Where is Beta Going?

The Riskiness of Value and Small Stocks

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Abstract

This paper finds that the market betas of value and small stocks have decreased by about 75% in the second half of the twentieth century. The path of beta can be closely tracked using variables that summarize the state of the economy. On the basis of this analysis, the decline in beta can be related to a long-term improvement in economic conditions that made these companies less risky. Decomposing beta into the cashflow and expected return news components confirms that the payoffs of these companies are less sensitive to market conditions. This finding has implications for the debate on the CAPM anomalies. The failure to account for time-series variation of beta in unconditional CAPM regressions can explain as much as 30% of the value premium. In some samples, about 80% of the value premium can be explained by assuming that investors tied their expectations of the riskiness of these stocks to the high values of beta prevailing in the early years.

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1 Introduction

Since the development of the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), beta risk has become an important input into many asset-pricing applications. The market beta of a portfolio plays a central role not only in the academic tests of the CAPM, but also in mutual fund performance evaluation, portfolio optimization and cost of capital estimation. Beta is also of independent interest, as it summarizes some of the relevant characteristics of the firm's fundamentals. The analysis of the direction and the causes of the change in a firm's beta is informative on the relationship between the company's payoffs and general business conditions, as well as on the correct asset-pricing model. Consequently, understanding whether and how the market beta changed for some portfolios is informative on the reasons behind the failure of CAMP in pricing those portfolios For all of these reasons, this paper takes a close look at the evolution of beta for book-to-market (B/M) and size portfolios, specifically those stocks that create major problems for the CAPM (e.g., Fama and French, 1992 and 1993).

Using monthly data from 1926 to 2000, I find a striking decrease in the market beta of value and small stocks. Beta fell by about 75% in sixty years for both these portfolios. In the case of value stocks beta dropped from 2.20 in the early forties to 0.55 in the late nineties. Similarly, small stocks' beta dropped from 2.50 to 0.65. This decline does not seem to follow mechanically from portfolio formation procedures, nor does it depend on a reduction in the leverage of these companies. Also, the magnitude of this decline is by no means solely imputable to the behavior of these portfolios in the late nineties. Moreover, the decrease in beta can be explained by a decline in the volatility of these portfolios relative to the rest of the market, rather than by a drop in their correlation with the market.

The paper also attempts to explain this evolution of beta. The conditional CAPM literature provides one way to go about this task. Following Shanken (1990), I assume a linear relation between beta and some state variables, and estimate the parameters of this function in a conditional CAPM time-series regression. The resulting fitted beta series tracks very closely the original estimated series, and it captures as much as 71% of its variance in the case of value stocks. The variables that I use as instruments (the T-bill rate, the dividend yield, the default spread, the term spread, and the growth rate of industrial production) are tightly linked to general economic conditions (see, e.g., Fama and French, 1989). The general result is that when the state variables predict an improvement in the economy, these stocks' betas become smaller. This result not only applies to the cyclical movements of beta, but also to the long run decrease, because some of these variables display a trending behavior that is believed to be related to a long-term improvement in business conditions. This evidence is consistent with the findings in Lettau and Ludvigson (2001), who show that the returns of value stocks are more highly correlated with fundamental factors when times are bad.

The evidence suggests that the decline in beta has to be tied to the effect of better economic conditions on the structure of value and small companies' cashflows. Since these companies are presumably more prone to financial distress (Chan and Chen, 1991, Fama and French, 1995), a general reduction in the likelihood of distress can have made their payoffs less risky. To investigate this explanation, I consider whether the decrease in the beta can be imputed to a decrease in these firms' cashflow sensitivity to the market. After breaking excess returns into components related to news about future dividends, news about future excess returns, and news about future real interest rates, following Campbell and Mei (1993), I express the overall market beta as the sum of the betas of each of these components with the market. Using this approach within a rolling regression framework, I can determine the importance of each component in the observed decrease of the overall beta. The conclusion of this analysis is that the decline occurs because of a fall in the dividend news beta. Overall, the results from the beta decomposition are consistent with the interpretation of the conditional CAPM analysis, because they point in the direction of reduced cashflow riskiness.

The decrease in the beta of value and small stocks is interesting by itself, as it sheds light on the behavior of portfolios widely used in empirical studies and in the asset management industry. However, the fact acquires even more relevance if it can be related to the debate on the CAPM anomalies. This paper establishes a connection between the decrease in the beta of these portfolios and the emergence of a premium in their expected return in two ways.

