios. The first column gives the full name of the industry. Columns followed the first column report the average and standard deviation of monthly returns, the number of the observation industry, full sample beta, the down-market average of each industry, the logs of the industry value-weighted average book-to-market equity and the logs average firm size. The order of the industries in the table is determined by the defensiveness of the industry, beginning with the most defensive (Tobacco) and ending with the least defensive (Construction & Material). This order is retained in all subsequent tables that report industry names.

The first 6 industries in the table (Tobacco, Forestry & Paper, Automobile & Part, General Retailers, Electricity and Mining), are the defensive industries, the next 16 industries are the medium-risk industries, and the last 6 industries (Electro & Electronic Equipment, Industrial Metals & Mining, Industrial Transportation, Telecommunication, Real Estate-service and Construction & Material) are the high-risk industries. For example, the Tobacco and Forestry & Paper industries are the most defensive industries because they achieve the best average returns in the down market months (1.98% and 1.55% per month, respectively), while the Construction & Material industry is the most high-risk because it achieves the worst average return in the down market months (–2.27% per month).

Table 1 contains a number of interesting features. Not surprisingly, full sample beta and the defensiveness measure are highly correlated: the defensive an industry tends to have the lower beta. The relationship between beta and down-market average is close to monotonic. Looking at the group averages in the final three rows of the table, the findings show that defensive industries tend to have (i) larger average returns, (ii) larger standard deviations, (iii) similar size firms, (iv) slightly smaller BE/ME ratios, and, (v) lesser betas than do high-risk industries.

3. Method

3.1 Applying the CAPM to Cost of Equity

The CAPM model for industry expected returns can be written:

$$E[R_i] = R_F + \beta_i\left(E[R_m] - R_F\right), \qquad (1)$$

Where R_i is the return of industry *i*, R_F is the risk-free rate, β_i is the CAPM beta, and $E[R_m] - R_F$ is the market risk premium. The standard CAPM beta estimate (called the OLS beta in this paper) is usually estimated by regressing the most recent five years of a security's monthly excess returns on the corresponding monthly excess returns of a value-weighted market index. Let β_{iOLSt} denote the OLS beta's value for industry *i* at the end of month *t*. Industry *i*'s expected return in (1) is then estimated by combining this beta estimate with the estimated risk-free rate for the next year (R_{Ft+1}), and with the chosen estimate (denoted MRP) of the annual market risk premium to produce the CE estimate for industry *i* at the end of month *t* given by:

$$CE_{iOLSt} = R_{Ft+1} + \beta_{iOLSt} MRP, \qquad (2)$$

where CE_{iOLSt} denotes the estimated (annual) cost of equity for industry *i* at the end of month *t* based on the standard OLS beta. In the current study, the standard method to estimating the CE described by (2) is denoted the 'CAPM approach' in order to differentiate it from the 'CAPM model' in (1) above and from the alternatives to be discussed below.

3.2 Alternative Beta and Cost of Equity Estimates

This paper compares the out-of-sample performance of industry CE estimates based on (2) with the corresponding results from estimating the CAPM with a number of alternative beta estimators. Let β_{igt} denote an estimate of β_i at the end of month *t* calculated applying approach *g*, where the subscript *g* simply indexes OLS or the various alternative beta estimation methods to be described below (e.g., *g* = OLS, Blume, 0.5, etc.). Replacing the OLS beta in (2) with the general beta estimate β_{igt} gives the estimated CE for industry *i* at the end of month *t* for beta estimation method *g*:

$$CE_{igt} = R_{Ft+1} + \beta_{igt} MRP. \qquad (3)$$

The remainder of this section demonstrates the alternative beta estimators that are used to produce alternative estimates of the CE based on (3).

The first alternative beta is called the Blume-adjusted beta. A common adjustment to standard OLS betas used by commercial data service providers (Bloomberg, Merrill Lynch) is the following Blume-type beta for industry *i* at the end of month *t*:

$$\beta_{iBlumet} = 0.33 + 0.67 \times \beta_{iOLSt} . \quad (4)$$

Blume (1975) observed a tendency for OLS beta estimates to mean-revert over time, and the Blume-type beta in (4) follows the general format that Blume (1975) developed. The Blume-adjusted beta is a shrinkage estimator in the sense that it is always closer to one than is the corresponding OLS beta from which it is constructed.

Given the imprecision of the CE estimates that result from using the OLS beta, researchers have investigated simply using a fixed value of one for beta in CE calculations. In particular, Gregory and Michou (2009) find that a beta of unity underperforms the other methods that they investigated in their study of all UK industries. Their finding is not that surprising because, a priori, I expect that a beta of unity would be too high for low-risk industries. Perhaps for Jordan industries case, and because OLS beta for Jordan industries range around 0 to 0.3, a beta of 0.1 would better suit a low-risk industry, and perhaps a beta of .50 would better suit a high-risk industry for Jordan industry case. Consequently, a variety of constant betas (beta = 0.10, 0.20, 0.30, 0.40,0.50 and 1) are included in this study in order to assess whether or not one or more of them have advantages over the standard OLS approach for some industries.

3.3 Performance Evaluation

The evaluation of the competing CE estimates (CE_{igt} for various *g*) from (3) should not ignore the uses to which CE estimates are frequently put by practitioners. Cost of equity estimates are appraisals of expected equity return that are predominantly calculated in order to incorporate into an estimate of the cost of capital that is then used to discount future cash flows of projects. Since the length of most projects is usually at least five years. For Jordan industry sample and because there is no enough frame time available in this sample which starts from November 2005 until April 2014. These CE estimates adopt reasonable estimates of industry expected return over at least the next one year.[1] However, expected returns are unobservable. This means that this study needs a proxy for the average expected annual return over at least the next one year, and one obvious choice is the average annual return over the next one year. As a robustness check, I investigate the performance of alternative betas over the next two years as well.

Therefore, let A_{it}^{1YR} (A_{it}^{2YR}) denote the average of the one (two) annual returns of industry *i* that pursue month *t*. With one of these averages chosen as the proxy for the expected industry return, this paper defines industry *i*'s forecast error at the end of month *t* based on method *g* (denoted e_{igt}) as this proxy value minus the CE estimate of method *g* at the end of month *t*. That is, $e_{igt} = A_{it}^{1YR} - CE_{igt}$, or $e_{igt} = A_{it}^{2YR} - CE_{igt}$.

