EVIDENCE ON INDUSTRY COST OF EQUITY ESTIMATORS

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ABSTRACT

Given that prior research into industry cost of equity indicates that CAPM-derived estimates are no worse than estimates from more complex models, we investigate the bias of the standard CAPM approach for each industry separately, and examine the effectiveness of alternative beta estimators. We find 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 appropriate practical application of the CAPM when estimating industry cost of equity.

JEL: G10, G12, G31, G32

KEYWORDS: Cost of Equity, Defensive Industries, Constant Beta

INTRODUCTION

In their UK study of industry cost of equity, Gregory and Michou (2009) comprehensively investigate the performances of the capital asset pricing model (CAPM), the Fama-French (1993, 1996) three-factor model, the Cahart (1997) four-factor model, conditional versions of the CAPM and 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. In practice, practitioners continue to rely on the CAPM for estimating the cost of equity. In this paper, we investigate the potential for improving on standard CAPM practice through the use of alternative beta estimators. Specifically, for each industry we examine a range of constant betas, together 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. 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 five and over the next eight years, where average annual return is the proxy for the unknown expected annual return. Unlike prior research, this study evaluates the alternative cost of equity estimates separately for each industry. The outcome is that we are able to advance methods for estimating industry cost of equity that produce economically and statistically significantly better estimates than current CAPM practice, especially for many defensive and high-risk industries. For the utilities industry, for example, a constant beta of 0.9 produces better cost of equity estimates than does the standard CAPM beta estimator. Importantly, our 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. The remainder of the paper is arranged as follows. Section 2 reviews the previous findings in the literature while Section 3 locates the sources of the data for the present study and introduces a measure of defensiveness. Section 4 outlines the methodological approaches that are followed. Section 5 presents the results and offers a brief application of the study to the utility industry, before Section 6 concludes the paper.

LITERATURE REVIEW

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. The beta coefficient in the CAPM is usually calculated as the slope coefficient estimate in a regression using ordinary least squares (OLS). The resulting OLS beta estimator is widely used by practitioners to estimate the CAPM beta (Martin & Simin, 1999). 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 (Dempsey, 2013) or that it does not provide precise results because it depends on the OLS beta which frequently produces biased results (Homaifar & 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 result 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. However, the Fama-French result is inconsistent with some early CAPM studies such as Chan and Chen (1988), Fama and MacBeth (1973), and Black, Jensen and Scholes (1972).

There are a number of possible reasons to explain this inconsistency. These earlier studies used a different market proxy (the equal-weighted NYSE portfolio) and estimated portfolio betas for portfolios sorted on the OLS betas of individual firms alone. On the other hand, Fama and French (1992) use the value-weighted NYSE portfolio as the market proxy, and their OLS betas are from portfolios sorted on firm sizes and OLS betas. The other main difference between the studies is that the Fama and French (1992) study covers a later sample period. Fama and French's (1993) three-factor model was major breakthrough. It adds a size factor and a book-to-market factor to the market factor. The three-factor model assumes that the size and book-to-market factors are proxies for risk, and is designed to capture the anomalies which caused problems for the CAPM. Using a sample including all NYSE, AMEX and NASDAQ stocks, they found there is positive relationship between expected return and book-to-market equity, and that expected return is negatively related to firm size. They proposed that 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 explain stock and bond returns. Three factors 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 found that average stock returns can be explained by the market, size and book-to-market factors. This result is consistent with Fama and French's (1992) earlier findings even though they use a different approach.

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 cost of equity estimation because it requires the user to estimate the three factor premiums and the three factor sensitivities. Thirdly, Bornholt's (2007) study showed that the three-factor model underperforms the reward beta approach in out-of-sample tests. Daniel and Titman (1997) argue that the problem with the three-factor model is that it does not take into consideration all the characteristics needed to explain expected returns. Furthermore, the three-factor model cannot explain various anomalies such as the momentum anomaly (Liu, 2006). Black (1993) argues that if the empirical failure of the CAPM that was observed by Fama and French (1992) is expected to continue then portfolio managers should tilt their portfolios towards low beta stocks. Other researchers have argued for the relevance of OLS beta estimates in portfolio management (Ibbotson, Kaplan, & Peterson, 1997) or have argued for robust beta estimation (Genton & Ronchetti, 2008).

Daves, Ehrhardt and Kunkel (2000) employ the CAPM for estimating the cost of equity. This study uses four return intervals, based on daily, weekly, two-weekly and monthly returns over the period 1982-1989. Additionally, Daves et al. (2000) use eight different estimation period lengths to estimate beta. They find that an estimation period length of three years gives the least standard error compared with other evaluation periods. Moreover, they find that estimating beta using daily returns provides the most precise estimates. This result is inconsistent with most previous studies, perhaps because the sample period of this study is too short. Gray, Hall, Bowman, Brailsford, Faff and Officer (2005) investigate alternative techniques for estimating the equity betas of Australian firms. The alternative methods include the Blume-adjusted beta, an outlier-adjusted beta, the unity beta and an industry beta. They contrast the performance of these betas with the OLS beta. The mean square error (MSE) criterion and the percentage of wins are used to compare actual returns to the predicted returns calculated using the competing techniques. They find that the OLS beta is inferior to a variety of alternative techniques. First, they showed that using the Blume-adjusted beta in the CAPM was better than using the OLS beta in the sense that it provides a lower mean square forecast error. Similarly, Gray et al. (2005) report that the OLS beta is inferior to both a beta of unity and an outlier-adjusted beta. Similarly, Martin and Simin (2003) report that an outlier-adjusted beta outperforms the OLS beta. In addition, the Blume-adjusted beta estimated over a long period is better than a beta of unity (better in the sense of lower mean square forecast error).

Theodossiou, Theodossiou and Yaari (2009) argue that some outlier-adjusted beta techniques can be criticized because they eliminate some observations from the sample, leading to a decrease in the size of the sample, hence reducing the statistical power of tests. Furthermore, removing extreme observations can lead to decreasing the explanatory power for the regression model. Merton (1973) presented the Intertemporal Capital Asset Pricing Model (ICAPM) as an alternative model to the CAPM. Cochrane (2001) points out that the ICAPM does not identify which macro variables affect the expected returns. Therefore, this model is not used in practice because it is difficult to identify which variables are important. Ross (1976) introduced the APT as an alternative to the CAPM. However, like the ICAPM, the problem with this model is that it does not provide details of which economic factors affect expected returns. As a result, this model is not widely used by practitioners to estimate cost of equity.

