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Long-Term and Short-Term Market Betas in Securities Prices*

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ABSTRACT

The market-beta computed from stock returns that are aged from 1 year to 10 years has a significant positive influence in explaining the cross-section of future stock returns. The market-beta computed from stock returns over the most recent 12 months has a significant negative influence. The change in beta is therefore even more significant, and the effect is as strong as—and independent of—the effects of the Fama-French factors. Previous research failed to find that market-beta matters, primarily because ordinary market-betas combine these two opposing forces and because betas based on monthly stock returns are too weak. Our results are stronger in recent years and when we control for Fama-French and momentum factors. Remarkably, perhaps the best explanation for our findings is one in which the short-term beta proxies for exposure to a novel factor, and the long-term beta captures the standard hedging motive.

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I Introduction

The seminal paper by Fama and French (1992) documented that the market-beta of U.S. stocks seems to have no influence on future stock returns when book-market and firm-size are controlled for. One does not have to believe in the CAPM to be astonished by this fact. The overall stock market rate of return seems to be the first principal component, so stocks that move less with the market should be useful hedges. They should therefore require lower expected rates of returns. This can be viewed as an unconditional statement (that betas should be important by themselves) and as a conditional statement (that betas should be important for investors that have hedged other factors).

Not surprisingly, there have been a number of attempts to resurrect market-beta as an important component of the pricing of stocks. Many of these attempts derive some power from the correlation of market-betas with the two Fama-French factors. A loose interpretation is that these papers suggest good reasons why one should apportion to market-beta at least some of the explanatory power that is joint. Prominent examples are Ang and Chen (2005), Avramov and Chordia (2006), and Campbell and Vuolteenaho (2004). The latter decompose beta into a cash flow related beta that has a positive influence, and a discount factor related market beta, that has a negative influence. Their betas, too, have power that is overlapping considerably with that of the other Fama-French factors. Thus, Fama and French (2006) would probably still argue that the "CAPM's general problem is that variation in beta unrelated to size and value-growth goes unrewarded throughout 1926–2004," and especially after 1962. Another attempt to "rescue" market beta was proposed by Jagannathan and Wang (1996). They work with conditional market-betas and control for labor income, and find that there are specifications in which market-beta remains significant. This is critiqued by Lewellen and Nagel (2006), who argue that the potential magnitude of their effect is small.

Our own paper adds to this literature, though with little overlap. We hypothesize that a beta computed from recent stock returns (say, 1 year) could play a different role than a beta computed from earlier and longer-term stock returns (say, 1 to 10 years). It may only be the latter that unambiguously captures the ordinary hedging motive, while the former may play a very different role—through forces which swamp its hedging influence. There are at least three reasons:

1. **Slow Adjustment to Changes in Beta:** If investors are slow to recognize and adjust to changes in beta, a reduction in beta could be associated with a short-lived increase in the stock price, and therefore a positive average rate of return. A simple perpetuity model suggests that even a small delay in the full adjustment could have significant

impact—holding future cash flows constant, a change from, say, a 5% to a 5.1% expected rate of return can induce a one-time price adjustment of about 2%—twenty times as high as the 0.1% change in the expected return itself. The effect of a partly delayed price adjustment would be less applicable to market betas computed from much earlier stock returns. In fact, in its purest form, this hypothesis suggests that one should find that the *change* in beta would matter.

2. **Tax Effects in Up vs. Down Markets:** It is well known that returns in January are correlated with stocks' prior calendar rates of return. Tax reasons are the most prominent explanation for this "inverse momentum" effect. However, there could also be beta-conditional effects: after bull years, low-beta stocks contain on average more losers than they would after bear years. The tax loss selling premium could therefore be related to stocks' recent calendar-year market beta (and especially in Januaries).

3. **Relative Mean Reversion:** If value stocks outperform growth stocks, investors could believe that there should be mild mean-reversion also relative to the market. Stocks that have recently underperformed relative to the market should become more attractive, while stocks that have recently outperformed even the market in a bull market should become less desirable. Thus after the market has just gone up, investors might pour money into those firms that have not yet similarly appreciated.

Again, these hypotheses are not based on standard hedging motives, and they are of course just conjectures.[1] It is the empirical evidence that matters. Our paper documents that future stock returns are well explained by long-term betas (computed from daily stock returns from one to ten years ago) that have a positive influence, and short-term market betas (computed from daily stock returns over the most recent year) that have a negative influence. Together, from 1962 to 2005, the importance of these two beta measures seems no worse than that of momentum factors or the two Fama-French factor—and unlike earlier attempts to rescue beta, the role of our two betas does not overlap with those of the two Fama-French factors or momentum. The influence of market betas also seems economically significant: An extreme corner quintile portfolio of stocks with high long-term betas and low short term betas outperforms its mirror image by an annualized 7.5% per year. If anything, the effect may have become stronger in recent years, unlike that of the other factors we are considering.

One issue in our tests is that estimated betas are auto-correlated. Stocks that have a high long-term beta also tend to have a high subsequent short-term beta. (If they did

[1] A combination of these hypotheses has also been proposed by Jacquier, Titman, and Yalcin (2001). They omit the most recent 12 months in computing beta, include a contemporaneous beta, and then explore the differences in portfolios across momentum losers and momentum winners.

not, betas would have no use in designing hedges.) Using only either the long-term or the short-term beta in a regression without including the other therefore inevitably picks up the opposite effect of the other beta. Thus, it is no wonder that earlier work has not found that market-betas by themselves are not important. Successful prediction requires working with both market-betas, or at least holding the other beta constant.

The concern is that predicting stock returns with both betas in a regression could simply pick up multicollinearity in betas, because regressions can sometimes "tweeze" apart two highly correlated predictors. We must take care not to report just such a regression artifact. Fortunately, the daily data allows us to estimate betas over non-overlapping intervals and so the correlation between our two beta measures is about 60%—high enough to be meaningful, but low enough not to make the cross-sectional premium regression estimates (gammas in Fama and MacBeth (1973) terminology) overly sensitive. We also have some additional evidence that our two betas are not just regression artifacts in which the OLS procedure just raises one beta's coefficient while lowering the other's. For example, if we group firms to keep short-term beta constant (in effect, just avoiding the fact that high long-term beta stocks also tend to have high short-term betas), then long-term beta usally comes in significant even without including the short-term regressor. The effect is especially strong among firms with high short-term beta. Among these, the long-term beta quintile portfolio spread is $10.7\% - 5.2\% = 5.5\%$ (despite the residual within-group unsuppressed short-term beta influence). It is positive in the other four short-term beta quintiles, but typically only about 2%.

Nevertheless, another conclusion that one can draw from our evidence is not that we have one independent long-term hedging beta effect and one short-term slow-adjustment beta effect, but that we have evidence that it is primarily a change-in-beta that predicts stock returns. Some of our evidence indeed points in this direction, while other evidence does not.

Our paper also explores the role of our two betas among different subsamples. Their influence is virtually identical among big and small firms, among value and growth firms, and among firms that have recently had low, medium, or high calendar year returns. The long-term beta effect is stronger in January, but the beta change effect is not. The short-term beta effect in Januaries is negative only when a stock has just had a bad year. Otherwise, in Januaries, the hedging effect outweighs our hypotheses even for short-term betas.

Having found a cross-sectional effect of short-term and long-term beta, one interesting question is whether these are the true characteristics themselves, or whether the betas simply proxy for some additional novel factors that are different from the market. This leads to a fourth potential explanation for our findings.

4. Risk Factor Proxy: Could a portfolio that loads up on firms with certain beta histories pick up the effects of omitted novel (time-series) factors?

To explore this hypothesis, we form three stock portfolios on the basis of our long-term and short-term beta estimates and their difference, i.e., one long-term beta, one short-term beta, and one beta-change factor portfolio. We find that these three beta-based factor portfolios contribute significantly to shrinking the RMSE of the intercepts in the well-known Fama-French 100 portfolios, above and beyond the Fama-French factors. The marginal influence of this portfolio in reducing the pricing error is stronger than that of the Fama-French momentum factor (UMD), and seems to subsume most of it.

To run further tests, we eliminate the stock market factor from these three "raw" factor portfolios. The the residuals of our three portfolios in a market model regression are our three candidates for potentially novel factors. We then computed standard five-year daily-stock-based exposures for each stock with respect to the potentially novel factors. Finally, we test whether the cross-section of stock returns is better explained by these novel factor exposures, or by stock's own lagged market-betas. The results suggest that the short-term beta effect is related to some novel factor (previously partly captured by UMD), while the long-term beta effect is not. That is, the long-term beta influence is best captured by the 1-10 year own exposure of each stock to the stock market (the hedging motive), while the 0-1 year exposure seems to be more of a proxy for am exposure to a novel factor. Although we were motivated by a behavioral individual-stock-characteristics-based hypothesis and did not set out to confirm a factor hypothesis, we are struck by the fact that this perspective offers at least as good an explanation for our findings.

II Data and Methods

The data used in our paper is familiar to financial empiricists. We rely only on CRSP stock returns from January 1962 to December 2005. We exclude firms with less then four years of past return data, firms with an ex-ante stock price of less than one dollar in the *prior* month, and firms that lack sufficient COMPUSTAT and CRSP data needed to construct our control variables. This leaves us with 1,479,279 firm-months, an average of a little more than 3,300 firms per month.

Our study uses the same four variables as those described in Davis, Fama, and French (2000)) as controls: Market size is the natural log of the CRSP market cap. The book-to-market ratio is the log of the Compustat-book-to-CRSP-market cap ratio. It is measured with a lag of 6 to 17 months relative to the month in which they are used to explain stock returns. (Figure 1 illustrates the timing of our variables when we predict the cross-section future [Insert Fig.1] stock returns.) The two six-months momentum variables are consecutive, but omit one month immediately prior to whatever returns we are predicting. Thus, the first begins one month earlier, the second seven months earlier. We shall refer to these four variables as the FFM (Fama-French-Momentum) set. Under reasonable but not undisputed assumptions—if these are indeed the characteristics that investors care about rather than mismeasured risk factor exposures—we would not need to form portfolios to reduce measurement noise in these independent variables (Daniel and Titman (1997)).

Our betas are computed from stock returns and the value-weighted market return with a 3-month lag. The *5 Year Beta* is the standard beta commonly used in the literature. Our paper introduces two new variables, a **long-term beta** and a **short-term beta**. The long-term beta is a market-beta computed from 10 year prior to 1 year prior. The short-term beta is a market-beta computed from 1 year prior to the time period when it is used.[2] The time-series regressions to compute betas are run in excess returns, with the value-weighted market rate of return net of the Treasury as the independent variable. Market betas are estimated with as much data as is available, but a firm must have a minimum four year track record or the firm-month is excluded.

Our data requirements lead us to exclude many micro-cap firms and recent IPOs. Because we are not trying to test the CAPM and because an investor can adopt the same criteria ex-ante, this is innocuous. Our data criteria also mean that our average beta is less than 1. Generally, our data criteria do allow us to retain most of the important, highly capitalized stocks in the economy.

A Summary Statistics

Table I provides the basic summary statistics for the data used in our paper, computed over all firm-years. Panel A shows statistics for the four FFM characteristics that are our controls. Panel B shows that the average stock had a rate of return of about 1.5% per month with a standard deviation of 16%, of which 0.5% per month was a time-premium relative to the 30-day Treasury rate. The FFM residual returns need explanation. We first run a Fama and MacBeth (1973) regression[3] for the firms in our data set, using only the four FFM variables [Insert Tbl.I]

[2]In computing market-betas, we omit the last stock return of each month, because the Dimson betas require a one-day look ahead. With the additional 3-month delay, the short-term beta is really computed from 4 months to 15 months before it is used to predict stock returns. For example, in order to predict the monthly net return of 1.64% − 0.83% = 0.81% in 1983/08 for PERM 78530, we compute a short-term beta from 1982/05/03 to 1983/04/28 (which has a value of 0.1196) and a long-term beta from 1973/05/01 to 1982/04/29 (which has a value of 0.2197).

[3]We term it a Fama-Macbeth regression when we obtain time-series coefficients first, then run a cross-sectional regression each month, and finally report statistics from the time-series of coefficients (gammas) from all months. (We do not mean the portfolio sorting and forming technique.)

as our independent variables. The time-series averages from the monthly cross-sectional regressione are (coefficients multiplied by 100):

$$\begin{aligned} \hat{r}_{i,t} - r_f &= 3.212 + 0.194 \cdot \log(\mathrm{Bk}_{i,t}/\mathrm{Mk}_{i,t}) + -0.102 \cdot \log(\mathrm{Mk}_{i,t}) \\ &\quad + 0.788 \cdot \mathrm{Momentum2\text{-}7}_{i,t} + 0.624 \cdot \mathrm{Momentum8\text{-}13}_{i,t} \end{aligned} \tag{1}$$

Our FFM residual returns are then $r_{i,t} - \hat{r}_{i,t}$. Explaining FFM returns is a difficult task, because any explanatory power that may be shared between a novel variable and the FFM variables would have been attributed to the FFM variables before this novel variable would get a chance to explain it.[4] This procedure is opposite to that proposed in Avramov and Chordia (2006), who first attribute return variation to beta, and then ask other variables to explain the beta-risk-residual return.

Panel C describes summary statistics for various measures of market-betas, which are the principal variables of interest to us. The first set shows that raw one-year beta estimates based on 12 monthly observations are poor—for one firm-year, the short-term beta estimate reaches as high as 152. This is clearly not sensible—we do not have enough power to obtain meaningful short-term betas with monthly stock return data.

In the next sets, betas are computed from daily data. It is well-known, at least since Merton (1980), that the accuracy of covariance estimation improves with the sampling frequency. The table shows that daily estimation provides much better short-term beta estimates than monthly : a range of estimated betas from –5 to +8. Obviously, this is still too high. Remarkably, the cross-sectional standard deviation of the 1-year beta estimates based on daily data is *lower* than the standard deviation of even the nine-year market-beta when monthly stock returns are used.

