Capitalizing on the Greatest Anomaly in Finance with Mutual Funds

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Comments are enormously welcome!

ABSTRACT

Contrary to the predictions of CAPM, empirical research has shown that investing in low-beta stocks can improve the mean-variance efficiency of an investor's portfolio. Through forming portfolios of mutual funds based on beta, I examine whether or not mutual fund investors can capitalize on this anomaly. I find that one investing in a portfolio of funds in the top quintile of beta can improve her excess returns by an average of 2.76% a year without increasing risk by holding a levered position in a portfolio of funds in the bottom quintile instead.

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1. Introduction

The Capital Asset Pricing Model (CAPM), developed by Lintner (1965), Mossin (1966), Sharpe (1964), and Treynor (1961), predicts that a stock's return generating process is characterized by the following form:

(1)

where is the expected return on the stock market in excess of the risk-free rate of interest, is the expected return on stock in excess of the risk-free rate, and (beta) denotes , i.e. the factor by which comoves with . is usually estimated through a univariate time-series regression of the following form:

(2)

The CAPM provides a simple and intuitive model of how investors should be compensated for bearing systematic (market) risk. It is the predominant asset pricing model taught in finance classes and used by practitioners (Association for Financial Professionals (2011), Bruner, Eades, Harris, and Higgins (1998), Fernández (2010), Gitman and Vandenberg (2000), and Graham and Harvey (2001)).

Despite the CAPM's theoretical appeal, a trilogy of empirical tests since the creation of the model have consistently shown that the beta-return relationship is flatter than that which is predicted by the model[1]. In other words, market participants are undercompensated for bearing incremental market risk. Most perplexingly, some of the more recent studies have even revealed a negative and economically significant beta-return relationship (Baker, Bradley, and Wurgler (2011) and Blitz and Van Vliet (2007)). Because the CAPM serves as the foundation of asset pricing theory, many practitioners consider the model's abysmal ability to describe the behavior of stock returns to be the greatest anomaly in finance (Considine (2012) and Fink (2011)). Borrowing constraints, tracking error constraints, and irrational investor behavior are some of the explanations that have been espoused for the anomaly. Baker, Bradley, and Wurgler (2011),

[1] See, for example, Black (1972), Black, Jensen, and Scholes (1972), Blume and Friend (1973), Douglas (1968), Fama and French (1992, 1996, 1998, 2004), Fama and MacBeth (1972), Frazzini and Pedersen (2011), Friend and Blume (1970), Lakonishok and Shapiro (1986), Lakonishok, Shleifer and Vishny (1994), Miller and Scholes (1972), Reinganum (1981), and Stambaugh (1982) for evidence of this.

Blitz and Van Vliet (2007), and Falkenstein (2010) provide an excellent discussion of these behavioral explanations. At a more fundamental level, Fama and French (2004) attribute the failure of CAPM to a misspecification of the model.

Given that research has consistently shown that investors are undercompensated for bearing market risk, a simple strategy of investing in low-beta stocks can improve the mean-variance efficiency of one's portfolio. However, Domian, Louton, and Racine (2007) show that one must own over 100 stocks in order to minimize nonsystematic risk. Yet according to the Federal Reserve Board's 2010 Survey of Consumer Finances, the median family holds only $21,500 in Financial Assets. It is therefore quite expensive for most individuals to directly own an adequately diversified portfolio of individual stocks, making mutual funds a more attractive candidate for investment. This motivates purpose of this paper, to explore the benefits of investing in low-beta mutual funds.

The findings of this empirical study are that low-beta mutual funds have lower out-of-sample risk than their high-beta counterparts, but offer similar levels of return. The practical implication of this study is that a simple strategy of investing in low-beta mutual funds improves the mean-variance efficiency of an investor's portfolio.

2. Performance of low-beta funds

2.1 The Samples

To evaluate the performance of low-beta mutual funds, I obtain monthly net-of-expense returns and total net assets (TNA) from Morningstar Direct's United States Mutual Funds database on all open-end equity funds (including "dead funds") classified by Morningstar as having a U.S. broad asset class of "U.S. Stock"[2]. Morningstar Direct is the most complete and timely database offered by Morningstar, Inc., a leading provider of mutual fund data. Monthly returns on share classes are aggregated to the portfolio level by weighting them by their contemporaneous month-

[2] Other asset classes are Balanced, Commodities, International Stock, Money Market, Municipal Bond, Sector Stock, and Taxable Bond. Morningstar does not assign funds to multiple asset classes.

end TNA. The time period of the study was December 1990 through September 2012 and the data was collected on October 31, 2012. December 1990 was chosen as the initial month of the study because the number of share classes with monthly TNA data from Morningstar Direct increased from 32 to 414 in that month[3].

I estimate rolling betas for each mutual fund over the prior 60 months using a CAPM regression (eq. 2) of the excess returns on each fund against the excess returns on the CRSP value-weighted portfolio of U.S. common stocks. Data on market returns and risk-free rates is gathered from Kenneth French's website[4]. Funds with less than 24 months of returns over the estimation period are discarded. I then sort the funds into five portfolios based on their quintile-rank of beta and compute the TNA-weighted returns on each of the five portfolios over the next month. I then repeat this process in each of the following months to arrive at a time-series of 202 monthly returns on the five beta-sorted portfolios. I also construct a time-series of TNA-weighted returns on a "Universal" portfolio consisting of the all of the funds that comprise the beta-sorted portfolios. To span the spectrum of beta estimation periods that are commonly used by practitioners, I also examine the performance of portfolios based on beta calculated from 12 months of returns[5]. A time plot illustrating the quintile breakpoints of beta is provided in Figure I. The variation in the cross-sectional dispersion of the breakpoints over time is likely an artifact of index fund investing, as discussed in Sullivan and Xiong (2012).

2.2 60-Month Estimation Period Results

Table I displays the results for the performance of portfolios that are constituted based on beta calculated over the 60-month estimation period. There is little difference in the average returns across the beta-sorted portfolios yet the out-of-sample CAPM betas are monotonically increasing across the portfolios, from 0.77 for the bottom quintile portfolio to 1.26 for the top

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[3] Prior to December 1990, TNA data was typically available from Morningstar Direct on a quarterly basis rather than a monthly basis. A time plot of the number of share classes in each month with TNA data is available from the author upon request.

