A Long-Horizon Perspective on the Cross-Section of Expected Returns

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Abstract

We provide evidence of the strong long-run relation between expected returns and market beta risk in the challenging (for the CAPM) post-1963 period as well as over longer time periods. We show that returns averaged over long horizons (up to 10 years) are related positively and significantly to the market risk betas computed over similar periods. For the Fama-French 25 size and book-to-market portfolios and the industry portfolios, the market risk premium is estimated significantly at economically-meaningful values between 6% and 11% per annum over a 5- to 10-year period. When paired with alphas whose economic and statistical significance decreases with the length of the horizon, our evidence is suggestive of the near long-run mean-variance efficiency of the market portfolio and an approximate long-run version of the classical CAPM.

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1 Introduction

The existence of a value premium, whereby stocks with high book-to-market ratios have higher average returns than stocks with low book-to-market ratios, is widely documented over the post-1963 period in U.S. stock returns (see, e.g., Fama and French, 1992). Whether the Capital Asset Pricing Model (CAPM) can explain the value premium continues to be a source of lively debate. Fama and French (1993), for instance, find that the post-1963 value premium is left unexplained by the CAPM, while Ang and Chen (2007) show that the CAPM captures the value premium over the 1926-1963 period. These authors also test a conditional CAPM with time-varying market betas and conclude that it can explain the value premium even in the post-1963 period. This is contested by Fama and French (2006) who conclude that it is size and book-to-market factors, or risks related to them, rather than market beta risk, which are priced in mean returns over this period.

We contribute to the debate by providing empirical evidence of the *long-run* relation between expected returns and market beta risk in the post-1963 period. We show that returns averaged over longer periods (three to ten years) are related positively and significantly to the market loadings also computed over similar periods. Moreover, for the Fama-French 25 size and book-to-market portfolios, the market risk premium over a five to ten year period is estimated at economically-reasonable values between 6 and 11% per annum.

The explanation for this result rests on the gradual alignment between the time-varying betas of the portfolios and their average returns, as the horizon lengthens. For a 1-month horizon, generally used in estimating and testing the CAPM, the estimated book-to-market and size betas are declining functions of the book-to-market values (low to high) and the size values (small to big), respectively, for all portfolios. However, for every size quintile, average returns rank inversely, with higher returns associated with higher book-to-market (value) firms (see Table 2).[1] When the horizon increases, the alignment of the betas in the value dimension improves markedly. As compared to the monthly values, the value premium and the size premium for the small and low book-to-market firms triple in value at the 10-year horizon, for instance. These premia are, in large part, compensation for market risk as indicated by the corresponding market betas.

The sensitivity to the return measurement interval of tests of the CAPM has been looked at previously. Handa, Kothari and Wasley (1993) perform multivariate tests of the Sharpe-Lintner CAPM using monthly and annual returns on size-ranked portfolios over the period 1926-1988. They employ MacKinlay's test (MacKinlay, 1987) based on which, under the null hypothesis of correct model specification, all assets' alpha's of the market model time-series regressions are equal to zero. They

[1] The large value premium for small firms and the low value premium for big firms has been put forward by Loughran (1997) for the post-1963 period. Fama and French (2006) present evidence of a similar value premium for both small and big stocks when portfolios are sorted on earnings-to-price ratios instead of book-to-market values.

reject the CAPM using monthly returns, but fail to reject it when annual holding period returns are used. We differ from their approach along several dimensions. First, we estimate betas using genuine low-frequency holding period returns (up to 120 months). Second, we follow Fama-MacBeth (1993) and test the CAPM cross-sectionally, with average returns computed over the same interval used to compute the rolling betas. Third, we look at portfolios ranked both by size and book-to-market. Finally, we estimate the model over the challenging (for the CAPM) post-1963 period. Importantly, contrary to Handa, Kothari and Wasley (1993), we report a negative premium over yearly intervals. It is only at lower frequencies (3 to 10 years) that we find positive, and statistically significant, market premia.

Kothari, Shanken, and Sloan (1995) look at the cross-section of returns with betas estimated at yearly intervals but average returns measured at a monthly interval. They find substantial ex-post compensation for beta risk over the 1941 to 1990 period, and even more over the 1927 to 1990 period, but virtually no relation between beta and average return over the post-1962 period. Our results indicate that relating average returns over longer periods to betas computed over similar intervals appears important to support the main empirical implication of the CAPM - a significant, positively sloped, linear relation between portfolios' expected rates of return and their market risk betas.

Finally, Cohen, Polk and Vuolteenaho (2009), adopting the perspective of a buy-and-hold investor, use price levels instead of short-horizon returns and measure betas from firms' cash show fundamentals over longer horizons. The rationale is that the price level becomes the dominant factor and news about cash flows dominate covariances and variances of returns as holding periods increase. They show that, in some specifications, cash-flow betas can explain a large proportion of the long-horizon returns on price-to-book-sorted portfolios. The estimated market premia when betas are measured over 5 to 15 years are high, ranging from 12% to 24% per annum, and higher than in our findings. Again, contrary to our results, for the post-1963 sample period, their return-based asset pricing tests fail to support the CAPM.

An important issue concerns the choice of portfolios used for testing asset pricing models. We follow Lewellen, Nagel and Shanken (2008) and increase the set of test assets with the industry portfolios. Specifically, we redo the analysis on a set of 30 industry portfolios and on the joint set of 25 size and book-to-market portfolios and 30 industry portfolios. Our results remain strong. In fact, the long-run pricing ability of market risk increases. Again, we find a positive, statistically significant, and economically plausible market premium. An interesting remark is that with the industry portfolios alone, the market premium is positive, albeit rather small, and statistically significant even for short horizons.

Adding the Fama-French SMB and HML factors does not modify our findings. When only considering the 25 Fama-French portfolios, as earlier, the market risk factor increases its statistical and economic relevance with the horizon. Conversely, SMB and HML become less statistically significant. As expected, employing the industry portfolios as test assets reduces the economic and statistical significance of the SMB and HML factors.

Long-horizon regressions raise important econometric issues. Running regressions without overlapping between the observations causes a serious loss of efficiency in the estimation of the betas, particularly at long horizons. On the other hand, estimation with overlapping observations is affected by induced persistence in both the regressand and the regressor. Again, this persistence becomes more severe when the horizon lengthens raising the possibility of spurious correlation (induced by the aggregation) between stochastic trends in the regressor and the regressand (Granger and Newbold, 1974, and Phillips, 1986). Having made these points, applying traditional corrections to the time-series (rolling) regressions used to compute the betas would not change our findings. More importantly for our purposes, the evidence we report is cross-sectional. There is no natural reason why spuriously estimated rolling betas in the time-series should (spuriously, once more) align cross-sectionally to deliver economically meaningful prices of risk.

Since aggregation can work as a signal-extraction mechanism in the presence of genuine structural dependencies, our findings are, possibly, not surprising. Monthly returns, typically used to test asset pricing models, are noisy. Aggregation reduces noise while bringing to light very slow-moving components to which pricing models may apply. In a similar vein, Bandi and Perron (2008) find that long-run market returns can be predicted by past long-run market variance, thereby inducing risk-return trade-offs at long horizons. One of the implications of the approach in Ortu, Tamoni, and Tebaldi (2010) is that it may be sufficient to view financial and economic time-series as being the sum of several components (details) with various persistence properties (as in a generalized Beveridge-Nelson decomposition) to derive a workable framework to uncover important structural relations upon aggregation. In the case of the dependence between market risk premia and market variance, their logic works as follows. If the trade-off applies to very slow-moving variance/return components, such a trade-off can only be viewed upon aggregation once the uncorrelated, more transient, variance/return components have been suitably washed out. The needed level of aggregation for best signal extraction depends on the persistence properties of the components to which the structural relation (i.e., the trade-off) applies. A similar intuition may be valid in our cross-sectional pricing framework. If the relevant beta risk is beta risk associated with a highly persistent market component, then the CAPM will perform more satisfactorily in the long run than in the short run. In agreement with this logic, we find that the time-varying market betas are estimated more precisely at low frequencies than at high frequencies. These time-varying betas are nicely priced cross-sectionally.

A long-run CAPM is of course not incompatible with time-varying investment opportunities and incomplete markets. In a world in which quadratic investors receive no outside income, the market payoff is on the long-run mean-variance frontier. Investors may hedge dynamically against short-term changes in investment opportunities leading to time-variation in the means and variances of asset returns. In particular, they might load more heavily on securities which represents better hedges at times, or whose returns are higher, but, in the end, this is simply going to lead to a long-run version of the classical two-fund separation result. In the long-run equilibrium, each investor's portfolio should be a linear combination of a long-run real zero-coupon bond and the long-run market payoff with weights which, as usual, depend on relative risk aversion. In this context, a long-run CAPM would therefore hold, as shown by Magill and Quinzii (2000) and Cochrane (2008). In the presence of outside income, long-run expected returns will instead obey a multifactor model and depend on long-run market betas as well as long-run betas with respect to the average outside-income hedge payoff. Outside income - businesses, jobs, real estate - are important. Identifying an average hedge portfolio and measuring its empirical contribution, if any, to long-run equilibrium returns is, however, hard. The good news is that, as we show, market beta risk plays a first-order role at long horizons. This may not be surprising since, as Cochrane (2008) stresses, "hedging outside income is as rare as hedging state variables in practise." It is simply not done in any systematic way by individual investors, pension funds, and money managers.

Our focus on low-frequency pricing is related to the recent work of Menzly, Santos, and Veronesi (2004), Bansal and Yaron (2004), Hansen, Heaton and Li (2005), Lettau and Wachter (2007), Bonomo, Garcia, Meddahi, and Tédongap (2010), among several others. Their interest is in the contribution to value of the stochastic components of discount factors, long-run cash flows, and long-run consumption. In terms of returns, their emphasis in on the short-term return implications of long-term variation in cash flows and consumption growth rates. This paper, however, focuses on long-run returns. Whether aggregation of short-term returns delivered by long-run risk models provides a first-order role for market payoff risk in long-run returns, as we find in this paper, is an important issue to which we return below but which we are planning to spell out in future work.

2 A long-run CAPM with the 25 size and book-to-market portfolios

Tests of the CAPM have been mainly conducted with returns computed for a holding period of one month. In the classical Fama-MacBeth procedure, portfolio betas are estimated (using rolling windows) by regressing the one-month excess returns on the portfolios on the one-month excess return on the market portfolio, where the latter is measured by the return of a suitable equity index. In this section, we extend the usual procedure to holding-period horizons of up to 120 months. We use a 60-observation rolling window to compute the OLS market loadings of the portfolios. As is customary, these are then used as independent variables in cross-sectional regressions, as follows

$$return_{j,t+h} = \alpha_j + \beta_{j,mkt} mkt_{t+h} + \nu_{j,t+h},$$

where h denotes the horizon (in months). We consider horizons of 1, 3, 12, 24, 36, 48, 60, 72, 84, 96, and 120 months (1 month to 10 years).