In the case of the OLS beta estimate, it is important to recognize if this estimator produces systematically biased CE estimates for a number of industries. This question can be answered by measuring whether each industry's mean forecast error (also denoted as its 'bias') is significantly different from zero. That is, if the OLS method produces *N* errors beginning with $t = \tau$ then

$$Bias_{iOLS} = \frac{1}{N} \sum_{t=\tau}^{N+\tau-1} e_{iOLSt} \quad (5)$$

This study uses mean absolute forecast error (MAE) to measure the performance of a method's CE estimates. Thus if method *g* produces *N* errors beginning with $t = \tau$ then

$$MAE_{ig} = \frac{1}{N} \sum_{t=\tau}^{N+\tau-1} \left| e_{igt} \right| . \quad (6)$$

To compare alternative CE estimates with standard CAPM estimates based on (2), the current study compares method g's mean absolute forecast error with the OLS method's mean absolute forecast error. Therefore the test statistic is the reduction in mean absolute error MAE, defined as

$$Reduction in\ MAE_{ig} = \frac{1}{N} \sum_{t=\tau}^{N+\tau-1} \left(\left| e_{iOLSt} \right| - \left| e_{igt} \right| \right) \quad (7)$$

The null hypothesis of no significant difference is tested using a paired *t*-test. A positive and significant reduction in MAE provides evidence that method *g* produces significantly better CE estimates than does the standard CAPM approach. Note that the forecast errors (the e_{iOLSt} ' s and the e_{igt} ' s) in equations (5) and (7) are

[1] While, in principle, different discount rates could be applied to a project's future cash flows that occur at different times, common practice is to use the one discount rate for all of the project's future cash flows. Hence the desired cost of equity is the average expected return over a suitably large number of years.

consecutive monthly rolling forecast errors that overlap by 11 months in the one-year case and by 23 months in the two-year case. As a result, the conventional *t*-tests for (5) and the paired *t*-tests for (7) use Newey-West (1987) adjusted standard errors that are based on the appropriate number of lags (equal to the degree of overlap).[2]

3.4 Estimating the Market Risk Premium

The cost of equity estimates in (2) and (3) require an estimate (MRP) of the market risk premium. Different choices will produce different degrees of industry bias. This paper defines *average industry bias* as the average of the biases of the 28 industries for the one-year case. To determine an appropriate value for the MRP, this study selects the value of MRP that produces zero average industry bias.

Table 2 compares the average bias across all industries that results from choosing market risk premium estimates ranging from 2% to 18%. As might be expected, the choice of estimate for the market risk premium has a dramatic effect on average industry bias. For example, an MRP of 2% generates an average bias of 1.79% per year. This means that using 2% as the estimate of the market risk premium produces CE estimates that are 1.79% too low on average across all industries. On the other hand, a 18% MRP would produce CE estimates that are 1.47% too high on average across all industries. An MRP of 10.78% results in zero average industry bias, and for this reason hereafter in this study all CE estimates are based on using MRP = 10.78% in equations (2) and (3).

It is clear that this CAPM-based method of determining MRP implicitly favours the OLS beta over alternative betas. Such favouritism means that the current study can rule out the choice of MRP as the likely cause of any evidence of OLS underperformance that the current study may find in investigations into alternative CE estimators. In addition, it is comforting to know that a MRP of 10.78% (in the context of using the annualized Treasury bill rate as the risk-free rate) is a plausible value that practitioners could have selected independently.

It is worth observing that the selection of the risk-free asset and the selection of the value for MRP are interrelated decisions. The traditional options for the risk-free asset are either Treasury bills or a medium-term government bond. Medium-term bonds tend to have bigger returns than Treasury bills, so had a medium-term bond been selected as the risk-free asset then a lower value of MRP would have resulted. For this reason, this study does not expect that different choices for the risk-free asset would materially change the relative rankings of the various CE estimation methods to be tested in this study.

The forecast error methodology in this paper differs in an important respect from the methodology used by many earlier studies. Fama and French (1997) and Gregory and Michou (2009), for example, employ out-of-sample CE estimates that combine beta estimates at time *t* with future market returns to produce their CE estimates. In contrast, the CE estimates at time *t* used in this paper are, except for the derivation of MRP discussed above, based solely on information known at time *t*.

4. Results

This section reports the empirical results for this paper, beginning with a preliminary analysis involving sorts before reporting the cost of equity main results.

4.1 Portfolio Sorts on Beta, Value, Size and Momentum

Gregory and Michou (2009) estimate industry CE for 35 UK industries using several models, including the CAPM, the Fama-French three-factor model, and the Carhart four-factor model that incorporates a momentum factor. They do not find that the more complex models produce significantly better forecasts than those based on rolling CAPM estimates. A potential explanation for the lack of success of the three-factor and four-factor models can be found in the results of Chou, Ho, and Ko (2012). These authors report that the size effect and the value effect are largely intra-industry effects, suggesting that the size and value factors are not relevant to the calculation of industry CE. Momentum also seems unlikely to be relevant to the calculation of industry CE over the time frames of interest in capital budgeting (at least one or two years) as the momentum effect tends to reverse eventually [see, for example, Jegadeesh and Titman (2001)].

To check the relevance of these conclusions to our sample of US industries, the current study first undertakes a preliminary analysis that involves sorting the 28 Jordan industries into five separate sets of portfolios (beta, value, size and momentum portfolios). The ranking variable for the beta sort for month *t* is each industry's OLS beta estimate from the 60 months of excess returns from month *t*-60 to *t*-1. The ranking variable

[2] Although this study could have tested for differences in mean squared error (MSE) rather than mean absolute error, this possibility is not pursued because such a hypothesis is a test about a particular combination of variance and expected value that seems of little direct relevance here. This latter point is derived from the observation that for any random variable *Y*, $E[Y^2] = var(Y) + (E[Y])^2$.

for the value (size) sort for month *t* is each industry's most recent database entry for its value-weighted BM ratio (average firm size) available at the end of month *t*-1. The ranking variable for the momentum sort for month *t* is each industry's six-month return from month *t*-6 to *t*-1.

Each month, the study forms five equally-weighted portfolios (P1, P2,…, P5) by ranking industries based on the past values of the ranking variable relevant to that sort. Thus, each month around the five or six industries with the lowest values of the ranking variable for that month are allocated to P1 while around the five or six industries that month with the highest values of the ranking variable are allocated to P5. This process ensures that portfolios are reformed monthly. Each portfolio's average annual return over the next one year is calculated each month.

Table 3 provides portfolio average annual returns over the first one year following portfolio formation for each of the ranking variables, together with P5−P1 return differences and their associated *t*-values. None of the P5−P1 return differences are significant at the 5% level.

The beta sort results show that the relationship between average industry returns and past OLS beta estimates is too flat to be consistent with the CAPM. A similar pattern has been observed in past studies of stock returns [see, for example Fama and French (1992)]. Such results, however, leave open the question of whether or not the CAPM fails for all industries or just for some. If the problems with the CAPM are restricted to a subset of industries, then further analysis may provide remedies. To address this issue, this study generates industry-specific results.

4.2 Industry Bias

Using 10.78% as the estimate of the market risk premium in equation (3) means that the CAPM based on the OLS beta has zero bias *on average* across the 28 industries. Now consider the industry bias (or mean forecast error) of each industry and each industry group.

Finally, consider the mean forecast errors for the defensive, medium-risk and high-risk industry group portfolios reported in the final three rows of Table 4. The defensive industries portfolio's 1-year and 2-year mean errors are both positive and significant at 9.12% (*t*-stat 2.25) and 10.15% (*t*-stat 4.34), respectively. On the other hand, while the high-risk industries portfolio's 1-year and 2-year mean errors are both negative at - 4.75% and – 4.99%, respectively, only its 2-year mean error is significant (*t*-stat – 3.37), while its 1-year mean error is weakly significant (*t*-stat -1.81). Overall, the results in Table 4 show that the degree of defensiveness of an industry provides useful information about the effectiveness of CE estimates based on the OLS beta.

4.3 Performance Comparisons

This section evaluates the performances of competing CE estimates for each of the 28 Jordan industries. Table 5 reports performance results using the one-year average return as the expected return proxy, while Table 6 uses the two-year average return as the expected return proxy. In these tables, the MAE results based on the OLS beta are reported in the second column as the 'OLS MAE'. The remaining columns provide the reduction in MAE that results from a particular beta method *g* ($\beta_{igt} = 0.33 + 0.67 \times \beta_{iOLSt}$ for the Blume-adjusted beta, and β_{igt} = 0.1, 0.2, 0.3, 0.4, 0.5, and 1 for the constant betas), jointly with the associated *t*-statistics. An alternative procedure is considered to have a better performance than the standard CAPM approach if it produces a reduction in MAE that is positive and significant.