[4] Details on the construction of the variables gathered from Kenneth French's website can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html. I am grateful to Kenneth French for providing this data.

[5] In Jacobs and Shivdasani's (2012) analysis of a survey of financial executives conducted by the Association for Financial Professionals, 98% of respondents reported that they calculated betas over a 1 (29%), 2 (13%), 3 (15%), or 5 (41%) year period.

quintile portfolio. The same pattern is apparent in the annualized standard deviation of portfolio returns, which are monotonically increasing across the portfolios from 14.00% to 22.38%. This results in Sharpe ratios that are globally decreasing across the portfolios, from 0.40 for the bottom quintile portfolio to 0.24 for the top quintile portfolio. These findings imply that mutual fund investors can indeed improve their mean-variance efficiency through investing in low-beta funds. A comparison of the empirical beta-return relationship with that which is predicted by the CAPM is illustrated in Figure II.

The alphas, albeit statistically insignificant, are generally decreasing across the portfolios, regardless of asset pricing model specification. The bottom quintile portfolio outperforms the top quintile portfolio by 3.06% per a year on average based on alpha derived from the CAPM. The statistic for the bottom quintile portfolio improves from 0.85 to 0.94 when the Carhart (1997) Four-Factor Model is used rather than the CAPM. The Carhart Four-Factor Model results show that some of the differential in CAPM alpha between the portfolios can be attributable to HML factor loadings, which indicate that low-beta funds have a greater orientation towards value stocks. However, even after accounting for the extramarket factors in Carhart's Model, the performance of the bottom quintile portfolio relative to the top quintile portfolio is still economically meaningful, as the difference in alpha derived from Carhart's model is 2.11% a year. This implies that the difference in CAPM alphas is only slightly subsumed by the book-to-market (value) effect. It is also interesting to note that the average dividend yield is greater among the portfolios with higher CAPM betas, suggesting that the outperformance of the low-beta funds is not a result of an orientation towards stocks with high dividends either.

It is important to address the possibility that the out-of-sample CAPM betas of the portfolios are driven by mutual fund cash holdings. If this is the case, then investors seeking to capitalize on the low-beta anomaly through investing in funds with low betas may inadvertently acquire an excessive allocation towards risk-free assets. However, average cash holdings are rather homogeneous among the portfolios, ranging from 3.18% (quintile 3) to 5.80% (bottom quintile)[6]. A "back of the envelope" calculation reveals that even if the funds in the bottom

[6] Monthly cash holdings are reported in Morningstar Direct based on feedback from surveys it conducts. Based on a conversation with a representative at Morningstar, if a fund fails to respond to a survey with its cash holdings data it is reported as having zero cash holdings. Therefore, fund-months with zero cash holdings are not included in the calculation of average cash holdings.

quintile portfolio did not hold any cash, the portfolio's out-of-sample CAPM beta would still be lower than that of any of other portfolio (0.77/(1-0.0580) = 0.82). In summary, the out-of-sample CAPM betas of the portfolios are mainly driven by the CAPM betas of stocks held by funds in the portfolios rather than cash exposures, assuaging concerns of an undesirable effect on an investor's allocation to risk-free assets[7].

A related concern is that the low-beta funds tend to have high out-of-sample idiosyncratic risk. If this is the case, then mutual fund investors seeking to capitalize on the low-beta anomaly may inadvertently acquire an excessively concentrated portfolio of risky assets. To address this concern, I calculate the average idiosyncratic volatility of funds in each of the five beta-sorted portfolios. Specifically, I estimate the standard deviation of the error term from a CAPM regression (eq. 2) of the excess returns on each fund against the excess returns on the CRSP value-weighted portfolio of U.S. common stocks over the prior 24 months. I do this for each fund in each month. Then for each of the five portfolios I examine the time-series means of the cross-sectional TNA-weighted mean values of idiosyncratic volatility for constituent funds. Put more formally, it is defined as follows:

$$. \qquad (3)$$

The results show considerable homogeneity in the average idiosyncratic volatilities across the five portfolios as they range from 10.40% (quintile 3) to 15.84% (top quintile). Moreover, the average idiosyncratic volatility of funds in the bottom quintile portfolio (12.26%) is similar to that of the TNA-weighted universe (12.06%), assuaging concerns of an undesirable effect on an investor's portfolio diversification.

[7] It is also interesting to note that the average portfolio turnover ratio of constituent funds is generally increasing across the portfolios and that the average expense ratio of the bottom quintile portfolio (0.91%) is similar to that of the universe of all funds (0.86%). These statistics are based on annual year-end values due to a lack of availability of monthly data from Morningstar.

2.3 12-Month Estimation Period Results

Table II conveys the results for the performance of portfolios that are constituted based on 12-month betas. The results are largely consistent with those derived through the use of the longer beta estimation period, marked by little differences in average returns but globally increasing out-of-sample CAPM betas across the portfolios, ranging from 0.77 (bottom quintile) to 1.28 (top quintile). An illustration of this in mean-beta space is provided in Figure III. The annualized standard deviation of portfolio returns is also monotonically increasing across the portfolios, from 12.96% to 21.22%. The sharp rise in standard deviations combined with the stable returns across the portfolios results in Sharpe ratios that are monotonically decreasing across the portfolios, from 0.52 to 0.30. Using the average risk-free rate over the time period of 3.02% as a proxy for the cost of borrowing, one investing in the top quintile portfolio of funds can improve his excess returns by an average of 2.76% a year while maintaining the same beta by simply holding a levered position in the bottom quintile portfolio instead of an unlevered position in the top quintile portfolio (((1.28/0.77) X 6.72%) - (((1.28/0.77)-1) X 3.02%) – 6.41% = 2.76%).