Comprehensive testing of the effectiveness of industry cost of equity estimates produced by competing models have been undertaken by Fama and French (1997) and Gregory and Michou (2009). Fama and French (1997) test the CAPM, the three-factor model and a conditional three-factor model. They report distressingly imprecise cost of equity estimates from all models. Gregory and Michou (2009) do not find that cost of equity estimates from the three-factor model are significantly better than those produced by the standard CAPM approach. They recommend further research should be undertaken to find better beta estimates for the CAPM. Bornholt (2013) argues that practitioners typically need cost of equity estimates to apply for at least five years because most projects in capital budgeting last five years or longer. He finds that the size and book-to-market effects are not significant over these longer five-year time frames. This result provides further evidence against the use of the Fama-French three-factor model for cost of equity estimation.

DATA AND METHODOLOGY

Our basic units of observation are the monthly returns for 48 US industries and for the US market. Annual returns are derived from these by compounding monthly returns. The time frame of the study is from July 1963 until the end of December 2010. In addition, we employ average firm size and the value-weighted average firm book-to-market ratio for the 48 US industries for the same period. The monthly returns (denoted R_{mt}^{m}) of the market are the monthly returns of the Center for Research in Securities Prices' (CRSP) value-weighted US market index of all US stocks. Additionally, the study uses the one-month Treasury bill rates as the risk-free rate (denoted R_{Ft}^{m}) reported at the beginning of each month for the period from July

1963 to December 2010. All data is downloaded from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The industry and market returns on this website are themselves derived from the CRSP database of all US stocks listed on the NYSE, AMEX and NASDAQ exchanges. The study commences from July 1963 because the CRSP database has a less comprehensive coverage of US stocks prior to July 1963. The final sample is composed of 570 monthly returns on each industry, on the 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 spectrum of industries, there are some industries that investors treat as 'defensive' in the sense that stocks in a defensive industry are not expected to drop as much as the stocks of other industries during market declines (Reilly & Brown, 2000). While there are a variety of ways that the concept of defensiveness could be defined, in this paper we 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 those 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 48 industries are ranked on the basis of their down-market averages, and classified into three groups. The 12 industries with the highest down-market averages will be called defensive industries, the 12 industries with the lowest down-market averages will be called high-risk industries, and the remaining 24 industries will be called medium industries. Table 1 provides summary statistics for the 48 US industry portfolios. The first column gives the abbreviated name of industry (to be used in subsequent tables), while the second table has the full name of the industry. Other columns report the average and standard deviation of monthly returns, the average firm size, value-weighted average book-to-market equity, full sample beta, and the down-market average of each industry. The order of the industries in the table is determined by the defensiveness of the industry, beginning with the most defensive (Smoke) and ending with the least defensive (Chips). This order is retained in all subsequent tables that report industry names.

The first 12 industries in the table (Smoke, Utility, Gold, Food, Beer, Oil, Soda, Drugs, Telcm, Hshld, Guns and MedEq), are the defensive industries, the next 24 industries are the medium industries, and the last 12 industries (PerSv, Toys, Mach, FabPr, Fun, Other, RIEst, BusSV, LabEq, Steel, Cnstr and Chips) are the high-risk industries. For example, the Smoke and Utility industries are the most defensive industries because they achieve the best average returns in the down market months (–1.14% and –1.36% per month, respectively), while the Chips industry is the most high-risk because it achieves the worst average return in the down market months (–4.96% per month). Table 1 contains a number of interesting features. Not surprisingly, full sample beta and the defensiveness measure are highly correlated: the more defensive an industry the lower its beta tends to be. 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, we see that defensive industries tend to have (i) slightly larger average returns, (ii) smaller standard deviations, (iii) larger firms, (iv) slightly smaller book-to-market ratios, and, (v) smaller betas than do high-risk industries. The CAPM model for industry expected returns can be written:

$$E[R_i] = R_F + \beta_i (E[R_m] - R_F) \tag{1}$$

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 cost of equity estimate for industry *i* at the end of month *t* given by:

$$CE_{iOLSt} = R_{Ft+1} + \beta_{iOLSt} MRP \,, \tag{2}$$

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 this paper, the standard approach to estimating the cost of equity described by (2) is denoted 'CAPM practice' in order to differentiate it from the 'CAPM model' in (1) above and from the alternatives to be discussed below. This paper compares the out-of-sample performance of industry cost of equity (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 using method *g*, where the subscript *g* simply indexes OLS or the various alternative beta estimation methods to be described below (e.g., *g* = OLS, Blume, 0.8, etc.). Replacing the OLS beta in (2) with the general beta estimate β_{igt} gives the estimated cost of equity for industry *i* at the end of month *t* for beta estimation method *g*:

$$CE_{igt} = R_{Ft+1} + \beta_{igt} MRP. \tag{3}$$

The remainder of this section describes the alternative beta estimators that are used in this paper to produce alternative estimates of the cost of equity 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*:

$$\beta_{iBlumet} = 0.33 + 0.67 \times \beta_{iOLSt} \,. \tag{4}$$

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 cost of equity estimates that result from using the OLS beta, researchers have investigated simply using a fixed value of one for beta in cost of equity 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 U.K. industries. Their result is not that surprising since, a priori, we expect that a beta of unity would be too high for low-risk industries and too low for high-risk industries. Perhaps a beta of 0.8 would better suit a low-risk industry, and perhaps a beta of 1.2 would better suit a high-risk industry. Consequently, a variety of constant betas (beta = 0.80, 0.90, 1, 1.10,1.20 and 1.30) 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. 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 estimates 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, these CE estimates need to be reasonable estimates of industry expected return over at least the next five years. (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.) However, expected returns are unobservable. This means that we need a proxy for the average expected annual return over at least the next five years, and one obvious choice is the average annual return over the next five years. Given that the life of many projects exceeds five years, we also use the average annual return over the next eight years as an alternative proxy for longer-lived projects. Therefore, let A_{it}^{5YR} (A_{it}^{8YR}) denote the average of the five (eight) annual returns of industry *i* that follow month *t*. With one of these averages selected as the proxy for the expected industry return, we can define 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, $e_{igt} = A_{it}^{5YR} - CE_{igt}$, or $e_{igt} = A_{it}^{8YR} - CE_{igt}$.