Selecting the size of the first-stage rolling windows is not an obvious task. One statistically-sound way to choose it "optimally" is to think carefully about the trade-off between accuracy (as delivered by a small window) and precision (as given by a larger window). Characterizing this trade-off is however generally not done. It would in fact require modelling the dynamics of the loadings up-front in just the same way as, for instance, (possibly stylized) parametric models help us search for better window widths in long-run variance estimation or superior smoothing sequences in nonparametric kernel estimation. Here, to make our results fully comparable with existing contributions, we opt for the most traditional window width used in applications of the Fama-McBeth procedure, namely 60 months. Shanken and Zhou (2007) have pointed out that the window should be long enough with respect to the number of portfolios entering the test. Even though we will later use up to 55 portfolios (the Fama-French portfolios, in addition to the 30 industry portfolios), we abide by common practise to capture genuine time-variation in the betas (at the cost of some inefficiency, relative to a larger 90-observation window) and choose a smaller 60-month window. Importantly, the use of a 90-observation window would not modify our results in any relevant way. For conciseness, the corresponding results are not reported but may be provided by the authors upon request.

2.1 Average returns and betas

Table 2 provides results for 25 portfolios sorted on size and book-to-market.[2] Panel A includes *i*) the excess returns on the portfolios in percentage and horizon by horizon from 1 month to 120 months and *ii*) the portfolios' betas obtained from the time series regression of a portfolio excess return on the market excess return, where the market is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) and the excess returns are with respect to the one-month Treasury bill rate (from Ibbotson Associates). The betas for each horizon have been obtained by regressing a portfolio's excess return on the market excess return for the corresponding horizon. These constant betas are therefore "aggregates" of the time-varying betas used in the cross-sectional regressions. Panel B reports the means and the standard deviations of the rolling betas (for each portfolio and each

[2] The returns on these portfolios have been extracted from the data library on Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

horizon) as well as the means of the NW (Newey-West) standard errors resulting from the estimation of the rolling betas (again, for each portfolio and each horizon). The data are *not* annualized and span the period July 1963 to December 2007.

First, looking at the value premium, we observe that it is present at every horizon. Interestingly, however, the premium increases with the horizon. At 1 month, it is about 11% per annum for the small-firm portfolio and 2.1% for the big-firm portfolio. At the 120-month horizon, the premium goes up to 43% per annum for the small-firm portfolio and about 7% for the big-firm portfolio. In terms of constant betas, at the 1-month horizon the low book-to-market and small-size portfolio has a higher beta (1.44) than both the high book-to-market and small-size portfolio (1.07) and the low book-to-market and big-size portfolio (0.99). This is the opposite of what we observe for mean returns. When combined with betas which do not increase in the value dimension, this is suggestive of the poor performance of the CAPM at short horizons. The picture is reversed in the long run. The betas align nicely with average returns for all of the book-to-market portfolios corresponding to small firms and all of the size portfolios corresponding to low book-to-market firms. Similarly, they generally increase with book-to-market (for most size portfolios) capturing the sizable variation in the value premium previously reported.

Albeit generally reported in the literature, the constant betas are, at best, merely illustrative. What matters for our purposes is the time-varying betas entering the cross-sectional regressions. Let us focus once more on the 1-month horizon and on the 120-month horizon. At the 1-month horizon, the usual misalignment of the betas occurs. At the 120-month horizon, the means of the time-varying betas align with average returns even better than in the constant beta case. Again, we find that the betas increase going from growth portfolios to value portfolios. Similarly, they decrease going from small firms to large firms. The only exception in the size dimension is portfolios in the first value quintile for which the betas increase going from small firms portfolios to big firms portfolios, but this is exactly what we find in terms of average historical returns. We also note that the constant betas do not align with average returns in the last value quintile. The average rolling betas do, instead. In sum, the overall structure of the means of the rolling betas is, *without exceptions*, consistent with the overall structure of the mean returns at the 10-year horizon. Impressively, this pattern is also, just like for the mean returns, almost monotonic.

Panel B, second column, clarifies that there is meaningful time-variation in the beta estimates, at all horizons. Finally, we notice that the time-varying market betas are estimated very accurately at all frequencies (Panel B, third column). However, remarkably, estimation accuracy tends to increase with the horizon. If aggregation works as a signal-extraction mechanism, the higher t-statistics associated with low frequencies are to be expected. Below, we return to this issue.

2.2 Cross-sectional results

Table 4 presents the results of cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market. For each window cross-sectional regressions are run in which the dependent variable is the portfolios' average returns in the window and the explanatory variable is the vector of $\beta_{j,mkt}$ loadings. The cross-sectional regression coefficients are obtained by averaging the OLS coefficients obtained for each window, t(NW) denotes Newey-West standard errors, Average R^2 stands for the average adjusted R^2 from the cross-sectional regressions and Max R^2 denotes the maximum adjusted R^2 from the same cross-sectional regressions. The parameter estimates are now annualized percentages.

The reversal in the ordering of the betas for longer holding periods translates into a drastic change in the cross-sectional CAPM tests. Up to one year, we obtain the usual failure with a negative premium associated with the market beta. However, starting at two years, the market premium changes sign while becoming more significant as the horizon increases. For the 5- to 10-year horizon, the premium is estimated as being equal to 6%, 5.6%, 7.38%, 7.22%, 7.38%, and 11.22% per annum, which is economically very reasonable. The recorded mean excess returns over the same period are equal to 7.36%, 7.85%, 8.55%, 9.47%, 10.6%, and 11.9% (see Table 1).

The average adjusted R^2 increases almost monotonically from 27% at the one-month horizon to 44% at the 10-year horizon. More importantly, the overall mispricing decreases drastically. The intercept is equal to 11.6 per cent per annum (with a t-statistic of 17.31) at the 1-month horizon and is equal to 5.56 (with an insignificant t-statistic of 1.31) at the 10-year horizon. Having made these points, there is still some economic evidence of (statistically insignificant) mispricing in that the alpha is of the same magnitude as the market premium for the 6- to 9-year horizon and is half the magnitude of the market premium only at the 10 year horizon.

The means and standard deviations of the implied market premia for all portfolios are reported in Table 7. A comparison with Table 3, Panel A, immediately reveals that these premia become more coherent with the historical mean excess returns on the portfolios as we move to longer horizons. Between 1-month and 1-year the estimated premia are *negative* for all portfolios, thereby implying that the portfolios' implied expected raw returns should be lower than the risk-free rate, which is clearly not the case in the data. The figures are, however, extremely meaningful at the 10-year frequency, for example. When divided by 10, the annualized mean excess returns for the 10-year horizon in Table 3, Panel A, are similar to the estimated portfolios' premia (or, equivalently, the implied mean portfolios' excess returns, given the model) in Table 7 for the same horizon.

3 Robustness

This section considers a variety of robustness checks. We add portfolios and additional factors (the size and book-to-market factors of Fama and French, 1992, 1993). We also lengthen the time horizon by starting the sample in 1925.

3.1 Inclusion of additional test portfolios

Pricing models should price all assets. In a similar vein, Lewellen, Nagel, and Shanken (2008) have expressed a skeptical view about the standard practice in the cross-sectional asset-pricing literature to evaluate pricing models solely based on how well they explain average returns on size and book-to-market sorted portfolios. One of their suggestions to improve empirical tests is to expand the set of test assets, for example by including the industry portfolios, since misleading findings may be induced by the strong factor structure of the size and book-to-market sorted portfolios.

Consistent with this observations, we redo the previous analysis with the 30 industry portfolios as well as with the full set of 25 size and book-to-market portfolios and the 30 industry portfolios. Results are reported in Table 8. With the industry portfolios alone, the sign of the market premium is positive *even* at the one-month interval. As before, however, the estimated premia, as well as their level of statistical significance, increase with the horizon. Importantly, as earlier, these premia become economically meaningful as the horizon lengthens. They are equal to about 2%, 2.8%, and 4% per annum at the 1-month, 3-month, and 1-year frequency. The corresponding figures from Table 1 are 5%, 5.15%, and 5%. Hence, the implied premia are underestimated, even though significant. For the 5- to 10-year horizon, however, the premia are estimated at very meaningful values equal to 7.55%, 6.19%, 7.86%, 7.78%, 8.52%, and 9.27% per annum.

Economically, the alphas continue to account for a sizable portion of the excess portfolio returns. This said, their statistical significance is considerably lower at low frequencies than at high frequencies. Adding the 25 size and book-to-market portfolios to the industry portfolios does not modify the overall picture.

3.2 A long-run Fama-French three-factor model with size, book-to-market and industry portfolios

We ask whether the two additional factors introduced by Fama and French (1992, 1993) to price the cross-section of short-term expected returns, i.e., the difference in returns between a small-firm portfolio and a big-firm portfolio (*smb*, thereafter) and the difference in returns between a high book-to-market portfolio and a low book-to-market portfolio (*hml*, thereafter) continue to play a prominent role at longer horizons.

In Table 9 we report the results of cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market and the 30 industry portfolios. We use again a 60-observation rolling window to compute the OLS market loadings of the portfolios which are then used as independent variables in the cross-sectional regressions as follows:

$$return_{j,t+h} = \alpha_j + \beta_{j,mkt} mkt_{t+h} + \beta_{j,smb} smb_{t+h} + \beta_{j,hml} smb_{t+h} + \nu_{j,t+h}.$$

Specifically, for each window, cross-sectional regressions are run in which the dependent variable is the portfolios' average return in the window and the explanatory variable is the vector of portfolio loadings. As before, the cross-sectional regression coefficients are obtained by averaging the OLS coefficients estimated for each window. The data span the challenging (for the CAPM) period July 1963 to December 2009. We use three sets of portfolios: the 25 size and book-to-market portfolios (Panel A), the 30 industry portfolios (Panel B), and the whole set of 55 portfolios (Panel C).

For all data sets, market beta risk increases its statistical significance with the horizon. When considering the 25 size and book-to-market portfolios in isolation, or jointly with the industry portfolios, the Fama-French factors see their statistical relevance reduced as we move to low frequencies.

Leaving the high adjusted R^2 aside, these multivariate specifications yield unreasonable estimates. The long-run premia on the market, *smb*, and *hml* are two to three times the mean excess returns for the same horizons as reported in Table 2. For example, using the 25 Fama-French portfolio, at the 10-year horizon, the estimated implied premia are 28%, 85%, and 148% for the market, *smb*, and *hml*, respectively. The recorded mean excess returns are instead 11.9%, 23.4%, and 69%. Not surprisingly the regressions alphas are economically sizable, with a negative sign, and extremely statistically significant. A long-run version of the classical CAPM appears to yield much cleaner economic implications with a small loss in terms of statistical goodness of fit (as implied by the adjusted R^2).

3.3 Extending the sample

Short-run versions of the CAPM have proven hard to verify empirically using post 1963-data. Our own results confirm that implied market premia are negative up to 1 year over this period. Since our focus is on the long run, however, there is obvious scope for gathering additional information about low frequency dynamics by virtue of an extended sample.