The next set of lines shows beta estimates when we use the Vasicek (1973) beta shrinking method, recommended in Elton, Gruber, Brown, and Goetzmann (2003, p.145). It is computed as

$$\begin{aligned} \hat{\beta}_i &= w \cdot \beta_{i,\mathrm{TS}} + (1-w) \cdot \mu_{\mathrm{XS}} \\ w &= 1 - \frac{\hat{\sigma}^2_{i,\mathrm{TS}}}{\hat{\sigma}^2_{i,\mathrm{TS}} + \hat{\sigma}^2_{\mathrm{XS}}} \end{aligned} \tag{2}$$

where $\beta_{i,\mathrm{TS}}$ is the ordinary OLS time-series beta for each firm with associated $\hat{\sigma}^2_{i,\mathrm{TS}}$ (the variance of the estimated beta); and μ_{XS} and $\hat{\sigma}^2_{\mathrm{XS}}$ are the mean and variance of all betas in a given month across firms. This shrinkage estimator places more weight on the historical time-series beta estimate if this estimated market-beta has lower variance and when there is a lot of heterogeneity in the cross-section of betas. When we apply this shrinking method,

[4] It is quickly confirmed that these returns share a standard property with OLS regressions: a Fama-MacBeth regression with FFM residuals as the dependent variable (instead of stock returns) provides gamma coefficients of exactly zero on each of these four characteristics.

our estimated betas have outright reasonable properties, ranging from about –1.4 to 4.0 for even the 1-year beta. The standard deviation of the 1-year betas (0.492) is now only slightly higher than the standard deviation of the 5-year betas (0.467).

One problem with daily data is that it could suffer from non-synchronicity—smaller firms often do not trade every day. We therefore experimented with the Dimson (1979) procedure, using a window of one day before and one day after the return. This estimator computes

$$\beta_i = \beta_{i,-1} + \beta_{i,0} + \beta_{i,+1}$$

where betas are obtained from a time-series regression of

$$\tilde{r}_{i,t} - r_{F,t} = a + \beta_{i,-1} \cdot (\tilde{r}_{m,t-1} - r_{F,t-1}) + \beta_{i,0} \cdot (\tilde{r}_{m,t} - r_{F,t}) + \beta_{i,+1} \cdot (\tilde{r}_{m,t+1} - r_{F,t+1}) + \epsilon_{i,t} \quad (3)$$

The standard errors of these betas are computed from the 3^2 terms in the covariance matrix associated with the Dimson model. These standard errors can in turn be used in the Vasicek shrinking method. The next set of lines in the Table shows that this dual procedure shrinks the estimated beta even further, although not by very much. The 1-year beta declines from 0.492 to 0.488, not a dramatic change.

The final set of estimates are from a "subsampling" procedure (which we shall abbreviate as "Sub" as distinct from the ordinary OLS method). This is best explained by example: to predict stock returns in April 1990, we compute 10 annual betas, one for each year from 1980 to 1989. The 1989 beta becomes the short-term beta. The long-term beta is the mean of the nine yearly betas from 1980 through 1988. Its standard error is the standard error of this mean. We would expect a subsampled estimator to have less efficiency, but perhaps be more robust with respect to changes in the market-beta. The main advantage of subsampled estimators is that they are easier and quicker to compute. We again shrink this subsampled beta via its standard error by the Vasicek method. And, again, the subsampled estimates are generally similar to the OLS estimates.

Not reported, when we compute standard deviations in each month, and then average across all months, the standard deviations are a little smaller (by 10% to 20%) than the pooled statistics reported in Table I. [Insert Tbl.I]

As already noted, Figure 1 illustrates that all our independent variables are measured with a lag relative to the month in which they are used to explain the cross-section of stock returns, ranging from 1-month for the momentum and market cap variables, to 3-months for our market-betas, to 6-17 months for our book-market measure. Our regressions are fully rolling each month, i.e., recomputed each month.

B Predicting Future Betas

With many different potential methods of computing market-betas, we begin by determining which beta estimator best predicts the future (OLS) market-beta. That is, we predict the future market beta over the next year. Our method is a simple pooled all-firm-months regressions, in which both dependent and independent betas are computed from overlapping data. Of course, both the dependent and independent variable contain noise relative to the true market-beta, and the underlying market-betas could themselves be changing.

The dependent variable here is always an unshrunk beta, computed either with daily or monthly data. There are two reasons for this. First, the realized beta is the one an investor would want to obtain for hedging purposes, even if it is not the true beta. Second, additional noise in the dependent variable applies to all beta estimates and does not change our inference. Of course, any downward biased market-beta estimator (such as an uncorrected OLS beta) would have lower RMSE in predicting its downwardly biased future market-beta equivalent. Therefore, we therefore do not rely on RMSE for model selection (although we do report it and although it comes to similar conclusions). The adjusted R^2 does not suffer from this problem, and is therefore the better metric. Vetting betas more carefully is beyond our own paper, but our procedure is better than simply specifying one method. We just want to determine which of our beta estimators seem most reasonable. The reader should see the results in this section only as suggestive.[5]

Table II shows how well differently estimated long-term betas (top) and short-term betas (bottom) predict future *realized* betas. It appears that betas computed from daily data are generally superior to betas computed from monthly data both in terms of lower mean-squared error and adjusted R^2 in all cases. For the nine-year long-term betas, we find that shrinking is at least as good as not shrinking in each and every case. However, there is no clear rank-ordering between the OLS, Dimson, and Sub-sampling methods.[6] For the one-year short-term betas, the message about methods is much clearer. Both the Dimson procedure and the subsampling procedure simply add too much noise relative to their benefits. The plain OLS estimator, suitably Vasicek shrunk, outperforms them. It offers the highest predictive R^2 in every column. In sum, one should always use daily stock return data to estimate market-betas. When it comes to short-term market-betas computed [Insert Tbl.II]

[5]Braun, Nelson, and Sunier (1995) model betas as a moving process with EGARCH conditional volatility for a set of industry portfolios. Their EGARCH model does better than a simple rolling beta model, but the differences are not huge. Their interest is to relate the change in market-betas to contemporaneous changes in stock returns. In contrast, our hypothesis is that some of this adjustment is not instantaneous, which leads us to split our market-betas into a long-term and short-term beta.

[6]Our paper improves the accuracy of beta estimates by using daily data, Another technique is the use of Instrumental Variables, e.g., in Avramov and Chordia (2006), Jagannathan and Wang (1996). One could also use combinations of sampling and statistical techniques, as suggested in Ghysels and Jacquier (2006), who suggest a combination of block samplers and instrumental variables.

over one year, it is best to avoid Dimson or subsampling methods. Therefore, the rest of our paper works primarily with OLS betas.[7] The reader should remain aware that we are accepting downwardly biased betas in exchange for better cross-sectional prediction.

Not reported in the table, the correlation between the Vasicek-shrunk long-term market beta and the short-term market beta is 65.2%. Obviously, it should be highly positive—or historical beta would be useless in estimating future betas. However, to disentangle the differential effect of short-term and long-term beta, we would prefer to see a correlation that is not too high. This observed correlation is therefore comforting—it is high enough to make estimated betas useful, but low enough to allow us to separate the effects of these two variables given our large sample size: our regression coefficient estimates are not likely to suffer greatly from variable multicollinearity.

C Error-in-Variables and Portfolio Formation

The most common method in financial economics to reduce the EIV in second-stage cross-sectional regressions is to form portfolios, typically between 10 and 100. Fama and MacBeth (1973) introduced this now common two-stage estimation procedure that uses (for each month to predict) five years of stock return history to form sorted portfolios, and five years of stock return data to estimate the portfolio market betas.

Our tests later in the paper intentionally do not group firms into portfolios, similar to Litzenberger and Ramaswamy (1979), Kim (1995) and Avramov and Chordia (2006)). Hoberg, Jacquier, and Welch (1997) show that tests against the NULL hypothesis (whether a factor is priced, i.e., $\gamma = 0$) based on portfolios are inferior to tests based on the individual stocks themselves. This holds in the presence of the EIV problem, and even if there is no Berk (2000) sort criterion identification problem. Thus, using individual stocks is the correct method for our paper.

[7] If we use inferior beta estimates, our results in predicting stock returns that are a little stronger or a little weaker (typically, along the lines of a T-statistic dropping from 2.2 to 1.9, as would be expected), but our results are generally robust to many variations we tried. In Table IV, we show some stock return predictions using other beta estimators.

III The Empirical Influence of Long-Term and Short-Term Market Betas

We begin by confirming the main result in the literature, using standard Fama and MacBeth (1973) regressions. Table III shows that the lagged 5-year market-beta does not help explain the cross-section of stock returns in the 1962 to 2005 period. In contrast, the lagged Fama-French factors and momentum variables have strong significance. This holds when we use either monthly betas, daily betas, or shrunk daily betas. The five-year market-beta is statistically and economically irrelevant. [Insert Tbl.III]

A Fama-MacBeth Regressions With Long-Term and Short-Term Betas

Table IV presents the main result of our paper. Betas are henceforth estimated using only daily stock return data.[8] In Panel A, the beta estimates are raw (unshrunk). In this table, we still present different best estimation techniques to show that our paper does not just cherry pick estimators. In Panel B, the betas are shrunk. [Insert Tbl.IV]

The regressions show that long-term beta generally has a statistically significant influence in explaining the cross-section of future stock returns. The premium on long-term beta is positive, as predicted by hedging motivations, e.g., by an APT model. (Of course, as Fama and French (2006) point out, the CAPM still fails, because there are other variables [including the short-term beta] that remain important in pricing securities.)

In contrast, the short-term beta has a statistically significant negative influence in explaining future stock returns. On the margin, stocks that have a high market-beta in the previous year (holding constant their earlier market-beta) earn a *lower* average rate of return. This is significant in all specifications and consistent with our hypothesis that short-term beta plays a different role.

Our results are robust to inclusion of the Fama-French factors, to subsampling, to Dimson correction, and shrinking. Not reported, when we conduct Fama-Macbeth regressions predicting the FFM residual returns (rr) as the dependent variable, the coefficient estimate on long-term beta is between 5.4 and 6.3 (with t-statistics between 3.5 and 4.2), and the coefficient estimate on short-term beta is between –4.0 and –4.3 (with t-statistics between –2.1 and –2.5). The two betas are not important because they "steal" explanatory power from the FFM variables.

Other Variables: Appendix XV shows that neither including idiosyncratic volatility nor including beta estimation error changes the estimate coefficients. Below, we shall also

[8] For the remainder of the paper, we do not report betas estimated from monthly stock return data. These results are typically insignificant, because these betas are simply worse predictors than betas computed from daily data (see Table II).

discuss using a "change in beta" variable instead of separate long-term and short-term betas. Finally, we also tried to include the absolute value of the change in beta. Unlike stock volatility, this variable generally was significant (with T-statistic around –2.5). But again, its inclusion merely strengthens the coefficient estimates we are reporting on our beta measures.

Average Monthly Contributions: It would be interesting to learn how important the two betas are when compared with either the Fama-French or the momentum variables in explaining the cross-section of future stock returns. One way to do this is to compare the adjusted $\overline{R}^2$'s or F-statistics in each month's cross-sectional regression. Of course, stock returns in a given month are *not* independent observations, which prevents the translation of these monthly statistics according to standard distributions. However, this correlation should not prevent gauging the relative importance of different variables based on their F-statistics—they are likely all equally affected by the multi-stock correlations. We therefore treat the two Fama-French variables as a set, the two momentum variables as a set, and the two betas as a set. We can determine which of these sets earned higher F or $\overline{R}^2$ statistics, on average. Table V shows that the inclusion of the two market-betas seems just about as important as inclusion of either the two momentum variables or the two Fama-French factors. For example, dropping the two betas from the set of six variables reduces the average monthly $\overline{R}^2$ from 6.08 to 4.03, more than dropping either the Fama-French variables (6.08 to 4.24) or dropping the momentum variables (from 6.08 to 5.01). Using only the two betas yields an average monthly $\overline{R}^2$ of 2.80, more than adding only the Fama-French variables (2.36) or adding only the momentum variables (2.12). However, no exact probability inference can be drawn from these observations, and we are not suggesting that our betas are more important than the other sets—just that they seem similarly important. [Insert Tbl.V]

B The Time-Series of Gammas (Factor Premiums)

Figures 2 and 3 plot the time-series of the Fama-Macbeth factor premiums (gammas). The red line is the 1-year moving average, the blue line are the 5-year moving average. Figure 2 shows the familiar four Fama-French-Davis factors. The book-market ratio has been reliably positive throughout most of our sample period (1962-2005), with the exception of the Tech "bubble period" of 1998 to 2000 and the period from 1979 to 1980. Its best period was however from 1972 to 1978 and from 1979 to 1998. In contrast, the firm-size effect seems rather unstable. In addition, the sign of the median and mean are opposite. The two momentum effects have been rather stable, but like the value effect, the moving average gamma seems to be just about zero as of 2005. [Insert Fig.2] [Insert Fig.3]

Figure 3 shows the performance of our long-term beta. It encountered a rough period from 1984 to 1990, but remained fairly solidly positive before and after. The negative short-term beta effect was similarly solid, except for the period of the Tech bubble. In general, the performance of the premiums on the two betas seems comparable to those of the FFM characteristics.

IV Long-term and Short-term Betas, or Market Beta Change?

With long-term beta always positive and short-term beta always negative, one interesting question is the extent to which one variable, the change in market-beta, can capture both effects. Indeed, our first motivating hypothesis was that investors price long-term beta positively, but do not react instantly and fully to a recent *change* in beta.

A Two-Dimensionally Sorted Returns

Table VI sorts (abnormal) returns into equal-weighted pooled portfolios. The first sort is by month, the second sort (in sequence) is on (lagged) short-term beta, and the third sort is on (lagged) long-term beta. The sorts are sequential and not independent because we want to keep the number of observations in each cell roughly constant.[9] [Insert Tbl.VI]

Table VI shows the resulting rates of returns on quintiles formed this way, making it easy to assess the economic significance of the two betas. The most interesting net portfolio is long in firms that had high long-term betas and low short-term betas (the SW corner) and short in firms that had the opposite pattern (the NE corner). anel A shows that it had raw and excess rates of return of 7.5% per year, statistically significant at the 2.5 level. If we first adjust for Fama-French-Momentum effects, the net return drops to 6.3% per year, but the statistical significance remains the same. These are economically meaningful spreads.[10]

Reading individual rows in the FFM Panel B shows that holding long-term market-beta constant, there is no monotonic (much less linear) relation between short-term market beta and stock returns. If anything, the relationship seems to be more U-shaped. Firms do more poorly if they have a short-term beta further from 1.[11] In contrast, reading individual columns shows that holding short-term market-beta constant, there is always a monotonic

[9]The cells do have slightly different numbers of observations (about 60,000 firm-years each), because the number of firms in each month does not divide by five. The results are similar if the sorts are unconditional, but then there are fewer observations in the NE and SW corners.