Table 1: Descriptive Statistics

Industry	Industry (Long-name)	Av.	Std. Dev.	Av. Firm	Value-	Beta	Down-
Smoke	**Tobacco products**	1.39	6.27	9207	0.52	0.67	-1.14
Util	**Utilities**	0.82	4.10	1589	1.00	0.54	-1.36
Gold	**Precious Metals**	1.14	10.40	696	0.43	0.66	-1.60
Food	**Food products**	1.06	4.51	1415	0.53	0.69	-1.65
Beer	**Beer and Liquor**	1.14	5.37	6390	0.52	0.78	-1.86
Oil	**Petroleum and Natural Gas**	1.09	5.37	2183	0.73	0.78	-2.13
Soda	**Candy and Soda**	1.17	6.65	1297	0.52	0.86	-2.23
Drugs	**Pharmaceutical products**	1.05	5.11	1735	0.27	0.80	-2.24
Telcm	**Communication**	0.83	4.73	2882	0.82	0.76	-2.28
Hshld	**Consumer Goods**	0.91	4.81	1717	0.36	0.82	-2.49
Guns	**Defense**	1.08	6.83	1427	0.81	0.85	-2.50
MedEq	**Medical Equipment**	1.11	5.42	549	0.33	0.91	-2.62
Boxes	Shipping Containers	0.99	5.70	871	0.56	0.95	-2.80
Agric	Agriculture	1.04	6.50	653	0.59	0.87	-2.82
Paper	Business Supplies	0.95	5.68	1294	0.68	0.98	-3.00
Insur	Insurance	0.98	5.80	1562	0.82	0.95	-3.03
Coal	Coal	1.53	9.89	910	0.79	1.16	-3.14
Rtail	Retail	1.03	5.58	1299	0.51	1.00	-3.15
Banks	Banking	0.90	6.10	856	0.78	1.05	-3.27
Chems	Chemicals	0.94	5.57	1348	0.60	1.03	-3.27
Ships	Shipbuilding, Railroad Equipment	0.94	6.93	905	0.79	1.05	-3.35
Mines	Non-Metallic and Industrial Metal Mining	1.20	7.20	782	0.69	1.11	-3.47
Autos	Automobiles and Trucks	0.87	6.88	1159	1.05	1.13	-3.48
Whlsl	Wholesale	1.04	5.81	364	0.61	1.08	-3.49
Books	Printing and Publishing	0.94	5.94	927	0.48	1.07	-3.50
Txtls	Textiles	0.97	7.34	320	1.08	1.13	-3.52
Aero	Aircraft	1.17	6.91	2799	0.73	1.14	-3.54
Meals	Restaurants, Hotels Motels	1.19	6.41	572	0.48	1.08	-3.56
Rubbr	Rubber and Plastic Products	1.06	6.22	251	0.67	1.09	-3.60
Clths	Apparel	1.05	6.63	389	0.67	1.13	-3.68
BldMt	Construction Materials	0.98	6.19	529	0.68	1.16	-3.71
Trans	Transportation	0.94	6.01	819	1.12	1.08	-3.72
ElcEq	Electrical Equipment	1.23	6.33	888	0.50	1.20	-3.72
Hlth	Healthcare	1.03	8.63	433	0.58	1.13	-3.84
Fin	Trading	1.14	6.27	916	0.79	1.24	-4.01
Comps	Computers	1.00	7.19	1534	0.36	1.22	-4.01
PerSv	*Personal Services*	0.71	7.08	343	0.52	1.12	-4.02
Toys	*Recreation*	0.84	7.38	278	0.53	1.18	-4.02
Mach	*Machinery*	0.99	6.27	693	0.64	1.22	-4.05
FabPr	*Fabricated Products*	0.68	7.43	134	0.81	1.15	-4.16
Fun	*Entertainment*	1.36	7.90	766	0.58	1.38	-4.20
Other	*Miscellaneous*	0.61	7.11	2187	0.66	1.18	-4.27
RlEst	*Real Estate*	0.64	7.74	217	0.93	1.20	-4.35
BusSv	*Business Services*	1.12	6.75	688	0.43	1.32	-4.47
LabEq	*Measuring and Control Equipment*	1.06	7.32	351	0.44	1.34	-4.57
Steel	*Steel Works Etc*	0.82	7.42	675	1.12	1.29	-4.62
Cnstr	*Construction*	1.02	7.43	423	0.73	1.31	-4.63
Chips	*Electronic Equipment*	1.00	7.60	829	0.50	1.42	-4.96
	Defensive	1.07	5.80	2591	0.57	0.76	-2.01
	Medium	1.05	6.57	933	0.69	1.09	-3.45
	High-risk	0.90	7.29	632	0.66	1.26	-4.36

This table details the descriptive statistics for 48 US industries utilized in this research. The first column is the abbreviated name of the industry, while the second column gives 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, average firm size (ME), the value-weighted average firm book-to-market equity (BE/ME), the full sample beta for each industry, and the down-market average over the period July 1963 to December 2010. 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 and high-risk.

In the case of the OLS beta estimate, it is important to know if this estimator produces systematically biased cost of equity estimates for some industries. This question can be answered by testing 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

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

We use mean absolute forecast error (MAE) to measure the performance of a method's cost of equity estimates. Thus if method g produces N errors beginning with $t = \tau$ then

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

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

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

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* is produces significantly better cost of equity estimates than does standard CAPM practice. Note that the forecast errors (the e_{iOLSt}'s and the e_{igt}'s) in equations (5) and (7) are consecutive monthly rolling forecast errors that overlap by 59 months in the five-year case and by 95 months in the eight-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. (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, $[Y^2] = var(Y) + (E[Y])^2$.) 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. We define *average industry bias* as the average of the biases of the 48 industries for the five-year case. To determine an appropriate value for the MRP, we select 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 3% to 10%. 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 3% generates an average bias of 4% per year. This means that using 3% as the estimate of the market risk premium produces cost of equity estimates that are 4% too low on average across all industries. On the other hand, a 10% MRP would produce cost of equity estimates that are 3.3% too high on average across all industries. An MRP of 6.8% results in zero average industry bias, and for this reason henceforth in this paper all cost of equity estimates are based on using MRP = 6.8% in equations (2) and (3). It is clear that this CAPM-based method of determining MRP implicitly favors the OLS beta over alternative betas. Such favoritism means that we can rule out the choice of MRP as the likely cause of any evidence of OLS underperformance that we may find in investigations into alternative CE estimators. In addition, it is comforting to note that an MRP of 6.8% (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.