The bottom quintile portfolio also outperforms all other portfolios based on CAPM, Fama-French (1993), and Carhart model alphas. Consistent with the results obtained over the 60-month beta estimation period, the HML factor loadings indicate that there is a greater orientation towards value stocks among the low-beta funds. However, the bottom quintile portfolio still outperforms the top quintile portfolio by over 2% per year on average after controlling for the extramarket factors in Carhart's model. Also consistent with the 60-month estimation period results, the average dividend yield, cash holdings, expense ratio, and fund-level idiosyncratic volatility of funds in the bottom quintile portfolio are similar to the general population of funds, represented by the Universal portfolio[8]. Moreover, there is little variation in these characteristics across the beta-sorted portfolios. In summary, the out-of-sample CAPM betas of the portfolios are not driven by cash holdings and low-beta funds outperform their high-beta counterparts even after controlling for factors other than market risk that may impact returns.

[8] Idiosyncratic volatilities were estimated over a 24-month period. Similar results, available from the author upon request, were generated through the use of a 12-month estimation period.

3. Persistence in beta exposure

Following much of the prior mutual funds literature, the aforementioned analysis assumes that investors can reconstitute their portfolios of mutual funds every month. Tax issues and transactions costs likely make such frequent reconstitution activity infeasible. This motivates an analysis of the stability of mutual fund beta exposures over time and also the performance of beta-sorted portfolios that are reconstituted less frequently.

3.1 Stability in Rankings

As a "first stab" at addressing persistence in mutual fund beta exposure, I construct two contingency tables of initial and subsequent beta rankings. The height of the bars in Table A of Figure IV indicate the percentage of funds in quintile rank of beta that are ranked in quintile of beta 60 months later based on betas calculated over 60-month estimation periods. Table B of Figure IV conveys the percentage of funds in quintile rank of beta that are ranked in quintile of beta 12 months later based on betas calculated over 12-month estimation periods.

The tables show that there is considerable persistence in beta exposure. For example, 52% of funds in that rank in the lowest quintile of beta are subsequently ranked in that same quintile 60 months later. Moreover, 42% of funds in the lowest quintile of beta that do change ranks transition to the second quintile of beta. The contingency tables show similar persistence within the other initial quintiles of beta as well.

3.2 Time Plots of Beta Ranking

To gain deeper insight into how mutual funds' beta exposures change over time I examine the percentage of funds initially ranked in quintile of beta that are subsequently ranked in quintile in each month from the 12th to 60th after initial ranking based on betas calculated over 12-month estimation periods. I display the event time plots for each quintile in separate graphics.

The graphics displayed in Figure V show that the beta exposure of mutual funds are rather stable over time. For example, of the funds ranked in the lowest quintile of beta, 49% remained in that quintile 12 months later and 40% remained in it 60 later. Moreover, of the funds initially in the lowest quintile that transition to another quintile, 44% transitioned to the second quintile 12 months later and 35% transitioned to the second quintile 60 months later.

3.3 Performance of portfolios with alternative reconstitution frequencies

The beta exposures of mutual funds tend to be rather stable over time. This suggests that the frequency at which mutual fund investors reconstitute their portfolios has little impact on their ability to capitalize on the low-beta anomaly. To examine this possibility, I construct beta-sorted portfolios of mutual funds that are reconstituted at various frequencies, ranging from once a month to once every five years.

The graphics in figure VI display the out-of-sample CAPM Beta, arithmetic average return, Sharpe ratio, and alphas of portfolios constituted based on betas derived over a 60-month estimation period. The frequency of portfolio reconstitution ranges from once every month to once every 60 months. Graphic A illustrate that betas converge towards unity as the length of time between reconstitution dates expands. However, the differences in the betas on each of the portfolios across reconstitution frequency specifications are rather modest. For example, the beta of the bottom quintile portfolio that is reconstituted once every 60 months (0.80) is still lower than that of the 2nd quintile portfolio that is reconstituted once every month (0.88). Moreover, the betas are monotonically increasing across the portfolios, regardless of the frequency of portfolio reconstitution. Unsurprisingly, there is little difference in the average return on each of the beta-sorted portfolios across all reconstitution frequency specifications.

The Sharpe ratios of the beta-sorted portfolios are rather stable across reconstitution frequency specifications, as illustrated in Graphic C, and do not exhibit any relationship with the reconstitution frequency. For example, the Sharpe ratio of the bottom quintile portfolio reconstituted once every 60 months (0.40) is the same as one that is reconstituted once every month. The frequency of portfolio reconstitution also has little impact on the CAPM alphas. For example, the annualized CAPM alpha of the bottom quintile portfolio reconstituted every 60 months (1.05%) is virtually identical to that of one that is reconstituted every month (1.06%). Moreover, the differential in annualized CAPM alphas between the bottom and top quintile portfolios reconstituted once every 60 months (2.97%) is only slightly lower than that which is observed when the portfolios are reconstituted every month (3.07%). The alphas are also fairly stable across reconstitution frequency intervals when more structured asset pricing models are used.

The graphics in figure VII illustrate the out-of-sample betas and performance of portfolios constituted based on betas derived over a 12-month estimation period. As was observed through the use of the 60-month beta estimation period, there is a trend of convergence towards unity in the out-of-sample CAPM betas as the time interval between reconstitution dates expands, as illustrated in Graphic A. However, the trend towards convergence is subtle. For example, the beta of the bottom quintile portfolio reconstituted once every 60 months (0.80) is only 4% greater than one that is reconstituted once a month (0.77).

In contrast to the 60-month estimation period specification, there is greater variation in the performance of the portfolios across reconstitution frequency specifications when the portfolios are reconstituted based on betas derived over a 12-month estimation period. This is illustrated in graphics C through F. The higher dispersion of performance across reconstitution frequency specifications suggests that investors who infrequently reconstitute their portfolios would be well-advised to use a longer beta estimation period when forming portfolios.

4. Conclusion

Prior research has shown that the beta-return relationship is flatter than that which is predicted by CAPM, which implies that mean-variance efficiency can be improved through investing in low-beta stocks. This paper explores how investors can use mutual funds to capitalize on this anomaly.