[10]The equivalent geometric average is 7.76%.

[11]As just noted, including a deviation of the short-term beta from 1 is significant, but does not take away anything from our own estimated coefficients.

influence of long-term betas on future stock returns. This suggests that the roles of the two market-betas is not symmetric: long-term market-betas seem to play the more robust role, while short-term market-betas are necessary primarily to keep constant.

B Controlled Spreading Sorts

A non-parametric test can further clarify whether our betas require simultaneous estimation (as in a regression estimation, in which both coefficients can be torn apart simultaneously), or whether they merely require the other beta not to have an influence. In each month, we first sort all stocks by short-term beta. We then take groups of five adjacent stocks each, and place each into one of five buckets based on their long-term beta. (The results are similar if we use different numbers of groups.) The stock with the lowest long-term beta in each group-of-five enters bucket L, the stock with the highest long-term beta enters bucket (H). This sorting procedure results in five portfolios that have similar short-term beta and different long-term betas:

	Long-Term Beta	Short-Term Beta
Portfolio L	0.40	0.72
Portfolio LM	0.57	0.72
Portfolio M	0.72	0.72
Portfolio HM	0.88	0.72
Portfolio H	1.11	0.72

Each bucket contains exactly 369,864 firm-months, spread over 528 months. The return differences of these portfolios (multiplied by 12 and quoted in percent) are

	Excess Returns	FFM Residual Returns
Portfolio L	10.05	−2.03
Portfolio LM	10.91	−0.33
Portfolio M	10.49	−0.27
Portfolio HM	11.36	+0.86
Portfolio H	12.15	+1.82
H-L Difference	+2.10%	+3.85%
TS T-statistic	+1.58	+2.97

(If we use quartiles, the mean return spreads drop to 1.37% and 2.93%, with associated T-statistics of 1.23 and 2.60.) If we repeat the same experiment for short-term betas, holding long-term betas constant (not reporting the two middle portfolios), the results are similar:

	Long-Term Beta	Short-Term Beta
Portfolio L	0.74	0.36
Portfolio H	0.74	1.12
	Excess Returns	FFM Residual Returns
Portfolio L	12.34	0.66
Portfolio H	8.77	–1.94
H-L Difference	–3.57	–2.60
TS T-statistic	–2.28	–1.80

(If we use quartiles, the mean return spreads drop to –3.06% and –2.21%, with T-statistics of –2.14 and –1.67.) The excess spread is more for these short-term beta difference portfolios than for equivalent long-term beta difference portfolios, but the FFM spread is less than its equivalent for long-term market-betas. Thus, holding either kind of beta constant seems to produce reasonably sized excess returns. Buying a portfolio that takes advantage of both, as in Table VI, provides solid economic and statistical significance.

C Categorized Fama-Macbeth Regressions

Table VII splits the sample into five groups, based on short-term beta. Within each group, even the long-term beta alone is significant or close to significant. The coefficients are similar in each group. However, not reported in the table, this result is dependent on having a good number of groups being formed. With fewer groups, the long-term beta does not have sufficient short-term control to attain meaningful coefficients. [Insert Tbl.VII]

We conclude from the sorts and these regressions that it is important to hold short-term beta constant to find that long-term beta is significant, and that it is not just a regression tweazing them artificially apart.

D Fama-Macbeth Regressions on Market Beta Change

Table VIII shows the Fama-Macbeth regressions if we rotate the variables, so that we are including one long-term beta variable and one *change* in beta variable. The first two regressions recap Table IV, regressions (6) and (8). Not surprisingly, with the long-term beta coefficient estimate positive and the short-term beta coefficient estimate negative, the beta change keeps its significance, but the long-term market beta gives up its significance to the beta change. [Insert Tbl.VIII]

The final two regressions are different from those in Table III, because they omit the long-term beta. The change-in-beta is now even more significant than it was in the upper two regressions, or in any regression in Table III. Figure 4 plots the time-series of the gamma from regression (4). The premium for this beta change seems stable, certainly no worse than it was for the other factors we examined. It performed a little better later in our sample, when we had more observations, i.e., in the period after 1995. (The correlation of this gamma with a time-index and/or the number of observations is statistically significant at the 5% level.) [Insert Fig.4]

V Sample-Specific Results

A natural question that arises is whether short-term and long-term betas work only in certain types of firms, or at certain times.

A Strength of Relations in Cross-Section (By Firm-Type)

Table IX repeats the final Fama-Macbeth regression of Table III to see how the betas perform in different subsets of firms: [Insert Tbl.IX]

Small vs. Large Firms: In the first two regressions, we split the sample into those in which a firm had a (one-month) prior market cap above median vs. those in which a firm was below median. The results show that both long-term and short-term beta explain future stock returns in both the subsample of large firms and the subsample of small firms.

Appendix Table XVI provides more details. Even if we follow time-varying inclusion rules that either include only firms with over \$1.5 billion in equity market cap today (38% of the sample firm-years) or only firms with over \$3 billion in market cap (21% of the sample firm-years), our T-statistics still generally remain around 1.8. This drop in *statistical* significance is just about what simulations suggest that a smaller (equally-numbered) sample of random firms would produce. However, our estimated coefficients drop by about one-third. Simulations suggest that this drop in *economic* significance is due to the different type of (bigger) firms in this (smaller) sample.

Value vs. Growth Firms: The next two regressions are analogous, but split firms according to their market-to-book ratios. The results show that long-term beta explains future stock returns in both the subsample of growth and value firms. However, the short-term beta loses its significance among value firms.

Past Own *Calendar* Year Returns: The next three regressions divide the sample based upon the firms' own historical 1-year stock return (without any delay). Again, there is not significant difference in how winners and losers respond to long-term and short-term market-betas. However, the table also shows that the first momentum variable only works when a firm has not performed poorly.

In sum, the gamma premium estimates for both market-betas and especially the long-term (APT) beta seem stable across different firm categories.

Not reported in a table, if we split our sample based on our own two variables, and then consider the FFM variables, we find that they, too, retain the same sign (and often similar coefficients) in high vs. low long-term beta or short-term beta groups.

B Strength of Relations By Time and Market Condition

Instead of subsets of firms, we can also consider different months and aggregate conditions. Table X shows the correlation of the Fama-Macbeth gamma coefficients over time, in Januaries vs. non-Januaries, and relative to recent and current market conditions. The sign above the row header indicates the sign of the estimated premium mean. [Insert Tbl.X]

Change over Time: The first row shows that over time, the premium on each of the FFM and on the short-term beta has mildly drifted towards zero. The only variables that seem to have become stronger over time are the long-term beta and the beta change, the latter even marginally statistically significantly so. (Not shown, the estimated Fama-Macbeth coefficient on STβ–LTβ is –4.97 for the first half of our sample (until 1982), and –5.05 for the second half. After 1990, the coefficient average is –8.10.)

Number of Observations: Over time, more firms were publicly listed. Our own beta variables, especially the difference, increase in significance with the number of observations in the cross-sectional regressions. This is not surprising—it takes a large number of firms to identify firms with beta reversals.

Not reported, we could have included firm-years prior to 1962, although Fama and French (2006) suggest that it is our 1962–2005 period that is of more interest. The reason is that, in a full sample from 1932 to 2005, only 15% of all firm-years with data precede 1962. Our power derives from an ability to tease out firm-years with high long-term beta and low short-term beta, or vice-versa. This requires a lot of observations in each month. Thus, it is no surprise that we find no relation in the pre-1962 sample. Therefore, although our beta measures keep similar gamma coefficients in a full 1932–2005 sample, they lose their statistical significance in a Fama-Macbeth regression (which weights all months equally).

Januaries: This row shows the two well known anomalies that all stocks tend to do well in January and that small firms do especially well. Momentum reverses in January—firms that have done *poorly* perform better in January. Long-term beta stocks perform much better in Januaries than in non-Januaries. The beta *change* performs better in Januaries than in non-Januaries, too. In Fama-Macbeth regressions, the January coefficient is –15.0 (T-statistic of –3.0), the non-January coefficient is –4.1 (T-statistic of –3.7). It remains statistically significant in both subsets.

Recent S&P500 Performance, lagged by one to four months: Although there is no correlation between consecutive S&P500 returns, there is a good correlation between the intercept (FFM/beta adjusted returns) and lagged 3-month index returns. In Fama-Macbeth regressions, the intercept is only reliably positive if the recent three-month S&P returns were above its median of 2.92%.

Large firms underperform small firms even more after good recent market conditions. Although size is the not the focus of our paper, *the premium on market size reverses sign depending on recent index stock returns.* The Fama-Macbeth regressions indicate that the firm-size premium is *negative* when the S&P500 outperformed its sample median over the preceding three months, and *positive* when it did not. It is only because the former coefficient is larger that the unconditional size premium is negative.

And, finally, most important from the perspective of our paper investigating betas, the change-in-beta becomes more significant after three bad recent months. An unreported Fama-Macbeth regression suggests that the coefficient is –8.1 following bear markets, while it is only –1.9 following bull markets. One can design a better trading strategy based on this difference, but it is not clear how much of it would be due to "specification search."

The last row shows that both the short-term and the long-term beta portfolios do well in up markets. Of course, beta portfolios are designed to react this way. The more interesting aspect is that this also holds for the beta difference portfolio: in a contemporaneous bull market, the beta difference is negative but not statistically significant. In a contemporaneous bear market, the beta difference is more significant.

C Strength of Relations by *Both* Time Period and Cross-Section

In Table IX, we considered how own lagged stock returns influence the gamma premiums on both betas. Indeed, the tax hypothesis suggests that firms that have performed well in the prior year should perform differently than firms that have done poorly—and if the January/tax-hypothesis holds, especially in Januaries. The easiest way to think about the [Insert Tbl.IX] results in Table XI is as follows: in Januaries, when a firm has done well over the most recent year, it has both a short-term and long-term market-beta that are positive—both now entirely in line with conventional factor hedging intuition. It is only when a firm has had a bad or very bad year—and therefore some additional value from a capital loss tax perspective—that firms with a positive short term-beta earn lower rates of return in Januaries.

VI Are Changing Market Betas Proxies For a Risk Factor?

One interesting question remains: Do our betas proxy for novel factors, or do they pick up firm-specific hedging components (the long-term beta) plus slow adjustment components (the short-term beta)?

A Fama-French Time-Series Regressions

If our beta exposures proxy for some novel factors, we should be able to use portfolios based on them to explain the time-series of excess rates of returns for a set of portfolios designed to spread returns. The most prominent such set are the 100 time-series Fama-French portfolios (posted on Ken French's website). One form of such tests is critiqued by Daniel and Titman (2006), but our own factors and procedures escape their critique, because [a] we know that our variables (and effects) do not derive their power from a correlation with the size or book-market ratio, and [b] we only measure the influence of our factors that is incremental to the Fama-French factors themselves.

Our three beta-based factor portfolios are:

$\mathsf{BLT}^{\mathbf{raw}}$ is a zero-investment portfolio based on the two extreme *quintile* portfolios from a controlled spreading sort method, analagous to that reported in Section B. It maximizes the difference in long-term betas, holding short-term betas constant. This portfolio has a daily mean of 0.007% (i.e., an annualized rate of return of $1.00007^{250} - 1 \approx 1.77\%$) with a standard deviation of 0.352%.

$\mathsf{BST}^{\mathbf{raw}}$ is the analogous portfolio that maximizes the short-term spread in short-term betas, holding long-term beta fixed. It has a daily mean of –0.015% (i.e., an annual rate of return of about –3.58%) and standard deviation of 0.543%.

$\mathsf{BCH}^{\mathbf{raw}}$ is the NE minus SW difference portfolio analogous to that in Table VI, but formed from a 3-by-3 matrix to keep more stocks in each portfolio.t has a daily mean of –0.032% (annual rate of return of –7.74%) and standard deviation of 0.899%.

By design, the $\mathsf{BLT}^{\text{raw}}$ and $\mathsf{BST}^{\text{raw}}$ factors should have high correlations with the market portfolio, XMKT. However, because we do not report coefficients, we are not concerned with multicollinearity among factors. Table XII shows the performance of various factor portfolios in explaining the daily stock returns for the 100 Fama-French portfolios. The columns report cross-sectional statistics for the 100 alpha estimates. The single most important factor is the market rate of return, so it is always included. [Insert Tbl.XII]

Not surprisingly, the Fama-French book-to-market and size factors explain alphas on 100 value and size based portfolios better than our $\mathsf{BCH}^{\text{raw}}$ factor. More interestingly, holding the Fama-French factors constant, our $\mathsf{BCH}^{\text{raw}}$ factor explains the cross-section of alphas *better* than the Fama-French UMD, their up minus down momentum factor. Indeed, including UMD improves the RMSE only by 0.00028 once $\mathsf{BCH}^{\text{raw}}$ is included, compared to 0.00052 if $\mathsf{BCH}^{\text{raw}}$ is not included. It is quite possible that the market-wide momentum factor portfolio UMD proxied primarily (and more weakly) for a factor that is better picked up by our market-wide beta factor portfolios $\mathsf{BCH}^{\text{raw}}$ or $\mathsf{BST}^{\text{raw}}$. In sum, most of the explanatory power beyond the market and the two Fama-French factors is due to the $\mathsf{BST}^{\text{raw}}$ factor, not to the the UMD factor or the $\mathsf{BLT}^{\text{raw}}$ factor. (This finding will be echoed in the next subsection.)

B Factor Correlations and Exposure Correlations

The next question is whether our long-term beta and short-term beta are themselves more like own-stock characteristics, or whether they proxy for exposure to novel risk factors (Daniel and Titman (1997)). The easiest way to investigate these questions is to explore portfolios based on historical betas as if they were the factors themselves. The logical procedure, then, is to form exposures with respect to these (our) portfolio factor portfolios, and test them in cross-sectional Fama-Macbeth regressions in competition with own market-betas and the other characteristics.