Table 2: Average Industry Bias

MRP	3%	4%	5%	6%	6.8%	7%	8%	9%	10%
Average Industry Bias	4.0%	2.9%	1.9%	0.8%	0.0%	-0.2%	-1.2%	-2.3%	-3.3%

Average industry bias is the average of the biases of the 48 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 five years 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 June 1968) from the most recent five years of past monthly excess returns.

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 choices for the risk-free asset are either Treasury bills or a medium-term government bond. Medium-term bonds tend to have larger 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, we do not expect that different choices for the risk-free asset would materially change the relative rankings of the various cost of equity 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 study are, except for the derivation of MRP discussed above, based solely on information known at time *t*.

RESULTS AND DISCUSSION

Using 6.8% 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 48 industries. Now consider the industry bias (or mean forecast error) of each industry and each industry group. Table 3 reports mean forecast error for each industry and, in the final three rows, for each industry group (defensive, medium and high-risk). Note that these mean forecast errors are annual percentages. A 5-year (8-year) mean error is the time-series mean of the average of the annual forecast errors over the five (eight) years following each CE estimate. Looking first at the individual defensive industries, we see that the conventional CAPM method significantly underestimates the cost of equity of three defensive industries. The Smoke, Utility and Oil industries have significant 5-year mean errors of 8.39% (*t*-stat 2.93), 2.59% (*t*-stat 1.99) and 3.76% (*t*-stat 2.10), respectively. In addition, the Guns industry mean error of 4.37% is weakly significant at the 10% level (*t*-statistic of 1.80). The Smoke, Utility and Oil industries also have significant 8-year mean errors of 8.2% (*t*-stat 3.26), 2.5% (*t*-stat 3.56) and 3.4% (*t*-stat 2.61), respectively. These results also illustrate an important common feature of all the significant results in this table.

The 5-year mean errors are very similar to the corresponding 8-year mean errors. This suggests that the results in this table are robust to the choice of proxy for expected return. (There is also a tendency for the 8-year *t*-statistics to be larger in absolute magnitude than the corresponding 5-year *t*-statistics due to the lower volatility that results from averaging over eight years rather than five.)Turning to medium industries, none have significant mean errors. On the other hand, there are a number of high-risk industries with significant negative mean forecast errors. The Mach, FabPr and Steel industries have significant 8-year mean errors of – 2.5% (*t*-stat – 2.50), - 6.4% (*t*-stat – 2.49) and – 3.3% (*t*-stat – 3.01), respectively. For the 5-year results, the FabPr mean error is significant (*t*-stat – 2.09), while the Mach and Steel mean errors are only weakly significant (*t*-stats – 1.69 and – 1.78, respectively). Other industries with weakly significant 8-year mean errors are Toys, Other and RlEst (*t*-stats – 1.80, – 1.87 and – 1.87, respectively).

Table 3: Five and Eight-year Industry Bias

	5-year		8-year			5-year		8-year	
industry	**Mean Error**	***t*-stat**	**Mean Error**	***t*-stat**	**industry**	**Mean Error**	***t*-stat**	**Mean Error**	***t*-stat**
Smoke	8.39%***	2.93	8.2%***	3.26	Books	-0.23%	-0.07	0.9%	0.33
Util	2.59%**	1.99	2.5%***	3.56	Txtls	-1.00%	-0.32	-0.5%	-0.15
Gold	1.91%	0.52	1.3%	0.33	Aero	2.42%	0.96	2.6%	1.35
Food	4.09%	1.54	4.2%	1.58	Meals	-0.65%	-0.38	-0.8%	-0.76
Beer	3.19%	0.88	3.4%	0.90	Rubbr	-0.79%	-0.44	-0.5%	-0.34
Oil	3.76%**	2.10	3.4%***	2.61	Clths	-0.06%	-0.03	0.4%	0.20
Soda	1.67%	0.64	1.4%	0.82	BldMt	-1.26%	-0.74	-1.0%	-0.90
Drugs	1.99%	0.69	2.2%	0.78	Trans	-1.67%	-0.99	-1.6%	-1.27
Telcm	1.80%	0.68	2.2%	0.86	ElcEq	1.31%	0.54	1.7%	0.81
Hshld	-0.84%	-0.41	-1.0%	-0.52	Hlth	4.67%	0.93	2.2%	0.52
Guns	4.37%*	1.80	3.9%*	1.94	Fin	1.68%	0.55	2.5%	0.91
MedEq	0.40%	0.22	0.4%	0.26	Comps	-1.81%	-0.47	-1.0%	-0.29
Boxes	0.37%	0.16	0.4%	0.17	*PerSv*	-4.38%	-1.20	-3.4%	-1.37
Agric	1.45%	0.58	1.0%	0.54	*Toys*	-4.55%*	-1.69	-4.2%*	-1.80
Paper	-0.81%	-0.96	-1.0%	-1.56	*Mach*	-2.33%*	-1.69	-2.5%**	-2.50
Insur	1.44%	0.78	1.9%	1.22	*FabPr*	-6.26%**	-2.09	-6.4%**	-2.49
Coal	5.14%	0.77	3.8%	0.52	*Fun*	1.51%	1.00	1.9%	1.64
Rtail	0.35%	0.15	0.8%	0.37	*Other*	-7.29%*	-1.84	-6.5%*	-1.87
Banks	0.15%	0.06	0.8%	0.31	*RlEst*	-6.42%	-1.53	-6.1%*	-1.87
Chems	-0.29%	-0.21	-0.7%	-0.71	*BusSv*	-0.79%	-0.21	0.4%	0.12
Ships	-1.36%	-0.44	-2.0%	-0.64	*LabEq*	-2.74%	-1.26	-2.3%	-1.26
Mines	0.71%	0.20	-0.7%	-0.24	*Steel*	-2.93%*	-1.78	-3.3%***	-3.01
Autos	-2.11%	-1.11	-1.6%	-0.96	*Cnstr*	-2.23%	-0.69	-1.8%	-0.65
Whlsl	-1.04%	-0.48	-0.9%	-0.47	*Chips*	-1.49%	-0.37	-0.2%	-0.05
					Defensive	2.78%**	1.98	2.68%**	2.33
					Medium	0.19%	0.14	0.22%	0.22
					High-risk	-3.33%	-1.64	-2.86%**	-2.06