The first observation that can be drawn from Table 5 is that alternative betas provide better performances for three industries: the Tobacco, Automobile & Part, General Retailers industries. In the Automobile & Part industry case, for instance, the Blume-adjusted beta has a 1.97% smaller MAE per year (*t*-statistic 3.42). The constant beta estimate 0.40 produces a significant MAE reduction of 2.37% per year (*t*-statistic 3.19), while the constant beta estimate 0.50 has a significant MAE reduction of 2.81% per year (*t*-statistic 2.97). This latter reduction amounts to a 10% improvement over the OLS MAE (i.e., 0.0281/0.2872 = 0.10). In short, the constant betas 0.50, 0.40, 0.30, 0.20, 0.10 and the Blume-adjusted beta produces economically and statistically significant reductions for the Automobile & Part industry, with beta = 0.5 producing the largest significant improvement over the standard CAPM approach. In contrast, for the General Retailers industry the constant betas 0.30 and 0.20 are the only techniques which produce a statistically significant reduction in MAE (0.97% and 0.44% with *t*-statistic 2.12 and 2.58, respectively). The constant beta estimates 0.40 has larger reductions (1.42%) but this is only weakly significant.

The performances of the alternative CE methods in Table 5 can be summarized as follows. The CE estimates for ten industries can be improved significantly by using one of these alternative techniques, while positive and weakly significant reductions can be observed for another one industry. The significant Blume-adjusted MAE reductions tend to be smaller than the corresponding MAE reductions for those industries from at least one of the constant betas investigated. Of the range of constant betas included in this study, a constant beta of 1 produces the largest significant MAE reductions for the Tobacco industry. Similarly, a constant beta of 0.5 gives the largest significant MAE reduction for the Automobile & Part and Chemical industries. For constant beta of 0.30 and 0.20 provide the largest significant MAE reduction for the General Retailers and Electro and Electronic Equip industries respectively, while a constant beta of 0.10 yields the largest significant reductions for the Travel & Leisure, Banks, Industrial Metals & Mining, and Industrial Transportation industries.

The robustness of these results to the choice of proxy can be checked by replacing the one-year proxy with the two-year proxy. Thus, whereas CE's are used to predict the average annual return over the following one year in Table 5, those same CE's are used to predict average annual returns over the next two years in Table 6. Inspection of the magnitudes of the OLS MAE's in column 2 of both tables shows that the OLS MAE's are smaller in Table 6 than the corresponding OLS MAE's in Table 5 *for every industry*. This strongly suggests that the average annual return over two years is a better proxy for expected annual return (the cost of equity) than is the average annual return over one year.

Recall that for the one-year case in Table 5 there are significant positive reductions in MAE for ten industries (the Tobacco, Automobile & Part, General Retailers, Chemical, Travel & Leisure, Banks, Financial Service, Industrial Metals & Mining, Electo & Electronic Equip and Telecommunication industries), and weakly significant positive reductions in MAE for an additional one industry (the Personal Goods industry). Inspection of Table 6 reveals stronger results. For the two-year case there are significant positive reductions for seventeen industries (the Tobacco, Forestry & Paper, Automobile & Part, General Retailers, Oil & Gas Producer, Chemical, Houshold Good Home, Health care equip. & services, Travel & Leisure, Industrial Engineering, Banks, Personal Goods, Financial Services, Industrial Metals & Mining, Industrial Transportation, Telecommunication and Construction & Material industries and weakly significant positive reductions in MAE for only one industry (the General industries).[3]

The significant results for seventeen industries can be summarized as follows. The largest significant positive reductions are created by a beta of 1 for the Tobacco, Forestry & Paper, General Retailers and Industrial Engineering industries (10.85%, 9.69%, 6.22% and 4.28%, respectively), by a beta of 0.5 for the Oil & Gas Producer and Industrial Transportation industries (0.12% and 1.64%, respectively), by a beta of 0.4 for the Financial Services industry (0.64%), and by a beta of 0.3 for the Houshold Good Home and Health care equip. & service (0.48%, 0.82%,, respectively), by a beta of 0.1 for the Chemical, Industrial Metal & Mining, Telecommunication and Construction & Material industries (3.70%, 5.28%, 1.47% and 1.23%, respectively). These beta/industry combinations can be viewed as indicating the best constant betas to use for these seventeen industries out of the range of constant betas included in this study. It is also reassuring that these best betas from the two-year case are also reasonable choices for the one-year case results in Table 5.

Overall, the results in Tables 5 and 6 show that there are significantly better ways to estimate the CE than the standard CAPM method for some industries. For many other industries there are constant betas that produce economically significant reductions in mean absolute forecast error that are not statistically significant. Such reductions may still be of interest to practitioners for whom any potential improvement is worth considering. An implication of these results is that recommendations about which CE estimation method is appropriate need to be industry-specific. Simple approaches such as always using the OLS beta or always using the beta of unity for all industries are clearly sub-optimal.

4.4 The MAE beta

The results in Tables 5 and 6 above are for a particular Blume-type beta and for constant betas ranging from 0.1 to 1. In this section the current study looks at how large a reduction in MAE can be achieved from a broader range of alternative beta estimators. First, note that the OLS beta, the Blume-adjusted beta and the constant beta estimates discussed above are all members of the class of positive linear transformations of the OLS beta. That is, they each can be written $a_{1i} + a_{2i}\beta_{iOLSt}$, for some nonnegative constants $a_{1i}, a_{2i} \geq 0$. This chapter defines the ex-post optimal beta from this class for a particular industry as the member which minimizes the mean absolute forecast error (MAE) of the CE estimates produced by *unbiased* members of this class. This optimal beta is denoted the MAE beta, and its value for industry i at the end of month t can be written as $\beta_{iMAEt} = \hat{a}_{i1} + \hat{a}_{i2}\beta_{iOLSt}$, where $\hat{a}_{i1}$ and $\hat{a}_{i2}$ are the values of a_{1i}, a_{2i}, respectively, that solve the optimization:

[3] Note that there are nine industries that experience significant reductions that are common to both the one-year and two-year cases (the Tobacco, Automobile & Part, General Retailers, Chemical, Travel & Leisure, Banks, Financial Services, Industrial Metals & Mining, and Telecommunication industries).

$$\underset{a_{i1}\geq 0, a_{i2}\geq 0}{\text{Min}} \quad MAE_{ig} = \frac{1}{N}\sum_{t=\tau}^{N+\tau-1}\left|e_{igt}\right|$$

$$\text{s.t.} \quad \frac{1}{N}\sum_{t=\tau}^{N+\tau-1} e_{igt} = 0, \text{ and}$$

$$\beta_{igt} = a_{i1} + a_{i2}\beta_{iOLSt}$$

where *N* is the number of forecast errors beginning at $t = \tau$, and where the following two-year average return is the expected return proxy used in the calculation of forecast errors $(e_{igt} = A_{it}^{2YR} - CE_{igt})$.

Table 7 reports results for the MAE beta and the corresponding results produced by the OLS beta for each industry. Industries are listed in the table in the order of the magnitude of the reduction in MAE, from largest to smallest. The second column (OLS MAE) contains the MAE produced by the OLS beta. The third column reports the reduction in MAE (OLS MAE less the MAE resulting from using the MAE beta), while the MAE beta's coefficients a_1 and a_2 are listed in columns four and five, respectively. This is followed in the last two columns by the average MAE beta and the average OLS beta over the sample.