Panel A of Table XIII shows that the correlations between the market portfolio XMKT and the three factors posted on the Fama-French website and our beta-based portfolios ($\mathsf{BLT}^{\text{raw}}$, $\mathsf{BST}^{\text{raw}}$, and $\mathsf{BCH}^{\text{raw}}$) range from 58.2% to 78.8%. These raw beta portfolios further have a strong correlation with HML, because HML itself is also strongly correlated with XMKT. Therefore, if we compute exposures with respect to our beta factor portfolios over the same five-year time-period as we compute the plain market beta, it is practically not possible to reliably disentangle them. (The correlations of exposures are much higher than the factor correlations themselves. We only obtained useful short-term vs. long-term beta estimates earlier, because the computation periods for long-term and short-term betas did not overlap.) In addition, we are now primarily interested in exposures of unknown potentially novel factors that are different from the market factor, not influence that is similar to that of the XMKT factor itself.

Therefore, we take out the problematic correlation with respect to the XMKT factor with the following regressions on daily stock returns:

$$\begin{aligned} \mathsf{BLT}^{\text{raw}} &= +0.0018\% + 0.229 \cdot \mathsf{XMKT} + \mathsf{BLT} \\ \mathsf{BST}^{\text{raw}} &= -0.0249\% + 0.479 \cdot \mathsf{XMKT} + \mathsf{BST} \\ \mathsf{BCH}^{\text{raw}} &= -0.0469\% + 0.683 \cdot \mathsf{XMKT} + \mathsf{BCH} \end{aligned} \tag{4}$$

We henceforth use BLT, BST, and BCH to refer to these revised factor portfolios. The daily standard deviations of these three portfolios are 0.286%, 0.335%, and 0.660%, respectively.[12] Daily returns on the six factor portfolios are posted on our websites.[13] It is important to note that these revised portfolios are somewhat misnamed, because they do not measure merely the influence of the beta factor portfolios, but the influence of the beta factor portfolios that is *no longer* correlated with the market. That is, they measure the additional fluctuation in the portfolio of firms in which the plain beta-exposure caused variation has been removed. Panel B of Table XIII shows that the resulting three factors also have rather benign correlations with respect to the Fama-French factors. Regressions explaining the beta factors with them have R^2 of less than 10%.

We can now compute the exposure of each stock with respect to the revised beta factor portfolios over the same 5-year interval. (As before, we impose a waiting period of 3 months.) Panel C of Table XIII shows the pooled cross-sectional correlations between different beta-based and beta-residual based exposures, based on 1,480,244 firm-years. The 5-year plain market beta and our original 1-year short-term and 9-year long-term betas have high correlation (79.7% and 92.0%), even higher than the correlation between the short-term and long-term beta (66.3%) itself. In contrast, the 5-year exposures with respect to the residual beta portfolios are only modestly correlated with either the original long-term and short-term betas on which their underlying factors were originally based (19.3% to 34.7%), or with the plain contemporaneous market beta (26.9% to 42.8%). However, the short-term beta exposure and the beta change exposure are highly correlated, and thus likely carry mostly the same information.

[12]When aggregated to monthly returns, the correlation between BST and XMKT becomes –20%; when aggregated to yearly returns, it rises to –34%. This why we do not present plots of aggregated time-series of BST and XMKT. For our purposes (exposures are correlated with respect to daily factor returns), this would be misleading.

[13]The current URL's are http://www.rhsmith.umd.edu/faculty/ghoberg/ and http://welch.econ.brown.edu/academics/hoberg-welch-betas.csv.

C Fama-Macbeth Regressions of Exposures to the Market vs. Novel Factors

Table XIV uses the exposures from Panel C of Table XIII in Fama-Macbeth regressions explaining monthly stock returns. As in Table III, the market-beta by itself is not significant. Remarkably, the table shows that the exposures with respect to our residual beta factor portfolios (not correlated with the market beta) *are* significant. The exposure with respect to the BLT portfolio has a T-statistic of 2.31; the exposure with respect to the BST portfolio has a T-statistic of –1.63; the exposure with respect to the BCH portfolio has a T-statistic of –2.83. The T-statistics become more important if we include the ordinary 5-year market-beta itself (3.02, –3.27, and –3.36, respectively). This evidence suggests that our factor portfolios indeed carry some information from a novel pricing factor. [Insert Tbl.XIV]

The next part of the table seeks to determine whether our original short-term and long-term betas worked primarily because they picked up exposures to such novel common factors, or whether they were more like market exposure characteristics of individual stocks. The long-term beta, LTβ, has explanatory power that seems to derive from both. The coefficient on LTβ (2.231) is larger than the coefficient on the BLT exposure(1.380), but the reverse is the case for the T-statistic. (In the final regression, in which we hold STβ constant, this is even more pronounced.)

In contrast, almost all of the explanatory power of the short-term beta seems to derive from some common unknown factor. The coefficient estimate on the remaining STβ is now even *positive* though insignificant. That is, it, too, seems to be playing more of a hedging role now that this novel factor unrelated to the market has been controlled for. However, this finding is sensitive to the inclusion of the LTβ portfolio, and thus should not be overread. In light of this finding, looking back at the earlier evidence about STβ in Table VI (the non-monotonicity), it suggests again that STβ is not so much picking up its own market-beta, as it is picking up some novel factor exposure.

The suggestion that short-term beta is more of a proxy for an unknown risk factor while long-term beta picks up ordinary hedging motives is also the message that emerges from the next regression, which is the "kitchen sink." When it comes to 5-year exposures, the strongest exposure is that with respect to the 5-year short-term beta portfolio, BST. The other (collinear) 5-year exposures with respect to BLT, BCH, or XMKT, seem fairly unimportant. The strongest own "beta characteristic" is the firm's own long-term beta (LTβ). It has a T-statistic of 4.96, and basically captures all the influence that otherwise would be captured by exposure to the BLT portfolio.

This suggests that a parsimonious model would include the Fama-Macbeth factors, plus the exposure to a 5-year factor portfolio that captures firms with low recent betas, and the firm's own beta, computed from daily stock returns from 1 to 10 years ago. This is the final model presented in the table. From Panel C of Table XIII, we know that the included beta-related exposures have a mild correlation (37%). Not reported, when we take residuals from this final model, analogous to the procedure in equation 1, none of the four other non-included beta-related variables have a T-statistic above 0.6. (This procedure is the equivalent of an F-test in the context of Fama-Macbeth regressions.) Therefore, we can conclude that the parsimonious model captures the important variation. Although our short-term beta factor BST did much better and almost subsume the common UMD factor in Table XII, the exposure to BST does not seem related to the explanatory power of firms' own momentum, at all. Not reported, if we split the sample into big and small firms (the prior year), necessarily halving the sample for each regression, the T-statistic on long-term beta is 2.1 for large firms and 3.1 for small firms. The exposure to BST is more market-cap related: the T-statistic is –1.7 for big firms and –4.7 for small firms. [Insert Tbl.XII]

The 5-by-5 table of sorted portfolio returns that is equivalent to Panel B (FFM excess returns) of Table VI for this parsimonious model is

Long-Term	Short-Term Market Beta (STβ)					
Market-Beta (LTβ)	Low	2	3	4	High	Average
Low	–1.8	–1.9	–1.6	–2.5	–4.6	–2.5
Quintile 2	–1.1	–0.8	–1.5	–1.3	–2.9	–1.5
Quintile 3	+0.6	+0.5	+0.9	+0.2	–3.2	–0.2
Quintile 4	+2.6	+1.6	+0.9	–0.5	–1.0	+0.7
High	+3.0	+3.9	+3.1	+4.7	+2.6	+3.5
Average	+0.6	+0.7	+0.4	+0.1	–1.8	–0.0

Cross-diagonal (NE-SW) Difference: $(3.0\%) - (-4.6\%) = -7.6\%$

T-statistic: -3.32

The spread in the NE-SW portfolio increases from –6.3% in Table VI to the –7.6% here, and both rows and columns now show monotonic orderings. (Down the columns, it even looks almost linear now, too.) Unreported, the corner portfolio's difference in raw or excess returns does not show better performance than the corresponding portfolio returns in Panel A of Table VI.

VII A Sample Trading Strategy for the NE-SW portfolio

A final question is how a trading strategy based on our characteristics would perform. The annualized Sharpe ratio is often misleading (Goetzmann, Ingersoll, Spiegel, and Welch (2004)), but it is the measure which is most familiar. In our sample, the Sharpe ratio of the NE-SW portfolio is 0.383 (0.548 after 1990). (Because this is a zero-cost portfolio, the ratio is simply the monthly mean divided by the monthly standard deviation, multiplied by the $\sqrt{12}$. For comparison, the Sharpe ratio of the market net of the risk free rate in our sample is 0.35.)

Moreover, because the short-term beta estimation duration is not critical (using 24 months rather than 12 months yields coefficient estimates weaker by only around 5%), and because the long-term beta computation period is not critical either (anything between 5 years and 9 years yields similar results), there is no urgency to rebalance the portfolio. To show this, we therefore compute no-rebalancing buy-and-hold returns beginning every January (or every second January) for the NE and SW portfolios from Table VI. We hold these portfolios for 1 year (or 2 years).

Figure 5 shows the performance of the two portfolios (in log returns) and their difference as a function of holding period. Indeed, the effect seems smooth and long-lasting. The strategy performs similarly regardless of whether we use all stocks, or only the top 500 stocks. We should note that this spread is directly related to betas (and changes in beta), and therefore could primarily be compensation for market risk. [Insert Fig.5]

VIII Conclusion

In sum, our evidence suggests that long-term betas have a solid positive influence in explaining the cross-section of future stock returns on the margin. The role of short-term betas is intertwined with the role of long-term betas because it needs to be held constant, but its role is less clear. It is intertwined because its influence on future stock returns is negative, and with long-term betas and short-term betas positively correlated, it is important not to let the negative short-term beta's influence negate the long-term beta's influence. In any case, even if we ultimately have two different beta-level effects, it is clear that the long-term beta after control, or the change-in-beta can capture a large part of the explanatory power of both of them.

Returning to the four hypotheses noted in our introduction, our evidence suggests the following:

1. **Slow Adjustment to Changes in Beta:** Given that a good part of the effect of the two betas is captured by one beta-change measure, this hypothesis has support in the data.

2. **Tax Effects in Up vs. Down Markets:** The stronger negative influence of short-term beta on future returns when the past market has done well is in line with this hypothesis. Moreover, the evidence that the short-term beta in January is negative only when the firm has had poor returns over the last year suggests that tax effects could play a role. However, the fact that the short-term beta premium is not higher in Januaries than non-Januaries does not favor this hypothesis.

3. **Relative Mean Reversion:** The correlation between the premium on value stocks and the premium on (both) betas is –35%. The correlation between the premium on value stocks and the premium on beta changes is –24%. This suggests that times in which value firms performed exceptionally well are also the times when betas have a more negative influence on stock returns. (Admittedly, our paper has not pursued this explanation in great detail.)

4. **Novel Factor Exposure:** We are particularly struck by the fact that this perspective seems to explain our findings at least as well as the behavioral hypothesis that we set out to test.[14]

   By itself, there is evidence that the short-term beta exposure is not so much a firm-specific slow-adjustment process, but a proxy for some novel underlying factor. That is, the short-term market beta is a proxy for exposure to a novel risk factor that is orthogonal to the market. This does not seem to be the case for the long-term beta, which seems to be a reliable measure of investors' hedging motives, once the novel (short-term beta related) factor exposure is controlled for.

   Our evidence is consistent with the view that past efforts to uncover beta have been stymied by this omitted factor. Captured at least partly by BST, it is related to but much stronger than the common momentum factor, UMD. In fact, BST almost subsumes UMD in Fama-French time-series regressions. (However, exposure to the BST factor has almost nothing to do with the influence of firms' own momentum on stock returns.)

   Our BST factor was constructed to be orthogonal to the market factor, so it is not that collinearity with the stock market that drives our results. Intuitively, firms with high or low market betas have exposures to this factor that pulls their stock returns in a direction that neutralizes the overall influence of exposure with respect to both the market and to this factor. If this novel factor is controlled for, firms with long-term

[14] We do not yet understand the meaning of our factor, and its correlation with investors' consumption set. Thus, we cannot determine whether it is rational or irrational.

beta estimates do indeed offer solidly higher rates of return, thus vindicating the hedging motive hypothesis.

In any case, the influence of long-term and short-term betas does not arise because these variables "steal" explanatory power from the Fama-French variables or from the momentum variables. On the contrary, the betas are stronger when the Fama-French factors are controlled for. Since 1962, their effect has been remarkably stable, both over time and in different market conditions, and within different groups of stocks.