Table 3 reports the mean forecast error (denoted Mean Error) for each industry, together with the associated t-statistics. The names of defensive (high-risk) industries are bolded (italicized). Industry i's five-year (eight-year) mean error is the time-series average of its five-year (eight-year) forecast errors. Industry i's five-year (eight-year) forecast error at time t is the average annual return of industry i over the next five (eight) years following month t less the OLS predicted CE estimate at time t based on an MRP of 6.8%, 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 July 1963 to December 2010. The last three rows show the mean forecast errors of the defensive, medium and high-risk group portfolios. The T-statistics have Newey-West (1987) adjusted standard errors with lags (59 or 95) equal to the degree of overlap.*

A feature of the table is that the significant defensive industry mean errors are all positive, whereas the significant high-risk industry mean errors are all negative. This means that standard CAPM practice leads to CE estimates that are systematically too low for some defensive industries and too high for particular high-risk industries. Such industries are prime candidates for the alternative CE methods discussed in the next section. Finally, consider the mean forecast errors for the defensive, medium and high-risk industry group portfolios reported in the final three rows of Table 3. The defensive industries portfolio's 5-year and 8-year mean errors are both positive and significant at 2.78% (*t*-stat 1.98) and 2.68% (*t*-stat 2.33), respectively. In contrast, while the high-risk industries portfolio's 5-year and 8-year mean errors are both negative at - 3.33% and – 2.86%, respectively, only its 8-year mean error is significant (*t*-stat – 2.06). Overall, the results in Table 3 show that the degree of defensiveness of an industry provides useful information about the effectiveness of CE estimates based on the OLS beta.

This section evaluates the performances of competing CE estimates for each of the 48 industries. Table 4 reports performance results using the five-year average return as the expected return proxy. (To conserve space, the performance results from using the eight-year average return as the expected return proxy are available from the authors.) Panel A reports results for the 12 defensive industries, Panel B contains the entries for the 24 medium industries, while Panel C lists the high-risk industries' results. The MAE results based on the OLS beta are reported in the second column of Table 4 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} = 0.8, 0.9, 1.0, 1.1, 1.2, and 1.3 for the constant betas), together with the associated *t*-statistics. An alternative method is considered to have a better performance than standard CAPM practice if it produces a reduction in MAE that is positive and significant.The first observation that can be drawn from Table 4 is that alternative betas provide better performances for eight industries: the Smoke, Utility, Oil, Coal, FabPr, Fin, BusSv and Constr industries. In the Utility industry case, for example, the Blume-adjusted beta has a 0.52% smaller MAE per year (*t*-statistic 2.59). The constant beta estimate 0.80 produces a significant MAE reduction of 0.89% per year (*t*-statistic 2.42), while the constant beta estimate 0.90 has a significant MAE reduction of 0.99% per year (*t*-statistic 2.20). This latter reduction amounts to a 20% improvement over the OLS MAE (i.e., 0.0099/0.0488 = 0.20). In short, the constant betas 0.90 and 0.80 and the Blume-adjusted beta produces economically and statistically significant reductions for the Utility industry, with beta = 0.9 producing the largest significant improvement over the standard CAPM approach. In contrast, for the Oil industry the Blume-adjusted beta is the only technique, which produces a statistically significant reduction in MAE (0.27% with *t*-statistic 2.01). The constant beta estimates 0.90 and 1.0 have larger reductions (0.57% and 0.73%, respectively) but these are only weakly significant. (Blume-adjusted betas can produce large *t*-statistics in the presence of small reductions in MAE because the forecast errors from the Blume-adjusted and OLS beta methods are highly contemporaneously-correlated (due to the way the Blume-adjusted beta is derived from the OLS beta), leading to a low standard deviation of the paired differences.)

The performances of the alternative CE methods in Table 4 can be summarized as follows. The cost of equity estimates for eight industries can be improved significantly by using one of these alternative techniques, while positive and weakly significant reductions can be observed for another five industries. 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 0.9 produces the largest significant MAE reductions for the Utility and FabPr industries. Similarly, a constant beta of 1.0 gives the largest significant MAE reduction for the Coal industry, while a constant beta of 1.3 yields the largest significant reductions for the Smoke, Fin, BusSv, and Cnstr industries.

The robustness of these results to the choice of proxy can be checked by replacing the five-year proxy with the eight-year proxy. Thus, whereas CE's are used to predict the average annual return over the following five years in Table 4, those same CE's can be used to predict average annual returns over the next eight years. We can report that the results for the eight-year case are stronger than the results for the five-year case (results available from the authors on request). Overall, the results in Table 4 show that there are significantly better ways to estimate the cost of equity 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 alternative CE methods need to be industry-specific. 'One-size-fits-all' approaches such as using a beta of unity for all industries are clearly sub-optimal.

Since the regulation of utility companies in many jurisdictions involves estimating the utility industry's cost of equity via the CAPM, the adequacy of such estimates is of particular interest. As reported in Table 3, the CAPM based on OLS betas produces US utility industry cost of equity estimates that are significantly downwardly-biased. In the eight-year case, for example, mean forecast error is a significant 2.5% (*t*-stat 3.56). When considering a range of constant betas, Table 4 shows that significant improvements in CE estimation for the utility industry can be achieved by using beta = 0.9 rather than the OLS beta to produce CE estimates (since beta = 0.9 produces a reduction in MAE of 0.99% p.a. with an associated *t*-stat 2.20). The time series of these alternative betas are displayed in Figure 1. The OLS beta dramatically falls to zero after the end of the 1997-1999 'internet bubble' as a result of the low correlation between utility returns and market returns during the internet bubble and subsequent bust. The figure clearly shows that the OLS beta estimates are *always* less than beta = 0.9.