The first way is suggested by the evidence that conditioning information tracks the variation in beta. Failing to consider the variability of betas causes the constant in the unconditional CAPM time-series regressions to capture some of the effect of the state variables on the beta. Since the portfolios for which the decrease in beta is bigger (value and small stocks) are the ones that load more heavily on the state variables, these portfolios are more likely to have a high premium. It turns out that for value stocks as much as 30% of the alpha in the time-series regressions can be explained by the time-varying beta.

A connection can also be drawn with the behavioral explanation of the CAPM anomalies. Daniel and Titman (1997), for example, argue that characteristics, rather than risk, are priced in equilibrium. They suspect that investors consider these stocks more risky than they actually are. I argue that the large drop that occurred in the betas of value and small stocks could have been the reason why investors made mistakes in the assessment of risk. The market could have incorrectly tied its expectation of the price for risk to the high levels of beta, which characterized these stocks until the early sixties, even after beta had experienced a major decrease. Support for this conjecture comes from the result that about 80% of the value premium in the second part of the sample (1963-2000) can be explained assuming a beta such as the one estimated in the first part of the sample (1926-1962).

This paper is organized as follows. Section 2 presents in detail the decrease in the estimated beta of value and small stocks, and tests the robustness of the fact to mechanical explanations. Section 3 explains the path of beta using conditional information, as in a conditional CAPM analysis. Section 4 implements Campbell and Mei's (1993) beta decomposition in order to identify the sources of the change in beta. Section 5 relates the decrease in the beta to the mispricing of value and small stock portfolios. Section 6 draws the conclusions of this work.

2 The decrease in the beta of value and small stocks

2.1 The data

The data come from the merger of three different sources. Monthly return data are taken from the Center for Research in Securities Prices (CRSP) database, which covers NYSE, Amex and Nasdaq stocks between January 1926 and December 2000. Accounting data come from two sources. The Compustat annual research file contains the relevant information for most publicly traded US stocks. This information is supplemented by Moody's book equity information manually collected by Davis, Fama, and French (2000) [1]. Their paper contains a precise definition of the book-value-of-equity variable.

Portfolios are formed according to the procedure described in Fama and French (1993). At the end of June of year t stocks are sorted on either B/M or size. B/M is measured as the ratio of book value of equity at the end of year $t-1$ to market value of equity in December of year $t-1$. Size is market capitalization, i.e. price times shares outstanding, at the end of June of year t. All stocks are assigned to ten deciles for each characteristic using the break-points of the distribution of NYSE stocks. For each decile a portfolio return is computed between July of year t and June of year $t+1$ as the value-weighted return of the stocks in the decile. The excess returns (returns minus the one-month Treasury Bill rate) on these ten B/M and ten size portfolios are the main variables of interest in this paper. From now on, unless otherwise specified, when I refer to 'value stocks' I mean the tenth B/M decile, and by 'small stocks' I mean the first size decile.

Panel A of Table **??** provides some summary statistics for the portfolios. Notice the similarities between the small and value stocks portfolios in terms of means and standard deviations of returns, and the high negative correlation between the B/M and size decile assignments, especially in the first part of the sample. These two categories of stocks become more homogenous to the rest of the market in terms of mean and standard deviation

[1] I thank Ken French for providing me with the accounting data. The portfolio returns can be downloaded directly from his web-site.

of returns in the second part of the sample, when also the correlation between the decile assignment decreases in absolute value. This last fact is consistent with the results in Fama and French (2001), who show that a large part of newly listed firms tend to be small firms with the glamour characteristic.

2.2 The evolution of beta

The first graphical impression of the decrease in the estimated beta of value and small stocks can be obtained from Figures 1 and 2. The figures plot the series of estimates of beta for these two portfolios. The estimates come from rolling regressions, with five-year estimation windows and one-month increments. The sample goes from July 1926 to December 2000. The tenth B/M decile portfolio (Figure 1) displays drastic changes in beta that can be as high as 2.2 between July 1938 and June 1943, and as low as 0.55 between December 1995 and November 2000. Similarly, the beta of the first size decile portfolio (Figure 2) peaks at 2.5 between September 1939 and August 1944, and it touches the minimum at 0.65 between April 1991 and March 1996. For both portfolios, betas display an increase at the beginning of the sample, peaking in the early forties. Then the series experience a large decline until the beginning of the sixties, when for both portfolios beta drops below one, this decrease being more pronounced in the case of small stocks. In the sixties the two series rebound above one, being more or less stable through the beginning of the eighties, when they start dropping again. From the mid-eighties through all the nineties the betas stay below one. In spite of the short-term swings, the long-term picture that emerges is the decreasing trend that caused value and small stocks' estimated beta to decrease by 75% in about sixty years.