Of the six defensive industries, five have reductions in MAE larger than 5%, with the largest three reductions for the Tobacco, General Retailers and Forestry & Paper industries (amounting to 62.06%, 40.10% and 27.66%, respectively). The situation for the six high-risk industries is similar. three high-risk industries produce reductions larger than 5%, with the largest three reductions for the Industrial Metals & Mining, Telecommunication and Construction &Material industries (24.26%, 12.59% and 5.78%, respectively). Turning to the 16 medium-risk industries, only five have reductions in MAE larger than 5% and only one (Industrial Engineering) has a reduction in MAE larger than 15%. In general, the defensive and high-risk industries tend to produce the largest reductions in MAE, and hence they dominate the top half of Table 7. However, there is exception, particularly amongst the defensive industries. The MAE beta of the Mining industry produces small reductions in MAE less than 0.1%.

Table 7 also includes average values for the three industry groupings in the final three rows. The defensive and high-risk industry groups have large reductions in MAE of 25.72% and 8.04%, respectively. In contrast, the average reduction for medium-risk industries is the smallest 6.23%. Notably, the defensive industries average MAE beta of 1.82 is larger than one, even though its average OLS beta is only 0.05. Conversely, the high-risk industries average MAE beta of 0.07 is less than one while its average OLS beta is 0.28. This is just another indication of the systematic failure of the CAPM documented in Tables 3 and 4.

Finally, the results in Table 7 provide an indication that the range of constant beta alternatives considered in Table 6 is not sufficient for those industries identified in Table 4 as having significantly biased OLS beta-based CE estimates. Consider two examples. First, the MAE beta for the defensive Tobacco industry is 4.33, a value far above the maximum value (1) for the constant betas considered in Table 6. Similarly, the MAE beta for the high-risk Industrial Transportation industry in Table 7 is 0.32, a value much lower than the minimum value (0.5) used in Table 6. Of the 15 industries in Table 7 with reductions in MAE exceeding 5% per year, there are 3 industries with MAE betas that are constant betas. This suggests that practitioners may find industry-specific constant betas a useful alternative to the OLS beta in many situations. The next section examines the General Retailers industry in more detail.

4.5 Application to the Automobile & Part industry

Since the regulation of Automobile & Part companies in many jurisdictions involves estimating the Automobile & Part industry's CE via the CAPM, the adequacy of such estimates is of particular interest. As reported in Table 4, the CAPM based on OLS betas produces Jordan Automobile & Part industry CE estimates that are significantly downwardly-biased. In the two-year case, for example, mean forecast error is a significant 2.27% (*t*-stat 3.97). When considering a range of constant betas, Tables 5 and 6 show that significant improvements in CE estimation for the Automobile & Part industry can be achieved by using beta = 1 rather than the OLS beta to produce CE estimates. Lastly, Table 7 shows that the Automobile & Part industry's MAE beta is $2.70 + 15.05\beta_{OLSt}$, and averages 3.57. The time series of these alternative betas and the Automobile & Part industry's OLS beta are displayed in Figure 1. The OLS beta dramatically falls to zero after the end of the 2008-2010 'Global Financial Crisis' as a result of the low correlation between Automobile & Part returns and market returns during the Global financial crisis and subsequent bust. The figure clearly shows that the OLS beta estimates are *always* less than beta = 1 and the corresponding MAE beta.

Note that the performance differences between beta = 1 and the MAE beta are still large. They both produce difference improvement over the OLS beta's CE estimates (a reduction in MAE of 8.20% per year for the two-year case in Table 6, while a reduction in MAE of 19% per year for the MAE beta case in Table 7).[4] Consequently, although the beta = 1 provides good improvement, the MAE beta = $2.70+15.05\beta_{OLSt}$ seems a good choice for the beta of the Jordan Automobile & Part industry.

5. Conclusion

The study finds that the CAPM is not an adequate explanation of Jordan industry returns. The findings show that an industry's degree of defensiveness provides useful information about the adequacy of the CE estimates produced by the standard application of the CAPM. Specifically, the standard application of the CAPM generates significant mean forecast errors for defensive and high-risk industry groups, in that standard practice produces CE estimates that are too low for many defensive industries and estimates that are too high for many high-risk industries. The findings show that for many of these industries, alternative CE estimators yield significantly better CE estimates than those produced by the standard CAPM approach.

The alternative CE estimates offer significant reductions in mean absolute error (MAE) for ten industries based on the one-year case (the Tobacco, Automobile & Part, General Retailers, Chemical, Travel & Leisure, Banks, Financial Service, Industrial Metals & Mining, Electo & Electronic Equip and Telecommunication industries) and weakly significant reductions in MAE for only one industry (the Personal Goods industry). For the two-year case, there are significant reductions in MAE for seventeen industries (the Tobacco, Forestry & Paper, Automobile & Part, General Retailers, Oil & Gas Producer, Chemical, Houshold Good Home, Health care equip. & services, Travel & Leisure, Industrial Engineering, Banks, Personal Goods, Financial Services, Industrial Metals & Mining, Industrial Transportation, Telecommunication and Construction & Material industries) and weakly significant reductions in MAE for only one industry (the General industries).

In summary, this paper reveals that for some industries there are significantly better ways to estimate the industry's CE than the standard CAPM procedure. For many other industries, constant betas produce reductions in MAE that, although not statistically significant, are still large enough to be of interest to practitioners. An implication of these results is that recommendations about CE methods need to be industry-specific. For example, over one-years the largest significant positive reductions in MAE are created by a beta of 0.1 for the Travel & Leisure, Banks, Industrial Metals & Mining and Telecommunication industries (0.34%, 0.78%. 3.95% and 1.17%, respectively), by a beta of 0.2 for the Electro & Electronic Equip industry (0.16%), by a beta of 0.3 for the General Retailers industry (0.97%), and by a beta of 0.5 for the Automobile & Part and Chemical industries (2.81% and 0.41%, respectively).

These results have important implications for these industries given the central role that cost of equity and cost of capital play in the modern economy and in the all-important capital budgeting decisions in these industries. Consider, for example, the implications for just one industry, the Automobile & Part industry. It has shown that the standard CAPM beta leads to significantly downwardly-biased cost of equity estimates because the CAPM beta is much too low. In the sample, the CAPM beta averages 0.30 whereas the research in this paper has found that using unity beta produces significantly better cost of equity estimates. Regulators of Automobile & Part who rely on the CAPM beta to estimate Automobile & Part cost of equity will be making biased decisions. Overall, this paper has shown that one-size-fits-all approaches such as the standard CAPM approach or assuming a beta of unity for all industries are not appropriate for many industries.

This paper has concentrated on the problem of estimating the CE for Jordan industries. A worthy topic for future research would be to see if those CE estimation techniques that perform well for Jordan industries also perform well for the same industries in other countries.

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[4] Without the unbiasedness constraint, the MAE beta's reduction in MAE would have been marginally larger at 0.81%.

