GLOBAL TENSIONS IN FINANCIAL MARKETS

RESEARCH IN FINANCE

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GLOBAL TENSIONS IN FINANCIAL MARKETS

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NOTE FROM THE PUBLISHER

Research in Finance has been edited by John W. Kensinger for nearly 20 years. John passed away last year, and it is with great sadness that we at Emerald publish this, the final volume compiled under his leadership.

We are very grateful to the new series editors, Rita Biswas and James Conover, for their assistance in finalizing this volume and for taking the helm on future volumes. We would like to extend to them a warm welcome to the Emerald family.

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INTRODUCTION

The volume starts with empirical investigations of the impact from macroeconomic variables on equity values in emerging economies compared with developed economies (such variables include the following: currency exchange rates, various market indices, and gross domestic product). Then we learn what happens immediately following a stock's new addition or removal from the "Dogs of the Dow" portfolio. The "Dogs of the Dow" strategy focuses on selecting the highest dividend-paying stocks from among those that compose Dow Jones Industrial Average. The investigation finds that new inclusion on the list is associated with significant immediate increase in stock price, and removal from the list is associated with significant immediate decrease in stock price. So, we have strong evidence that dividends are important.

Next is an empirical affirmation of the efficiency of the Midcontinent Independent System Operator (MISO) electricity exchange following its recent (2014) major expansion in terms of market participants and geographic scope. MISO (headquartered in Carmel, Indiana) operates one of the world's largest real-time energy markets, trading electrical power across Middle America (including parts of the United States and Canada).

Next we find several investigations into the efficacy of efforts to stimulate the arousal of emerging nations around the world. We have here investigations into the banking industry in Egypt and Jordan, plus investigations of the "micro-finance" tools intended to relieve poverty in Peru and Vietnam. Also here, we see an empirical investigation of the question whether "Loyalty Voting Rights" add value to stock in Italy (compared with France).

We conclude the volume with examination of how financial discipline might be made more comfortable by effective hedging of real property values. Then we have a comparison of "insider" versus "outsider" chief executive officers in various situations. Finally, we have a critique of the real-world impact of financial research.

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A PRACTITIONER'S GUIDE TO THE CAPM: AN EMPIRICAL STUDY

Jordan French

ABSTRACT

The most popular method for calculating asset prices is the Capital Asset Pricing Model (CAPM). What is the appropriate amount of years to use in the estimation and which variation of the capital asset pricing beta provides the best results? This research looks at the out-of-sample forecasting capabilities of three popular CAPM ex-post constant beta models from 2005 to 2014. A total of 11 portfolios, five from developed and six from developing markets, are used to test the amount of input years that will reduce the mispricing in both types of markets. It is found that the best beta model to use varies between developed and developing markets. Additionally, in developing markets, a shortened span of historical years improves the pricing, contrary to popular studies that use 5 to 10 years of historical data. There are many different CAPM studies implementing various betas, using different data input lengths and run in various countries. This study empirically tests the best practices for those interested in successfully using the CAPM for their basic needs, finding that overall the simple ex-post constant beta is mispriced by 0.2 (developing) to 0.3 percent (developed).

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It is better to use short three-year estimation windows with the market beta in developing economies and longer nine-year estimation windows with the adjusted beta in developed economies.

Keywords: Forecast; in-sample length; historical (market) beta; adjusted beta; consumption beta; Fama–MacBeth

JEL classification: C22; C52; C53; G12; G15

OVERVIEW

Since William Sharpe published his pivotal paper on the capital asset pricing model (CAPM) (1964), academia has subjected the model to a battery of tests. Early on, most of these tests supported the CAPM's main predictions. One of the earliest tests was performed by Black, Jensen, and Scholes (1972). Their study found a positive relationship between returns and beta, in support of the CAPM. However, the difference in returns between high and low beta stocks was found to have created a security market line (SML) that was too flat over time. Evidence escalated indicating that the CAPM had serious shortcomings. Fama and Macbeth (1973) published results showing that there is a relationship between beta and returns and that it was unstable from one five-year period to the next. Testing the CAPM has since posed challenges to researchers in the application of the theory.

The CAPM uses historical returns to estimate for expected returns. This is possible because although investors make mistakes, in aggregate their nonsystematic errors are reduced and investors become correct on average. This qualifies the assumption that investors have rational expectations. The CAPM explains the returns investors expect when they trade assets. The expected returns of an asset are an unobservable variable that the CAPM predicts with a single factor proxy for risk. It is very useful in evaluating a project, the cost of capital, or fund performance.