The magnitude of the standard errors of the betas is such that we can statistically rule out the equality of the estimates from different subsamples. For example, the 2.2 estimate of beta for value stocks in the 7/38-6/43 subsample has a standard error of 0.17, while the standard error for the 0.55 estimate from the 12/95-11/00 interval is 0.07. In the middle of the sample, namely in the first half of the sixties, when beta lingers around 1.2, the standard error is about 0.10. More generally, one can check if beta takes on statistically different values over time by performing tests of structural change. The results of these tests for the tenth B/M and first size decile portfolios (not reported) reject the equality of the betas over any subsample in which the total 1926-2000 sample can be split. Even in the shorter 1963-1991 sample, which is the one used by Fama and French (1993), the tests reject the equality of the betas between subsamples for many possible splits. The beta in the second subsample is significantly smaller than the one in the first subsample.

In order to compare the time behavior of the beta for the different B/M and size deciles, I regress (the log of) each beta series on a time trend. The results are reported in Table 1. The t-statistics are computed using Newey-West estimator of variance which corrects for the autocorrelation due to the use of overlapping windows in estimating beta. In the entire 1926-2000 sample, the trend for B/M portfolios (Panel A) is negative for deciles four through ten, and it decreases uniformly from the first to the tenth decile. The fact that beta increases for the lower deciles is the mirror image of the increase for the highest deciles, and it is consistent with the theoretical constraint that the value-weighted sum of the betas is one. The estimated trend in the beta of the tenth B/M decile portfolio is -0.1% per month (1.1% annually). In the case of size portfolios (Panel B) the trends are negative for all the deciles but the last one. The trend in the small stock portfolio is -0.08% per month (-0.9% annually).

One might wonder if the responsibility of the negative trend lies with the big drop that the betas experienced in the fifties. In fact, the trend in the beta estimates for the high B/M and low size deciles is still there, even when I let the estimation sample start in July 1963, which is the beginning of Fama and French's (1993) sample. From Table 1 one can see that trend coefficients for value and small stocks are actually larger in absolute value in the shorter samples. The trend in beta for the first size decile portfolio in the 1963-2000 sample is twice as much as in the overall sample.

Given the large correlation between the small and value characteristics reported in Table **??**, the question could rise whether the decrease in the betas is a small stock phenomenon. A first reply to this question can be the fact that the negative trend is actually larger for the tenth B/M decile portfolio than for the first size portfolio. The relevance of the value characteristic also appears from a double sort of stocks by size and B/M. Companies are assigned to five quintiles for each characteristic, and then twenty-five portfolios are formed from the intersection of the two sorts, like in Fama and French (1993). I perform the rolling regressions analysis on these twenty-five portfolios and obtain the series of beta estimates. The estimated trend (not reported) in the portfolio of big high B/M stocks (fifth size quintile and fifth B/M quintile) is still -0.1% per month (t-stat. = -6.54). Moreover, these stocks are on average bigger than the companies in other portfolios that are in lower B/M deciles, and for which the trend is positive. For example, the average size of the companies in this portfolio is over twenty times that of the stocks in the intersection of the second size and first B/M quintiles, for which the trend in the beta is instead 0.03% (t-stat. = 2.26). This evidence confirms that the value characteristic is relevant independently of size. I can infer that also the size characteristic matters by itself from the fact that the beta of the portfolio of small glamour stocks (first size and first B/M quintiles) has a significantly negative trend (-0.04%, t-stat. = -2.69)/footnoteI consider the effect on the observed trend in the market sensitivity of small and value stocks of the introduction of Fama and French's (1993) HML and SMB factors. As one might expect, the coefficient on the market factor is no longer decreasing over time for value and small stocks. In fact, this coefficient captures returns sensitivity to the component of the market that is orthogonal to HML and SMB, and these portfolios mimic the behavior of value and small stocks. Therefore, the trending behavior in the beta that is peculiar of these two categories of stocks is filtered out by the inclusion of HML and SMB..