Through constructing portfolios of domestic equity mutual funds that are reconstituted each month based on quintile rank of beta, I show that investors can decrease their risk without compromising returns through simply owning low-beta mutual funds. I also show that mutual fund beta exposures are considerably stable over time, suggesting that it may not be necessary for one to engage in frequent portfolio reconstitution activity in order to benefit from investing in low-beta funds. To test this possibility, I examine the performance of beta-sorted portfolios of funds that are reconstituted at alternative frequencies ranging from bi-monthly to once every five years. The performance of the portfolios formed based on betas derived over a 60-month estimation period does vary somewhat across the reconstitution frequency specifications. However, the performance of the bottom quintile portfolio is not diminishing in the length of time between reconstitution dates and it typically dominates that of its counterparts across reconstitution frequencies.

The central implication of this study is that through simply tilting their portfolios towards low-beta mutual funds, investors can improve their mean-variance efficiency, regardless of how frequently they trade. However, I make no statement on if and when the low-beta anomaly will cease to exist.

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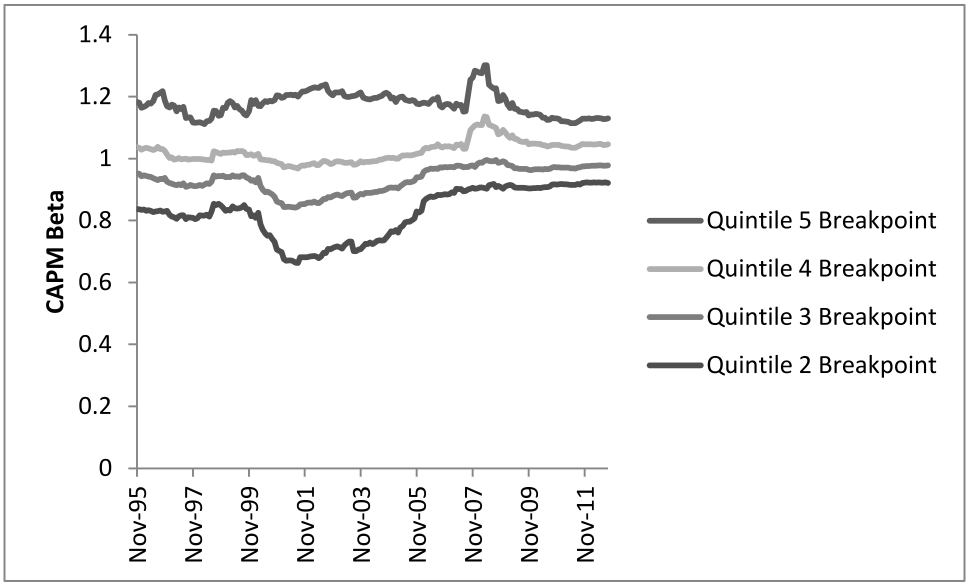
Figure I
Time Plots of Quintile Breakpoints of Mutual Fund Betas

Graph A plots the quintile breakpoints of U.S. Stock mutual fund betas derived through the use of the CAPM over a 24-60 month (as available) estimation period. Graph B plots the quintile breakpoints of betas derived through the use of the CAPM over a 12 month estimation period. The excess returns on the stock market from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012.

Graph A: 60-Month Estimation Period Results



Graph B: 12-Month Estimation Period Results

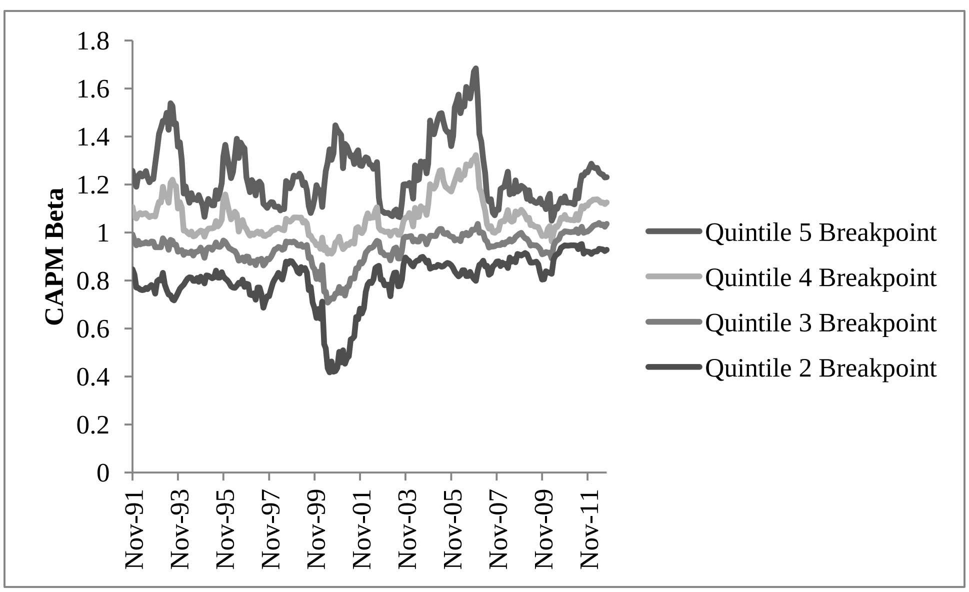


Table I

Main Results by Quintile of Beta Derived Over a 60-Month Estimation Period

Panel A displays performance metrics for TNA-weighted portfolios of U.S. Stock mutual funds reconstituted monthly based on quintile ranking of trailing beta derived through the use of the CAPM over a 24-60 month (as available) estimation period. The returns on the research factors and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012. Returns are annualized through multiplying monthly values by 12. Standard deviations are annualized through multiplying monthly values by the square root of 12. Panel B displays the average dividend yields, cash holdings, turnover ratios, expense ratios, and idiosyncratic volatilities of funds that constitute the portfolios. These characteristics are reported as time-series means of the cross-sectional TNA-weighted means. Idiosyncratic volatilities are derived through the use of the CAPM over a 24-month estimation period.