CAPM has long reigned supreme as the most used method for calculating cost of equity and asset prices. The U.S. Federal Reserve, the New York Utilities Commission, and numerous other agencies have voted down the use of multifactor models in favor of the CAPM. The two government agencies cited that the multifactor literature has no consensus on how many or which factors to use. In a research conducted by Graham and Harvey (2001), they interviewed over 400 CFOs and found that

75 percent almost always or always use the CAPM to determine the return that the market required on their stock. The second most popular method was using the historical average return. In the 1980s, fewer than 30 percent of CFOs surveyed reported using the CAPM in the United States. The CAPM's popularity has clearly grown. However, outside the United States, it has been underutilized, with only about 30 percent of the CFOs using CAPM, giving room to grow as it did in the United States. With its widespread use on the rise, this research seeks to uncover the most accessible and accurate method to find beta in developed and developing markets using data spanning from 2005 to 2014. A random selection of 250 securities from the United States is used to represent the developed market and 300 securities are used from the South Pacific Asian region and South Africa to represent developing markets. Six of the 11 portfolios represent the developing market, one for each country sampled. The developing countries are Indonesia, Malaysia, Philippines, Singapore, Thailand, and South Africa.

The CAPM remains a simple, straightforward approach to estimate the cost of capital and use historical data to capture investors' behavior toward required returns and their betas. This study for practitioners tests the best ex-post constant beta from three popular methods (market, mean reverting, and consumption betas) and the optimal length of the estimation window needed to implement the CAPM as judged by the smallest forecast pricing error. The three beta models were selected as they are easy to implement, which is a key to CAPM's continued success with its ease of use for managers.

There is a plethora of studies that support the CAPM developed by Sharpe and Litner; Fama and MacBeth (1973) empirically find a relationship between risk, as measured by beta, and returns; Amihud, Christensen, and Mendelson (1992) find a strong relationship with portfolio returns and betas; Breen and Korajczyk (1993) postulate that tests performed in an attempt to prove that other factors (i.e., book to market) are significant, and not beta, suffer from selection bias; Jagannathan and McGrattan (1995) pose that the CAPM may be useful for long run estimates; and lastly Kothari, Shanken, and Sloan (1995) find betas and returns to be significant when using portfolio returns and also demonstrate the book-to-market factor to be insignificant.

This chapter is structured as follows: The "Data and Methodology" section provides an overview of the data before discussing the methodology. The "Results: Constant Betas, Years, and Regions" section reveals the main results. Finally the main conclusions are drawn.

DATA AND METHODOLOGY

The CAPM defines the relationship between risk and return.

Let,

$E(R_i)$ = the expected return investors require for asset *i*

R_f = the risk-free rate of return, using the historical period average

R_m = the market portfolio return, using the historical period average

β_i = the beta is a measure of systematic risk for asset i

$$E(R_i) = R_f + \beta_i(R_m - R_f) \tag{1}$$

CAPM Assumptions:

1. Many identical investors who are price takers
2. All investors plan to invest over the same time horizon
3. No taxes or transaction costs
4. Can borrow and lend at risk-free rate
5. Investors only care about expected return and variance
   (a) Prefer high *mean* but low *variance*
   (b) Market consists of all publicly traded assets
   (c) Market portfolio of assets = value-weighted index of all publicly traded assets

Data

Market Return (R_m)

A problem that users of the CAPM face involves the market portfolio, a combination of all assets in the economy. It assumes that all assets are tradable, but in practice, there is no such index or tool to allow investors to hold everything and all in the right proportions. Empirically, this market portfolio must have a proxy used in its place. The betas and market premium calculations use this proxy. Research by Stambaugh (1982) suggests that inferences are not sensitive to the error in the proxy when viewed as a measure of the market return and thus using the proxy does not represent an empirical problem.

In this study, each developing country uses their stock market exchange to represent the market return possible. Given the relatively small size of each developing country's one stock exchange market for publicly traded capital, each exchange is inclusive of all exchange-traded securities available. For the five U.S. portfolios, which contain securities that are traded on a variety of U.S. exchanges, the Wilshire 5000 Index is used to represent the market return. Using five U.S., five ASEAN, and one South African portfolio increases the robustness of the tests. In most research, the S&P 500 is used as the determinant of the U.S. stock market, although it only includes the top 500 companies in the United States. On the other hand, the Wilshire 5000 includes over 3,500 companies that are all headquartered in the United States (over-the-counter stocks, penny stocks, American depositary receipts, limited partnerships, and stocks of extremely small companies are excluded). The index currently includes over 22 trillion dollars of U.S. capital, more than that of the S&P 500 and NYSE. Using the larger proxy for market returns decreases the error from proxy bias. Kandel and Stambaugh's (1987) research found that the proxy needs to be correlated at least 70 percent with the true market returns to eliminate bias. If the proxy is less than 0.7 correlated, then a rejection of the CAPM may only be a rejection of the proxy used. A study by French (2017) found that the Wilshire 5000 is more likely to be correlated to the tangency portfolio than the S&P 500 and NYSE.

Risk-Free Rate (R_f)

Another problem confronting empirical studies is the risk-free rate. Naturally, it is known that no investment is truly risk free and that the proxies for such an asset vary over time; however, the CAPM also assumes the rate to remain constant. As for the risk-free rate used in this study, the 10-year U.S. Treasury bond is used in all calculations where a risk-free rate is required. In the event that the U.S. Federal Government goes bankrupt, the dollar itself would become worthless at this point.