2.3 A different perspective

A different way to look at the decline in beta is asking whether it is imputable to a decrease in the correlation of these portfolios with the rest of the market, or to a drop in their relative volatility. This analysis generates some additional evidence that any explanation of the decrease in beta will have to account for.

We can consider the market index as composed of two portfolios. Portfolio 1 is either the value or small stock portfolio, and portfolio 2 is the rest of the market.

$$R_m = w_1 R_1 + w_2 R_2, \tag{1}$$

where $w_1 + w_2 = 1$.

The beta of portfolio 1 can be written as

$$\begin{aligned} \beta_1 &= \frac{Cov(R_1, R_m)}{Var(R_m)} \\ &= \frac{Cov(R_1, w_1 R_1 + w_2 R_2)}{Var(w_1 R_1 + w_2 R_2)} \\ &= \frac{w_1 \sigma_1^2 + w_2 \sigma_{12}}{w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2 w_1 w_2 \sigma_{12}} \\ &= \frac{w_1 r + w_2 \rho}{w_1^2 r + w_2^2 \frac{1}{r} + 2 w_1 w_2 \rho}, \end{aligned} \tag{2}$$

where σ_i^2 is the variance of return i, σ_{12} is the covariance between R_1 and R_2, $r = \frac{\sigma_1}{\sigma_2}$ and ρ is the correlation coefficient between R_1 and R_2 [2].

The changes in beta are governed by the changes in its two components r and ρ. We can study the sign of the derivatives of beta with respect to these components:

$$\frac{\partial \beta_1}{\partial r} > 0, \qquad \frac{\partial \beta_1}{\partial \rho} > 0 \Leftrightarrow \frac{w_2}{w_1} > \frac{\sigma_1}{\sigma_2}$$

The size of both the value and small stock portfolios relative to the rest of the market is so small [3] that the condition for $\frac{\partial \beta_1}{\partial \rho} > 0$ is always respected.

[2] A more straightforward way of decomposing beta is:

$$\beta_1 = \rho_{1,m} \frac{\sigma_1}{\sigma_m},$$

where $\rho_{1,m}$ is the correlation coefficient between R_1 and the market return, σ_1 is the standard deviation of R_1, and σ_m is the standard deviation of the market return. This decomposition yields the same results as the one in the text. In particular, $\frac{\sigma_1}{\sigma_m}$ and $\rho_{1,m}$ track closely $\frac{\sigma_1}{\sigma_2}$ and ρ, respectively. The advantage of the decomposition in the text is that portfolio 2 does not contain stocks from portfolio 1, which makes the interpretation of the results unambiguous.

[3] The share of the tenth B/M decile portfolio is on average 2% of total market capitalization, and that of the first size decile is on average 1%.

Equation 1 implies that

$$w_1\beta_1 + w_2\beta_2 = 1$$

Therefore β_1 and β_2 mechanically move in opposite directions, if weights are constant.

Figure 3 graphs the estimated beta for the tenth B/M decile portfolio along with its two components: the ratio of the volatility of high B/M stocks (10th decile) to the volatility of the rest of the market (1st to 9th deciles), and the correlation coefficient between these two portfolios. The volatility is estimated as the standard deviation of the portfolio monthly excess returns over a five-year rolling window. Similarly, the correlation is the correlation coefficient between the returns of the two portfolios over five-year rolling windows.

It appears clearly from the figure that the driving force behind the movements in the betas is the ratio of the volatilities. This impression is confirmed by regressing (the log of) the ratio on a time trend. The coefficient is 0.08% per month, very close to the 0.1% of the betas in Table 1, while the estimated correlation decreases only by 0.01% per month, and this trend is largely driven by the drop in the nineties. From Figure 3 one can notice that the estimated volatility of value stocks was 2.6 times that of the rest of the market between August 1938 and July 1943, and it dropped to 0.7 times in the period between December 1995 and November 2000. A similar picture (not reported) describes small stocks' beta and its components.

One might be concerned that the change in the weights of the portfolios might affect the comparability of the series in Figure 3 with the decomposition in Equation (2). In fact, I obtain a similar plot when I use portfolios constructed to have constant weights throughout the sample.