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Table 1: Descriptive Statistics

Industry (Long-name)	Av. monthly Return (%)	Std. Dev. (%)	No. of Obs.	Beta	Dawn-market av. (%)	Ln B/M	Ln MV
Tobacco	1.71	9.05	102	-0.09	1.98	-0.68	4.46
Forestry & Paper	0.77	14.47	102	-0.32	1.55	0.12	1.96
Automobile & Part	1.42	19.67	102	-0.01	1.21	-0.12	1.84
General Retailers	0.84	7.21	102	0.00	0.95	-0.39	3.87
Electricity	1.36	11.61	102	0.26	0.78	-0.96	4.98
Mining	-0.57	8.52	102	-0.06	0.58	-1.31	2.28
Food Producer	0.48	5.41	102	-0.13	0.53	-0.06	2.80
Oil & Gas producer	0.56	10.80	102	0.22	0.17	-0.76	4.84
Beverage	-0.15	8.55	102	-0.10	-0.17	-0.52	3.70
Chemical	1.48	12.26	102	0.33	-0.20	0.13	6.10
Nonlife Insurance	0.09	3.93	102	0.09	-0.31	-0.16	2.81
Household Good Home Construction	0.04	6.45	102	0.32	-0.48	-0.33	2.55
Health care equipment & service	-0.16	7.62	102	0.11	-0.58	-0.42	2.80
Travel and Leisure	-0.41	5.17	102	0.14	-0.58	-0.24	3.92
Industrial Engineering	0.74	8.14	102	0.40	-0.65	-0.07	2.55
pharmaceutical & biotechnology	-0.19	4.75	102	0.02	-0.73	-0.34	3.34
Banks	-0.14	6.00	102	0.15	-1.16	-0.27	6.85
Leisure Goods	-0.81	7.80	98	0.13	-1.92	0.26	2.70
Media	-0.80	7.57	102	0.12	-1.24	0.00	3.40
Personal Goods	-0.14	5.53	102	0.28	-1.28	-0.10	2.98
General Industries	0.66	14.24	102	0.47	-1.41	0.71	2.36
Financial Service	-0.07	6.95	102	0.28	-1.41	0.27	3.66
Industrial Metals & Mining	-0.11	9.34	102	0.34	-1.80	0.03	2.43
Electro & Electronic Equipment	-0.76	8.41	102	0.31	-1.65	0.06	3.07
Industrial Transportation	-0.81	7.80	102	0.13	-1.92	0.04	3.24
Telecommunication	-0.26	6.25	102	0.30	-2.02	-1.13	7.13
Real Estate -service	-1.17	11.32	102	0.28	-2.08	0.07	3.57
Construction & Material	-1.05	6.80	102	0.36	-2.27	0.05	4.05
Defensive	0.92	11.75	102	-0.03	1.17	-0.56	3.23
Medium	0.07	7.57	102	0.18	-0.71	-0.12	3.59
High-risk	-0.69	8.32	102	0.29	-1.96	-0.15	3.92

This table details the descriptive statistics for 28 Jordanian industries utilized in this research. The first column is the full industry name. The names of defensive (high-risk) industries are bolded (italicized). This is followed by the average monthly percent returns, the standard deviation of monthly percent returns, the number of monthly observations for the industry, the full sample beta for each industry, the down-market average, , the logs of the industry average book-to-market ratios and market capitalizations over the period November 2005 to April 2014. Down-market average refers to the industry's average monthly return in the negative market excess return months. The last three rows report average values for the three industry groupings: defensive, medium-risk and high-risk.

Table 2: Average Industry Bias

MRP	2%	4%	6%	8%	10%	10.78%	12%	14%	16%	18%
Average Industry Bias	1.79%	1.38%	0.98%	0.57%	0.16%	0.00%	-0.25%	-0.65%	-1.06%	-1.47%

Average industry bias is the average of the biases of the 28 industries, where bias is mean forecast error. For each industry, forecast error at time t is the difference between that industry's average annual return over the following one year and the OLS predicted cost of equity at time t. The OLS predicted value for various estimated values of the market risk premium uses rolling OLS beta estimates that are calculated each month (beginning with November 2005) from the most recent five years of past monthly excess returns

Table 3: One-year average returns for beta, value, size and momentum portfolios.

Sort	P1	P2	P3	P4	P5	P5-P1
Beta	-10.44%	-3.52%	-4.60%	-0.62%	-2.53%	7.91%
	(-1.9)	(-0.65)	(-1.45)	(-0.19)	(-0.64)	(1.55)
Value	-3.28%	1.95%	-1.82%	6.18%	-0.36%	2.92%
	(-1.12)	(0.28)	(-0.34)	(0.6)	(-0.07)	(0.97)
Size	9.65%	2.63%	-2.77%	0.13%	-4.80%	-14.45%
	(0.7)	(0.36)	(-0.65)	(0.02)	(-1.87)	(-1.17)
Mom.	-0.20%	0.25%	0.28%	-0.06%	0.25%	0.46%
	(-0.51)	(0.34)	(0.52)	(-0.15)	(0.44)	(0.98)

The 28 Jordanian industries are sorted at the end of each month into five portfolios using four ranking variables. The table reports average annual return over the one year following the end of each formation month. Sample period is from November 2005 to April 2014. The Beta sort each month is based on each industry's OLS beta estimated over the previous 60 months. The Value sort each month is based on each industry's past book-to-market ratio. The Size sort each month is based on each industry's average firm size. The Momentum sort (Mom.) each month is based on each industry's most-recent six-month return. P1 each month is composed of the 20% of industries with the smallest value of the ranking variable, while P5 is composed of the 20% of industries with the largest value of the ranking variable. The t-values in parentheses incorporate Newey-West adjusted standard errors using 11 lags.

Table 4: One and Two-year Industry Bias

industry	1-year Mean Error (%)	t-stat	2-year Mean Error (%)	t-stat
Tobacco	5.36	(6.71)	5.45	(8.29)
Forestry & Paper	1.94	(1.86)	2.45	(5.04)
Automobile & Part	2.49	(2.05)	2.27	(3.97)
General Retailers	0.99	(2.21)	1.09	(3.36)
Electricity	-0.56	(-1.32)	-0.41	(-1.59)
Mining	-1.1	(-1.27)	-0.7	(-6.38)
Food Producer	-0.72	(-1.56)	-0.85	(-3.91)
Oil & Gas producer	0.44	(1.33)	0.45	(1.91)
Beverage	-0.05	(-0.18)	0.02	(0.08)
Chemical	-1.43	(-1.7)	-1.14	(-2.07)
Nonlife Insurance	0.01	(0.03)	-0.06	(-0.36)
Household Good Home Construction	0.44	(1.06)	0.38	(1.38)
Health care equipment & service	0.28	(0.88)	0.41	(1.53)
Travel & Leisure	-0.48	(-0.96)	-0.35	(-1.27)
Industrial Engineering	1.48	(1.33)	1.45	(3.15)
pharmaceutical and biotechnology	-1.11	(-2.34)	-1.33	(-5.79)
Bank	-0.45	(-0.93)	-0.44	(-1.17)
Leisure Goods	-0.06	(-0.12)	0.12	(0.98)
Media	-3.62	(-9.45)	-3.74	(-22.15)
Personal Goods	-0.63	(-2.8)	-0.7	(-3.36)
General Industries	0.97	(0.9)	1.31	(4.16)
Financial Service	0.57	(0.71)	0.59	(1.1)
Industrial Metals & Mining	-1.83	(-2.92)	-2.15	(-21.86)
Electro & Electronic Equipment	-0.5	(-0.32)	-0.84	(-0.97)
Industrial Transportation	0.21	(0.46)	0.45	(4.37)
Telecommunication	-1.59	(-2.56)	-1.45	(-2.94)
Real Estate -service	0.58	(0.7)	0.47	(1.26)
Construction & Material	-1.61	(-2.31)	-1.47	(-2.42)
Defensive	9.12	(2.25)	10.15	(4.34)
Medium-Risk	-4.37	(-1.56)	-3.86	(-1.96)
High-Risk	-4.75	(-1.81)	-4.99	(-3.37)