Asset Returns (R_i)

Five countries that are ASEAN member nations and South Africa have been selected to represent the developing markets, and the ASEAN includes Indonesia, Malaysia, Philippines, Singapore, and Thailand. The other exchanges of ASEAN member states were not included because their exchanges lacked enough publicly traded companies or were too young and did not span back to 2005. Also, five sectors have been selected to represent the U.S. market. Each ASEAN country, each U.S. sector, and South Africa has a random sample of 50 individual stocks for each of the 11 equally weighted portfolios, making a total of 300 stocks for developing and 250 stocks for developed economies.

A total of 522 weeks is used for the 550 stocks, 7 indexes, and the U.S. 10-year Treasury bond for a grand total of 291,276 observations used in this research. The stocks were randomly selected by taking the total list of publicly traded stocks in random order and dividing by 50, then selecting every *i*th company on the list. The list excludes those companies that were recently listed within the past 10 years. The data use the weekly adjusted close to calculate percent changes from January 3, 2005, to December 29, 2014. Again following best practices, the weekly data are used, instead of daily or monthly. Over one-third of the U.S. companies listed on exchanges are not traded daily and the ASEAN markets are far less liquid. Therefore, using daily data would be inappropriate because it would include the days that the assets are not traded and the value of the asset is not known until a sale is made. The nontraded days would be incorrectly included in the averages and skew the results of the calculations. Likewise, the monthly data are not used because it provides too few data points for the results to be meaningful and would smooth out the fluctuations in the price changes too much.

There are 50 individual stocks that comprise each of the 11 replicating portfolios. The portfolios are for South Africa and one for each of the five ASEAN member states and sectors of the U.S. economy used, for 11 total portfolios. The most obvious and accurate way would be to use several industry and country-specific stock indexes. However, due to lack of information in the ASEAN markets, portfolios were created from 50 randomly selected stocks. This approach is justified by the fact that companies within a sector share characteristics, such as business cycles, tariffs, country risk, technological development, and raw material availability. This method is also commonly performed in CAPM studies and also benefits from the law of large numbers. When testing the CAPM, it is best to use portfolios rather than individual stocks to overcome the errors in variables, data snooping, and information loss issues. The former problem is due to the sensitivities to risk factors specified by the asset pricing models which are estimated from data that contain sampling errors. Since factor sensitivities for portfolios are estimated more precisely than for individual stocks, the factor risk premium estimates will be less biased due to errors-in-variables problems if one uses portfolios and not individual stocks. The use of portfolios over individual stocks has been favored by numerous studies including Black, Jensen, and Scholes (1972) and Kraus and Litzenberger (1976). Additionally, a problem arises when one uses portfolios that are sorted based on characteristics known to predict returns. Lewellen, Nagel, and Shanken (2010) show that as a result even factors with weak correlation with the sorting characteristic would explain differences in average returns across test portfolios regardless of economic merit underlying the factors. To address this issue, the portfolios in this research are not sorted by any fundamental characteristics. The portfolio method that aggregates weekly adjusted returns of the firm into an equally weighted portfolio was used, as recommended by Jaffe (1974), and not the capitalization-weighted method. Capitalization-weighted portfolio is not used, as the portfolio would then be weighted with data of stocks the market bid up and possibly made overvalued.

Methodology of ex-post, constant betas

All three formulas use the CAPM expected return (E_r) of Eq. (1) and only the method for calculating beta is altered. The betas are calculated using time series data, then the actual out of sample returns are regressed against the estimated expected returns. The difference between the E_r and the out of sample mean are compared to rank models that are preferred to have a difference closest to zero (Enders, 2010). To also test which beta is more related to returns, the Fama–MacBeth and cross-sectional approach are used as the regression models and the standard errors and test statistics are used to rank the betas (Mankiw & Shapiro, 1986). To test to see if the results are subject to the length of the estimation window, the models are tested with one, three, five, and nine years of inputs into the beta and expected return formulas. The accuracy of the expected return is then differenced by the out of sample actual returns. A two-year rolling estimation window of the expected returns are also calculated over the entire sample (four windows in total) and two rolling four-year estimation windows are also used. This will show if the data properties are changing over time (structural breaks) and if a beta was accurate in forecasting in some periods but not others. The mean absolute errors will be used in averaging of the results of the rolling estimation windows across time periods and markets.

Three-factor ANOVA is used to determine if there are any differences in the predictions of the constant models. Using too long historical data spans has disadvantages in that companies change their business' markets, managers, and investments, thus changing betas. Another disadvantage is that most companies do not have the historical data needed to compute their expected returns in an applied setting. This is even truer for companies residing in ASEAN member states. The average tenure of a CEO is close to nine years and that of a Fortune 500 CEO is close to three years. This is why the study tests using nine and three years. Also the five years of historical inputs is used, as this is a common time period in CAPM studies, and past researchers have found that beta remains constant within five-year windows.