To this extent, in Table 10 we consider data spanning the July 1926 - December 2009 period. Our findings are unaffected by the longer sample. As expected, over this longer period, the short-run performance of the CAPM is superior, particularly when pricing the industry portfolios. In all cases, importantly, the statistic and economic significance of market beta risk increases with the horizon and is accompanied by a reduced role played the regressions' alphas. With the 25 size and book-to-market portfolios (Table 10, panel A), the one-month pricing error is a statistically significant (t-statistics equal to 14.12) 8.62% per annum while the implied risk premium ($\lambda\beta$) associated with the market is less than 1% per annum per portfolio (depending on the specific portfolio's beta). The 10-year pricing error is a statistically insignificant (t-statistics equal to 1.63) 5.63% per annum while the implied risk premium associated with the market is in a neighborhood of 12% per annum per portfolio (depending, again, on the specific portfolio's beta). The market loadings feature substantial variation as we move to long horizons. This variation is priced and the resulting pricing errors are economically, and statistically, much smaller than in the short run.

4 Aggregation and long-run pricing

The challenges posed by aggregation in estimating and testing economic relations have been spelled out at length in a time series context. A rolling summation of time series which appear to be $I(0)$ leads to series which, as the level of aggregation increases, behave asymptotically as series which are $I(1)$ yielding unit-root type behavior. The induced stochastic trends are of course problematic in that they may produce significant statistical outcomes *irrespective* of the true structural relation between the variables of interest. This observation is in the spirit of the traditional spurious regression problem illustrated by Granger and Newbold (1974) and justified formally by the work of Phillips (1986). The predictability literature in finance is well aware of the statistical issues posed by aggregation. Work on long-run stock return predictability necessarily ought to confront these issues. For recent approaches to long-run predictability, and a discussion of the existing literature, we refer the reader to Valkanov (2003), Boudoukh, Richardson, and Whitelaw (2008), Hijalmarsson (2008), and Sizova (2010).

Aggregation may lead to spurious outcomes in the absence of structural relations but, importantly, may lead to cleaner signals when a structural relation does exist. To this extent, one can view economic and financial time series as being characterized by components (details) with various persistence properties, as in a generalized Beveridge-Nelson decomposition, see e.g. Ortu, Tamoni and Tebaldi (2010). If there is an economic relation between very slow-moving details of the time series of interest, aggregation will reveal the existing relation by reducing noise and increasing signal. The recent approach in Ortu, Tebaldi and Tamoni (2010), hinging on multiresolution spectral analysis, is a clear illustration of this signal-extraction process. There, the existence of low frequency predictability concentrated on a single slow-moving component of the series of interest will translate, upon aggregation, into significant regression coefficients at horizons corresponding to the inverse of the spectral frequency at which predictability occurs. In other words, the level of aggregation needed for best signal extraction will depend on the persistence properties of the time-series components for which the true structural relation applies. Higher persistence will require longer aggregation to uncover potential relations. Based on this logic, the 5- to 10-year risk-return trade-off illustrated by Bandi and Perron (2008) and, more recently, by Jacquier and Okou (2010) and Sizova (2010), may therefore point to the existence of very slow-moving components in market returns and market variance to which the classical trade-off applies.

A similar intuition is likely valid in our framework, with a crucially important caveat. Aggregation can uncover slow-varying components in portfolio returns and market returns to which market beta models apply, thereby translating into the identification of reliable long-run betas. We, in fact, saw earlier that the NW t-statistics associated with the rolling beta estimates are very large for all frequencies, and particularly large at low frequencies. At the same time, crucially for our purposes, the cross-sectional nature of our study makes the likelihood of spurious pricing results lower than in more traditional time-series contexts, such as those used in the long-run stock return predictability literature. As discussed above, our findings hinge on long-run market betas which, at long horizons, align with recorded expected returns more effectively then in the short term, thereby matching the large risk premia associated with value stocks. The rotation in the ranking of the betas from short-term betas, which do not explain the value premium, to long-run betas, which explain it, cannot simply be a spurious outcome of aggregation. Instead, we seem to be able to estimate very accurately long run market betas which, equally accurately, conform with mean historical returns.

We can look at the problem differently. Our long-run application of the classical Fama-MacBeth approach has the potential to either pick up genuine long-run dependencies (market betas) between slow-moving return components or deliver spurious results as a result of the aggregation implicit in the first-stage rolling time-series regressions. The cross-sectional second stage can now be viewed as an economic criterion capable of evaluating the economic relevance of the first-stage long-run market loadings. When passed through the lenses of our second stage - and the resulting premia and pricing errors - the estimated long-run market loadings are economically meaningful.

5 The relative role of consumption risk

In classical endowment economies, for instance, equilibrium asset prices have an immediate formulation in terms of consumption-CAPM (CCAPM) and an equivalent formulation in terms of CAPM, being the market payoff a claim to the aggregate consumption stream. In addition to a long-run CAPM specification, we test analogous long-run versions of the CCAPM in which low-frequency consumption betas are obtained by regressing low-frequency portfolio returns on low-frequency consumption growth. Measuring consumption is not obvious. Here we use real per-capita consumption on nondurables and services as in Lettau and Ludvingson (2001). We emphasize that we purposely do not employ notions of long-run consumption to estimate the short-run betas (see, e.g., Parker and Julliard, 2005). Specifically, the horizon of aggregation in the computation of the time-varying betas is the same for portfolio returns and consumption growth. This is coherent with our previous analysis in the CAPM context and effectively puts the two investigations on an equal footing. In sum, we focus on *contemporaneous* consumption growth.

5.1 Average returns and betas

In the consumption case, the difference between the time-varying betas and the constant betas is evident, and more evident than in the market case. Focusing on the 10-year horizon, for example, we note that the estimated constant betas are virtually all *negative*, implying that the book-to-market and size-sorted portfolios are virtually all long-run hedges (Table 3, Panel A). As such, in a classical consumption model, they should all have low average long-run returns, but they do not, in practise. In addition, the value portfolios and the small portfolios, i.e., those with relatively higher average returns, have long-run betas which are relatively more negative implying that they are relatively superior long-run hedges. This, again, makes little economic sense. The rolling betas, however, behave as expected (Table 3, Panel B). At 10 years, they are generally positive and relatively higher for value portfolios and small portfolios. The alignment, however, is not as clean as in the market case. In addition, the dispersion of these betas is dramatic. Finally, contrary to the market case, the betas are not estimated very precisely. On average, they are, in addition, more precisely estimated at high frequencies than at low frequencies.

To summarize, allowing for time-varying betas is important. In the market case, the use of time-varying betas uncovers strong dependencies, shown and discussed above, between portfolios returns and market returns. These dependencies would appear weaker with constant loadings. In the consumption case, allowing for time-variation in the betas is crucial to even hope to give some role to consumption growth as a meaningful pricing factor. Yet, these time-varying consumption betas do not align as nicely as the market betas with average returns at lower frequencies, they are generally smaller in the long run than in the short run, and they are very dispersed. Contrary to the market betas, they are, also, identified rather imprecisely, particularly at low frequencies.

5.2 Cross sectional results

Because of the less aligned and more dispersed betas, we do not witness a roughly monotonic increase in the economic and statistical significance of the prices of risk, as reported in the CAPM case. This is, again, further evidence that there is nothing mechanical about time-series aggregation (in the computation of the beta loadings) which should yield spurious cross-sectional pricing in the long run.

Contemporaneous consumption risk simply plays a smaller role as compared to contemporaneous market beta risk. We however find meaningful economic and statistical effects at business-cycle frequencies or close to business-cycle frequency, i.e., 1-to-4 years for the 25 Fama-French portfolios (Table 5) and 4 to 5 years for the industry portfolios (Table 7, Panel B). There are also meaningful effects in the very long run (9 to 10 years).

Focusing on the 25 Fama-French portfolios, at 3 years, for example, the rolling consumption betas nicely increase (decrease) in the value (size) dimension, without, however, capturing the higher excess returns of large firms in the first value quintile at this frequency (c.f., Table 2). Coherently, the corresponding estimated prices of consumption risk are statistically significant (Table 4). The pricing errors, however, are sizable. Parker and Julliard (2005) also find that contemporaneous consumption risk explains little of the variation in monthly average returns across the 25 Fama-French portfolios, but that a measure of consumption risk at a horizon of three years explains a large fraction of this variation. As stressed earlier, in order to compare the consumption results with the CAPM meaningfully, contrary to Parker and Julliard (2005), we price long-run returns, rather than short-run returns, with long-run consumptions betas. In analogy with Parker and Julliard (2005), however, we find that consumption loadings measured over (roughly) business-cycle frequencies contain valuable information about asset prices (see, e.g, Hansen, Heaton, and Li, 2008, *inter alia*, for a justification).

5.3 A mixed CAPM-CCAPM model

Naturally, a two-factor model with market returns and consumption growth may perform reasonably well at frequencies at which the two factors perform well individually (Table 6 and Table 8, Panel C). However, the statistical benefit over a simple CAPM specification is rather marginal. The economic benefit is also questionable in that a small reduction in the size of the alphas, as yielded by the bi-variate model, is counteracted by less reasonable, larger, estimates of the implied market prices of risk.

It is well known that a mixed CAPM-CCAPM model can be rationalized by virtue of recursive Kreps-Porteus preferences as in Epstein and Zin (1989). The recent work of Bansal and Yaron (2004), Hansen, Heaton, and Li (2008), Bonomo, Garcia, Meddahi, and Tédongap (2010), and many others, has emphasized the importance of the separation, implied by these preferences, between risk aversion and intertemporal substitution, coupled with slowly-varying expected consumption growth components and stochastic consumption volatility, to reconcile stylized evidence in asset pricing. This literature postulates slow-moving consumption components leading to long-run risk premia in short-term returns. The focus is on the short-term valuation of long-run risky cash-flows. Our focus is on long-run valuation.

We find that, cross-sectionally, an important long-run driving risk factor is market risk, with a marginal role left for contemporaneous consumption growth. Whether aggregation of short-term returns delivered by long-run risk models would lead to our pricing implications for long-run expected returns is an interesting issue for future work.

6 Conclusions

Adopting a long-run perspective for measuring the relationship between risk and return has changed our view about a traditional, often unsuccessful, explanatory variable of the cross-section of expected returns - market risk. Market risk appears in the long run to be a major contributing factor. Value and size, which are still broadly considered as fundamental risk factors when adopting a short-term perspective, lose their prominence in the long run. This is good news for the CAPM since it remains the workhorse model in many areas of finance, such as capital budgeting and event studies.

It is in the measurement of risk that our low-frequency perspective helps. Aggregation works as a signal-extraction mechanism allowing us to uncover low-frequency structural dependencies between portfolios' returns and market returns. These dependencies align cross-sectionally to deliver economically meaningful, and statistically significant, prices of market risk, as well as smaller long-run pricing errors.

We contribute to a fundamental idea emerging from the recent asset pricing literature: long-run risk matters to investors and is priced cross-sectionally. We show that, in the long run, a basic tenet of finance - the classical CAPM - is revived.

References

[1] Ang, A. and J. Chen (2007), "CAPM over the long run", *Journal of Empirical Finance* 14, 1-40.