Table 4 reports the mean forecast error (denoted Mean Error) for each industry, together with the associated t-statistics. Industry i's one-year (two-year) mean error is the time-series average of its one-year (two-year) forecast errors. Industry i's one-year (two-year) forecast error at time t is the average annual return of industry i over the next one (two) years following month t less the OLS predicted CE estimate at time t based on an MRP of 10.78%, and the annualized treasury bill rate and OLS beta estimate at the end of month t:

$$CE_{iOLSt} = R_{Ft+1} + \beta_{iOLSt} MRP.$$

An industry's OLS beta at the end of month t is calculated each month from the most recent five years of past monthly excess returns. The sample covers the period from November 2005 to April 2014. The last three rows show the mean forecast errors of the defensive, medium-risk and high-risk group portfolios. The t-statistics have Newey-West (1987) adjusted standard errors with lags (11 or 23) equal to the degree of overlap.

Table 5: Performance of alternative beta methods (one-year case)

	OLS	Reduction in MAE						
Industry	**MAE**	**Blume**	**1**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**
Panel A: Defensive Industries								
Tobacco	0.536	0.0373	0.113	0.0591	0.0483	0.0375	0.0267	0.0159
		(37.19)	(37.19)	(19.44)	(15.89)	(12.34)	(8.79)	(5.24)
Forestry & Paper	0.317	0.0157	0.0393	0.0215	0.0163	0.011	0.0058	0.0006
		(1.52)	(1.27)	(1.28)	(1.18)	(1.01)	(0.72)	(0.11)
Automobile & Part	0.287	0.0197	0.0389	0.0281	0.0237	0.0192	0.0141	0.0082
		(3.42)	(1.65)	(2.97)	(3.19)	(3.5)	(3.73)	(3.14)
General Retailers	0.117	0.0154	0.0324	0.0177	0.0142	0.0097	0.0044	-
		(1.52)	(0.85)	(1.34)	(1.66)	(2.12)	(2.58)	(-0.46)
Electricity	0.080	-0.0111	-0.0479	-0.0055	-0.0004	0.0025	0.0036	0.0042
		(-1.95)	(-4.03)	(-1.29)	(-0.25)	(1.31)	(0.62)	(0.44)
Mining	0.192	-0.014	-0.0554	-0.0247	-0.0187	-0.0137	-0.0092	-
		(-1.14)	(-1.67)	(-1.31)	(-1.18)	(-1.09)	(-1)	(-0.8)
Panel B: Medium-Risk Industries								
Food Producer	0.105	-0.0248	-0.1052	-0.0516	-0.043	-0.0357	-0.0284	-
		(-2.03)	(-5.22)	(-2.59)	(-2.35)	(-2.27)	(-2.16)	(-2)
Oil & Gas producer	0.098	0.0025	-0.0018	0.0022	-0.0004	-0.0042	-0.0087	-
		(0.77)	(-0.19)	(1.29)	(-0.34)	(-1.91)	(-2.44)	(-2.59)
Beverage	0.058	-0.0155	-0.0749	-0.0321	-0.0249	-0.0183	-0.0117	-
		(-1.86)	(-3.88)	(-2.48)	(-2.22)	(-1.99)	(-1.6)	(-1.13)
Chemical	0.168	-0.0085	-0.0265	0.0041	0.0076	0.0107	0.0126	0.0136
		(-3.12)	(-3.4)	(2.16)	(1.91)	(1.66)	(1.36)	(1.11)
Nonlife Insurance	0.059	-0.0085	-0.0347	-0.0111	-0.008	-0.0048	-0.0017	0.0008
		(-0.76)	(-1.16)	(-0.79)	(-0.79)	(-0.79)	(-0.8)	(0.38)
Household Good Home	0.098	-0.0008	-0.0176	-0.0008	0.0002	0.0011	0.001	-
		(-0.12)	(-0.93)	(-0.1)	(0.04)	(0.31)	(0.74)	(-0.11)
Health care equipment & service	0.080	0.0097	-0.0019	0.0086	0.0078	0.0044	-0.0004	-
		(1.14)	(-0.09)	(0.91)	(1.13)	(1.18)	(-0.28)	(-1.58)
Travel & Leisure	0.088	-0.0091	-0.0605	-0.0148	-0.0088	-0.0032	0.001	0.0034
		(-0.78)	(-3.1)	(-1.02)	(-0.74)	(-0.36)	(0.17)	(2.24)
Industrial Engineering	0.239	0.0109	0.0253	0.0086	0.004	-0.0009	-0.0061	-
		(1.39)	(0.95)	(1.45)	(1.66)	(-0.42)	(-1.19)	(-1.33)
pharmaceutical & biotechnology	0.156	-0.0207	-0.0671	-0.0296	-0.023	-0.0164	-0.0098	-
		(-2.27)	(-2.75)	(-2.23)	(-2.2)	(-2.16)	(-2.05)	(-1.49)
Bank	0.104	-0.0127	-0.0475	-0.0127	-0.0073	-0.0021	0.0032	0.0078
		(-1.57)	(-2.02)	(-1.41)	(-1.24)	(-0.74)	(4.27)	(2.05)
Leisure Goods	0.091	-0.0014	-0.0118	0.0016	0.0019	0.0021	0.0008	-
		(-0.17)	(-0.5)	(0.32)	(0.85)	(0.48)	(0.1)	(-0.14)
Media	0.361	-0.0322	-0.0975	-0.0436	-0.0328	-0.022	-0.0112	-
		(-	(-	(-47.49)	(-	(-	(-	(-0.48)
Personal Goods	0.085	-0.0199	-0.068	-0.0228	-0.0147	-0.0072	0	0.0066
		(-2.88)	(-4.23)	(-2.6)	(-2.14)	(-1.42)	(0.01)	(1.71)
General Industries	0.228	-0.0006	-0.0023	-0.0048	-0.0068	-0.0099	-0.013	-
		(-0.15)	(-0.18)	(-0.52)	(-0.52)	(-0.59)	(-0.64)	(-0.67)
Financial Service	0.153	0.0014	0.001	0.0026	0.0023	0.0019	0.0014	0.0004
		(0.12)	(0.03)	(0.24)	(0.42)	(3.4)	(0.26)	(0.03)
Panel C: High Risk-Industries								
Industrial Metals & Mining	0.193	-0.0106	-0.0336	0.0078	0.0158	0.0238	0.0318	0.0395
		(-3.49)	(-4.11)	(2.68)	(3.25)	(3.41)	(3.47)	(3.4)
Electro & Electronic Equipment	0.295	-0.0041	-0.0135	-0.0037	-0.0019	-0.0002	0.0016	0.0033
		(-0.3)	(-0.33)	(-0.23)	(-0.18)	(-0.03)	(3.38)	(0.71)
Industrial Transportation	0.091	0.002	-0.0118	0.0016	0.002	0.0021	0.0008	-
		(0.18)	(-0.36)	(0.11)	(0.2)	(0.37)	(0.4)	(-0.96)
Telecommunication	0.16	-0.0267	-0.0828	-0.0289	-0.0181	-0.0074	0.0023	0.0117
		(-28.31)	(-59.89)	(-20.88)	(-	(-5.61)	(2.54)	(7.43)
Real Estate -service	0.159	-0.0049	-0.0165	-0.0043	-0.0025	-0.0008	0.0009	0.0015
		(-0.46)	(-0.52)	(-0.57)	(-0.99)	(-0.32)	(0.13)	(0.13)
Construction & Material	0.189	-0.0156	-0.0496	-0.0176	-0.0117	-0.0058	0.0001	0.0057
		(-1.91)	(-2.17)	(-2.78)	(-3.59)	(-1.89)	(0.02)	(0.61)