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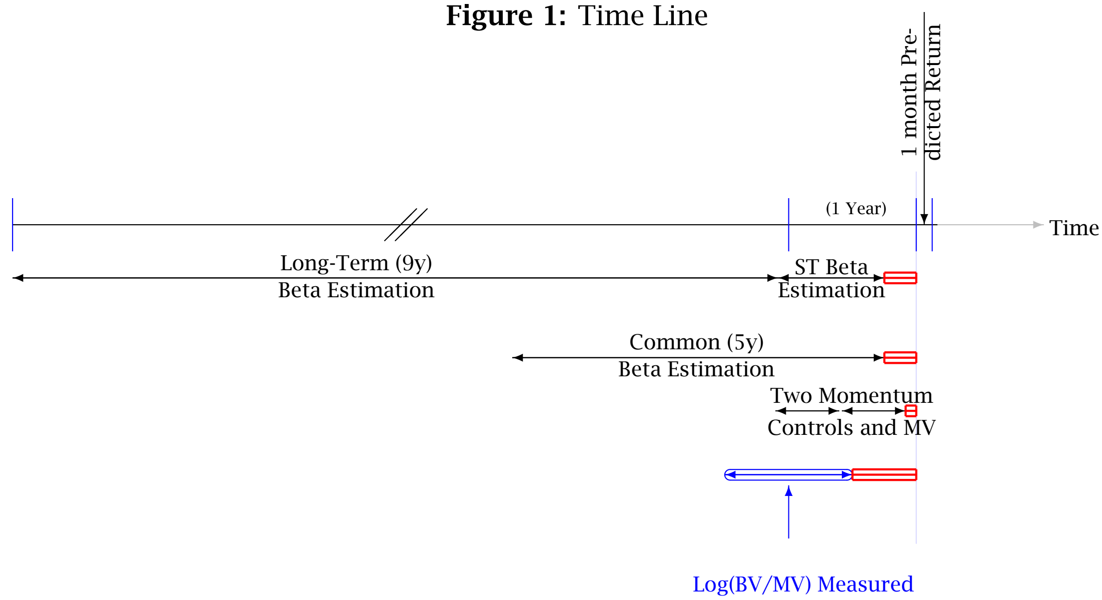
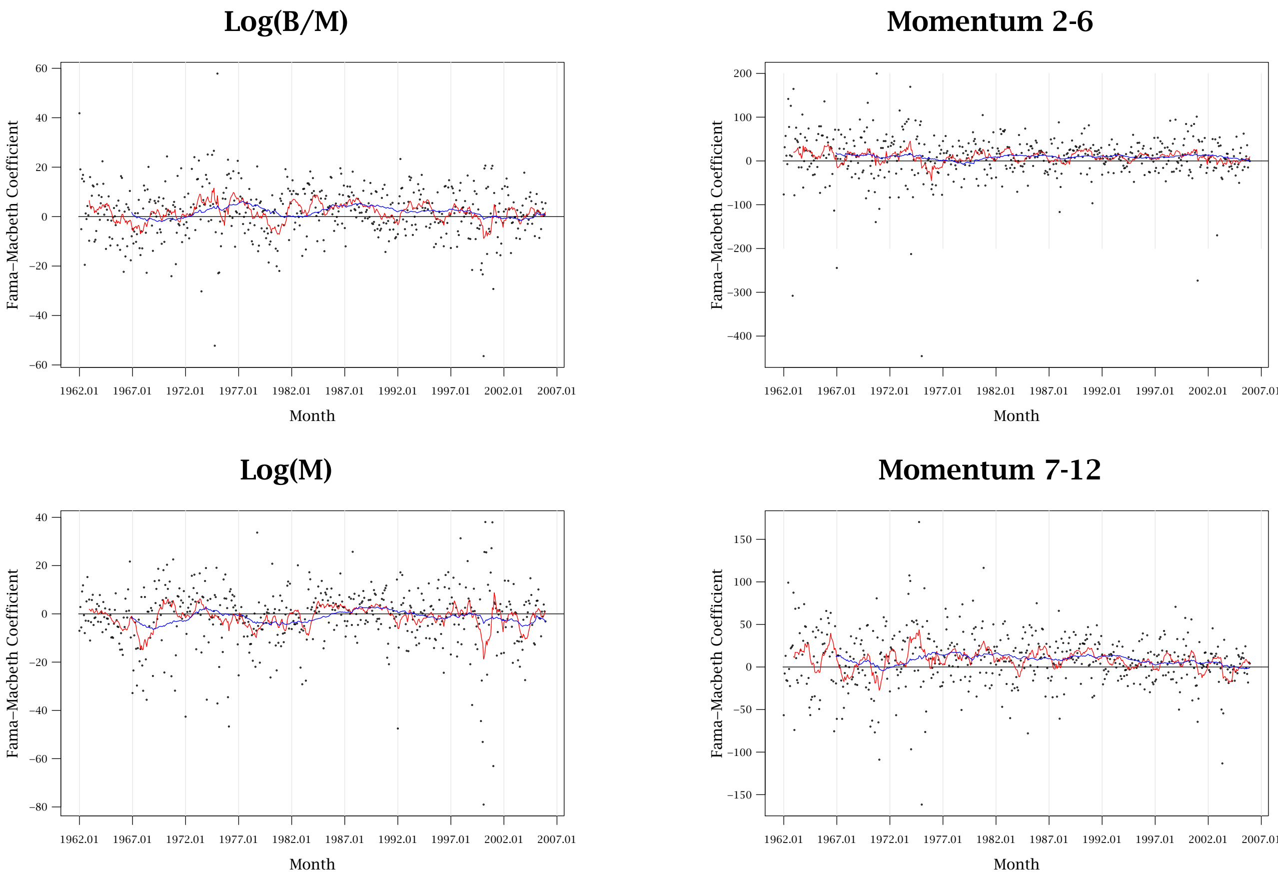
Figure 1: Time Line



Portfolios and statistics are recomputed every month (fully rolled). Red boxes mark periods when information is assumed to be not yet available. The timing of the momentum controls and of the Fama-French characteristics follows Davis, Fama, and French (2000). (Momentum has 1 month delay, Compustat-related variables have 6 to 17 months delay.) Betas are assumed to be available 3 months after they are computed.

Figure 2: Monthly Time Series of Fama-Macbeth Gammas (Premia)

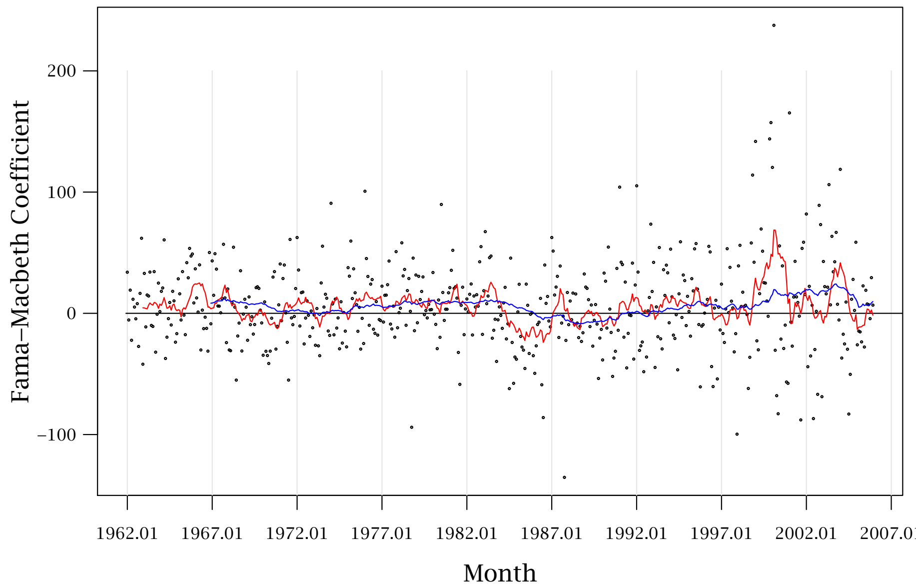


Name	Min	Median	Max	Mean	Sd	Tstat	N
Log(B/M)	-56.42	2.08	57.86	1.903	10.70	4.085	528
Log(M)	-79.01	0.08	38.04	-1.430	12.76	-2.575	528
Mom(2-7)	-445.74	11.14	199.53	9.163	52.31	4.025	528
Mom(8-13)	-161.60	8.83	170.27	8.168	32.60	5.757	528
Beta LT	-135.30	4.67	237.56	6.018	37.46	3.692	528
Beta ST	-160.70	-4.69	165.72	-4.186	34.11	-2.820	528

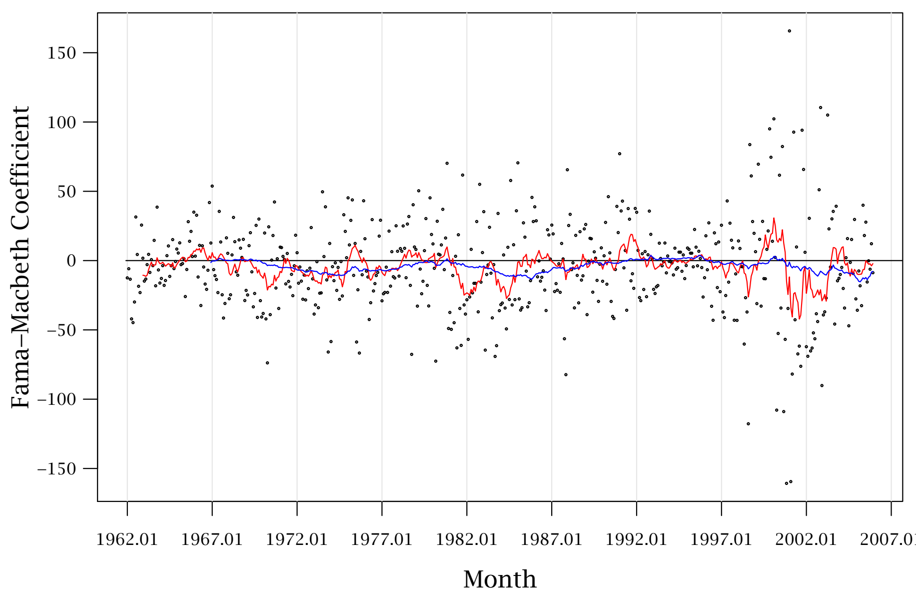
Explanation: The red line is the 1-year moving average, the blue line is the 5-year moving average. The data is the gamma series from specification (8) in Table IV.

Figure 3: Monthly Time Series of Fama-Macbeth Gammas (Premia)

Premium on Long-Term Beta

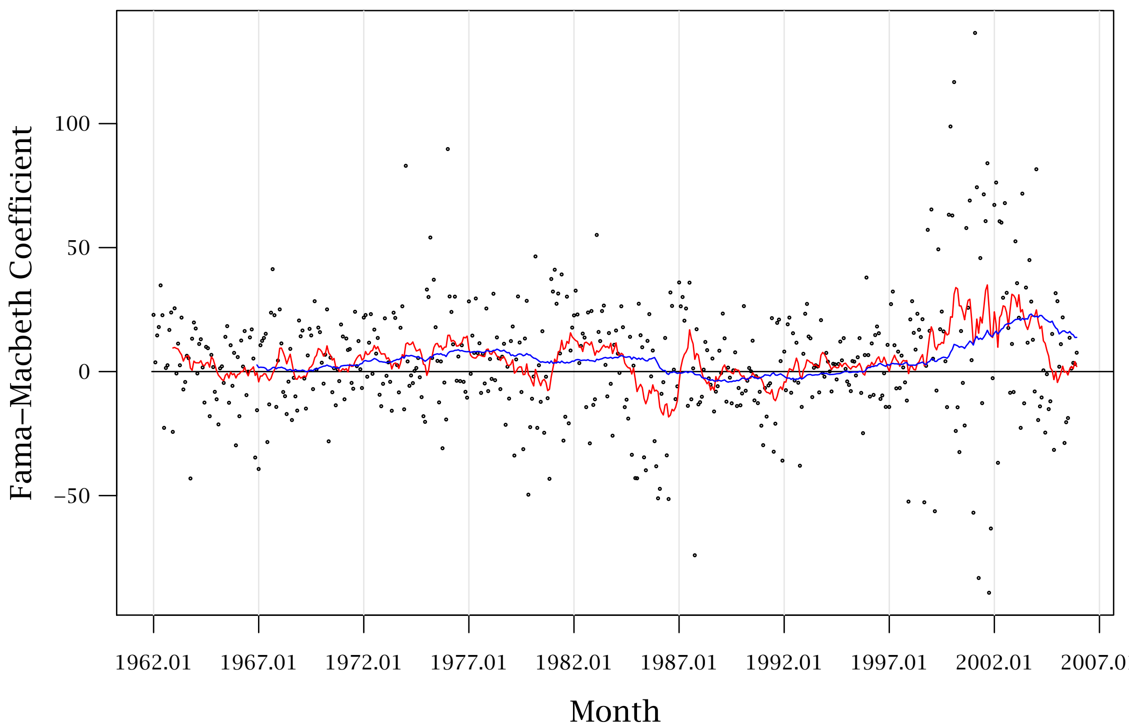


Premium on Short-Term Beta



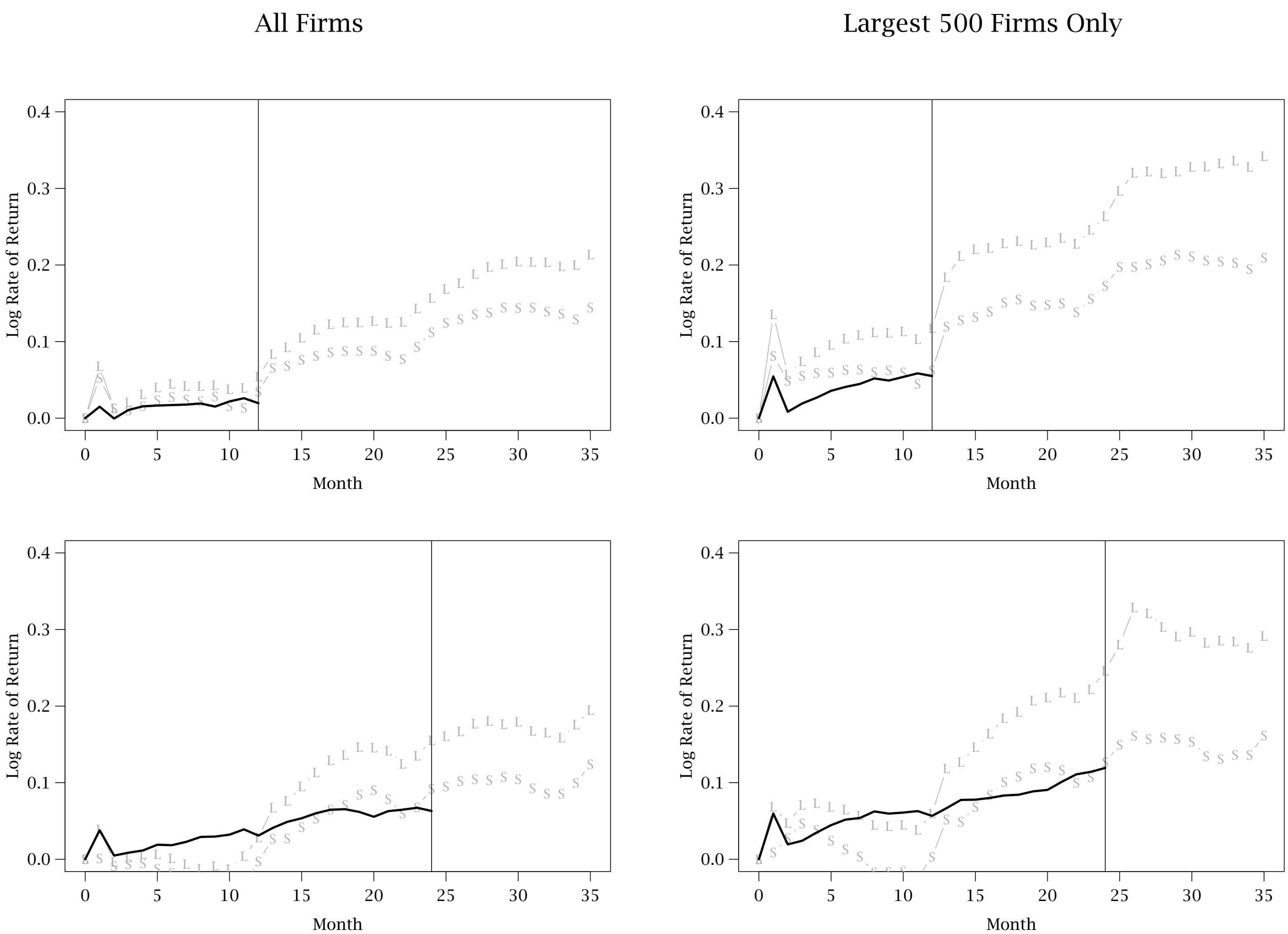
Explanation: The red line is the 1-year moving average, the blue line is the 5-year moving average. The data is the gamma series from specification (8) in Table IV.