Historical (market) beta

$$\frac{\mathrm{Covar}(R_i, R_\mathrm{m})}{\mathrm{Var}(R_\mathrm{m})}$$

Historical betas are estimated from the stock's characteristic line by running a linear regression between past returns on the stock and past returns on some market index, ex post data.

Adjusted beta

$$\frac{1}{3} + \frac{2}{3} * (\text{Historical beta})$$

The need for a beta based on the future, not the past, has created the development of the adjusted beta. It grew in part from the work of Blume and Friend (1973), who showed that over time betas mean revert back to 1.0. Therefore the adjusted beta, on average, will be a better predictor of the future beta than the historical unadjusted beta.

Consumption beta

$$\frac{\mathrm{Covar}(R_i, \mathrm{CG})}{\mathrm{Covar}(R_\mathrm{m}\ \mathrm{CG})}$$

where CG is the consumption growth rate.

The Consumption Capital Asset Pricing Model (CCAPM) is a more elegant and theoretically superior model, but in practice it is difficult to implement and obtain accurate results which has made it inferior to the traditional model. Robert Lucas, a Nobel laureate in economics, and Douglas Breeden provided the groundwork of the CAPM in 1978 and 1979. Their model is an extension of the CAPM, and the empirical evidence suggests it is best used as a theoretical model. In the CCAPM, risky assets create uncertainty in consumption, and thus what they will consume will decrease because their wealth is uncertain as a result of a decision to invest in risky assets. CCAPM explains how much the entire stock market changes relative to the consumption growth.

This more accessible version of the CCAPM can use the same linear representation, as the CAPM, between a risky asset and the market risk premium. The implied returns and risk premium are determined by the investors' risk aversion and consumption growth. The systematic risk is provided by the beta, just as the standard CAPM. The CCAPM links investment decision with wealth and consumption.

RESULTS: CONSTANT BETAS, YEARS, AND REGIONS

For each of the 11 portfolios, its mean return over the entire sample period and the three different beta risk measures are computed. Table 1 contains sample statistics with the returns (R_i) in decimal format. Note that the correlation between betas and the portfolio returns (R_i) is negative. This is indicative that as the beta increased the returns decreased, which occurs when the market (R_m) is falling as it did during the sample period. The high correlation, 0.8412, between the portfolio and market returns demonstrates a low sampling error and gives confidence in the portfolio diversification. All beta risk measures have high, positive correlation with each other, meaning that risky portfolios measured under one beta method tend to be risky under other beta methods as well.

The out of sample forecast errors were calculated using three different techniques and the results appear in Tables A.2 and A.3. The first table, in Table A.2, calculates the various expected returns (E_r) using the different lengths of time periods and betas and then finds the difference between the E_r and actual out of sample means. The second table, in Table A.2, uses the same E_r, which is found using the weekly averages, then annualizes it to find the difference of each portfolio's actual annual percent change. From the tables, the first method is preferred and is used in empirical studies of the CAPM.

Table 1. Sample Statistics of the Portfolio Returns (R_i), Market Returns (R_m), Historical (B_h), Adjusted (B_a), and Consumption Beta (B_c).

	R_i	B_h	B_a	B_c	R_m
Mean	0.0040	0.2707	0.5138	0.8241	0.0019
Median	0.00341	0.12109	0.41406	0.8702	0.0015
σ	0.00215	0.33134	0.2209	0.55777	0.0008
Correlation with:					
R_i	1				
B_h	−0.4173	1			
B_a	−0.4173	1	1		
B_c	−0.1245	0.7257	0.7257	1	
R_m	0.8412	−0.3605	−0.3605	−0.1493	1

In Table A.3, rolling two- and four-year estimation windows are used over the full sample with one year out of the sample periods used to derive the forecast mean absolute errors (FMAE). The FMAE are used across 11 markets and 6 time periods. This allows the research to make sure the results hold from period to period and are not susceptible to structural breaks. The FMAE indicates that the CAPM predicted utilities (developed) and South Africa (developing) with the greatest accuracy. Philippines proved to be the most difficult market for the CAPM with an average FMAE of 1.17 percent across sample periods, whereas utilities and South Africa were 0.26 and 0.32 percent, respectively. The lowest errors across all 11 markets from 2005 to 2012 to estimate expected returns was in the 2009 to 2010 (developed) and 2005 to 2006 (developing) windows. There was an overall FMAE average of 0.35 (developed) and 0.39 percent (developing). Although t-test results indicate no statistical difference between the rolling time periods used (no structural breaks), the worst time period across all 11 portfolios was 2007 to 2008 with FMAE averages of 1.09 (developed) and 1.60 percent (developing). This period contained the financial crisis that began at the end of 2007 and lasted throughout 2008. Regardless of a market bubble or a devastating global scale financial crisis, the CAPM was still quite accurate!