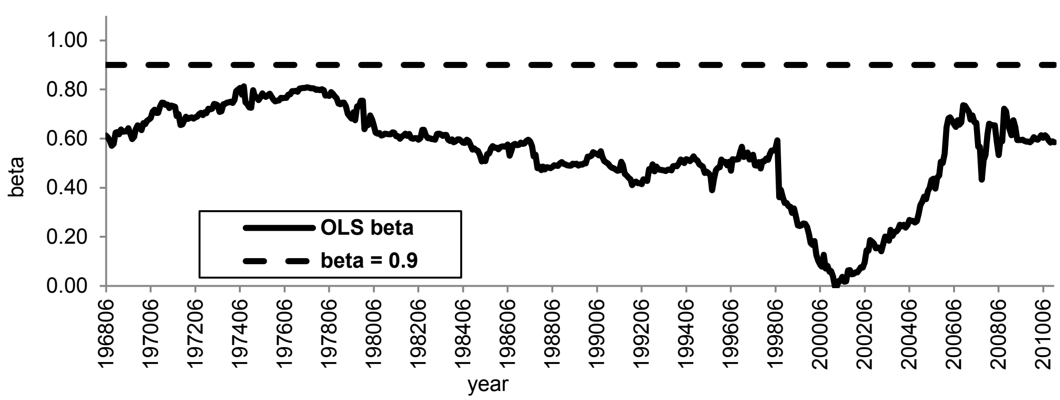
Table 4: Performance of Alternative Beta Methods (Five-Year Case)

Industry	OLS MAE	Reduction in MAE Blume	0.8	0.9	1	1.1	1.2	1.3
Panel A: Defensive Industries								
Smoke	0.1047	0.0050**	0.0077	0.0110**	0.0141**	0.0170**	0.0195**	0.0216**
		(2.33)	(1.60)	(1.96)	(2.10)	(2.13)	(2.09)	(1.99)
Util	0.0488	0.0052***	0.0089**	0.0099**	0.0100*	0.0095	0.0079	0.0053
		(2.59)	(2.42)	(2.20)	(1.85)	(1.49)	(1.09)	(0.65)
Gold	0.1121	-0.0011	-0.0057	-0.0063	-0.0072	-0.0084	-0.0098	-0.0115
		(-0.38)	(-0.82)	(-0.81)	(-0.82)	(-0.85)	(-0.89)	(-0.95)
Food	0.0729	*0.0025	0.0031	0.0039	0.0042	0.0040	0.0033	0.0023
		(1.68)	(1.28)	(1.41)	(1.08)	(0.75)	(0.49)	(0.27)
Beer	0.1033	0.0004	-0.0023	-0.0013	-0.0005	0.0000	0.0003	0.0005
		(0.28)	(-0.68)	(-0.48)	(-0.16)	(0.00)	(0.05)	(0.06)
Oil	0.0690	0.0027**	0.0036	0.0057*	0.0073*	0.0083	0.0090	0.0093
		(2.01)	(1.29)	(1.72)	(1.74)	(1.61)	(1.44)	(1.26)
Soda	0.0851	0.0022	0.0050	0.0053	0.0053	0.0049	0.0040	0.0027
		(1.33)	(1.24)	(1.28)	(1.13)	(0.87)	(0.60)	(0.35)
Drugs	0.0811	-0.0010	-0.0048	-0.0044	-0.0042	-0.0043	-0.0047	-0.0052
		(-0.78)	(-1.64)	(-1.32)	(-0.93)	(-0.71)	(-0.61)	(-0.56)
Telcm	0.0764	0.0034*	0.0062*	0.0073*	0.0081	0.0084	0.0085	0.0079
		(1.80)	(1.76)	(1.65)	(1.43)	(1.21)	(1.00)	(0.80)
Hshld	0.0567	0.0007	0.0012	0.0010	0.0002	-0.0013	-0.0035	-0.0064
		(0.96)	(0.43)	(0.54)	(0.11)	(-0.46)	(-0.90)	(-1.27)
Guns	0.0861	0.0046	0.0067	0.0097	0.0121	0.0141*	0.0157*	0.0171*
		(1.61)	(0.78)	(1.17)	(1.48)	(1.70)	(1.82)	(1.87)
MedEq	0.0563	-0.0012*	-0.0063*	-0.0051*	-0.0044**	-0.0041*	-0.0042	-0.0048
		(-1.70)	(-1.66)	(-1.83)	(-2.08)	(-1.86)	(-1.42)	(-1.19)
Panel B: Medium Industries								
Boxes	0.0666	-0.0001	-0.0018	-0.0011	-0.0006	-0.0004	-0.0007	-0.0014
		(-0.13)	(-0.57)	(-0.40)	(-0.18)	(-0.10)	(-0.12)	(-0.19)
Agric	0.0769	0.0018	0.0038	0.0044	0.0046	0.0047	0.0043	0.0033
		(1.07)	(0.76)	(0.92)	(0.91)	(0.80)	(0.62)	(0.42)
Paper	0.0400	-0.0002	-0.0001	-0.0003	-0.0013	-0.0031	-0.0054*	-0.0083**
		(-0.33)	(-0.03)	(-0.14)	(-0.75)	(-1.42)	(-1.79)	(-2.07)
Insur	0.0643	0.0001	-0.0031	-0.0015	-0.0004	0.0002	0.0004	0.0002
		(0.12)	(-0.82)	(-0.54)	(-0.19)	(0.09)	(0.13)	(0.04)
Coal	0.1797	0.0030**	0.0088	0.0089*	0.0089**	0.0087**	0.0084*	0.0080
		(2.38)	(1.30)	(1.75)	(2.28)	(2.47)	(1.95)	(1.39)
Rtail	0.0726	-0.0002	-0.0014	-0.0010	-0.0011	-0.0014	-0.0021	-0.0031
		(-0.35)	(-0.32)	(-0.37)	(-0.52)	(-0.54)	(-0.54)	(-0.57)
Banks	0.0776	-0.0007	-0.0034	-0.0028	-0.0025	-0.0027	-0.0034	-0.0046
		(-0.61)	(-0.61)	(-0.61)	(-0.68)	(-0.81)	(-0.91)	(-0.97)
Chems	0.0512	0.0002	-0.0005	0.0000	-0.0002	-0.0011	-0.0025	-0.0043
		(0.36)	(-0.15)	(0.02)	(-0.12)	(-0.55)	(-0.86)	(-1.08)
Ships	0.0847	0.0021	0.0046	0.0051	0.0052	0.0051	0.0047	0.0041
		(1.61)	(0.80)	(1.13)	(1.43)	(1.49)	(1.20)	(0.84)
Mines	0.0953	0.0013	0.0046	0.0042	0.0035	0.0026	0.0014	0.0001
		(0.98)	(1.24)	(1.21)	(0.90)	(0.54)	(0.24)	(0.02)
Autos	0.0669	0.0005	0.0024	0.0021	0.0013	0.0001	-0.0015	-0.0036
		(0.86)	(0.77)	(1.03)	(0.74)	(0.05)	(-0.40)	(-0.71)
Whlsl	0.0644	0.0018	0.0036	0.0042	0.0043	0.0038	0.0027	0.0011
		(1.10)	(0.53)	(0.75)	(0.92)	(0.94)	(0.70)	(0.25)
Books	0.0924	-0.0004	-0.0022	-0.0016	-0.0013	-0.0013	-0.0015	-0.0019
		(-0.29)	(-0.40)	(-0.37)	(-0.35)	(-0.33)	(-0.31)	(-0.30)
Txtls	0.0901	0.0014*	0.0034	0.0036	0.0034	0.0027	0.0016	0.0004
		(1.74)	(0.67)	(1.02)	(1.39)	(1.06)	(0.43)	(0.08)
Aero	0.0853	-0.0003	-0.0057	-0.0035	-0.0020	-0.0008	0.0000	0.0006
		(-0.26)	(-0.91)	(-0.71)	(-0.53)	(-0.30)	(0.02)	(0.20)
Meals	0.0549	0.0019	-0.0014	0.0007	0.0023	0.0032	0.0034	0.0029
		(1.17)	(-0.20)	(0.12)	(0.45)	(0.72)	(0.83)	(0.72)
Rubbr	0.0535	0.0000	-0.0026	-0.0015	-0.0010	-0.0009	-0.0014	-0.0025
		(-0.03)	(-0.46)	(-0.33)	(-0.27)	(-0.30)	(-0.43)	(-0.61)
Clths	0.0739	0.0009	-0.0006	0.0007	0.0014	0.0017	0.0016	0.0012
		(0.70)	(-0.10)	(0.16)	(0.41)	(0.66)	(0.71)	(0.41)
BldMt	0.0600	0.0003	-0.0019	-0.0006	0.0001	0.0003	0.0000	-0.0008
		(0.37)	(-0.37)	(-0.16)	(0.04)	(0.15)	(0.00)	(-0.31)
Trans	0.0568	0.0014	0.0039	0.0040	0.0036	0.0029	0.0017	0.0002
		(1.30)	(0.70)	(0.90)	(1.10)	(1.18)	(0.80)	(0.07)
ElcEq	0.0715	-0.0007	-0.0056	-0.0038	-0.0026	-0.0019	-0.0016*	-0.0017
		(-0.71)	(-0.96)	(-0.87)	(-0.88)	(-1.10)	(-1.66)	(-1.09)
Hlth	0.1112	-0.0018	-0.0107	-0.0095	-0.0088	-0.0084	-0.0085	-0.0089*
		(-0.75)	(-1.12)	(-1.13)	(-1.18)	(-1.29)	(-1.46)	(-1.65)
Fin	0.0917	0.0018	0.0010	0.0028	0.0043	0.0055**	0.0066***	0.0073***
		(1.41)	(0.15)	(0.56)	(1.18)	(2.24)	(3.46)	(3.02)
Comps	0.1070	0.0017	0.0035	0.0027	0.0016	0.0002	-0.0015	-0.0035
		(1.23)	(0.84)	(0.93)	(0.75)	(0.09)	(-0.47)	(-0.79)