[2] Bandi, F. and B. Perron (2008), "Long-run risk-return trade-offs", *Journal of Econometrics*, 143(2), 349-374.

[3] Bansal, R. and A. Yaron (2004), "Risks for the long run: A potential resolution of asset pricing puzzles", *Journal of Finance*, 59(4), 1481-1509.

[4] Bonomo, M., R. Garcia, N. Meddahi, and R. Tédongap (2010). "Disappointment aversion, long-run risks, and aggregate prices." *Review of Financial Studies*, forthcoming.

[5] Boudoukh, J., M. Richardson, and R. Whitelaw (2008). The myth of long-horizon predictability. *Review of Financial Studies* 21, 1577-1605.

[6] Cochrane, J. (2008), "A mean variance benchmark for intertemporal portfolio theory", Working Paper.

[7] Cohen, R., C., Polk and T. Vuolteenaho (2009), "The price is (almost) right", *Journal of Finance*, forthcoming.

[8] Epstein, L. and S. Zin (1989), "Substitution, risk aversion, and the temporal behavior of consumption and asset returns: a theoretical framework", *Econometrica* 57, 937-969.

[9] Fama, E. and K. French (1992), "The cross-section of expected stock returns", *Journal of Finance* 47, 427-465.

[10] Fama, E. and K. French (1993), "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics* 33, 3-56.

[11] Fama, E. and K. French (2006), "The value premium and the CAPM", *Journal of Finance* 66, 2163-2185.

[12] Fama, E. and J. MacBeth (1973), "Risk, return, and equilibrium: empirical tests", *Journal of Political Economy* 81, 607-636.

[13] Granger, C. and P. Newbold (1974), "Spurious regressions in econometrics", *Journal of Econometrics* 2, 111-120.

[14] Hamilton, J., 1994, "Time series analysis", Princeton University Press.

[15] Handa, P., P. Kothari and C. Wasley (1993), "Sensitivity of Multivariate Tests of the Capital Asset-Pricing Model to the Return Measurement Interval", *Journal of Finance* XLVIII, 1543-1551.

[16] Hijalmarsson, E. (2008). "Inference in long-horizon regressions". Working paper.

[17] Jacquier, E. and C. Oku (2010). "Segregating continuous volatility from jumps in long-run risk-return trade-offs", working paper.

[18] Kothari, S., J. Shanken and R. Sloan (1995), "Another Look at the Cross-Section of Expected Returns", *Journal of Finance* 50, 185-224.

[19] Lettau, M. and S. Ludvigson (2001), "Consumption, aggregate wealth, and expected stock returns", *Journal of Finance* 56, 815-849.

[20] Lettau, M. and J. Wachter (2007), "Why is long-horizon equity less risky? A duration-based explanation of the value premium", *Journal of Finance* 62, 55-92.

[21] Lewellen, J., S. Nagel and J. Shanken (2008), "A skeptical appraisal of asset pricing tests", *Journal of Financial Economics*, forthcoming.

[22] Loughran, T. (1997), "Book-to-market across firm size, exchange, and seasonality", *Journal of Financial Economics* 18, 341-371.

[23] MacKinlay, C. (1987), "On multivariate tests of the CAPM", *Journal of Financial Economics* 18, 341-371.

[24] Magill, M. and M. Quinzii (2000), "Infinite horizon CAPM equilibrium", *Economic Theory* 15(1), 103-138.

[25] Menzly, L., T. Santos, and P. Veronesi (2004). "Understanding predictability", *Journal of Political Economy* 112, 1-47.

[26] Ortu, F., A. Tamoni, and C. Tebaldi (2010), "Long run and the temporal aggregation of risks", Working paper.

[27] Parker, J. and C. Julliard (2005), "Consumption risk and the cross-section of expected returns", *Journal of Political Economy*, 113(1), 185-222.

[28] Phillips, P.C.B. (1987), "Understanding spurious regressions in econometrics", *Journal of Econometrics* 33, 311-340.

[29] Shanken, J. and G. Zhou (2007), "Estimating and testing beta pricing models: Alternative methods and their performance in simulations", *Journal of Financial Economics* 84, 40-86.

[30] Sizova, N. (2010), "Long-horizon return regressions with historical volatility and other long-memory variables", Working paper.

[31] Valkanov, R. (2003), "Long-horizon regressions: theoretical results and applications", *Journal of Financial Economics* 68, 201-232.

Table 1: returns/growth rates

The table presents returns (in percentages) on the risk free asset, the market, hml and smb, as well as consumption growth rates. The first column denotes horizons (1 month to 10 years).

	rf	**mkt**	**smb**	**hml**	Δc
1m	0.451	0.422	0.252	0.416	0.160
3m	1.363	1.289	1.073	1.289	0.480
1y	5.657	5.050	4.485	6.079	1.942
2y	11.863	10.960	9.469	17.492	3.925
3y	18.598	18.115	17.073	34.191	5.935
4y	25.840	26.724	31.085	59.897	7.955
5y	33.664	36.825	45.794	95.865	10.000
6y	42.165	47.136	57.046	144.342	12.022
7y	51.401	59.922	81.117	220.257	14.067
8y	61.429	75.825	124.226	325.386	16.162
9y	72.367	95.877	225.391	476.819	18.278
10y	84.224	119.032	234.782	690.478	20.343

Table 2: Summary Statistics for the CAPM

The table presents results for the 25 portfolios sorted on size and book-to-market. Panel A reports the excess returns of the portfolios in percentage, and horizon by horizon from 1 month to 120 months, and the portfolios' betas obtained from the time series regression of a portfolio excess return on the market excess return. The excess returns are with respect to the one-month Treasury bill rate (from Ibbotson Associates). The beta for each horizon has been obtained by regressing a portfolio's excess return for one horizon on the market excess return for the corresponding horizon. Data are not annualized and span the period from July 1963 to December 2009. Panel B reports information on the time-varying betas (means, standard deviations, and Newey-West t-statistics).

Panel A: Excess returns and constant betas

				Excess Return					β_{CAPM}		
		L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
1m	**S**	0.17	0.75	0.78	0.96	1.09	1.44	1.23	1.09	1.01	1.07
	2	0.37	0.64	0.88	0.89	0.98	1.41	1.17	1.05	1.00	1.10
	3	0.39	0.68	0.73	0.82	1.02	1.34	1.11	0.99	0.94	1.01
	4	0.50	0.49	0.65	0.79	0.81	1.23	1.08	1.02	0.95	1.03
	B	0.38	0.44	0.41	0.49	0.55	0.99	0.93	0.87	0.82	0.86
1y	**S**	2.98	9.96	10.35	13.00	14.52	1.46	1.27	1.16	1.07	1.16
	2	4.44	7.80	11.24	11.68	12.08	1.33	1.08	1.03	0.98	0.95
	3	4.67	8.67	9.09	10.42	12.76	1.28	1.10	0.91	0.92	0.85
	4	6.12	5.88	8.14	9.82	9.97	1.16	1.00	0.97	0.92	0.98
	B	4.55	5.34	4.85	5.98	6.87	1.00	0.93	0.84	0.81	0.84
3y	**S**	8.32	35.05	38.60	50.56	56.83	0.78	0.83	0.80	0.74	0.88
	2	12.81	27.11	40.63	45.22	45.94	0.90	0.75	0.81	0.92	0.78
	3	14.39	30.55	32.29	37.67	46.47	0.96	0.86	0.81	0.70	0.71
	4	19.56	19.77	29.87	34.71	36.61	0.94	0.83	0.84	0.70	0.80
	B	16.54	19.90	18.20	22.51	25.52	1.13	1.01	0.90	0.87	0.98
5y	**S**	13.77	71.41	81.72	108.31	122.20	0.51	0.75	0.76	0.73	0.82
	2	23.39	54.86	83.60	96.63	97.58	0.72	0.70	0.78	0.91	0.70
	3	26.77	62.48	64.99	77.93	100.61	0.87	0.81	0.80	0.68	0.78
	4	37.12	40.02	61.99	70.37	76.74	0.91	0.82	0.76	0.62	0.76
	B	34.01	42.23	38.24	46.56	52.72	1.21	1.06	0.90	0.87	1.01
8y	**S**	0.80	138.36	174.68	241.06	267.63	0.17	0.74	0.84	0.87	0.88
	11	31.85	113.97	175.58	219.37	218.43	0.53	0.74	0.93	1.13	0.80
	12	47.37	132.15	136.92	165.83	228.13	0.84	0.93	0.84	0.81	1.04
	13	74.15	83.94	133.37	149.05	173.00	0.99	0.84	0.74	0.59	0.96
	B	70.99	92.03	81.38	100.39	113.55	1.23	1.09	0.88	0.88	1.24
10y	**S**	-11.35	204.98	268.81	380.78	428.58	0.14	0.79	0.90	0.99	0.92
	17	38.58	172.73	275.33	355.76	353.13	0.50	0.76	1.10	1.25	0.83
	18	69.23	205.13	212.12	262.12	371.73	0.84	1.01	0.84	0.90	1.17
	19	112.62	128.90	208.39	232.68	282.67	1.07	0.88	0.73	0.67	1.08
	B	113.40	145.94	128.25	158.42	182.61	1.32	1.08	0.87	0.85	1.24

Panel B: Means, standard deviations and NW t-statistics of the time-varying betas.