Three-factor ANOVA tables were computed to see if there exists any difference between amount of years, betas, or region used. The ANOVA assumption of independent samples has been violated, increasing the chance of type II error. This violation would have the test fail to reject the null of no significance when it should reject. The length of years used have overlapping sample periods, which understates the test significance. Fortunately, tests reveal with significance that there exists a difference of the years.

The ANOVA (Appendix A.1) results for all effects and interactions show at the 99 percent confidence level that there is a difference between using CAPM on developed and developing markets. The 95 percent confidence level shows that a difference between the amount of years used to calculate CAPM plays an important role and finally that the optimal amount of years used differs between the two regions at the 90 percent level. A battery of two-tailed standardized Student's t-tests were also performed and concur with the ANOVA results with a range of 29 to 59 degrees of freedom. The t-tests reject the null of no difference for the years as well as the region factors. Further testing fails to reject a difference for betas on 39 degrees of freedom; this can be explained by the high correlation among the betas as seen in Table 1. In many of the samples used in testing difference between years:regions and betas:regions the t-tests also report significance. The average of the forecast errors from the first table in Appendix A.2 are shown in Table 2. Data show that overall the

Table 2. Average Portfolio Out of Sample Misprice of Expected Returns and Actual Returns.

Economy				
Developing	−0.00206			
Developed	0.00324			
Input years used				
1	3	9	5	
0.00394	0.00107	0.00012	−0.00279	
Input years used by economy				
Region	1	3	9	5
Developing	−0.00209	−0.00113	−0.00251	−0.00253
Developed	0.00997	0.00328	0.00275	−0.00305

more years of data used the better the fit to predict the following year. Years one, three, and nine were used with 2014 as the out of sample. Year five used five years of data to predict 5 years into the future. In many influential CAPM articles, five years of data are used to forecast out five years. As can be seen, this result is worse than using nine or three years. It is important to point out that in many published research articles, this five-year approach is used in the testing of the model. As can be seen, this is detrimental to the model's performance. From the regions analysis, it can be seen that CAPM expected returns (E_r) under-predict the actual returns in the developing countries, whereas in the United States, the E_r on average over predicted; and the CAPM actually predicted better in the emerging markets than in the developed United States. This finding should inspire confidence in the 30 percent of CFOs outside the United States using the CAPM and hopefully recruit more in using it. For years and regions, it can be seen that using one to three years of data input is preferred in the developing markets, whereas in the developed markets of the United States, more data are better.

The fact that the developing portfolios do better with a shorter span of historical inputs suggests that the markets may be less efficient and the smaller markets may also be prone to disrupting variations.

When running ANOVA with only two-way interactions, the betas used between the regions become highly significant at almost the 1 percent level. From Table 3, we see that the historical beta is best used in the developing economies, as these markets exhibit less mean reversion and market efficiency than the United States. In the United States, on the other hand, the simple

Table 3. Average Out of Sample Misprice with the Three Different Beta Models in Each Region.

	Betas and Regions		
	Historical β	Adjusted β	Consumption β
Developing	−0.00202	−0.00206	−0.00210
Developed	0.00326	0.00323	0.00322

consumption beta, which is the covariance of returns with GDP consumption per capita growth, had lower average forecast errors.

So, overall which beta is more related to returns? The Fama–MacBeth two-stage and a cross-sectional regression, with the three betas as explanatory variables and the returns as the dependent variable, were performed. The historical beta was found to be statistically significant and the consumption beta was not (Appendix A.4). In a study using OLS with quarterly data over 23 years, Mankiw and Shapiro (1985) also found consumption beta to not be significant.

CONCLUSIONS

The beta is the most widely used instrument among financial economists and specialists for risk management and is one of a handful of regression coefficients that people willingly pay money to obtain. The simple constant beta method is the most widely used model by finance practitioners and the like. When using a constant model in the United States, the results favor using nine years of inputs and a simplified consumption beta or mean reverting adjusted beta over the historical market beta. For those wishing to value risk in smaller markets, use of the shorter three-year period of inputs and the nonmean reverting, more stochastic, historical beta should be used. Also, analysts should keep in mind that from 2005 to 2014, the expected returns in the United States on average are slightly higher than actual (over predicting), whereas in the developing economies, it is slightly lower than actual (under predicting). The results give a smaller variance (better prediction) on the ASEAN portfolios over the United States. The out of sample tests reveal that the CAPM mispriced by at most 0.99 percent on average for the proceeding year's return. However, if one selects the proper input length and beta for their market type, it can be reduced to as low as 0.01 percent. Overall, the simple beta models mispriced by 0.2 to 0.3 percent, which is commendable if not superior to all the fancy advanced versions of the CAPM (i.e., time-varying betas and ex-ante betas). This result will hopefully instill practicality to the remaining 70 percent of the CFOs outside the United States not using the CAPM.