Panel C: High-Risk Industries								
PerSv	0.0968	0.0016	0.0038	0.0039	0.0037	0.0032	0.0024	0.0014
		(0.73)	(0.43)	(0.50)	(0.57)	(0.58)	(0.48)	(0.28)
Toys	0.0865	0.0015	0.0046	0.0039	0.0026	0.0008	-0.0013	-0.0038
		(0.85)	(0.57)	(0.57)	(0.45)	(0.17)	(-0.30)	(-0.90)
Mach	0.0557	0.0010	0.0036	0.0033	0.0024	0.0009	-0.0010**	-0.0037***
		(1.40)	(0.83)	(1.03)	(1.13)	(0.97)	(-2.48)	(-2.63)
FabPr	0.1022	0.0020*	0.0096*	0.0079**	0.0058*	0.0034	0.0006	-0.0026
		(1.88)	(1.92)	(1.98)	(1.82)	(1.17)	(0.18)	(-0.71)
Fun	0.0619	-0.0013	-0.0119**	-0.0084	-0.0053	-0.0027	-0.0006	0.0007
		(-0.84)	(-1.98)	(-1.59)	(-1.17)	(-0.68)	(-0.19)	(0.23)
Other	0.1203	0.0030	0.0116	0.0102	0.0085	0.0066	0.0044	0.0018
		(1.56)	(1.29)	(1.38)	(1.45)	(1.41)	(1.14)	(0.47)
RlEst	0.1404	0.0019	0.0090	0.0073	0.0052	0.0030	0.0005	-0.0022
		(0.94)	(1.15)	(1.06)	(0.85)	(0.52)	(0.08)	(-0.37)
BusSv	0.1080	0.0019	0.0019	0.0032	0.0041	0.0047	0.0049	0.0050***
		(0.87)	(0.21)	(0.41)	(0.66)	(1.03)	(1.63)	(2.74)
LabEq	0.0834	0.0024	0.0064	0.0064	0.0060	0.0051	0.0040	0.0027
		(1.34)	(0.80)	(0.96)	(1.13)	(1.31)	(1.49)	(1.45)
Steel	0.0675	0.0009	0.0038	0.0028	0.0012	-0.0009	-0.0036***	-0.0067***
		(1.17)	(0.77)	(0.71)	(0.42)	(-0.44)	(-2.68)	(-4.82)
Cnstr	0.1060	0.0030	0.0082	0.0083	0.0082	0.0079	0.0073*	0.0066**
		(1.32)	(0.84)	(1.02)	(1.23)	(1.51)	(1.88)	(2.22)
Chips	0.1169	0.0036	0.0093	0.0094	0.0092	0.0089	0.0084*	0.0077*
		(1.40)	(0.90)	(1.05)	(1.24)	(1.46)	(1.69)	(1.83)

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). The names of defensive (high-risk) industries are bolded (italicized). 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 five 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 59 lags is employed in the t-test to adjust for overlapping observations. The t-statistics are shown in parentheses.