		mean					std					t(NW)				
		L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
1m	**S**	1.47	1.25	1.10	1.01	1.04	0.21	0.18	0.19	0.21	0.22	10.40	9.73	9.60	8.43	8.15
	2	1.46	1.19	1.05	1.00	1.08	0.12	0.13	0.18	0.18	0.21	14.03	12.41	10.63	11.08	9.67
	3	1.37	1.12	1.00	0.94	1.02	0.11	0.10	0.14	0.16	0.20	17.70	15.70	13.04	12.57	10.88
	4	1.25	1.08	1.01	0.94	1.01	0.09	0.12	0.14	0.15	0.21	22.95	19.79	18.51	15.42	12.52
	B	1.00	0.96	0.87	0.81	0.86	0.07	0.10	0.09	0.13	0.18	18.79	21.27	15.62	12.28	11.45
1y	**S**	1.64	1.39	1.23	1.17	1.23	0.47	0.43	0.41	0.45	0.50	7.76	8.69	7.45	7.88	6.40
	2	1.46	1.17	1.12	1.05	1.04	0.28	0.32	0.43	0.40	0.40	10.39	11.39	8.94	8.91	6.82
	3	1.35	1.14	0.98	1.01	0.95	0.21	0.31	0.31	0.40	0.42	13.43	11.83	10.23	10.71	6.34
	4	1.19	1.02	1.02	0.97	1.01	0.20	0.29	0.29	0.35	0.37	12.69	16.00	14.77	11.35	10.15
	B	0.98	0.95	0.82	0.83	0.83	0.14	0.19	0.18	0.27	0.26	18.20	15.12	11.46	13.19	7.52
3y	**S**	1.46	1.26	1.11	1.10	1.26	1.13	0.96	0.80	0.91	0.96	9.42	8.81	7.93	7.57	6.09
	2	1.31	1.07	1.13	1.15	1.09	0.70	0.61	0.70	0.58	0.66	12.64	11.46	9.63	8.79	6.65
	3	1.23	1.13	1.02	1.00	0.91	0.52	0.51	0.47	0.56	0.58	16.37	12.29	10.29	9.21	5.56
	4	1.09	0.97	1.02	0.93	0.94	0.37	0.37	0.37	0.42	0.43	16.85	19.41	11.96	11.00	9.17
	B	1.00	0.99	0.87	0.83	0.89	0.30	0.25	0.19	0.24	0.32	18.50	22.37	18.43	15.69	12.90
5y	**S**	1.32	1.32	1.20	1.22	1.46	1.19	1.04	0.88	1.03	1.09	9.70	7.99	9.38	8.79	7.61
	2	1.23	1.14	1.19	1.25	1.21	0.80	0.69	0.75	0.71	0.79	14.24	14.92	13.32	11.55	9.89
	3	1.14	1.16	1.07	1.06	1.11	0.51	0.64	0.52	0.67	0.78	17.21	13.77	13.29	11.36	8.91
	4	1.02	0.95	1.02	0.93	1.02	0.36	0.42	0.41	0.45	0.51	16.31	23.71	16.01	12.01	8.92
	B	0.97	1.01	0.89	0.85	0.94	0.39	0.23	0.19	0.24	0.33	23.27	23.10	18.42	17.75	14.13
8y	**S**	1.02	1.48	1.55	1.81	1.87	1.38	1.58	1.59	1.65	2.00	7.97	9.62	10.23	10.52	8.58
	2	1.07	1.28	1.30	1.62	1.52	1.02	1.16	1.03	1.25	1.38	10.70	12.48	14.77	13.77	10.94
	3	1.10	1.31	1.23	1.16	1.44	0.68	0.93	0.87	0.71	0.99	15.11	17.70	15.01	18.22	11.58
	4	1.04	0.98	1.12	0.95	1.26	0.45	0.47	0.53	0.59	0.81	17.69	23.25	18.75	14.60	18.58
	B	1.05	1.03	0.89	0.91	0.97	0.45	0.32	0.25	0.26	0.34	25.96	29.18	23.56	21.57	18.78
10y	**S**	0.78	1.45	1.47	1.80	1.96	0.88	1.19	1.32	1.56	1.81	11.47	15.45	13.39	15.04	13.76
	2	0.94	1.20	1.41	1.67	1.61	0.64	0.93	0.77	1.16	1.30	16.75	14.20	17.86	16.56	14.27
	3	1.03	1.28	1.15	1.25	1.60	0.45	0.72	0.70	0.68	0.91	22.58	21.61	18.30	19.11	13.46
	4	1.05	0.91	1.15	1.02	1.27	0.27	0.37	0.53	0.55	0.69	43.11	19.49	22.75	19.69	14.23
	B	1.11	1.01	0.84	0.89	0.94	0.45	0.23	0.24	0.25	0.35	21.24	40.29	30.71	27.67	14.10

Table 3: Summary Statistics for the CCAPM

This table presents results for the 25 portfolios sorted on size and book-to-market. Panel A reports the excess returns of the portfolios in percentage, and horizon by horizon from 1 month to 120 months, and the portfolios' betas obtained from the time series regression of a portfolio excess return on consumption growth. The excess returns are with respect to the one-month Treasury bill rate (from Ibbotson Associates). The beta for each horizon has been obtained by regressing a portfolio's excess return for one horizon on consumption growth for the corresponding horizon. Data are not annualized and span the period from July 1963 to December 2009. Panel B reports information on the time-varying betas (means, standard deviations, and Newey-West t-statistics).

Panel A: Excess returns and constant betas

		Excess Return					β_{CCAPM}				
		L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
1m	**S**	0.17	0.75	0.78	0.96	1.09	3.72	3.61	2.75	2.64	2.77
	2	0.37	0.64	0.88	0.89	0.98	3.48	3.10	2.50	2.56	2.87
	3	0.39	0.68	0.73	0.82	1.02	3.36	2.93	2.48	2.45	2.34
	4	0.50	0.49	0.65	0.79	0.81	2.91	2.33	2.42	2.33	2.34
	B	0.38	0.44	0.41	0.49	0.55	2.17	1.73	1.60	1.70	1.14
1y	**S**	2.98	9.96	10.35	13.00	14.52	5.30	5.38	5.33	5.35	6.39
	2	4.44	7.80	11.24	11.68	12.08	3.89	3.92	4.92	4.48	5.24
	3	4.67	8.67	9.09	10.42	12.76	4.12	4.44	4.12	4.15	4.28
	4	6.12	5.88	8.14	9.82	9.97	3.57	3.39	4.07	4.75	5.14
	B	4.55	5.34	4.85	5.98	6.87	4.07	2.56	3.53	3.50	3.88
3y	**S**	8.32	35.05	38.60	50.56	56.83	1.16	1.66	2.52	3.31	3.99
	2	12.81	27.11	40.63	45.22	45.94	-0.43	0.98	3.35	2.73	3.41
	3	14.39	30.55	32.29	37.67	46.47	0.22	2.04	2.25	2.79	2.56
	4	19.56	19.77	29.87	34.71	36.61	0.64	1.12	2.39	4.08	4.19
	B	16.54	19.90	18.20	22.51	25.52	2.86	1.31	2.16	2.42	3.37
5y	**S**	13.77	71.41	81.72	108.31	122.20	-2.80	-2.75	-1.31	0.44	-0.48
	2	23.39	54.86	83.60	96.63	97.58	-4.11	-2.44	1.75	-0.22	-0.42
	3	26.77	62.48	64.99	77.93	100.61	-2.78	-0.66	-0.45	1.91	0.59
	4	37.12	40.02	61.99	70.37	76.74	-0.89	-0.28	1.15	3.85	3.34
	B	34.01	42.23	38.24	46.56	52.72	3.59	1.62	1.56	2.12	2.79
8y	**S**	0.80	138.36	174.68	241.06	267.63	-10.21	-12.55	-10.28	-7.66	-13.00
	2	31.85	113.97	175.58	219.37	218.43	-8.90	-8.01	-3.81	-10.01	-9.33
	3	47.37	132.15	136.92	165.83	228.13	-6.14	-6.26	-6.98	-4.01	-7.02
	4	74.15	83.94	133.37	149.05	173.00	-2.25	-3.75	-3.77	1.20	-0.65
	B	70.99	92.03	81.38	100.39	113.55	2.33	-2.03	-2.10	-1.35	-0.07
10y	**S**	-11.35	204.98	268.81	380.78	428.58	-10.39	-15.59	-13.48	-11.39	-20.54
	2	38.58	172.73	275.33	355.76	353.13	-9.65	-11.32	-5.74	-15.24	-16.63
	3	69.23	205.13	212.12	262.12	371.73	-7.02	-8.48	-9.88	-6.36	-11.91
	4	112.62	128.90	208.39	232.68	282.67	-2.80	-4.19	-5.87	0.62	-3.63
	B	113.40	145.94	128.25	158.42	182.61	0.85	-3.59	-3.71	-3.95	-2.50

Panel B: Means, standard deviations and NW t-statistics of the time-varying betas.

		mean					std					t(NW)				
		L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
1m	**S**	4.10	4.09	2.95	2.78	3.01	2.69	2.35	1.70	1.81	1.94	1.88	2.13	1.92	1.83	1.83
	2	4.04	3.38	2.71	2.72	3.12	2.74	2.16	1.82	1.80	2.39	2.03	2.11	1.92	1.92	1.93
	3	4.07	3.19	2.61	2.67	2.67	3.02	2.25	1.91	1.56	2.31	2.21	2.48	2.00	2.04	1.67
	4	3.32	2.60	2.60	2.34	2.30	3.31	1.71	1.48	2.11	1.90	1.98	1.94	1.94	1.86	1.65
	B	2.28	1.80	1.77	1.73	0.89	2.04	1.33	1.28	1.20	1.47	1.77	1.55	1.42	1.38	0.79
1y	**S**	9.82	8.79	7.15	6.48	8.45	11.85	8.67	7.22	6.95	8.67	1.74	2.10	2.15	2.15	2.57
	2	7.29	6.02	5.84	4.92	7.11	10.10	6.11	6.63	7.21	8.25	1.61	1.83	2.35	2.18	2.46
	3	7.09	6.08	4.91	4.66	6.49	8.94	6.13	5.87	7.12	7.28	1.91	2.14	2.13	1.81	2.38
	4	6.20	4.38	4.73	5.27	5.88	9.50	5.21	6.59	6.25	6.41	1.42	1.63	1.82	2.06	2.31
	B	5.14	3.71	4.05	3.28	5.68	7.06	5.59	5.12	5.07	6.22	2.41	1.41	2.16	1.71	2.51
3y	**S**	7.55	7.26	6.51	5.61	9.01	12.33	10.52	8.38	9.90	11.99	2.35	2.62	2.75	2.38	3.34
	2	5.71	5.83	6.08	5.75	7.90	10.74	7.15	8.88	9.68	9.65	2.00	2.80	3.80	3.25	3.66
	3	5.65	6.05	5.63	3.98	5.97	9.55	7.73	7.42	7.64	7.68	2.52	3.37	3.89	3.14	3.73
	4	5.09	4.44	5.43	5.83	6.44	9.72	5.54	7.52	6.67	6.93	2.81	2.80	3.45	4.31	5.11
	B	6.00	4.98	5.12	4.84	7.95	9.99	6.50	5.68	5.76	7.67	3.99	2.87	4.15	4.39	5.66
5y	**S**	1.95	1.70	2.39	2.02	0.20	13.02	11.97	11.22	13.21	18.05	0.46	0.57	0.98	0.84	0.37
	2	1.04	1.68	1.23	1.36	0.94	9.83	7.99	10.24	12.07	11.73	0.01	0.98	1.09	0.91	0.70
	3	1.47	1.85	2.03	1.10	1.46	8.81	8.78	9.01	10.11	10.84	0.33	0.98	0.94	0.95	1.20
	4	4.53	2.74	3.49	5.39	4.78	9.61	7.08	9.26	6.80	6.86	1.50	1.45	1.76	3.16	2.83
	B	9.74	6.49	5.91	5.81	5.48	12.97	8.97	8.55	8.83	9.44	4.27	3.17	3.08	3.47	4.27
8y	**S**	-3.45	-1.15	4.21	6.05	5.17	15.09	18.34	19.78	21.54	25.63	0.06	0.62	2.10	1.66	0.63
	2	-3.82	1.03	3.32	0.00	3.41	11.42	11.80	12.54	17.07	17.68	-1.38	0.66	1.35	-1.29	0.44
	3	-1.22	1.59	-0.60	0.50	4.37	9.77	11.13	12.21	10.40	13.87	0.55	0.55	-1.12	0.34	1.22
	4	0.10	0.14	1.49	3.90	5.77	8.91	6.26	7.86	6.30	9.69	1.47	0.10	0.21	2.32	2.42
	B	-0.19	-0.84	-1.10	-0.80	1.37	15.85	11.60	10.29	12.55	17.51	5.71	0.15	0.65	0.45	2.97
10y	**S**	-3.00	0.66	5.74	8.02	3.90	17.84	30.11	32.69	37.80	45.85	-0.17	0.28	1.78	2.24	1.80
	2	-3.41	1.40	6.92	2.72	2.47	15.71	19.64	19.54	31.81	30.14	-1.16	1.06	3.93	1.48	1.75
	3	-1.21	3.61	0.75	3.12	6.41	16.58	20.00	18.30	14.83	26.18	1.06	3.11	0.51	1.88	3.27
	4	1.98	2.38	3.92	7.89	8.94	17.52	10.09	14.99	11.47	15.57	2.06	1.09	1.31	3.67	5.97
	B	-0.22	0.07	-0.35	-0.41	2.64	23.81	11.84	9.86	11.10	17.58	4.61	1.78	2.27	0.80	5.84