REFERENCES

Amihud, Y., Christensen, B. J., & Mendelson, H. (1992). *Further evidence on the risk-return relationship*. Working Paper No. S-93-11. Salomon Brothers Center for the Study of Financial Institutions, New York University, New York, NY.

Black, F., Jensen, M., and Scholes, M. (1972). *The Capital Asset Pricing Model: Some Empirical Tests. Studies in the theory of capital markets*, Praeger Publishers.

Blume, M., & Friend, I. (1973). A new look at the capital asset pricing model. *Journal of Finance, 28*, 19–33.

Enders, W. (2010). *Applied econometric time series*. Chichester: Wiley.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607–636.

French, J. (2017). The one: A simulation of CAPM market returns. *Journal of Wealth Management, 20*, 126–147.

Jaffe, J. F. (1974). The effect of regulation changes on insider trading. *Bell Journal of Economics and Management Science, 5*, 93–121.

Kandel, S., & Stambaugh, R. F. (1987). On correlations and inferences about mean-variance efficiency. *Journal of Financial Economics, 18*, 61–90.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *Journal of Finance, 31*(4), 1085–1100.

Lewellen, J., Nagel, S., & Shanken, J. (2010) A skeptical appraisal of asset pricing tests. *Journal of Financial Economics, 96*, 175–194.

Mankiw, N. G., & Shapiro, M. D. (1985). Trends, random walks, and tests of the permanent income hypothesis. *Journal of Monetary Economics, 89*(5), 165–174.

Mankiw, N. G., & Shapiro, M. D. (1986). Do we reject too often? Small sample properties of tests of rational expectations models. *Economic Letters, 20*, 139–145.

Stambaugh, R. F. (1982). On the exclusion of assets from tests of the two-parameter model: A sensitivity analysis. *Journal of Financial Economics, 10*(3), 237–268.

APPENDIX

Table A.1. Three-Factor ANOVA Results.

All effects and interactions

	DF	Sum Sq.	Mean Sq.	*F* value	Pr(>*F*)
Betas	2	0.0000001	0.00000004	0.0005	0.999513
Years	3	0.0006957	0.00023191	2.7699	0.045792*
Regions	1	0.0008432	0.00084323	10.0713	0.002024**
betas:years	6	0.0002337	0.00003895	0.4652	0.832473
betas:regions	2	0.0000000	0.00000000	0.0000	0.999963
years:regions	3	0.0006015	0.00020050	2.3948	0.73056
betas:years:region	6	0.0001568	0.00002614	0.3122	0.929229
Residuals	96	0.0080377	0.00008373		

Only effects, no interactions

	Df	Sum Sq.	Mean Sq.	*F* value	PR(>*F*)
betas	2	0.0000001	0.00000004	0.0005	0.999490
years	3	0.0006957	0.00023191	2.9022	0.038011*
regions	1	0.0008432	0.00084323	10.5524	0.001528**
Residuals	113	0.0090297	0.000007991		

Only two-way interactions

	Df	Sum Sq.	Mean Sq.	*F* value	Pr(>*F*)
betas:years	11	0.0009295	8.4504E-05	1.0518	0.40764
betas:regions	3	0.0008432	2.8108E-04	3.4987	0.01824*
years:regions	3	0.0006015	2.0050E-04	2.4958	0.06405
Residuals	102	0.0081945	8.0338E-05		

Notes:
* 5 percent significance level
** 1 percent significance level

Table A.2. Two Tables Displaying Different Variance Methods of Forecast and Out of Sample.

1) Average forecast errors [E(r) – Actual out of sample mean]

	Historical β				Adjusted β				Consumption β			
Years	1	3	9	5	1	3	9	5	1	3	9	5
Indo	0.0042	−0.0023	−0.0031	−0.0053	0.0032	−0.0017	−0.0026	−0.0048	−0.0187	−0.0081	−0.0018	−0.0042
Malay	0.0006	0.0006	0.0005	−0.0004	0.0024	0.0006	0.0007	−0.0007	0.004	0.0007	0.0012	0.0005
Phil	0.0033	−0.0045	−0.0049	−0.0055	0.0006	−0.004	−0.0038	−0.0048	−0.0057	−0.0092	−0.0046	0.0069
Sing	0.0007	−0.0014	−0.0005	−0.0004	−0.0002	−0.0015	−0.0005	−0.0004	−0.0067	0.0355	−0.0003	−0.0002
Thai	−0.0021	−0.0068	−0.0064	−0.0067	−0.004	−0.007	−0.0063	−0.0066	−0.0128	−0.0078	−0.0052	−0.0055
S. Africa	0.0023	−0.0004	−0.0002	−0.0009	0.0017	−0.0003	0.0001	−0.0006	−0.0004	−0.0017	−0.0030	0.0078
Developing	0.0015	−0.0025	−0.0024	−0.0032	0.0006	−0.0023	−0.0021	−0.0030	−0.0067	0.0016	−0.0023	0.0009
U.S. BM	0.032	0.0251	0.0244	0.0005	0.0312	0.0257	0.0248	−0.0002	0.0356	0.0264	0.0251	−0.0001
U.S. HC	0.0046	−0.0038	−0.0045	−0.0054	0.0032	−0.0033	−0.0042	−0.0054	0.0056	−0.0034	−0.0044	−0.0054
U.S. IG	0.0075	0.0004	−0.0005	−0.0035	0.0065	0.0009	0.0000	−0.0034	0.0074	0.0016	0.0004	−0.0034
U.S. RE	0.0053	−0.0027	−0.0032	−0.0046	0.004	−0.0022	−0.0023	−0.0036	−0.0009	−0.0029	−0.0001	−0.0035
U.S. UT	0.0053	−0.0041	−0.0049	−0.0026	0.0036	−0.0036	−0.0045	−0.0026	−0.0013	−0.0049	−0.0048	−0.0026
Developed	0.0109	0.0030	0.0023	−0.0031	0.0097	0.0035	0.0028	−0.0030	0.0093	0.0034	0.0032	−0.0030