Figure 1: Utility Industry Beta Estimates



This figure shows the time series of the OLS beta and a constant beta = 0.9 for the utility industry from June 1968 through December 2010.

CONCLUDING COMMENTS

The standard approach to estimating the cost of equity involves using the OLS beta estimate in the CAPM. This paper investigates the effectiveness of a number of alternative beta estimators for the task of estimating industry cost of equity. Our sample includes the returns for 48 US industries for the period from 1963 to 2010. We calculate the bias of cost of equity (CE) estimates resulting from the standard use of the CAPM for each industry separately. Next we investigate the out-of-sample performances of the industry CE's that result from estimating the CAPM with a number of alternative beta estimators. The performance criterion for an industry is its mean absolute forecast error. The first alternative beta is the Blume-adjusted beta. The other alternative betas are a range of fixed value betas (beta = 0.80, 0.90, 1, 1.10, 1.20 and 1.30). The paper uses paired *t*-tests to determine whether an alternative beta estimation method produces significantly better CE estimates than those produced by the standard OLS beta.

We find that an industry's degree of defensiveness provides useful information about the adequacy of the cost of equity estimates produced by the standard application of the CAPM. Specifically, we find that 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. Our 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 eight industries based on the five-year case (the Smoke, Utility, Oil, Coal, FabPr, Fin, BusSv and Cnstr industries) and weakly significant reductions in MAE for an additional five industries (the Food, Telcm, Guns, Textl and Chips industries).

In summary, our findings reveal that for some industries there are significantly better ways to estimate the industry's cost of equity 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. One-size-fits-all approaches such as standard CAPM practice or assuming a beta of unity for all industries are not recommended. This paper has concentrated on the problem of estimating the costs of equity for US industries. A worthy topic for future research would be to see if those CE estimation techniques that perform well for US industries also perform well for the industries of other countries.

REFERENCES

Black, F. (1993). 'Beta and Return'. *Journal of Portfolio Management*.

Black, F., Jensen, M. C., & Scholes, M. (1972). The Capital Asset Pricing Model: Some empirical tests. . *Studies in the Theory of Capital Markets, 81*, 79–121.

Blume, M. E. (1975). Betas and their regression tendencies. *The Journal of Finance, 30*(3), 785-795.

Bornholt, G. (2007). Extending the capital asset pricing model: the reward beta approach. *Accounting & Finance, 47*(1), 69-83.

Bornholt, G. (2013). The Failure of the Capital Asset Pricing Model (CAPM): An Update and Discussion. *Abacus, 49*(S1), 36-43.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*(1), 57-82.

Chan, K., & Chen, N. F. (1988). An Unconditional Asset-Pricing Test and the Role of Firm Size as an Instrumental Variable for Risk. *The Journal of Finance, 43*(2), 309-325.

Chui, A. C. W., & Wei, K. C. J. (1998). Book-to-market, firm size, and the turn-of-the-year effect: Evidence from Pacific-Basin emerging markets. *Pacific-Basin Finance Journal, 6*(3-4), 275-293.

Cochrane, J. (2001). *Asset pricing*: Princeton University Press Princeton, NJ.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance, 52*(1), 1-33.

Daves, P., Ehrhardt, M., & Kunkel, R. (2000). Estimating systematic risk: the choice of return interval and estimation period. *Journal of Financial and Strategic Decisions, 13*(1), 7–14.

Dempsey, M. (2013). The capital asset pricing model (CAPM): the history of a failed revolutionary idea in finance? *Abacus, 49*(S1), 7-23.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance, 51*(1), 55-84.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics, 43*(2), 153-193.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607-636.

Genton, M. G., & Ronchetti, E. (2008). Robust prediction of beta *Computational Methods in Financial Engineering* (pp. 147-161): Springer.

Gray, S., Hall, J., Bowman, G., Brailsford, T., Faff, R., & Officer, R. (2005). The performance of alternative techniques for estimating equity betas of Australian firms. *Report prepared for the Energy Networks Association (May)*.

Gregory, A., & Michou, M. (2009). Industry Cost of Equity Capital: UK Evidence. *Journal of Business Finance & Accounting, 36*(5-6), 679-704.

Homaifar, G., & Graddy, D. (1991). Variance and lower partial moment betas as bases for costing equity capital among regulated utilities. *Applied Economics, 23*(11), 1771-1777.

Ibbotson, R., Kaplan, P., & Peterson, J. (1997). Estimates of Smallstock Betas Are Much Too Low. *The Journal of Portfolio Management, 23*(4), 104-111.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, 47*(1), 13-37.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics, 82*(3), 631-671.

Martin, R. D., & Simin, T. (1999). Robust Estimation of Beta. *University of Washington-Dept. of Statistics working paper*.

Martin, R. D., & Simin, T. T. (2003). Outlier-resistant estimates of beta. *Financial Analysts Journal*, 56-69.

Merton, R. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society, 41*(5), 867-887.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica: Journal of the Econometric Society*, 703-708.

Reilly, F. K., & Brown, K. C. (2000). *Investment Analysis and Portfolio Management* (7 ed.). Ohio: Thomson South-Western.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*(3), 341-360.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance, 19*(3), 425-442.

Theodossiou, A., Theodossiou, P., & Yaari, U. (2009). Beta estimation with stock return outliers: The case of US pharmaceutical companies. *Available at SSRN 1410371*.

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