Figure 4: Monthly Time Series of Fama-Macbeth Gamma (Premium) on Beta Change



Explanation: The red line is the 1-year moving average, the blue line is the 5-year moving average. The data is from the gamma series from specification (4) in Table VIII.

Figure 5: Annual and Biannual Buy-and Hold Performance



Explanation: The bold line is the performance of a buy-and-hold portfolio that is long the NE portfolio and short the SW portfolio from Table VI. The top figure rebalances every January, the bottom figure rebalances every second January.

Table I: Summary statistics

Panel A: FFM Control Variables

Variable Description	Abbrev	Mean	Sdv	Min	Med	Max
Log Book to Market Ratio	B/M	-7.193	1.019	-16.164	-7.172	1.866
Log Market Size	SZ	11.710	2.055	3.624	11.572	20.078
Momentum: Lagged 2-7 Return	M2.7	0.096	0.421	-0.981	0.047	41.429
Momentum: Lagged 8-13 Return	M8.13	0.095	0.422	-0.979	0.047	41.429

Panel B: Stock Returns

Variable Description	Abbrev	Mean	Sdv	Min	Med	Max
Raw Return	r	0.014	0.143	-0.981	0.003	9.374
Excess Return (net of 30-day Treasury)	xr	0.009	0.143	-0.983	-0.002	9.371
Residual FFM Return	rr	-0.000	0.143	-0.976	-0.010	9.367

Panel C: Market-Beta Estimates

Variable Description		Abbrev	Mean	Sdv	Min	Med	Max
Monthly, OLS, Raw	5 Year Beta	β	1.047	0.666	-6.116	0.997	10.461
	Long-Term Beta	STβ	1.078	0.600	-7.339	1.039	7.756
	Short-Term Beta	LTβ	1.038	1.293	-55.518	0.941	152.187
Daily, OLS, Raw	5 Year Beta	β	0.734	0.485	-1.292	0.664	5.096
	Long-Term Beta	LTβ	0.743	0.467	-1.534	0.676	3.704
	Short-Term Beta	STβ	0.737	0.599	-5.549	0.656	8.390
Daily OLS, Shrunk	5 Year Beta	β	0.731	0.467	-1.015	0.663	3.282
	Long-Term Beta	LTβ	0.737	0.447	-0.679	0.675	3.285
	Short-Term Beta	STβ	0.721	0.492	-1.380	0.655	3.991
Daily Dimson, Shrunk	5 Year Beta	β	0.842	0.480	-1.134	0.799	3.703
(Dimson (1979))	Long-Term Beta	LTβ	0.856	0.443	-0.677	0.827	3.634
	Short-Term Beta	STβ	0.816	0.488	-1.198	0.774	3.855
Daily, Sub, Shrunk	Long-Term Beta	LTβ	0.726	0.435	-0.868	0.672	3.340
	Short-Term Beta	STβ	0.726	0.551	-4.519	0.656	7.643

Explanation: The sample includes 1,480,244 firm months from January 1962 to December 2005. Stocks had to have four years of past return data, an ex-ante share price of at least $1, and a valid positive book value of equity on Compustat. Variable Timing is illustrated in Figure 1.

The variable definitions in Panel A are common in the literature (e.g., Davis, Fama, and French (2000)): The log market size is the natual logarithm of the firm's CRSP market capitalization. The log B/M Ratio is the natural logarithm of the firm's book value of equity divided by the firm's CRSP market value of equity. Momentum are two six-months measures, with the most recent month omitted.

In Panel B, to compute residual FFM returns, we first ran a full Fama-Macbeth regression using the FFM variables from Panel A (including an intercept), and then used the overall in-sample coefficients to compute a residual returns for each firm-month return.

In Panel C, the short-term beta is computed over the most recent year (–1 to 0); the long-term beta is computed over the preceding nine years (–10 to –1). Monthly and daily refer to the stock returns used to compute the betas. "Shrunk" means adjusted using the Bayesian method in Vasicek (1973). OLS betas are standard; subsampled long-term betas are averages of nine individually computed annual market betas.

Table II: Predicting Future Betas with Past Betas

With Lagged Long-Term Betas (–1 to –10 years)			Future 1-year Market Betas Computed From: Daily Stock Returns, w/ Dimson		Daily Stock Returns, w/o Dimson		Monthly Stock Returns	
Method to estimate Lagged Beta			RMSE	$\overline{R}^2$	RMSE	$\overline{R}^2$	RMSE	$\overline{R}^2$
Daily	OLS	Raw	0.639	0.217	0.527	0.305	1.473	**0.051**
Daily	OLS	Shrunk	0.634	**0.219**	0.520	**0.308**	1.472	**0.051**
Daily	Dimson	Raw	0.638	0.214	0.565	0.271	1.450	**0.055**
Daily	Dimson	Shrunk	0.625	**0.219**	0.544	0.279	1.449	**0.056**
Daily	Sub	Raw	0.642	**0.218**	0.528	0.306	1.476	**0.051**
Daily	Sub	Shrunk	0.635	**0.218**	0.517	**0.311**	1.476	0.049
Monthly	OLS	Raw	0.765	0.138	0.751	0.149	1.467	0.046
Monthly	OLS	Shrunk	0.666	0.153	0.617	0.178	1.450	0.043
Monthly	Sub	Raw	0.813	0.128	0.799	0.141	1.494	0.040
Monthly	Sub	Shrunk	0.667	0.150	0.612	0.179	1.456	0.040

With Lagged Short-Term Betas (0 to –1 years)			Future 1-year Market Betas Computed From: Daily Stock Returns, w/ Dimson		Daily Stock Returns, w/o Dimson		Monthly Stock Returns	
Method to estimate Beta			RMSE	$\overline{R}^2$	RMSE	$\overline{R}^2$	RMSE	$\overline{R}^2$
Daily	OLS	Raw	0.683	0.222	0.566	0.319	1.497	0.051
Daily	OLS	Shrunk	0.633	**0.246**	0.502	**0.358**	1.478	**0.057**
Daily	Dimson	Raw	0.735	0.185	0.665	0.235	1.501	0.046
Daily	Dimson	Shrunk	0.632	0.218	0.533	0.282	1.462	0.053
Daily	Sub	Raw	0.683	0.222	0.566	0.319	1.497	0.051
Daily	Sub	Shrunk	0.666	0.221	0.544	0.321	1.493	0.050
Monthly	OLS	Raw	1.304	0.059	1.290	0.068	1.797	0.021
Monthly	OLS	Shrunk	0.989	0.064	0.952	0.077	1.619	0.020
Monthly	Sub	Raw	1.304	0.059	1.290	0.068	1.797	0.021
Monthly	Sub	Shrunk	0.955	0.061	0.913	0.076	1.603	0.019

Explanation: For sample and variable definitions, refer to Table I. Each correlation is computed based on firm-years (not firm-months) to avoid overlap. The table shows how different beta methods predict future betas over the following 12 months (the dependent market-beta is never shrunk, and is either OLS-daily betas [with or without Dimson adjustment], or monthly betas). The predicting variable is the past LTβ market beta (top set) or STβ market-beta (bottom set), with computation method described in columns 1 to 3. The best performances are highlighted. There are 114,290 future market betas in the daily columns, and 115,517 in the monthly columns. Due to bias, the appropriate metric is R^2, not RMSE. (However, it would offer similar recommendations.)

Interpretation: Betas estimated from daily stock returns generally predict better than betas estimated from monthly stock returns. For long-term betas (computed over nine years with one year lag), the estimation method is not too important. For betas computed over the most recent single year, it is best if we use OLS, shrunk via Vasicek (1973). The Dimson correction is better avoided.

Table III: Fama-MacBeth Regressions Explaining the Cross Section of Monthly Stock Returns with Market-Betas and FFM controls.

Panel A: OLS Market-Betas computed using monthly data

	Inter-cept	5-Year Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(1)	9.747	0.264					528
	(6.08)	(0.15)					2,803
(2)	38.358	0.320	2.180	-1.299	9.957	7.576	528
	(6.71)	(0.22)	(4.41)	(-2.81)	(4.34)	(5.07)	2,803

Panel B: OLS Market-Betas computed using Daily Stock Returns

	Inter-cept	5-Year Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(3)	11.831	-2.138					528
	(6.22)	(-1.00)					2,803
(4)	38.396	0.496	2.046	-1.376	9.085	7.566	528
	(6.03)	(0.21)	(4.31)	(-2.52)	(3.97)	(5.12)	2,803

Panel C: OLS Market-Betas computed using daily Stock Returns, then Shrunk

	Inter-cept	5-Year Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(5)	11.772	-2.062					528
	(6.23)	(-0.93)					2,803
(6)	38.439	0.685	2.058	-1.383	9.087	7.578	528
	(6.06)	(0.28)	(4.33)	(-2.52)	(3.97)	(5.12)	2,803

Explanation: For sample and variable definitions, refer to Table I. The table presents statistics on the gamma (premium) coefficients from a Fama-Macbeth regression. The number in parenthesis is the T-statistic. The dependent variable is a stock return multiplied by 1200.

Interpretation: This table confirms the results in the literature—since 1962, market-betas have had no explanatory power for the cross-section of stock returns, either unconditionally or conditional on the FFM controls.

Table IV: Fama-MacBeth Regressions Explaining the Cross Section of Monthly Stock Returns with Short-Term and Long-Term Market-Betas and FFM controls.

Panel A: Raw Market-Betas computed using Daily Stock Returns

	Method	Inter-cept	Long-Term Market Beta	Short-Term Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(1)	OLS	10.974	3.066	-4.475					528
		(5.96)	(2.08)	(-2.94)					2,803
(2)	OLS	36.634	4.803	-3.680	1.890	-1.381	9.108	8.025	528
		(5.87)	(3.11)	(-2.82)	(4.10)	(-2.52)	(4.02)	(5.67)	2,803
(3)	Sub	10.676	3.666	-4.769					528
		(5.80)	(2.61)	(-3.11)					2,803
(4)	Sub	36.520	5.262	-3.914	1.869	-1.398	9.120	8.116	528
		(5.86)	(3.59)	(-2.92)	(4.05)	(-2.56)	(4.02)	(5.73)	2,803
(5)	OLS w/ Dim-son -1,0,+1	37.149	3.764	-2.196	1.997	-1.397	9.342	7.958	528
		(6.24)	(2.51)	(-2.15)	(4.33)	(-2.74)	(4.14)	(5.53)	2,801

Panel B: *Shrunk* Market-Betas computed using Daily Stock Returns

	Method	Inter-cept	Long-Term Market Beta	Short-Term Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(7)	OLS	11.178	3.283	-5.060					528
		(6.13)	(2.11)	(-2.70)					2,803
(8)	OLS	37.040	5.165	-4.140	1.928	-1.388	9.175	8.035	528
		(5.96)	(3.22)	(-2.56)	(4.16)	(-2.50)	(4.04)	(5.66)	2,803
(9)	Sub	10.636	4.153	-5.191					528
		(5.85)	(2.75)	(-3.05)					2,803
(10)	Sub	36.835	6.018	-4.186	1.903	-1.430	9.163	8.168	528
		(5.92)	(3.69)	(-2.82)	(4.08)	(-2.57)	(4.03)	(5.76)	2,803

Explanation: For sample and variable definitions, refer to Table I. Like Table III, this table presents Fama-Macbeth regression results, except that market-betas are now split into one computed from the most recent 12 months (with 3 months delay), called the **Short-term Beta** (STβ), and one computed from 1 year to 10 years ago (with 3 months delay), called the **Long-term Beta** (LTβ). "Sub" rows refers to market-betas that are computed from nine sub-sampled annual betas, rather then from one nine-year OLS regression.

Interpretation: The gamma coefficient on long-term market-betas is positive, the gamma coefficient on short-term betas is generally negative. Together, the two betas help explain the cross-section of stock returns.

Table V: "Suggestive" Relative In-Each-Month Significance Including or Excluding Sets of Two Variables Each

Hypothesis A	Hypothesis B	$\overline{p(F)}$	$p(F) > 5\%$	$\overline{R}_A^2$	$\overline{R}_B^2$
All Variables	No Variables	0.22	0.95	6.08	0.00
All Variables	No FF	6.55	19.89	6.08	4.24
All Variables	No Momentum	8.04	22.92	6.08	5.01
All Variables	No Betas (FFM incl)	5.00	18.18	6.08	4.03
Fama-French	No Other Variables	4.13	13.26	2.36	0.00
Momentum	No Other Variables	6.45	15.72	2.12	0.00
Betas	No Other Variables	5.65	14.58	2.80	0.00

Explanation: This table provides statistics for the average monthly rejection rates of significance of the two variables described under the incorrect assumption that observations are independent. Therefore, it is only useful to consider the *relative* performance of these variable sets. $\overline{p(F)}$ is the statistic for the hypothesis that the A variables are useful above and beyond those in B. $p(F) > 5\%$ gives the fraction of rejections of no-use that are at least at the 5% level.

Interpretation: [A] Omitting the two betas from the set of six variables seems at least as problematic as omitting either the two Fama-French variables or the two momentum variables. [B] Adding only two variables, the two betas seem about equally important as the two other sets of variables.