Panel A: Portfolio Performance Metrics

	Low	2	3	4	High	Universal
Geometric average R_p - R_f	5.70%	5.83%	5.55%	5.98%	5.54%	5.57%
Average R_p - R_f	5.56%	5.68%	5.41%	5.82%	5.40%	5.44%
Standard deviation	14.00%	15.13%	16.49%	18.38%	22.38%	16.62%
Skewness	-0.77	-0.73	-0.68	-0.59	-0.40	-0.69
Kurtosis	1.63	1.39	1.13	1.03	0.88	1.02
Sharpe ratio	0.40	0.38	0.33	0.32	0.24	0.33
Average R_p - R_m	-0.31%	-0.19%	-0.46%	-0.05%	-0.47%	-0.44%
Tracking error	6.75%	3.94%	1.97%	3.69%	8.45%	1.38%
Information ratio	-0.05	-0.05	-0.23	-0.01	-0.06	-0.32
CAPM Beta	0.77	0.88	0.97	1.07	1.26	0.99
CAPM Alpha	1.06%	0.53%	-0.31%	-0.49%	-2.00%	-0.35%
t(CAPM Alpha)	0.79	0.64	-0.66	-0.57	-1.13	-1.06
CAPM	0.85	0.95	0.99	0.96	0.90	0.99
Fama-French Alpha	-0.13%	-0.12%	-0.29%	-0.43%	-1.49%	-0.47%
t(Fama-French Alpha)	-0.15	-0.22	-0.73	-0.62	-1.45	-1.52
Fama-French	0.94	0.98	0.99	0.98	0.97	0.99
Carhart Alpha	0.20%	-0.02%	-0.29%	-0.68%	-1.91%	-0.58%
t(Carhart Alpha)	0.24	-0.04	-0.72	-1.00	-1.87	-1.89
	-0.07	-0.06	-0.08	0.13	0.32	0.04
t( )	-3.10	-4.60	-7.71	7.80	12.89	6.02
	0.32	0.18	0.03	-0.07	-0.26	0.01
t( )	14.05	13.10	2.79	-3.85	-9.89	1.33
	-0.04	-0.01	0.00	0.03	0.05	0.01
t( )	-2.95	-1.41	-0.03	2.82	3.09	2.73
Carhart	0.94	0.98	0.99	0.98	0.97	0.99

Panel B: Characteristics of Portfolio Constituents

	Low	2	3	4	High	Universal
Average dividend yield	1.01%	1.32%	1.44%	1.16%	1.39%	1.35%
Average cash holdings	5.80%	4.39%	3.18%	4.28%	3.66%	4.17%
Average turnover	43.50%	47.78%	46.69%	67.07%	84.83%	55.34%
Average expense ratio	0.91%	0.81%	0.68%	0.95%	1.10%	0.86%
Average idiosyncratic volatility	12.26%	11.03%	10.40%	12.76%	15.84%	12.06%

Figure II

Empirical versus Theoretical Security Market Line - 60-Month Estimation Period Results

This figure plots the average excess return and out-of-sample CAPM beta of TNA-weighted portfolios of U.S. Stock mutual funds reconstituted monthly based on quintile ranking of trailing CAPM beta derived over a 24-60 month (as available) estimation period. The excess returns on the stock market and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012. Returns are annualized through multiplying monthly values by 12. The figure contrasts the return-beta relationship with that which would be predicted by CAPM given the average excess return on the stock market over the time period.

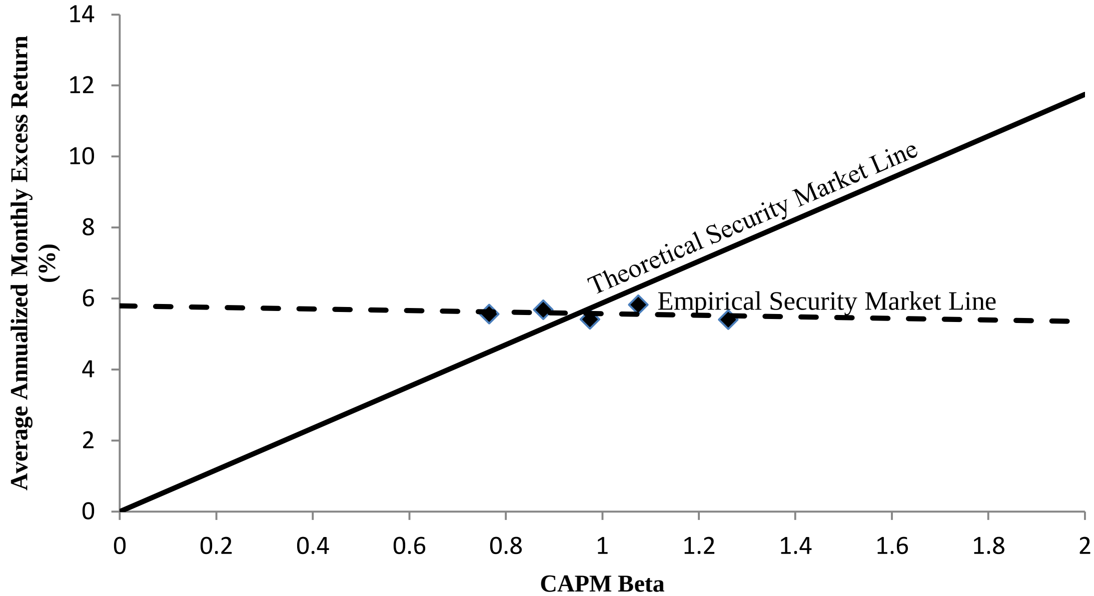


Table II
Main Results by Quintile of Beta Derived Over a 12-Month Estimation Period

Panel A displays performance metrics for TNA-weighted portfolios of U.S. Stock mutual funds reconstituted monthly based on quintile ranking of trailing beta derived through the use of the CAPM over a 12 month estimation period. The returns on the research factors and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012. Returns are annualized through multiplying monthly values by 12. Standard deviations are annualized through multiplying monthly values by the square root of 12. Panel B displays the average dividend yields, cash holdings, turnover ratios, expense ratios, and idiosyncratic volatilities of funds that constitute the portfolios. These characteristics are reported as time-series means of the cross-sectional TNA-weighted means. Idiosyncratic volatilities are derived through the use of the CAPM over a 24-month estimation period.