Table 4: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions: CAPM

This table presents the results of the cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market. We use a 60 observations rolling window to compute the OLS market loadings of the portfolios as follows:

$$\text{return}_{j,t+h} = \alpha_j + \beta_{j,mkt}\text{mkt}_{t+h} + \upsilon_{j,t+h}$$

For each window a cross section is run where the dependent variable is the portfolios' average excess return in the window and the explanatory variable is the vector of loadings $\beta_{j,mkt}$ of the portfolios. The cross-sectional regression coefficients (rows "Coeff.") are obtained by averaging the OLS coefficients obtained for each window, t(NW) stands for Newey-West t-statistics, Av. R^2 stands for the average adjusted R^2 from the cross sectional regressions and Max. R^2 corresponds to the maximum R^2 from successive cross-sectional regressions. The data span the period July 1963 to December 2009.

		Constant	**mkt**	**Av. R^2**	**Max. R^2**
1m	Coeff.	11.66	-3.88	0.27	0.82
	t(NW)	17.31	-5.72		
3m	Coeff.	10.72	-2.46	0.28	0.85
	t(NW)	10.34	-2.48		
1y	Coeff.	10.33	-1.91	0.19	0.89
	t(NW)	6.68	-1.43		
2y	Coeff.	7.75	0.38	0.20	0.91
	t(NW)	3.65	0.20		
3y	Coeff.	5.44	3.32	0.21	0.84
	t(NW)	2.56	1.53		
4y	Coeff.	6.33	2.54	0.23	0.89
	t(NW)	2.47	1.02		
5y	Coeff.	3.65	6.01	0.26	0.92
	t(NW)	0.99	1.57		
6y	Coeff.	5.58	5.59	0.27	0.91
	t(NW)	1.60	1.71		
7y	Coeff.	5.19	7.38	0.28	0.82
	t(NW)	1.43	2.61		
8y	Coeff.	7.43	7.22	0.31	0.93
	t(NW)	1.87	2.35		
9y	Coeff.	8.55	7.38	0.36	0.91
	t(NW)	1.86	3.88		
10y	Coeff.	5.56	11.22	0.44	0.93
	t(NW)	1.31	3.44		

Table 5: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions: CCAPM

This table presents the results of the cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market. We use a 60 observations rolling window to compute the OLS market loadings of the portfolios as follows:

$$return_{j,t+h} = \alpha_j + \beta_{j,\Delta c}\Delta c_{t+h} + \upsilon_{j,t+h}$$

For each window a cross section is run where the dependent variable is the portfolios' average excess return in the window and the explanatory variable is the vector of loadings $\beta_{j,\Delta c}$ of the portfolios. The cross-sectional regression coefficients (rows "Coeff.") are obtained by averaging the OLS coefficients obtained for each window, t(NW) stands for Newey-West t-statistics, Av. R^2 stands for the average adjusted R^2 from the cross sectional regressions and Max. R^2 corresponds to the maximum R^2 from successive cross-sectional regressions. The data span the period July 1963 to December 2009.

		Constant	Δc	**Av. R^2**	**Max. R^2**
1m	Coeff.	7.52	0.09	0.26	0.91
	t(NW)	21.08	0.54		
3m	Coeff.	8.37	0.20	0.27	0.83
	t(NW)	13.38	1.23		
1y	Coeff.	7.45	0.44	0.23	0.75
	t(NW)	6.57	2.33		
2y	Coeff.	7.32	0.46	0.22	0.82
	t(NW)	5.25	2.37		
3y	Coeff.	8.00	0.46	0.20	0.84
	t(NW)	4.05	2.57		
4y	Coeff.	8.58	0.34	0.18	0.83
	t(NW)	4.08	1.83		
5y	Coeff.	9.87	0.16	0.16	0.75
	t(NW)	4.33	1.04		
6y	Coeff.	10.74	0.16	0.18	0.83
	t(NW)	3.61	1.21		
7y	Coeff.	12.84	0.15	0.18	0.76
	t(NW)	3.78	0.92		
8y	Coeff.	13.24	0.29	0.23	0.84
	t(NW)	4.10	1.79		
9y	Coeff.	12.76	0.34	0.28	0.92
	t(NW)	3.51	2.55		
10y	Coeff.	13.89	0.17	0.34	0.92
	t(NW)	3.33	0.97		

Table 6: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions: CAPM + CCAPM

This table presents the results of the cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market. We use a 60 observations rolling window to compute the OLS market loadings of the portfolios that are used as the independent variable in the cross section from as follows:

$$return_{j,t+h} = \alpha_j + \beta_{j,mkt} mkt_{t+h} + \beta_{j,conso} \Delta c_{t+h} + \varepsilon_{j,t+h}$$

For each window a cross section is run where the dependent variable is the portfolios' average return in the window and the explanatory variables are the loadings of the portfolios. The cross-section regression coefficients (rows "Coeff.") are obtained by averaging the OLS coefficients obtained for each window, t(NW) stands for Newey-West t-statistics, Av. R^2 stands for the average adjusted R^2 from the cross sectional regressions and Max. R^2 corresponds to the maximum of R^2 from the successive cross sections. Data span the period July 1963 to December 2009.

		Constant	**mkt**	Δc	**Av. R^2**	**Max. R^2**
1m	Coeff.	11.18	-3.98	0.29	0.39	0.94
	t(NW)	18.83	-6.78	2.05		
3m	Coeff.	11.51	-3.98	0.67	0.39	0.85
	t(NW)	12.12	-4.63	4.36		
1y	Coeff.	8.68	-1.30	0.55	0.36	0.90
	t(NW)	5.05	-0.80	2.67		
2y	Coeff.	5.29	2.18	0.70	0.36	0.92
	t(NW)	2.62	1.10	2.57		
3y	Coeff.	2.37	5.10	0.74	0.38	0.85
	t(NW)	0.89	1.91	2.17		
4y	Coeff.	3.45	3.87	0.38	0.40	0.92
	t(NW)	1.13	1.43	1.38		
5y	Coeff.	-1.92	10.14	0.34	0.39	0.95
	t(NW)	-0.53	2.49	1.68		
6y	Coeff.	-0.17	9.83	0.48	0.43	0.92
	t(NW)	-0.04	2.08	1.63		
7y	Coeff.	0.37	10.54	0.10	0.46	0.87
	t(NW)	0.08	2.36	0.40		
8y	Coeff.	1.39	12.10	0.42	0.47	0.93
	t(NW)	0.36	3.37	3.03		
9y	Coeff.	2.59	12.60	0.44	0.53	0.94
	t(NW)	0.68	10.01	4.65		
10y	Coeff.	2.03	13.04	0.26	0.61	0.95
	t(NW)	0.66	3.33	1.35		

Table 7: Prices of market risk for the 25 portfolios

		mean					std					t(NW)				
		L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
1m	**S**	-4.45	-3.53	-2.86	-2.55	-2.41	22.64	19.93	18.21	17.03	17.46	-3.12	-2.82	-2.50	-2.38	-2.19
	2	-5.15	-4.05	-2.83	-2.71	-2.75	22.39	18.81	17.48	16.34	17.77	-3.65	-3.42	-2.57	-2.64	-2.46
	3	-5.21	-3.93	-3.24	-2.83	-2.57	20.90	17.63	15.85	15.16	16.86	-3.96	-3.53	-3.25	-2.96	-2.42
	4	-5.05	-4.45	-3.68	-2.99	-2.90	18.83	16.93	15.77	15.07	16.77	-4.26	-4.17	-3.70	-3.16	-2.75
	B	-4.21	-4.12	-3.81	-2.95	-2.84	15.10	14.73	13.21	12.97	13.42	-4.43	-4.45	-4.58	-3.62	-3.36
1y	**S**	-1.13	-0.97	-0.81	-0.86	-0.49	15.66	13.87	12.74	12.28	12.30	-0.48	-0.47	-0.42	-0.47	-0.27
	2	-1.98	-1.42	-0.79	-1.01	-0.87	13.93	11.89	11.98	11.28	10.13	-0.95	-0.80	-0.44	-0.60	-0.59
	3	-2.23	-1.48	-1.39	-0.94	-0.65	12.64	11.82	10.01	10.45	9.79	-1.19	-0.84	-0.94	-0.62	-0.46
	4	-2.44	-1.66	-1.60	-1.34	-1.09	11.13	10.65	9.84	10.10	10.30	-1.48	-1.06	-1.13	-0.91	-0.73
	B	-2.24	-2.03	-1.49	-1.47	-1.27	9.38	9.71	8.00	8.14	8.51	-1.65	-1.47	-1.30	-1.27	-1.05
3y	**S**	5.90	5.78	6.36	7.14	6.64	13.78	11.39	9.69	9.32	11.67	1.89	2.41	3.39	4.28	2.95
	2	4.45	4.81	5.80	6.52	5.23	12.35	9.95	10.98	11.19	10.95	1.60	2.34	2.91	3.17	2.52
	3	4.14	5.16	5.23	5.47	5.31	12.08	11.62	9.73	9.72	9.97	1.58	2.25	2.87	3.17	2.85
	4	3.25	4.60	5.02	3.90	4.27	11.20	9.65	10.67	9.55	10.33	1.35	2.49	2.48	2.21	2.34
	B	2.94	4.12	3.82	3.58	2.51	10.90	11.62	9.71	8.39	10.70	1.30	1.79	2.08	2.23	1.17
5y	**S**	9.99	11.11	11.42	13.14	13.09	21.25	18.09	16.95	16.76	19.69	1.63	2.15	2.43	2.95	2.44
	2	8.37	10.13	10.36	10.83	11.25	17.29	17.18	15.92	16.38	17.82	1.68	2.09	2.36	2.35	2.27
	3	7.69	9.70	8.89	10.17	11.14	15.96	17.15	15.05	15.22	15.82	1.70	2.00	2.11	2.45	2.56
	4	6.33	8.14	9.36	7.37	9.32	14.17	13.55	15.36	13.15	16.29	1.59	2.17	2.24	2.09	2.09
	B	4.44	7.29	6.60	6.17	5.53	12.67	14.47	13.01	12.35	13.95	1.31	1.82	1.83	1.83	1.38
8y	**S**	8.81	13.95	16.10	17.65	18.37	10.71	17.10	18.90	17.87	19.75	2.59	2.94	3.44	4.63	3.69
	2	8.44	11.59	12.24	14.68	13.94	10.87	16.62	16.78	19.70	17.49	2.70	2.76	3.11	3.13	3.18
	3	8.79	11.43	10.30	9.99	13.20	13.58	17.08	13.54	13.76	16.90	2.57	2.87	3.12	3.07	3.65
	4	7.53	7.66	9.40	7.95	11.33	13.48	11.13	12.57	10.16	17.16	2.33	3.01	3.65	3.30	2.84
	B	7.06	7.22	6.40	6.71	6.26	14.12	14.12	10.83	11.36	14.08	1.81	1.98	2.24	2.29	1.85
10y	**S**	11.58	22.45	24.70	30.37	32.86	10.35	20.39	20.97	23.59	26.22	2.87	3.73	4.55	6.08	4.27
	2	12.07	17.31	21.19	25.74	26.01	12.62	19.94	23.71	26.24	22.87	3.24	3.33	3.82	4.10	3.93
	3	12.16	17.53	17.52	19.66	23.58	18.66	22.11	16.12	20.47	24.17	2.78	3.29	4.21	4.06	4.90
	4	11.58	12.40	16.50	14.50	19.50	19.88	14.62	16.07	14.55	21.24	2.78	4.57	5.31	5.53	3.90
	B	11.63	11.36	11.03	11.51	10.14	20.87	16.17	12.62	13.28	16.34	2.41	4.40	4.54	4.42	3.66