Table VI: Rank Tables displaying Future Stock Returns by Beta Quintiles (conditional sorts)

Panel A: Excess Returns (xr)

Long-Term Market-Beta (LTβ)	LTβ↓	STβ→	Short-Term Market Beta (STβ) Low (0.1)	2 (0.4)	3 (0.7)	4 (0.9)	High (1.4)	Average (0.7)	
Lowest	(0.3)		11.2	11.5	12.6	10.8	5.2	10.3	Monotonic
Quintile 2	(0.5)		11.1	11.8	12.2	10.8	6.1	10.4	
Quintile 3	(0.7)		11.4	12.0	11.5	10.7	7.8	10.7	
Quintile 4	(0.9)		12.6	11.9	12.6	11.0	8.8	11.4	
Highest	(1.2)		12.7	13.1	12.2	12.2	10.7	12.2	
Subtotal Averages	(0.7)		11.8	12.0	12.2	11.1	7.7	11.0	

Not Monotonic

Cross-diagonal (NE-SW) Difference: (5.2%) − (12.7%) = −7.5%

T-statistic: −2.51

Panel B: FFM Residual Returns (rr)

Long-Term Market-Beta (LTβ)	LTβ↓	STβ→	Short-Term Market Beta (STβ) Low (0.1)	2 (0.4)	3 (0.7)	4 (0.9)	High (1.4)	Average (0.7)	
Lowest	(0.3)		-2.2	-1.4	-0.1	-1.6	-5.9	-2.2	Monotonic
Quintile 2	(0.5)		-1.8	0.1	0.8	0.0	-3.2	-0.8	
Quintile 3	(0.7)		-1.1	0.4	0.8	0.8	-0.9	-0.0	
Quintile 4	(0.9)		0.3	0.6	2.2	1.6	0.6	1.1	
Highest	(1.2)		0.4	1.8	2.1	3.0	2.6	2.0	
Subtotal Averages	(0.7)		-0.9	0.3	1.2	0.8	-1.4	-0.0	

Not Monotonic

Cross-diagonal (NE-SW) Difference: (−5.9%) − (0.4%) = −6.3%

T-statistic: −2.52

Explanation: For sample and variable definitions, refer to Table I. All firm-months were sorted first by month, then into 5 roughly equal-sized (lagged) groups based on ST market beta, then for each of these 5 groups into 5 further roughly equal-sized (lagged) groups based on LT market beta. Each cell shows the *equal-weighted* average rate of return (multiplied by 12 and in percent) of between 58,965 and 59,349 observations. The market-betas are estimated from daily stock return data, using Vasicek-shrunk betas from OLS regressions.

Interpretation: [A] The difference between firms with high long-term beta and low short-term beta and those showing the opposite pattern is economically meaningful. [B] Holding Short-term beta constant, the final column shows that there is a monotonic positive relationship between long-term beta and stock returns. [C] Holding long-term beta constant, the final row of each panel shows that there is no monotonic relationship between short-term beta and stock returns. Instead, firms with short-term betas of around 1 do best, and not firms with very low short-term beta.

Table VII: Monthly Fama-MacBeth Regressions, By Short-Term Betas

	Short-term Beta (STβ)	Inter-cept	Long Term Market Beta	Short Term Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(1a)	Low	-7.666	4.860						528
		(-2.17)	(2.66)						560
(1b)		-0.704	5.496	-7.005	0.960	0.727	0.307	-0.027	528
		(-0.08)	(3.10)	(-3.10)	(1.29)	(1.08)	(0.10)	(-0.01)	560
(2a)	Mid-Low	-4.927	5.001						528
		(-1.68)	(2.89)						560
(2b)		6.324	4.804	-12.109	-0.183	-0.098	-0.295	0.877	528
		(0.72)	(2.53)	(-3.40)	(-0.28)	(-0.15)	(-0.11)	(0.43)	560
(3a)	Mid	-0.949	1.920						528
		(-0.40)	(1.07)						560
(3b)		1.298	2.893	1.135	-0.248	-0.575	0.984	3.248	528
		(0.17)	(1.53)	(0.27)	(-0.41)	(-0.97)	(0.38)	(1.65)	560
(4a)	Mid-High	-3.292	4.373						528
		(-1.67)	(2.15)						560
(4b)		-2.700	4.610	-7.707	-1.047	-0.431	-1.200	-0.491	528
		(-0.40)	(2.30)	(-1.59)	(-1.86)	(-0.77)	(-0.46)	(-0.24)	560
(5a)	High	-3.446	3.723						528
		(-2.15)	(1.62)						560
(5b)		-4.820	4.634	2.202	-1.513	-0.903	-1.515	1.865	528
		(-0.86)	(2.05)	(0.69)	(-2.88)	(-1.85)	(-0.61)	(0.76)	560

Explanation: For sample and variable definitions, refer to Table I. This table runs the same Fama-Macbeth regressions as those in Table IV, but splits the sample according to the short-term beta first. Like other Fama-Macbeth tables, we use the shrunk daily OLS method to compute beta.

Interpretation: Long-Term beta seems positive and significant, if we control for short-term beta (i.e., we do not need the regression to tease the two coefficients in opposite directions).

Table VIII: Monthly Fama-MacBeth Regressions, Change in Beta (Short-Term Minus Long-Term)

	Method	Inter-cept	Long-Term Market Beta	Delta Beta (STβ–LTβ)	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Mths /Avg # Firms
(1)	OLS	37.040	1.025	–4.140	1.928	–1.388	9.175	8.035	528
		(5.96)	(0.38)	(–2.56)	(4.16)	(–2.50)	(4.04)	(5.66)	2,803
(2)	Sub	36.835	1.832	–4.186	1.903	–1.430	9.163	8.168	528
		(5.92)	(0.69)	(–2.82)	(4.08)	(–2.57)	(4.03)	(5.76)	2,803
(3)	OLS	9.559		–4.816					528
		(3.50)		(–3.19)					2,803
(4)	OLS	37.131		–5.013	2.197	–1.210	9.420	7.984	528
		(6.40)		(–4.58)	(4.01)	(–2.66)	(3.60)	(4.78)	2,803

Explanation: For sample and variable definitions, refer to Table I. This table runs the same Fama-Macbeth regressions as those in Table IV (shrunk daily OLS betas), but rotates the two market-betas in each month into one long-term beta and one change in beta. The first two regressions are identical to those in Table IV, (6) and (8). Only the final two regressions are novel.

Interpretation: Consistent with the earlier Fama-Macbeth coefficients, subtracting a variable that has a negative influence on returns (short-term beta) from a variable that has a positive influence on returns (long-term beta) produces a single variable that captures the effects of both. This change-in-beta variable can subsume the statistical influence of long-term market-beta.

Table IX: Monthly Fama-MacBeth Regressions, By Firm-Specific Categories

	Sub-Sample	Inter-cept	Long Term Market Beta	Short Term Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(1a)	Big Firms	30.596	4.145	-3.762	2.362	-0.665	9.461	10.751	528
		(4.39)	(2.82)	(-2.22)	(4.45)	(-1.30)	(3.47)	(6.01)	1,622
(1b)	Small Firms	50.079	6.611	-3.863	1.245	-3.192	10.024	6.889	528
		(6.47)	(3.18)	(-2.03)	(2.26)	(-3.81)	(4.43)	(4.58)	1,181
(2a)	Value Firms	30.029	4.770	-1.627	0.245	-1.788	9.487	7.573	528
		(4.60)	(2.80)	(-1.01)	(0.45)	(-3.29)	(4.31)	(4.88)	1,506
(2b)	Growth Firms	38.728	5.540	-5.410	2.632	-1.068	8.979	8.434	528
		(5.30)	(3.37)	(-3.07)	(3.86)	(-1.80)	(3.39)	(5.08)	1,296
(3a)	Low Returns	39.252	6.202	-4.918	1.674	-1.794	10.581	16.561	528
	(Mean= -23.9%)	(5.57)	(3.41)	(-3.05)	(2.80)	(-2.98)	(3.53)	(6.41)	874
(3b)	Med Returns	41.089	3.743	-2.416	2.312	-1.480	13.351	11.868	528
	(Mean= 11.2%)	(6.66)	(2.30)	(-1.54)	(4.64)	(-3.10)	(5.20)	(5.60)	894
(3c)	High Returns	35.730	5.198	-4.339	2.044	-1.124	13.121	5.643	528
	(Mean= 77.7%)	(5.63)	(3.19)	(-2.44)	(3.56)	(-2.00)	(6.07)	(3.62)	883

Explanation: For sample and variable definitions, refer to Table I. This table runs the same Fama-Macbeth regressions as those in Table IV (shrunk daily OLS betas), but splits the sample each prior month according to the characteristic that is explained in the second column. Size and book-market splits are for stocks above vs. below median in each month. Lagged stock returns are from the past calendar year, and computed without delay.

Interpretation: The influence of long-term and short-term betas holds in both small and large firms, in value and growth firms, and in firms with high, medium, or low past stock returns.

Table X: Correlations of Monthly Fama-Macbeth Gammas Over Time and Market Conditions

	+	+	–	+	+	+	–	–
	Intrcpt	B/M	SZ	M(-2,-7)	M(-8,-13)	LTβ	STβ	STβ–LTβ
Time Index	–1.0	–2.9	+ 1.2	–3.3	–6.5	+ 3.4	0.0	*–8.3*
Num Obs in Reg	–0.3	–4.2	–0.1	–2.9	–4.3	+ 3.7	0.0	*–7.3*
January	**+49.4**	+ 2.4	**–43.1**	**–33.1**	**–24.0**	**+24.8**	+ 7.1	**–12.0**
Correlation with Lagged S&P500 Returns								
%S&P(-1,-4)	**+24.3**	–3.5	**–22.4**	–2.9	–6.3	**+ 8.9**	–6.9	**–12.8**
%S&P(-1,-12)	+ 3.3	+ 3.5	–1.1	+ 4.1	+ 0.8	–1.8	*–8.0*	+ 0.5
%S&P(-2,-5)	+ 5.2	+ 3.3	–3.6	*+ 8.4*	+ 2.8	–0.9	**–11.3**	*–7.7*
%S&P(-4,-16)	–6.4	**+11.8**	**+10.6**	+ 5.8	+ 2.7	–6.2	–6.3	+ 3.8
Correlation with Contemporaneous S&P500 Returns								
%S&P(-0)	**+21.1**	**–18.6**	**–15.3**	*–8.0*	+ 3.1	**+43.5**	**+63.7**	**+23.5**

Explanation: Except for the final column, these gammas are from regression (8) in Table IV. The final column is from regression (4) in Table VIII. All correlations are in percent. %S&P(x,y) denotes the percent change of the S&P 500 index from month x to month y. Boldface denotes two-sided significance at the 5% level, italic at the 10% level.

Interpretation: [1] Only the premiums for the long-term beta and the beta change have not shrunk towards zero over time. [2] The table shows a strong January effect on all returns (the intercept), on small firms, on firms with inverted momentum, and firms with high long-term market-beta. [3] If the stock market has gone up over the most recent three months, then residual alphas are higher, small firms do better, and high beta stocks do better.

Table XI: Monthly Fama-Macbeth Performance, by Own Stock Return in January

	Calendar Year Sub-Sample	Inter-cept	**Long Term Market Beta**	**Short Term Market Beta**	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
(1)	Low Returns	300.142	**41.147**	**−6.003**	2.629	−21.895	−47.822	−12.809	44
		(9.40)	**(5.17)**	**(−0.94)**	(0.81)	(−9.77)	(−2.58)	(−1.33)	903
(2)	Mid Returns	258.560	**34.403**	**2.128**	7.741	−15.755	−2.803	18.264	44
		(8.38)	**(4.77)**	**(0.40)**	(3.15)	(−8.21)	(−0.26)	(2.65)	910
(3)	High Returns	228.044	**25.900**	**4.145**	3.790	−15.893	−11.877	3.641	44
		(8.34)	**(4.23)**	**(0.61)**	(1.78)	(−6.81)	(−1.52)	(0.61)	906

Explanation: For sample and variable definitions, refer to Table I. This table runs the same Fama-Macbeth regressions as those in Table IV (shrunk daily OLS betas), only for January returns, but splits the sample based on the stock's own performance in the prior *calendar* year without delay.

Interpretation: Short-term beta has the unintuitive negative correlation in Januaries only when a stock has had large capital losses.

Table XII: Explaining Alphas for the 100 FF Portfolios

	Daily Alpha α_p		
		X-Sect	
Predicting $(r_{p,t} - r_{f,t})$ =:	RMSE	Mean	Sdv
α_p	0.0329	+0.0306	0.0121
$\alpha_p + \beta_p \cdot \mathsf{XMKT}$	0.0192	+0.0123	0.0148
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \rho_p \cdot \mathsf{BCH}$	0.0204	+0.0151	0.0138
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB}$	0.0109	−0.0023	0.0107
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB} + \rho_p \cdot \mathsf{BCH}$	0.0097	−0.0013	0.0096
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB} + \nu_p \cdot \mathsf{UMD}$	0.0104	−0.0015	0.0103
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB} + \nu_p \cdot \mathsf{UMD} + \rho_p \cdot \underline{\mathsf{BCH}^{\mathrm{raw}}}$	0.0094	−0.0007	0.0094
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB} + \nu_p \cdot \mathsf{UMD} + \rho_p \cdot \underline{\mathsf{BST}^{\mathrm{raw}}}$	0.0094	−0.0005	0.0094
$\alpha_p + \beta_p \cdot \mathsf{XMKT} + \gamma_p \cdot \mathsf{HML} + \delta_p \cdot \mathsf{SMB} + \nu_p \cdot \mathsf{UMD} + \rho_p \cdot \underline{\mathsf{BLT}^{\mathrm{raw}}}$	0.0104	−0.0015	0.0103

Explanation: XMKT, HML, SMB, and UMD are the well-known Fama-French factor portfolios. $\mathsf{BLT}^{\mathrm{raw}}$ is a portfolio formed to maximize the spread in long-term betas holding short-term betas constant, $\mathsf{BST}^{\mathrm{raw}}$ is a portfolio formed to maximize the spread in short-term betas holding long-term betas constant, and $\mathsf{BCH}^{\mathrm{raw}}$ is the NE-SW portfolio formed to maximize the spread in the change in betas (Table VI). The table reports cross-sectional statistics for the alphas explaining the 100 Fama-French size and book-market portfolios. All numbers are in percent.

Interpretation: Our beta factor portfolios help to further reduce the pricing error in the Fama-French portfolios, and do so better than the UMD factor.