Panel A: Portfolio Performance Metrics

	Low	2	3	4	High	Universal
Geometric average R_p - R_f	6.93%	6.48%	6.90%	7.03%	6.60%	6.86%
Average R_p - R_f	6.72%	6.30%	6.69%	6.81%	6.41%	6.65%
Standard deviation	12.96%	14.25%	15.43%	17.05%	21.22%	15.52%
Skewness	-0.87	-0.77	-0.69	-0.64	-0.42	-0.71
Kurtosis	2.18	1.88	1.53	1.35	1.21	1.46
Sharpe ratio	0.52	0.44	0.43	0.40	0.30	0.43
Average R_p - R_m	-0.17%	-0.59%	-0.20%	-0.07%	-0.48%	-0.23%
Tracking error	6.08%	3.68%	2.06%	3.14%	8.39%	1.43%
Information ratio	-0.03	-0.16	-0.10	-0.02	-0.06	-0.16
CAPM Beta	0.77	0.89	0.98	1.07	1.28	0.99
CAPM Alpha	1.44%	0.20%	-0.04%	-0.58%	-2.38%	-0.15%
t(CAPM Alpha)	1.34	0.28	-0.09	-0.89	-1.50	-0.47
CAPM	0.86	0.95	0.98	0.97	0.89	0.99
Fama-French Alpha	0.07%	-0.55%	-0.14%	-0.41%	-1.40%	-0.25%
t(Fama-French Alpha)	0.09	-1.12	-0.32	-0.70	-1.42	-0.86
Fama-French	0.93	0.98	0.98	0.98	0.96	0.99
Carhart Alpha	0.25%	-0.39%	-0.08%	-0.46%	-1.84%	-0.40%
t(Carhart Alpha)	0.32	-0.78	-0.17	-0.76	-1.86	-1.42
	-0.07	-0.08	-0.04	0.08	0.34	0.05
t( )	-3.79	-6.71	-3.86	5.38	13.45	7.20
	0.28	0.16	0.03	-0.05	-0.26	0.01
t( )	13.52	12.07	2.34	-3.13	-9.82	1.34
	-0.02	-0.02	-0.01	0.00	0.04	0.02
t( )	-1.44	-2.03	-0.85	0.46	2.69	3.40
Carhart	0.93	0.98	0.98	0.98	0.96	0.99

Panel B: Characteristics of Portfolio Constituents

	Low	2	3	4	High	Universal
Average dividend yield	1.16%	1.39%	1.18%	1.00%	0.94%	1.35%
Average cash holdings	6.10%	4.08%	4.01%	4.27%	3.99%	4.50%
Average turnover	50.59%	47.94%	53.74%	69.97%	84.85%	59.11%
Average expense ratio	0.93%	0.77%	0.79%	0.94%	1.10%	0.87%
Average idiosyncratic volatility	12.00%	10.63%	10.85%	12.45%	15.69%	11.86%

Figure III

Empirical versus Theoretical Security Market Line - 12-Month Estimation Period Results

This figure plots the average excess return and out-of-sample CAPM beta of TNA-weighted portfolios of U.S. Stock mutual funds reconstituted monthly based on quintile ranking of trailing CAPM beta derived over a 12 month estimation period. The excess returns on the stock market and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012. Returns are annualized through multiplying monthly values by 12. The figure contrasts the return-beta relationship with that which would be predicted by CAPM given the average excess return on the stock market over the time period.

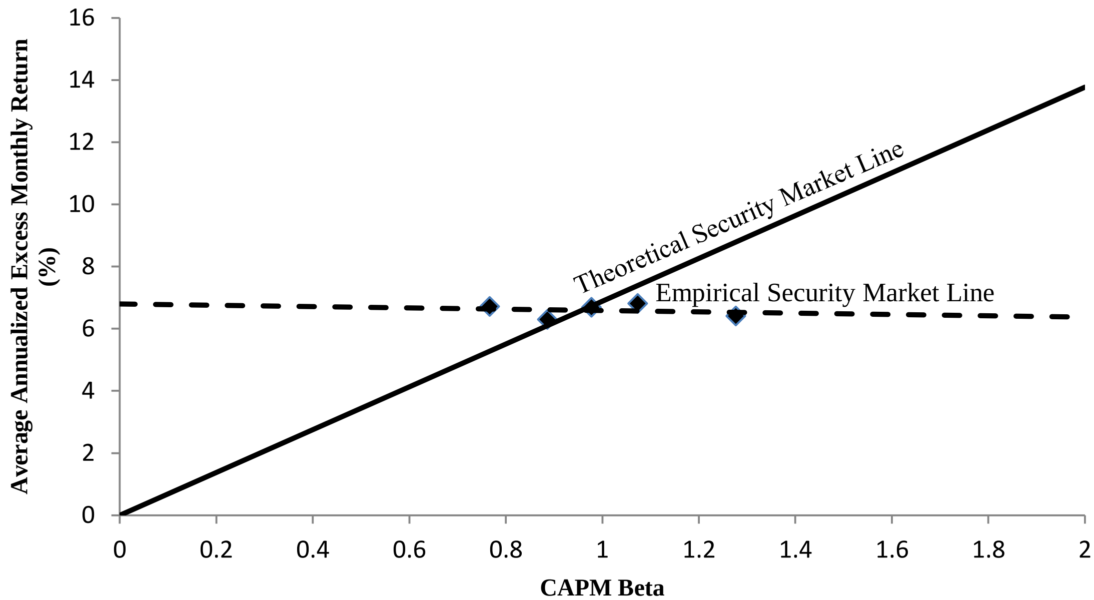


Figure IV
Contingency Tables of Beta Rankings

The bars in Table A indicate the percentage of U.S. Stock mutual funds ranked in quintile that are ranked in quintile 60 months later based on betas derived through the use of the CAPM over a 24-60 month (as available) estimation period. The bars in Table B indicate the percentage of U.S. stock mutual funds ranked in quintile that are ranked in quintile 12 months later based on betas derived through the use of the CAPM over a 12 month estimation period. The excess returns on the stock market from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012.