Table 8: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions:
25 SBM and 30 INDUSTRY portfolios

Panel A: CAPM

30 Industry portfolios

		Constant	mkt	Av. R^2	Max. R^2
1m	Coeff.	4.53	2.01	0.10	0.64
	t(NW)	13.04	4.73		
3m	Coeff.	3.74	2.88	0.11	0.66
	t(NW)	8.71	5.12		
1y	Coeff.	2.87	4.04	0.12	0.60
	t(NW)	4.03	4.32		
2y	Coeff.	3.05	4.37	0.14	0.69
	t(NW)	3.16	3.99		
3y	Coeff.	3.17	4.97	0.15	0.80
	t(NW)	3.75	3.88		
4y	Coeff.	1.93	6.93	0.19	0.72
	t(NW)	1.35	3.83		
5y	Coeff.	2.12	7.55	0.22	0.73
	t(NW)	1.12	3.69		
6y	Coeff.	3.77	6.19	0.29	0.78
	t(NW)	1.54	3.52		
7y	Coeff.	2.56	7.86	0.35	0.86
	t(NW)	1.10	2.77		
8y	Coeff.	4.68	7.78	0.32	0.87
	t(NW)	2.24	2.35		
9y	Coeff.	5.98	8.52	0.32	0.76
	t(NW)	2.44	2.86		
10y	Coeff.	6.88	9.27	0.35	0.87
	t(NW)	2.38	4.29		

25 SBM and 30 Industry portfolios

		Constant	mkt	Av. R^2	Max. R^2
1m	Coeff.	6.31	0.78	0.12	0.71
	t(NW)	14.71	1.66		
3m	Coeff.	5.35	1.87	0.13	0.69
	t(NW)	9.33	3.05		
1y	Coeff.	4.48	3.07	0.12	0.73
	t(NW)	4.98	3.34		
2y	Coeff.	4.24	3.79	0.13	0.81
	t(NW)	3.72	3.71		
3y	Coeff.	4.06	4.73	0.15	0.75
	t(NW)	3.76	4.44		
4y	Coeff.	3.39	6.00	0.18	0.77
	t(NW)	2.13	4.12		
5y	Coeff.	2.81	7.57	0.22	0.79
	t(NW)	1.17	3.34		
6y	Coeff.	4.71	6.36	0.27	0.69
	t(NW)	1.66	3.15		
7y	Coeff.	3.95	7.94	0.32	0.82
	t(NW)	1.47	3.19		
8y	Coeff.	6.65	7.59	0.29	0.83
	t(NW)	2.50	2.79		
9y	Coeff.	7.92	8.50	0.29	0.82
	t(NW)	2.37	4.00		
10y	Coeff.	7.98	10.08	0.32	0.86
	t(NW)	2.35	5.36		

Panel B: CCAPM

30 Industry portfolios

		Constant	Δc	Av. R^2	Max. R^2
1m	Coeff.	7.50	-0.56	0.08	0.76
	t(NW)	33.34	-7.33		
3m	Coeff.	7.88	-0.14	0.06	0.53
	t(NW)	19.25	-2.34		
1y	Coeff.	7.57	-0.11	0.07	0.60
	t(NW)	10.03	-1.48		
2y	Coeff.	7.00	-0.01	0.10	0.72
	t(NW)	6.34	-0.10		
3y	Coeff.	6.83	0.09	0.12	0.79
	t(NW)	4.81	0.92		
4y	Coeff.	6.54	0.29	0.11	0.73
	t(NW)	4.04	2.75		
5y	Coeff.	7.55	0.27	0.13	0.67
	t(NW)	4.18	2.31		
6y	Coeff.	8.46	0.15	0.16	0.58
	t(NW)	3.38	1.42		
7y	Coeff.	9.76	0.05	0.19	0.75
	t(NW)	3.30	0.36		
8y	Coeff.	11.49	0.15	0.20	0.78
	t(NW)	3.76	0.83		
9y	Coeff.	12.29	0.27	0.25	0.81
	t(NW)	3.65	1.52		
10y	Coeff.	12.44	0.27	0.29	0.77
	t(NW)	3.35	2.02		

25 SBM and 30 Industry portfolios

		Constant	Δc	Av. R^2	Max. R^2
1m	Coeff.	7.47	-0.23	0.14	0.71
	t(NW)	28.50	-2.07		
3m	Coeff.	8.00	0.05	0.11	0.61
	t(NW)	17.28	0.59		
1y	Coeff.	7.73	0.09	0.08	0.46
	t(NW)	9.64	0.91		
2y	Coeff.	7.42	0.18	0.10	0.56
	t(NW)	6.77	1.72		
3y	Coeff.	7.47	0.27	0.10	0.60
	t(NW)	5.17	2.39		
4y	Coeff.	7.61	0.37	0.11	0.63
	t(NW)	4.35	3.47		
5y	Coeff.	9.12	0.20	0.13	0.63
	t(NW)	4.43	2.11		
6y	Coeff.	10.04	0.09	0.15	0.54
	t(NW)	3.66	1.03		
7y	Coeff.	11.65	0.01	0.16	0.75
	t(NW)	3.64	0.09		
8y	Coeff.	12.95	0.13	0.19	0.70
	t(NW)	4.02	0.80		
9y	Coeff.	13.41	0.23	0.26	0.76
	t(NW)	3.70	1.50		
10y	Coeff.	14.78	0.18	0.24	0.81
	t(NW)	3.56	1.59		

Panel C: CAPM + CCAPM

30 Industry portfolios

		Constant	mkt	Δc	Av. R^2	Max. R^2
1m	Coeff.	4.28	2.02	-0.57	0.17	0.79
	t(NW)	13.21	4.70	-8.12		
3m	Coeff.	2.51	4.11	-0.49	0.19	0.72
	t(NW)	5.92	6.77	-6.17		
1y	Coeff.	2.78	4.00	-0.13	0.23	0.59
	t(NW)	3.47	3.74	-1.42		
2y	Coeff.	2.93	4.32	0.05	0.26	0.71
	t(NW)	2.65	3.62	0.54		
3y	Coeff.	1.71	6.19	0.02	0.33	0.85
	t(NW)	1.54	4.61	0.16		
4y	Coeff.	0.14	8.37	0.33	0.33	0.73
	t(NW)	0.08	3.94	2.24		
5y	Coeff.	-1.54	10.34	0.29	0.40	0.82
	t(NW)	-1.09	4.55	2.35		
6y	Coeff.	-0.36	9.41	0.18	0.46	0.80
	t(NW)	-0.19	4.24	1.43		
7y	Coeff.	0.43	9.75	-0.10	0.54	0.85
	t(NW)	0.14	2.70	-0.55		
8y	Coeff.	2.64	9.36	0.11	0.48	0.87
	t(NW)	0.93	2.16	0.40		
9y	Coeff.	1.94	11.88	0.26	0.51	0.88
	t(NW)	1.10	4.30	1.78		
10y	Coeff.	2.17	13.02	0.40	0.59	0.96
	t(NW)	0.89	7.04	3.58		

25 SBM and 30 Industry portfolios

		Constant	mkt	Δc	Av. R^2	Max. R^2
1m	Coeff.	5.92	0.83	-0.20	0.21	0.74
	t(NW)	14.55	1.80	-2.25		
3m	Coeff.	4.33	2.83	-0.23	0.21	0.71
	t(NW)	8.68	4.81	-2.46		
1y	Coeff.	3.94	3.40	0.08	0.19	0.73
	t(NW)	4.36	3.35	0.70		
2y	Coeff.	3.50	4.22	0.27	0.24	0.81
	t(NW)	2.89	3.46	2.07		
3y	Coeff.	2.31	5.97	0.24	0.29	0.79
	t(NW)	1.58	4.32	1.31		
4y	Coeff.	1.29	7.53	0.42	0.31	0.78
	t(NW)	0.67	4.11	2.40		
5y	Coeff.	-1.61	11.04	0.30	0.38	0.81
	t(NW)	-0.81	4.30	2.53		
6y	Coeff.	-0.30	10.11	0.21	0.43	0.74
	t(NW)	-0.12	3.65	1.58		
7y	Coeff.	0.24	10.82	-0.09	0.47	0.81
	t(NW)	0.07	2.77	-0.49		
8y	Coeff.	3.09	10.46	0.13	0.41	0.82
	t(NW)	1.11	2.80	0.56		
9y	Coeff.	2.40	12.86	0.26	0.52	0.89
	t(NW)	1.02	5.78	2.17		
10y	Coeff.	3.30	13.56	0.33	0.54	0.95
	t(NW)	1.29	6.51	2.98		

Table 9: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions: Fama and French Three Factors Model