The table reports each industry's OLS mean absolute forecast error (MAE) and the Reduction in MAE over OLS from using alternative betas (Blume, and six constant betas). Panel A and C provide the names of defensive and high-risk industries.while the Panel B reports the medium-risk industry. Reduction in MAE for beta method g is the OLS MAE less method g's mean absolute forecast error. Forecast error for month t and method g is method g's average annual forecast error over the following one year. A paired t-test is used to test whether an alternative method produces a significant reduction in MAE. The Newey-West (1987) correction for serial correlation up to 11 lags is employed in the t-test to adjust for overlapping observations. The t-statistics are shown in parentheses.

Table 6: Performance of alternative beta methods (two-year case)

	OLS	Reduction in MAE						
Industry	**MAE**	**Blume**	**1**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**
Panel A: Defensive Industries								
Tobacco	0.5452	0.0358	0.1085	0.0546	0.0438	0.033	0.0222	0.0114
		(125.11)	(125.11)	(62.91)	(50.47)	(38.03)	(25.59)	(13.15)
Forestry & Paper	0.2452	0.0374	0.0969	0.0565	0.0477	0.0379	0.0271	0.0163
		(35.46)	(23.73)	(26.02)	(18.99)	(11.84)	(8.47)	(5.1)
Automobile & Part	0.2291	0.0327	0.082	0.0488	0.0414	0.034	0.0251	0.0155
		(9.01)	(4.37)	(5.96)	(6.49)	(7.42)	(7.16)	(5.53)
General Retailers	0.1091	0.0294	0.0622	0.0381	0.0296	0.0198	0.009	-0.0018
		(25.3)	(4.71)	(19.75)	(32.59)	(24.31)	(11.07)	(-2.18)
Electricity	0.0478	-0.0173	-0.0651	-0.0113	-0.0035	0.0025	0.0054	0.0076
		(-10.33)	(-39.44)	(-7.11)	(-3.14)	(1.48)	(1.48)	(1.28)
Mining	0.0718	-0.0363	-0.1135	-0.0596	-0.0488	-0.038	-0.0272	-0.0164
		(-57.78)	(-176.19)	(-92.48)	(-75.74)	(-59)	(-42.26)	(-25.52)
Panel B: Medium-Risk Industries								
Food Producer	0.0867	-0.0426	-0.1333	-0.0794	-0.0686	-0.0578	-0.047	-0.0362
		(-43.96)	(-116.23)	(-69.2)	(-59.8)	(-50.39)	(-40.99)	(-31.58)
Oil & Gas producer	0.0649	0.0016	-0.0066	0.0012	-0.0017	-0.0069	-0.013	-0.0212
		(0.67)	(-0.89)	(3.82)	(-2.16)	(-4.81)	(-6.22)	(-8.4)
Beverage	0.0372	-0.02	-0.0805	-0.0353	-0.029	-0.0228	-0.0165	-0.0103
		(-1.93)	(-3.63)	(-2.11)	(-2.07)	(-2.01)	(-1.91)	(-1.71)
Chemical	0.1255	-0.008	-0.0269	0.0128	0.0201	0.0263	0.0321	0.037
		(-3.06)	(-4.34)	(4.39)	(3.95)	(3.55)	(3.3)	(3.05)
Nonlife Insurance	0.0315	-0.0057	-0.066	-0.0122	-0.0036	0.0001	0.0001	-0.0011
		(-0.97)	(-10.11)	(-1.87)	(-0.67)	(0.02)	(0.1)	(-0.85)
Household Good Home Construction	0.0569	0.0041	-0.0137	0.0041	0.0056	0.0048	0.0005	-0.0046
		(0.64)	(-0.62)	(0.53)	(1.17)	(2.15)	(0.65)	(-4.81)
Health care equipment & service	0.0556	0.0123	-0.0031	0.0129	0.0114	0.0082	0.0023	-0.004
		(1.53)	(-0.13)	(1.3)	(1.73)	(2.25)	(2.18)	(-2.34)
Travel & Leisure	0.0518	-0.0189	-0.0815	-0.028	-0.0185	-0.0107	-0.0037	0.0025
		(-2.56)	(-9.89)	(-3.48)	(-2.54)	(-1.91)	(-1.08)	(2.95)
Industrial Engineering	0.1529	0.0157	0.0428	0.0123	0.0049	-0.0025	-0.0108	-0.0194
		(4.55)	(3.89)	(5.61)	(7.27)	(-2.04)	(-4.03)	(-4.65)
pharmaceutical & biotechnology	0.1335	-0.0331	-0.1013	-0.0473	-0.0365	-0.0258	-0.015	-0.0042
		(-158.62)	(-404.57)	(-189.08)	(-145.98)	(-102.88)	(-59.78)	(-16.68)
Bank	0.0784	-0.0148	-0.0524	-0.015	-0.008	-0.0026	0.0026	0.0077
		(-2.11)	(-2.93)	(-1.98)	(-1.51)	(-1.1)	(2.96)	(1.93)
Leisure Goods	0.0326	0.0032	-0.0144	0.0011	-0.0022	-0.0062	-0.0122	-0.0201
		(0.65)	(-1.85)	(0.63)	(-1.38)	(-2.1)	(-2.51)	(-3.18)
Media	0.3739	-0.0327	-0.099	-0.0451	-0.0343	-0.0235	-0.0127	-0.0019
		(-350.44)	(-350.44)	(-159.54)	(-121.36)	(-83.18)	(-45.01)	(-6.83)
Personal Goods	0.0777	-0.0197	-0.0752	-0.0212	-0.0107	-0.0012	0.0065	0.0139
		(-5.03)	(-30.08)	(-8.49)	(-4.62)	(-0.74)	(3.94)	(4.12)
General Industries	0.1676	0.0057	0.0163	-0.0138	-0.0201	-0.0263	-0.0331	-0.0405
		(1.93)	(1.74)	(-3.1)	(-2.81)	(-2.68)	(-2.71)	(-2.84)
Financial Service	0.1046	0.0104	0.0206	0.0104	0.0064	0.0015	-0.0036	-0.0087
		(1.32)	(0.88)	(1.56)	(2.02)	(3.31)	(-1.12)	(-1.37)
Panel C: High Risk-Industries								
Industrial Metals & Mining	0.2154	-0.0146	-0.0443	0.0097	0.0205	0.0312	0.042	0.0528
		(-23.82)	(-23.82)	(5.2)	(11)	(16.81)	(22.61)	(28.41)
Electro & Electronic Equip	0.1762	-0.0137	-0.0468	-0.0155	-0.01	-0.0049	0.0002	0.0053
		(-1.7)	(-2.09)	(-1.73)	(-1.68)	(-1.73)	(0.63)	(1.55)
Industrial Transportation	0.0478	0.0145	0.0009	0.0164	0.013	0.009	0.003	-0.0049
		(2.66)	(0.07)	(2.37)	(2.67)	(2.8)	(2.57)	(-7.3)
Telecommunication	0.1448	-0.0272	-0.0825	-0.0285	-0.0177	-0.0069	0.0039	0.0147
		(-381.88)	(-381.88)	(-132.02)	(-82.05)	(-32.08)	(17.9)	(67.87)
Real Estate -service	0.0905	0.0077	0.0184	0.0052	0.0017	-0.003	-0.0081	-0.0133
		(1.07)	(0.88)	(1)	(0.89)	(-1.93)	(-1.76)	(-1.71)