Table XIII: Characteristics of Beta-Based Portfolios and Exposures Thereto

Panel A: Bivariate Time-Series Correlations before the Market Factor is Eliminated, Daily Stock Returns

	XMKT	SMB	HML	UMD	BLT^{raw}	BST^{raw}
SMB	−25.3					
HML	−58.3	−5.8				
UMD	+3.6	+7.4	−3.6			
BLT^{raw}	+58.2	−2.5	−34.7	+4.0		
BST^{raw}	+78.8	−8.8	−56.9	−4.0	+29.6	
BCH^{raw}	+67.8	−5.6	−47.3	−4.3	+20.2	+84.2

Panel B: Bivariate Time-Series Correlations after the Market Factor is Eliminated, Daily Stock Returns

	XMKT	SMB	HML	UMD	BLT	BST	BCH
BLT	0.0%	+15.0%	−1.0%	+2.3%		−32.4%	−32.2%
BST	0.0%	+18.1%	−17.9%	−11.1%	−32.4%		+67.9%
BCH	0.0%	+15.8%	−10.5%	−9.1%	−32.2%	+67.9%	

Panel C: Pooled Correlations of Individual Exposures, Monthly Stock Returns

	5-Year, Different Portfolios				Original, Different Years	
	Plain	.... Orthogonal to Market Factor			$LT\beta_i$	$ST\beta_i$
	$b_{i,XMKT[0,-5]}$	$b_{i,BLT[0,-5]}$	$b_{i,BST[0,-5]}$	$b_{i,BCH[0,-5]}$	$b_{i,XMKT[-1,-10]}$	$b_{i,XMKT[0,-1]}$
$b_{p,BLT[0,-5]}$	+26.9%					
$b_{i,BST[0,-5]}$	+42.8%	−33.1%				
$b_{i,BCH[0,-5]}$	+29.9%	−48.5%	+89.3%			
$LT\beta$, $b_{i,XMKT[-1,-10]}$	+92.0%	+31.8%	+34.7%	+26.1%		
$ST\beta$, $b_{i,XMKT[0,-1]}$	+79.7%	+19.3%	+34.2%	+26.9%	+66.3%	

Explanation: For sample and variable definitions, refer to Table I and Table XII. Panels A and B present the bivariate correlations among the rates of return of daily time-series factor portfolios. The Panel B factors have eliminated the role of the market via a first-stage market model regression. Panel C presents monthly pooled correlations among exposures (betas), computed either over the last 5 years, or over 1-year and 9-year lagged time-periods. The XMKT betas are still computed from daily stock returns and shrunk; the BLT, BST, and BCH exposures are based on daily data, but not shrunk. The first data column is the most common 5-year beta. The next three columns are exposures with respect to our novel factor portfolios. The final two data columns are the long-term and short-term beta exposures of each firm-month itself.

Interpretation: BLT^{raw}, BST^{raw}, and BCH^{raw} are too highly correlated with the market (XMKT) and the HML portfolio to make it easy to uncover their unique components. The revised beta factor portfolios have only moderate correlation, but (because they take out the market) are perhaps misnamed—they are not really market-beta portfolios anymore. The factor exposures have benign correlation characteristics, except BST and BCH seem similar. Thus, we can likely disentangle the influence of any unknown novel factor from the influence of a firm's own lagged beta.

Table XIV: Monthly Fama-MacBeth Regressions:
5-year Exposures to Residual Factor Portfolios vs. Own Differently Timed Betas

		Exposures, all over 0-5 years, Different Portfolios				Direct Betas, Different Years, for XMKT						
	Inter-cept	[0,-5] XMKT Beta	BLT Exposure	BST Exposure	(NE–SW) BCH Exposure	LT[-1,-10] XMKT Beta (LTβ)	ST[0,-1] XMKT Beta (STβ)	Diff[] XMKT Beta	Log B/M Size	Log Firm Return	Lagged 2-7 Return	Lagged 8-13 Firms
5-Year Exposures Only	38.439	0.685							2.058	−1.383	9.087	7.578
	(6.06)	(0.28)							(4.33)	(−2.52)	(3.97)	(5.12)
	36.984		2.529						2.030	−1.223	9.275	7.369
	(6.32)		(2.31)						(3.91)	(−2.64)	(3.70)	(4.60)
	37.773	−0.006	2.353						1.776	−1.419	8.960	7.493
	(6.29)	(−0.00)	(3.02)						(3.89)	(−2.77)	(3.96)	(5.16)
	37.612			−1.764					1.762	−1.375	8.636	7.095
	(6.33)			(−1.63)					(3.44)	(−3.01)	(3.49)	(4.50)
	38.055	4.174		−3.005					1.793	−1.623	8.997	7.259
	(6.25)	(1.63)		(−3.27)					(3.83)	(−3.07)	(3.96)	(5.01)
	38.024				−5.939				1.772	−1.406	8.858	7.187
	(6.42)				(−2.83)				(3.42)	(−3.07)	(3.54)	(4.48)
	39.103	3.287			−5.836				1.881	−1.615	9.119	7.456
	(6.32)	(1.31)			(−3.50)				(4.00)	(−3.04)	(4.01)	(5.08)
	37.206		2.665	−1.553					1.602	−1.431	8.602	7.210
	(6.49)		(2.51)	(−1.51)					(3.42)	(−3.23)	(3.60)	(4.75)
	37.859	2.950	1.754	−2.423					1.613	−1.628	8.893	7.362
	(6.41)	(1.27)	(2.34)	(−2.75)					(3.55)	(−3.26)	(3.96)	(5.13)
Factor or Exposure?	37.566		1.380			2.231			1.905	−1.442	9.228	7.580
	(6.35)		(1.75)			(1.12)			(3.98)	(−2.82)	(4.01)	(5.11)
	37.223			−1.615			0.828		1.761	−1.399	8.774	6.736
	(6.15)			(−2.01)			(0.38)		(3.80)	(−2.80)	(3.79)	(4.65)
	36.804				−6.265			−5.221	1.684	−1.386	8.856	7.669
	(6.42)				(−3.05)			(−5.10)	(3.34)	(−3.08)	(3.57)	(4.87)
	36.948		0.901	−2.600		6.550	−2.414		1.595	−1.647	9.015	7.540
	(6.32)		(1.27)	(−3.31)		(4.80)	(−1.53)		(3.59)	(−3.26)	(4.04)	(5.36)
Final Models	36.926	−2.278	0.542	−2.006	−1.327	8.517	−2.574		1.582	−1.651	8.960	7.535
	(6.34)	(−0.94)	(0.75)	(−1.85)	(−0.68)	(4.87)	(−1.79)		(3.58)	(−3.29)	(4.03)	(5.41)
	37.929			−3.255		5.772			1.726	−1.741	9.040	7.430
	(6.39)			(−3.80)		(2.67)			(3.59)	(−3.59)	(3.91)	(5.04)

Explanation: For sample and variable definitions, refer to Table I. This table runs the same monthly Fama-Macbeth regressions as those in Table IV (shrunk daily OLS betas), but adds additional variables: the exposure to the market-orthogonalized long-term beta factor portfolio, to the market-orthogonalized short-term beta factor portfolio, and to the plain NE-SW portfolio (Table VI), each computed over the same 5 years.

Interpretation: The short-term beta effect seems to capture (at least in part) an exposure to an unknown factor. The long-term beta is (at least in part) a characteristic of each individual stock.

Table XV: (APPENDIX) Monthly Fama-MacBeth Regressions, adding Short-Term and Long-Term Sigmas.

	Inter-cept	Market Beta Long Term	Market Beta Short Term	Volatility Long Term	Volatility Short Term	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
No Volatility Controls										
(1)	37.040	5.165	-4.140			1.928	-1.388	9.175	8.035	528
	(5.96)	(3.22)	(-2.56)			(4.16)	(-2.50)	(4.04)	(5.66)	2,803
Standard Error of Betas										
(2)	36.993	5.724	-4.118	-19.397	7.599	1.872	-1.405	9.572	7.792	528
	(7.71)	(3.84)	(-2.71)	(-2.42)	(1.39)	(4.41)	(-3.58)	(4.30)	(5.56)	2,803
Stock Return Volatility										
(3)	37.526	4.957	-3.601	23.014	-38.882	1.961	-1.394	9.832	7.703	528
	(7.90)	(3.24)	(-2.35)	(0.48)	(-0.68)	(4.59)	(-3.65)	(4.44)	(5.54)	2,803

Explanation: These regressions use the shrunk OLS method. The first regression is identical to regression (6) in Table IV.

Interpretation: Including volatility measures does not diminish the influence of our beta estimates.

Table XVI: Monthly Fama-MacBeth Regressions:
Alternative Firm Market Capitalization Selection Criteria

Panel A: Short-Term BST Exposure (Parsimonious Model)

	Inter-cept	Long Term Market Beta	Short Term BST Exposure	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
Market Cap > S&P × 0	9.014	3.253	-3.451					528
100% of the sample	(4.82)	(1.60)	(-2.67)					2,803
	37.929	5.772	-3.255	1.726	-1.741	9.040	7.430	528
	(6.39)	(2.67)	(-3.80)	(3.59)	(-3.34)	(3.91)	(5.04)	2,803
Market Cap > S&P × 0.01	8.643	3.559	-3.353					528
97.1% of the sample	(4.62)	(1.72)	(-2.56)					2,725
	37.509	5.570	-3.002	1.941	-1.581	9.413	7.602	528
	(6.15)	(2.59)	(-3.45)	(3.99)	(-3.03)	(3.98)	(5.08)	2,725
Market Cap > S&P × 0.1	7.454	3.885	-3.310					528
71.4% of the sample	(3.96)	(1.87)	(-2.53)					2,005
	33.136	4.349	-2.344	2.143	-1.071	8.990	8.433	528
	(5.03)	(2.16)	(-2.39)	(4.19)	(-2.15)	(3.45)	(5.05)	2,005
Market Cap > S&P × 1	5.459	4.164	-2.649					528
30.8% of the sample	(2.64)	(1.83)	(-1.92)					866
	32.792	3.652	-2.132	1.710	-1.261	6.294	14.000	528
	(4.48)	(1.80)	(-1.72)	(2.75)	(-2.79)	(1.99)	(6.22)	866
Market Cap > S&P × 2	4.269	4.655	-3.210					528
21% of the sample	(1.97)	(2.00)	(-2.20)					589
	29.469	4.109	-2.924	1.624	-1.084	3.800	13.483	528
	(3.83)	(1.97)	(-2.22)	(2.44)	(-2.38)	(1.11)	(5.36)	589
Market Cap > S&P × 10	3.768	3.244	-2.093					528
5.6% of the sample	(1.43)	(1.16)	(-1.14)					156
	9.227	1.719	-1.559	0.641	-0.063	4.681	16.174	528
	(0.92)	(0.69)	(-0.89)	(0.74)	(-0.10)	(1.11)	(4.46)	156

Sidenote on Judging the Drop in Coefficients and T-statistics: If we draw in each month the same number of firms as in the S&P×1 regression (i.e., 30.8% of our full sample), the mean estimates based on 1,000 random draws are:

	Long-Term Beta	Short-Term Exposure
Coefficient	5.79	-3.07
T-Statistic	2.12	-1.89

(although with much dispersion). The first row shows that our estimates are still unbiased when drawn from a different sample. This means that most of the drop in the coefficients can be attributed to the fact that the market caps of firms in the smaller sample are bigger. More interestingly, the drop in statistical significance (from a T of 2.67 to 1.80 for LTβ; -3.80 to -1.72 for BST exposures) is primarily due to the reduction in the number of firms in the sample, not due to the fact that the firms in this sample are much larger.

(Table XVI continued)

Panel B: Direct Short-Term Market Beta (STβ)

	Intercept	Long Term Market Beta	Short Term Market Beta	Log B/M Ratio	Log Firm Size	Lagged 2-7 Return	Lagged 8-13 Return	# Months /Avg # Firms
Market Cap > S&P × 0, 100% of the sample	11.178	3.283	-5.060					528
	(6.13)	(2.11)	(-2.70)					2,803
	37.040	5.165	-4.140	1.928	-1.388	9.175	8.035	528
	(5.96)	(3.22)	(-2.56)	(4.16)	(-2.50)	(4.04)	(5.66)	2,803
Market Cap > S&P × 0.01, 97.1% of the sample	10.723	3.649	-5.129					528
	(5.88)	(2.28)	(-2.74)					2,724
	36.271	5.282	-4.513	2.117	-1.221	9.541	8.245	528
	(5.66)	(3.29)	(-2.79)	(4.53)	(-2.19)	(4.11)	(5.73)	2,724
Market Cap > S&P × 0.1, 71.4% of the sample	9.229	3.102	-3.912					528
	(5.08)	(2.06)	(-2.04)					2,005
	31.655	4.444	-4.473	2.326	-0.722	9.257	9.122	528
	(4.64)	(3.03)	(-2.69)	(4.73)	(-1.36)	(3.62)	(5.70)	2,005
Market Cap > S&P × 1, 30.8% of the sample	6.090	2.965	-1.700					528
	(2.96)	(1.78)	(-0.83)					866
	31.095	3.886	-3.127	1.958	-0.925	6.723	14.283	528
	(4.11)	(2.50)	(-1.76)	(3.25)	(-1.94)	(2.16)	(6.65)	866
Market Cap > S&P × 2, 21% of the sample	4.895	3.464	-1.723					528
	(2.26)	(1.99)	(-0.81)					589
	28.967	4.205	-2.942	1.969	-0.780	4.072	14.009	528
	(3.65)	(2.59)	(-1.62)	(3.04)	(-1.65)	(1.21)	(5.76)	589
Market Cap > S&P × 10, 5.6% of the sample	3.268	3.776	-2.156					528
	(1.23)	(1.51)	(-0.90)					156
	8.331	3.665	-4.230	1.020	0.249	4.649	17.129	528
	(0.81)	(1.65)	(-2.07)	(1.19)	(0.43)	(1.11)	(4.95)	156

Explanation: For sample and variable definitions, refer to Table I. This table runs the same monthly Fama-Macbeth regressions as those in Table IV (shrunk daily OLS betas) and Table XIV. Indeed, the first regressions reports the original equivalent. The next four regressions require firms to have a minimum market capitalization that depends on the month, as follows (and noted in the first column): To qualify, a firm had to have an equity market cap of at least the *level* of the S&P500 multiplied by X as of the prior month. For example, to quality in May 2007, to survive an S&P500/1 cut, any firm would have had to be at least \$1.5 billion in market cap, because the S&P500 level in April 2007 stood at about 1,500.

Interpretation: Although the results become statistically weaker with fewer firms, as expected, the results are not driven by small firms. Even among the 150–200 largest firms, the effect is still visible in Panel B (and for the 500 or so largest firms in Panel A)—often with similar size coefficients, but lower statistical significance.