Panel A: FF3 25 portfolios

		Constant	mkt	smb	hml	Av. R^2	Max. R^2
1m	Coeff.	10.92	-5.10	2.21	5.02	0.59	0.93
	t(NW)	20.42	-12.12	7.35	26.42		
3m	Coeff.	9.03	-3.06	3.14	5.26	0.59	0.93
	t(NW)	10.35	-4.07	5.47	16.66		
1y	Coeff.	4.03	1.83	6.82	6.95	0.56	0.93
	t(NW)	2.25	1.32	3.16	9.86		
2y	Coeff.	-7.45	13.34	8.55	12.34	0.64	0.95
	t(NW)	-3.39	6.21	1.73	8.49		
3y	Coeff.	-13.59	19.46	13.22	17.49	0.71	0.96
	t(NW)	-6.40	7.79	1.30	7.01		
4y	Coeff.	-15.89	22.07	12.98	24.63	0.76	0.96
	t(NW)	-7.87	6.79	0.72	5.91		
5y	Coeff.	-17.23	23.81	20.52	35.34	0.81	0.96
	t(NW)	-11.29	6.71	0.79	4.98		
6y	Coeff.	-15.18	23.00	28.80	45.02	0.83	0.97
	t(NW)	-9.39	7.21	0.77	4.50		
7y	Coeff.	-16.32	25.10	38.07	63.95	0.88	0.99
	t(NW)	-13.36	6.78	0.64	4.58		
8y	Coeff.	-15.33	25.16	43.00	78.09	0.89	0.98
	t(NW)	-13.29	6.25	0.46	4.48		
9y	Coeff.	-15.51	27.21	75.66	105.53	0.91	0.98
	t(NW)	-15.70	6.36	0.53	3.95		
10y	Coeff.	-15.43	28.31	85.10	148.00	0.92	0.99
	t(NW)	-13.17	5.87	0.48	4.17		

Panel B: FF3 30 portfolios

		Constant	mkt	smb	hml	Av. R^2	Max. R^2
1m	Coeff.	5.30	0.95	0.51	-1.56	0.31	0.77
	t (NW)	14.10	2.29	1.49	-5.63		
3m	Coeff.	3.90	2.56	0.79	-1.67	0.28	0.78
	t (NW)	6.79	3.26	1.51	-3.68		
1y	Coeff.	1.25	5.23	1.62	-1.01	0.29	0.79
	t (NW)	1.52	4.76	1.60	-1.15		
2y	Coeff.	1.00	5.90	3.53	0.33	0.36	0.85
	t (NW)	1.05	5.34	1.46	0.24		
3y	Coeff.	-0.04	7.46	4.08	1.15	0.45	0.81
	t (NW)	-0.04	4.62	1.01	0.78		
4y	Coeff.	-1.95	10.29	7.27	3.59	0.46	0.79
	t (NW)	-1.39	6.38	0.82	1.57		
5y	Coeff.	-3.40	11.80	6.15	10.38	0.51	0.91
	t (NW)	-3.15	5.71	0.53	2.43		
6y	Coeff.	-1.78	10.65	16.77	13.60	0.55	0.90
	t (NW)	-0.92	8.19	0.77	2.78		
7y	Coeff.	-4.25	14.30	22.17	20.65	0.65	0.95
	t (NW)	-1.78	5.22	0.81	3.67		
8y	Coeff.	-0.81	12.43	3.07	24.19	0.55	0.93
	t (NW)	-0.30	2.99	0.09	2.77		
9y	Coeff.	-1.89	14.87	36.66	48.33	0.63	0.92
	t (NW)	-0.84	5.95	0.49	3.42		
10y	Coeff.	-0.09	14.72	10.50	57.47	0.69	0.96
	t (NW)	-0.04	6.63	0.14	4.17		

Panel C: FF3 55 portfolios

		Constant	mkt	smb	hml	Av. R^2	Max. R^2
1m	Coeff.	6.67	-0.50	1.81	1.86	0.37	0.78
	t (NW)	16.73	-1.26	5.92	8.16		
3m	Coeff.	4.89	1.52	2.30	1.74	0.34	0.80
	t (NW)	9.98	2.32	4.39	4.89		
1y	Coeff.	1.86	4.89	4.10	1.79	0.31	0.82
	t (NW)	1.94	4.74	3.10	2.67		
2y	Coeff.	0.86	6.25	6.39	3.65	0.37	0.83
	t (NW)	0.83	5.97	2.23	3.05		
3y	Coeff.	-0.13	7.69	8.21	5.37	0.45	0.77
	t (NW)	-0.11	5.54	1.51	3.45		
4y	Coeff.	-1.76	10.13	12.02	8.74	0.48	0.78
	t (NW)	-1.10	7.90	1.05	3.26		
5y	Coeff.	-4.86	13.39	19.30	17.03	0.56	0.86
	t (NW)	-3.00	6.49	1.05	3.19		
6y	Coeff.	-2.16	11.29	25.96	21.44	0.57	0.93
	t (NW)	-0.90	9.24	0.96	3.72		
7y	Coeff.	-5.11	15.18	34.98	34.82	0.63	0.93
	t (NW)	-1.89	5.34	0.92	3.68		
8y	Coeff.	-1.17	13.22	49.94	43.98	0.57	0.92
	t (NW)	-0.51	3.71	0.83	2.89		
9y	Coeff.	-2.48	15.68	72.14	69.35	0.69	0.92
	t (NW)	-0.90	6.40	0.76	2.98		
10y	Coeff.	-1.44	16.42	38.20	89.33	0.72	0.95
	t (NW)	-0.64	6.42	0.41	3.71		

Table 9: Fama-Macbeth OLS/OLS Long Horizon Cross Sectional Regressions: CAPM for a larger sample

This table presents the results of the cross-sectional regressions using the excess returns on the 25 portfolios sorted on size and book-to-market. We use a 60 observations rolling window to compute the OLS market loadings of the portfolios as follows:

$$\text{return}_{j,t+h} = \alpha_j + \beta_{j,mkt}\text{mkt}_{t+h} + \upsilon_{j,t+h}$$

For each window a cross section is run where the dependent variable is the portfolios' average excess return in the window and the explanatory variable is the vector of loadings $\beta_{j,mkt}$ of the portfolios. The cross-sectional regression coefficients (rows "Coeff.") are obtained by averaging the OLS coefficients obtained for each window, t(NW) stands for Newey-West t-statistics, Av. R^2 stands for the average adjusted R^2 from the cross sectional regressions and Max. R^2 corresponds to the maximum R^2 from successive cross-sectional regressions. The data span the period July 1926 to December 2009.

Panel A: 25 portfolios

		Constant	**mkt**	**Av. R^2**	**Max. R^2**
1m	Coeff.	8.62	0.20	0.23	0.83
	t(NW)	14.12	0.32		
3m	Coeff.	7.73	1.71	0.25	0.87
	t(NW)	9.63	2.02		
1y	Coeff.	5.50	4.09	0.24	0.94
	t(NW)	4.46	3.54		
2y	Coeff.	4.10	5.55	0.28	0.92
	t(NW)	2.29	3.56		
3y	Coeff.	3.41	6.87	0.33	0.95
	t(NW)	1.90	4.24		
4y	Coeff.	4.66	6.22	0.36	0.95
	t(NW)	2.37	3.64		
5y	Coeff.	3.14	8.41	0.39	0.95
	t(NW)	1.33	4.10		
6y	Coeff.	3.81	8.80	0.44	0.98
	t(NW)	1.64	4.74		
7y	Coeff.	4.24	10.06	0.43	0.93
	t(NW)	1.82	5.61		
8y	Coeff.	5.15	10.76	0.45	0.93
	t(NW)	2.08	5.17		
9y	Coeff.	7.35	9.52	0.45	0.92
	t(NW)	2.19	6.38		
10y	Coeff.	5.63	12.05	0.51	0.93
	t(NW)	1.63	7.18		

Panel B: 30 portfolios

		Constant	mkt	Av. R^2	Max. R^2
1m	Coeff.	4.09	4.45	0.12	0.64
	t(NW)	15.04	13.87		
3m	Coeff.	2.39	6.30	0.16	0.74
	t(NW)	5.35	11.79		
1y	Coeff.	2.49	6.72	0.19	0.83
	t(NW)	3.13	8.31		
2y	Coeff.	3.22	6.60	0.22	0.83
	t(NW)	3.04	6.92		
3y	Coeff.	3.98	6.51	0.26	0.83
	t(NW)	3.64	6.41		
4y	Coeff.	3.89	7.34	0.29	0.86
	t(NW)	2.79	6.13		
5y	Coeff.	4.39	7.59	0.30	0.92
	t(NW)	2.53	6.43		
6y	Coeff.	5.47	7.09	0.34	0.94
	t(NW)	2.93	7.04		
7y	Coeff.	5.71	7.81	0.36	0.96
	t(NW)	2.78	5.05		
8y	Coeff.	7.07	7.99	0.36	0.90
	t(NW)	3.54	4.56		
9y	Coeff.	8.58	8.10	0.34	0.86
	t(NW)	3.38	5.01		
10y	Coeff.	9.24	8.98	0.33	0.90
	t(NW)	3.63	6.35		

Panel C: 55 portfolios

		Constant	mkt	Av. R^2	Max. R^2
1m	Coeff.	5.25	3.42	0.16	0.74
	t(NW)	17.01	9.13		
3m	Coeff.	3.92	5.01	0.19	0.85
	t(NW)	8.47	9.39		
1y	Coeff.	3.16	6.25	0.20	0.87
	t(NW)	3.76	7.67		
2y	Coeff.	3.41	6.59	0.24	0.87
	t(NW)	2.87	6.41		
3y	Coeff.	3.88	6.80	0.29	0.88
	t(NW)	3.05	6.31		
4y	Coeff.	4.29	7.15	0.31	0.90
	t(NW)	2.88	6.38		
5y	Coeff.	4.23	8.02	0.34	0.93
	t(NW)	2.23	6.26		
6y	Coeff.	5.12	7.82	0.39	0.95
	t(NW)	2.48	6.82		
7y	Coeff.	5.71	8.56	0.39	0.95
	t(NW)	2.70	6.23		
8y	Coeff.	7.30	8.71	0.38	0.91
	t(NW)	3.51	5.82		
9y	Coeff.	8.77	8.82	0.37	0.86
	t(NW)	3.14	6.61		
10y	Coeff.	8.77	10.21	0.39	0.87
	t(NW)	3.12	8.28		

1. Long-term expected returns 1.1 Inflation, cash and bonds 1.1.1 Cash 1.1.2 Government bonds 1.1.3 Credits 1.1.4 High yield 1.1.5 Inflation-linked bonds 1.1.6 Emerging market debt 1.2 Equities 1.3 Alternatives 1.3.1 Private equity 1.3.2 Real estate 1.3.3 Commodities.Â In this section we build on the methodology from previous editions to derive the expected long-term returns on a wide set of asset classes, in a similar fashion to Bekkers, Doeswijk and Lam (2009). We take an unconditional long-term view, which means that the current economic environment is not relevant. These long-term expected returns can be used as the equilibrium returns for asset-liability management (ALM) studies for long-term investors such as pension or endowment funds. That is, if the expected market return is higher than 6%, then on average a 2x LETF generates higher compound returns and increased long horizon wealth, as compared to a non-levered 1x holding. As an example, continuously holding a daily 2x leveraged U.S. stock market position from 1951-2014 would have generated an annual compound return that was 1.87 times the annual unlevered compound return. If a 1% per year management fee was included, you would end up with 1.76x returns.Â They reveal that optimal leverage is somewhere between 2x and 3x depending on the market and time horizon under consideration. However, the analysis below is based only on price index movements and not reflective of dividends reinvested over time.