Notes:
Years: 1 = 2013; 3 = 2011–2013; 9 = 2005–2013 and uses 2014 for out of sample to calculate variance.
5 = 2005–2009 and uses 2010–2014 for out of sample forecast.

Table A.2. (*Continued*)

*2) Annualized forecast errors [(E(r) * 52) – Actual out of sample percent change]*

	Historical β				Adjusted β				Consumption β			
Years	1	3	9	5	1	3	9	5	1	3	9	5
Indo	0.242	−0.0966	−0.1394	−3.0021	0.1909	−0.0648	−0.1107	−2.9758	−0.9508	−0.3981	−0.0733	−2.9446
Malay	0.091	0.088	0.0862	−0.2955	0.1813	0.0903	0.0952	−0.3132	0.2646	0.094	0.1214	−0.2518
Phil	0.312	−0.0917	−0.1169	−0.3652	0.1709	−0.3397	−0.0976	0.2812	−0.1561	−0.3397	−0.0976	0.2812
Sing	0.017	−0.0946	−0.0466	−0.4889	−0.0318	−0.097	−0.0448	−0.4863	−0.3682	1.8263	−0.0328	−0.4789
Thai	−0.0688	−0.313	−0.2932	−1.1508	−0.1673	−0.3209	−0.2875	−1.1436	−0.6255	−0.3659	−0.2293	−1.0873
S. Africa	0.1676	−0.0247	−0.0122	−0.5063	0.1248	−0.0177	0.0071	−0.3352	−0.0286	−0.1075	−0.2174	4.3336
Developing	0.1268	−0.0888	−0.0870	−0.9681	0.0781	−0.1250	−0.0730	−0.8288	−0.3108	0.1182	−0.0882	−0.0246
U.S. BM	0.4936	0.1323	0.0933	−0.0802	0.4481	0.1637	0.1152	−0.0783	0.6776	0.1979	0.1326	−0.0767
U.S. HC	0.2308	−0.2055	−0.2433	−1.8474	0.1569	−0.1775	−0.2252	−1.8452	0.286	−0.1856	−0.2365	−1.8468
U.S. IG	0.3742	0.0035	−0.0327	−1.0919	0.3222	0.0315	−0.0151	−1.0899	0.3701	0.0686	0.0075	−1.0877
U.S. RE	0.1993	−0.2167	−0.241	−1.2522	0.1319	−0.189	−0.1972	−1.2007	−0.1224	−0.2269	−0.0837	−1.1935
U.S. UT	0.2719	−0.2172	−0.2549	−0.9814	0.1825	−0.1871	−0.2346	−0.979	−0.0689	−0.2595	−0.2511	−0.9803
Developed	0.3140	−0.1007	−0.1357	−1.0506	0.2483	−0.0717	−0.1114	−1.0386	0.2285	−0.0811	−0.0862	−1.0370

Notes:
Years: 1 = 2013; 3 = 2011–2013; 9 = 2005–2013 and uses 2014 for out of sample to calculate variance.
5 = 2005–2009 and uses 2010–2014 for out of sample forecast.

Table A.3. Subsample Periods of FMAE.

Historical beta (developed)

Estimation Window	U.S. BM	U.S. HC	U.S. IG	U.S. RE	U.S. UT	Average
2005–2006	0.0049	0.0028	0.0032	0.0050	0.0017	0.0035
2007–2008	0.0179	0.0124	0.0085	0.0126	0.0031	0.0109
2009–2010	0.0065	0.0013	0.0012	0.0020	0.0024	0.0027
2011–2012	0.0028	0.0113	0.0064	0.0033	0.0031	0.0054
2005–2008	0.0146	0.0120	0.0082	0.0127	0.0031	0.0101
2009–2012	0.0038	0.0059	0.0044	0.0056	0.0021	0.0044
Average	0.0084	0.0076	0.0053	0.0069	0.0026	**0.0062**

Historical beta (developing)