Table A: 60-Month Evaluation Interval

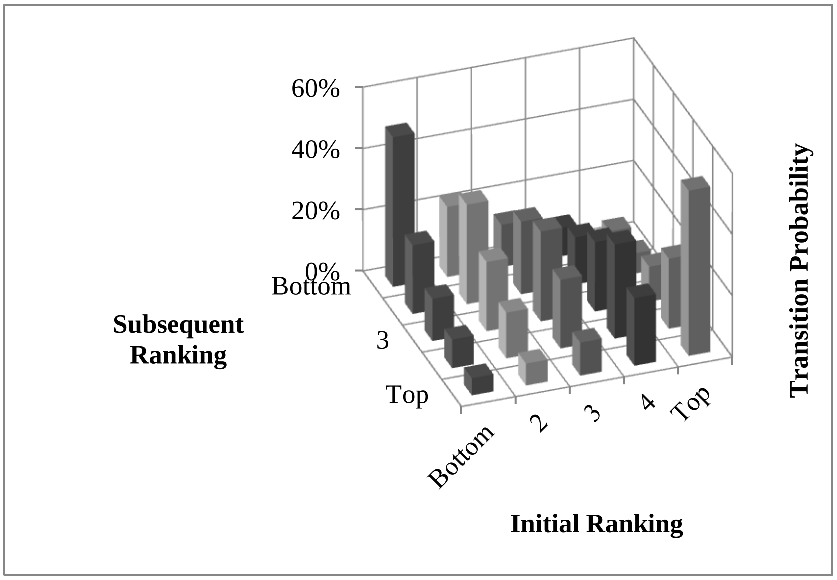


Table B: 12-Month Evaluation Interval

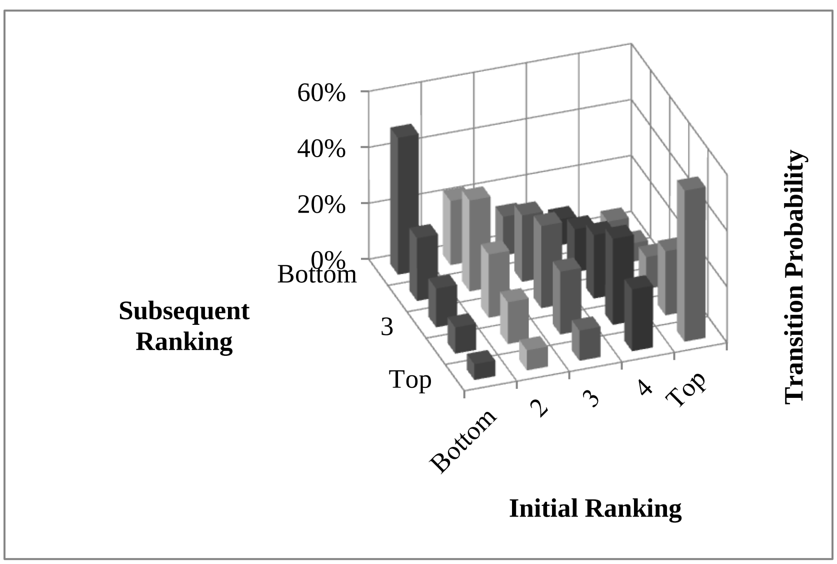


Figure V
Time Plots of Postranking Beta Quintiles by Preranking Beta Quintile

These graphs plot the percentage of U.S. Stock mutual funds in each month from through that are ranked in each quintile of trailing beta derived through the use of the CAPM over a 12-month estimation period. Graphs A, B, C, D, and E pertain to funds in the bottom, 2nd, 3rd, 4th, and top quintile of beta in respectively. The excess returns on the stock market from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012.