Construction & Material	0.1507	-0.0239	-0.0771	-0.0241	-0.0144	-0.0048	0.0041	0.0123
		(-11.08)	(-21.19)	(-7.75)	(-5.9)	(-2.65)	(4.51)	(11.64)

The table reports each industry's OLS mean absolute forecast error (MAE) and the Reduction in MAE over OLS from using alternative betas (Blume, and six constant betas). Panel A and C provide the names of defensive and high-risk industries.while the Panel B reports the medium-risk industry. Reduction in MAE for beta method g is the OLS MAE less method g's mean absolute forecast error. Forecast error for month t and method g is method g's average annual forecast error over the following two years. A paired t-test is used to test whether an alternative method produces a significant reduction in MAE. The Newey-West (1987) correction for serial correlation up to 23 lags is employed in the t-test to adjust for overlapping observations. The t-statistics are shown in parentheses.

Table 7: MAE beta.

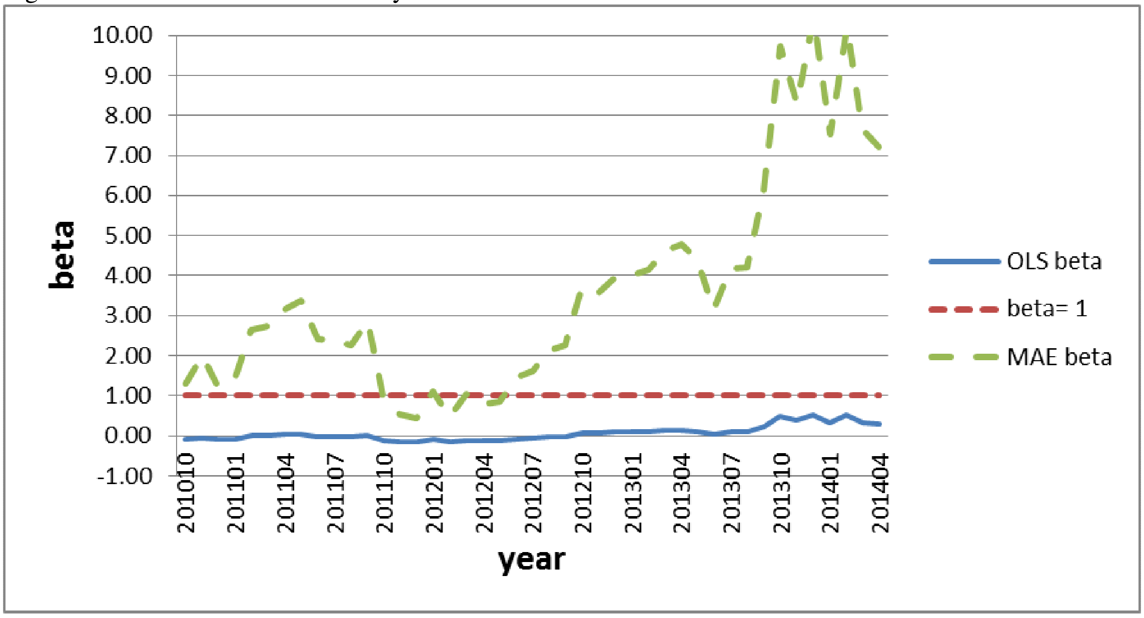
Industry	**OLS MAE (%)**	**Reduction in MAE (%)**	$\hat{a}_{i1}$	$\hat{a}_{i2}$	**Av. MAE beta**	**Av.OLS beta**
Tobacco	53.62	62.06	4.33	0	4.33	-0.19
General Retailers	11.78	40.16	0.45	6.21	1.41	0.18
Forestry & Paper	31.70	27.66	1.86	12.62	1.59	0.01
Industrial Engineering	23.90	24.42	0	6.56	1.99	0.29
Industrial Metals & Mining	19.31	24.26	0	0	0	0.44
Automobile & Part	28.72	19.00	2.70	15.05	3.57	0.02
Personal Goods	8.58	14.74	0	0	0	0.14
Telecommunication	16.00	12.59	0	0	0	0.11
Bank	10.42	10.99	0	0	0	0.15
Health care equipment & service	8.08	10.83	0.53	0	0.53	0.29
Food Producer	10.50	8.53	0	2.63	-0.60	-0.20
Chemical	16.82	8.49	0	0.11	0.05	0.32
Construction & Material	18.93	5.78	0	0	0	0.36
Travel & Leisure	8.88	5.63	0	0	0	0.09
Electricity	8.01	5.39	0.12	0	0.12	0.29
Nonlife Insurance	5.90	4.36	0	0	0	0.11
Oil & Gas producer	9.80	3.12	0.61	0	0.61	0.31
Media	36.19	2.86	0	0	0	0.08
Industrial Transportation	9.13	2.44	0.32	0	0.32	0.19
Leisure Goods	9.13	2.42	0.32	0	0.32	0.40
Financial Service	15.37	2.16	0.70	0	0.70	0.29
Electro & Electronic Equipment	29.55	1.71	0	0	0	0.26
Real Estate -service	15.93	1.45	0	0.37	0.13	0.34
Household Good Home Construction	9.89	1.21	0.26	0	0.26	0.14
General Industries	22.80	1.04	0	2.54	1.65	0.62
Beverage	5.88	0.11	0	0.94	-0.10	-0.10
Mining	19.29	0.06	0	2.45	-0.12	-0.01
pharmaceutical & biotechnology	15.63	-1.18	0	0	0	0.04
Defensive	25.52	25.72	1.58	6.05	1.82	0.05
Medium-risk Industries	13.61	6.23	0.15	0.80	0.34	0.19
High-risk Industries	18.14	8.04	0.05	0.06	0.07	0.28

This table reports MAE beta results. The names of defensive (high-risk) industries are bolded (italicized). Each industry's OLS MAE is the mean absolute forecast error that results from basing CE estimates on the OLS beta. Reduction in MAE is the OLS MAE less the MAE beta's mean absolute forecast error (MAE). Forecast error for month *t* and method *g* is method *g*'s average annual return over the following eight years less method *g*'s CE estimate for that month. The MAE beta in month *t* for industry *i* is

$$\beta_{iMAEt} = \hat{a}_{i1} + \hat{a}_{i2}\beta_{iOLSt} ,$$

where $\hat{a}_{i1}$ and $\hat{a}_{i2}$ determine which unbiased member of the class of positive linear transformations of the OLS beta minimizes the MAE for that particular industry. 'Av.MAE beta' and 'Av.OLS beta' denote the time series averages of the MAE beta and OLS beta, respectively. The last three rows report average values for the three industry groups: defensive, medium and high-risk.

Figure 1: Automobile & Part industry beta estimates.



This figure shows the time series of the OLS beta, MAE beta and a constant beta = 0.3 for the Automobile & Part industry from October 2010 through April 2014.

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