Estimation Window	Indo	Malay	Phil	Sing	Thai	S. Africa	Average
2005–2006	0.0099	0.0002	0.0085	0.0019	0.0004	0.0026	0.0039
2007–2008	0.0192	0.0097	0.0240	0.0182	0.0184	0.0063	0.0160
2009–2010	0.0020	0.0048	0.0019	0.0097	0.0070	0.0029	0.0047
2011–2012	0.0093	0.0047	0.0047	0.0017	0.0003	0.0035	0.0040
2005–2008	0.0159	0.0073	0.0206	0.0146	0.0164	0.0026	0.0129
2009–2012	0.0088	0.0008	0.0107	0.0024	0.0085	0.0011	0.0054
Average	0.0109	0.0046	0.0117	0.0081	0.0085	0.0032	**0.0078**

Adjusted beta (developed)

Estimation Window	U.S. BM	U.S. HC	U.S. IG	U.S. RE	U.S. UT	Average
2005–2006	0.0048	0.0024	0.0026	0.0056	0.0009	0.0032
2007–2008	0.0175	0.0150	0.0114	0.0166	0.0068	0.0135
2009–2010	0.0066	0.0003	0.0013	0.0019	0.0009	0.0022
2011–2012	0.0013	0.0135	0.0087	0.0055	0.0054	0.0069
2005–2008	0.0143	0.0131	0.0094	0.0142	0.0045	0.0111
2009–2012	0.0031	0.0062	0.0050	0.0063	0.0023	0.0046
Average	0.0080	0.0084	0.0064	0.0083	0.0035	**0.0069**

Adjusted beta (developing)

Estimation Window	Indo	Malay	Phil	Sing	Thai	S. Africa	Average
2005–2006	0.0086	0.0000	0.0072	0.0018	0.0005	0.0031	0.0035
2007–2008	0.0182	0.0092	0.0233	0.0181	0.0182	0.0058	0.0155
2009–2010	0.0004	0.0049	0.0004	0.0097	0.0075	0.0029	0.0043
2011–2012	0.0076	0.0039	0.0021	0.0015	0.0014	0.0031	0.0033
2005–2008	0.0148	0.0069	0.0196	0.0144	0.0163	0.0021	0.0124
2009–2012	0.0068	0.0005	0.0086	0.0024	0.0078	0.0009	0.0045
Average	0.0094	0.0042	0.0102	0.0080	0.0086	0.0030	**0.0072**

Table A.3. (*Continued*)

Consumption beta (developed)

Estimation Window	U.S. BM	U.S. HC	U.S. IG	U.S. RE	U.S. UT	Average
2005–2006	0.0056	0.0013	0.0019	0.0086	0.0000	0.0035
2007–2008	0.0162	0.0169	0.0128	0.0188	0.0090	0.0147
2009–2010	0.0064	0.0015	0.0045	0.0047	0.0011	0.0036
2011–2012	0.0014	0.0129	0.0054	0.0079	0.0131	0.0081
2005–2008	0.0140	0.0137	0.0095	0.0134	0.0051	0.0111
2009–2012	0.0020	0.0068	0.0009	0.0048	0.0026	0.0034
Average	0.0076	0.0089	0.0058	0.0097	0.0052	**0.0074**

Consumption beta (developing)

Estimation Window	Indo	Malay	Phil	Sing	Thai	S. Africa	Average
2005–2006	0.0112	0.0000	0.0074	0.0781	0.0044	0.0016	0.0171
2007–2008	0.0297	0.0078	0.0209	0.0175	0.0184	0.0151	0.0182
2009–2010	0.0038	0.0051	0.0022	0.0097	0.0061	0.0027	0.0049
2011–2012	0.0079	0.0031	0.0142	0.0049	0.0604	0.0189	0.0182
2005–2008	0.0168	0.0052	0.0028	0.0149	0.0163	0.0080	0.0107
2009–2012	0.0018	0.0008	0.0017	0.0016	0.0145	0.0050	0.0042
Average	0.0119	0.0037	0.0082	0.0211	0.0200	0.0086	**0.0122**

Table A.4. Regression of Betas.

Which beta is more related to returns?
A. Fama–MacBeth approach
(*Dependent Variable* R_i)

	Estimate	Std. Error	t Value	Pr(>|t|)
Historical β	−0.0027	0.0008	−3.2540	0.0017
Adjusted β	−0.0040	0.0012	−3.2543	0.0017
Consumption β	0.0001	0.0003	0.2508	0.8026

B. Cross-sectional regression approach
(*Dependent Variable* R_i)

	Estimate	Std. Error	t Value	Pr(>|t|)
Intercept	−27.2357	10.9445	−2.4885	0.0473
Historical β	−54.4866	21.8902	−2.4891	0.0472
Adjusted β	81.7242	32.8356	2.4889	0.0472
Consumption β	0.0005	0.0015	0.359	0.7319

Residual standard error: 0.001632941