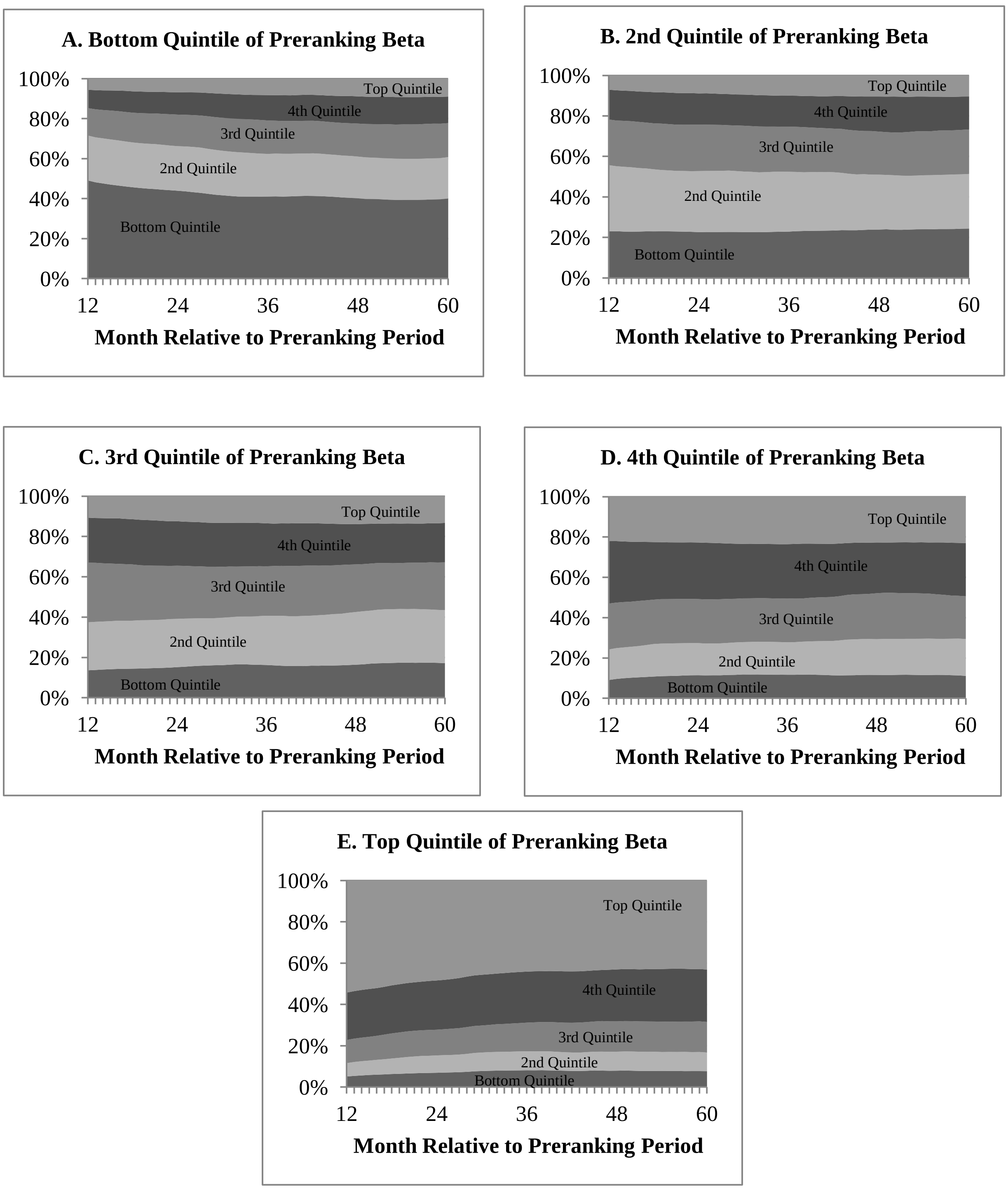


Figure VI

Returns on Beta-Sorted Portfolios Reconstituted at Low Frequencies - 60-Month Estimation Period Results

This table displays selected risk and performance metrics for TNA-weighted portfolios of U.S. Stock mutual funds constituted based on quintile ranking of trailing beta derived through the use of the CAPM over a 24-60 month (as available) estimation period. The period between reconstitution dates ranges from 1 to 60 months. The returns on the research factors and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012.

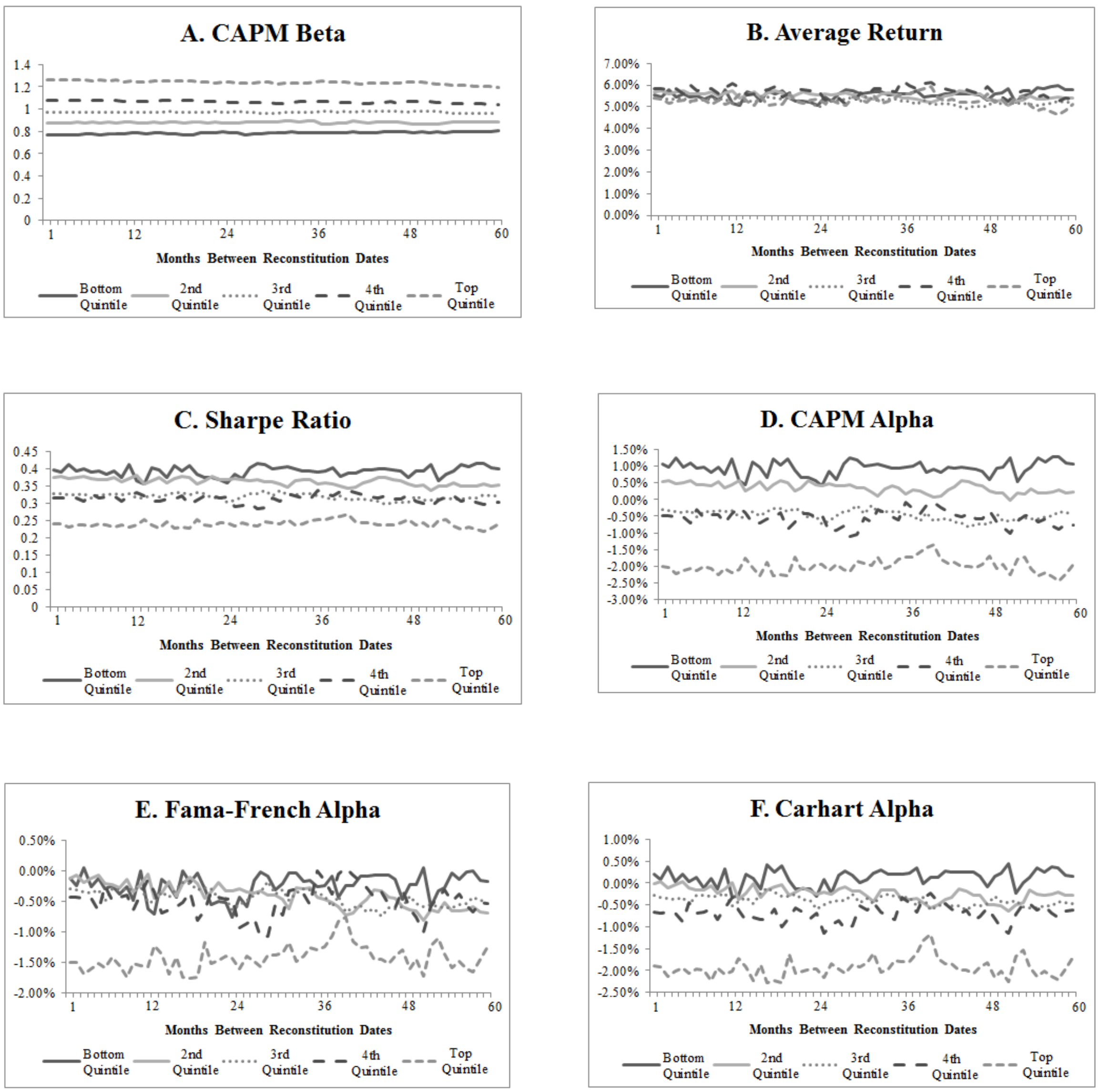


Figure VII

Returns on Beta-Sorted Portfolios Reconstituted at Alternative Frequencies - 12-Month Estimation Period

This table displays selected risk and performance metrics for TNA-weighted portfolios of U.S. Stock mutual funds constituted based on quintile ranking of trailing beta derived through the use of the CAPM over a 12 month estimation period. The period between reconstitution dates ranges from 1 to 60 months. The returns on the research factors and the risk-free rate, , from December 1990 through September 2012 are from Kenneth French's website. Returns on mutual funds were gathered from Morningstar Direct on October 31, 2012.