To complete the picture one needs to describe the evolution of idiosyncratic risk for these portfolios. For both value and small stocks, idiosyncratic risk, computed as the estimated standard deviation of the residuals from rolling window CAPM regressions, follows broadly the path of market volatility, which is documented in Schwert (1989) and Campbell et al. (2001). Hence, idiosyncratic risk peaks in the years of the Great Depression and World War II, but then it drops drastically, without displaying any trending behavior. However, unlike market volatility, the idiosyncratic volatility of these portfolios is high in the first half of the nineties. The absence of a trend in portfolio idiosyncratic risk is not inconsistent with the finding in Campbell et al. (2001) that individual stocks have become more volatile. In fact their paper also finds that portfolio idiosyncratic volatility (in their case at industry level) is not trending.

From a market model, where portfolio return is broken into market risk and idiosyncratic risk, it follows that the variance of portfolio 1 can be expressed as

$$\sigma_1^2 = \beta^2 \sigma_m^2 + \sigma_{1,\varepsilon}^2, \tag{3}$$

where σ_m^2 is the variance of the market return, and $\sigma_{1,\varepsilon}^2$ is the idiosyncratic variance of portfolio 1. Since beta can be expressed as the product of the correlation coefficient between portfolio 1 and the market return ($\rho_{1,m}$) times the ratio of portfolio 1 standard deviation to market standard deviation (see footnote 2), Equation (3) can be rearranged to obtain

$$\frac{\sigma_{1,\varepsilon}^2}{\sigma_m^2} = \frac{\sigma_1^2}{\sigma_m^2}\left(1 - \rho_{1,m}\right). \tag{4}$$

Given that $\frac{\sigma_1}{\sigma_m}$, like $\frac{\sigma_1}{\sigma_2}$, is decreasing much more strongly than $\rho_{1,m}$, which in turn tracks closely ρ, it has to follow that idiosyncratic risk as a fraction of market volatility has decreased. The data confirm this prediction, and the evolution of the ratio of idiosyncratic volatility to market volatility follows closely the ratio of total portfolio volatility to the volatility of the rest of the market that is plotted in Figure 3 (thick solid line).

2.4 Robustness checks

The decrease in the estimated market beta of value and small stocks might be the artifact of portfolio formation procedures or, more generally, it can be a mechanical result with little economic content. In order to investigate this possibility I perform a number of robustness checks.

The share of value and small stocks' capitalization over total market size has changed over time. This could have caused the decrease in these portfolios' betas, by mechanically reducing their weight in the market. I construct a portfolio that includes the highest B/M stocks up to a certain share of market capitalization, which I keep constant over the entire sample. I try with a market share of 2%, which is the average market share of the tenth decile portfolios, and with other values as well (1%, 3%, 5%, and 10%). In all of these cases the beta of the resulting portfolio, estimated with the rolling regression methodology described above, displays a comparable decrease to the one for the original value portfolio. Similarly, I rank the stocks by size, and construct a portfolio of small stocks that has a constant share of market capitalization. For different market shares (0.1%, 1%, and 5%), the beta of this small stock portfolio is still decreasing.

Another change that occurred in the portfolio composition is the strong increase in the number of stocks included in the portfolios. There were 42 companies in the value portfolio in July 1926 (52 in the small stocks portfolio), while this number was 480 in December 2000 (the number is 2502 in the case of small stocks) [4]. The increased number of included stocks might have affected the portfolio beta if it was combined with some change in the shape of the cross-sectional distribution of betas. Hence, I form portfolios of high B/M and small stocks that have a constant number of stocks throughout the sample period. These portfolios continue to display a decline in their estimated betas, for all the number of stocks at which the composition is held fixed.

A related fact is the inclusion in the data set of Nasdaq stocks in 1973. This event was relevant especially for the small stock portfolio, since Nasdaq stocks were in general smaller than NYSE stocks. This inclusion could have affected the portfolio beta because the market index is heavily tilted towards NYSE stocks. However, when Nasdaq stocks are excluded from the portfolios, the trend in both the small stocks' beta and the value stocks' beta is unaffected.

Another objection that could be raised against the relevance of the fact under examination, is that the industry composition of the value and small stocks portfolios might have

[4] The reason why there are so many stocks in the lower size deciles is that size portfolios are formed using NYSE capitalization break-points, and many Nasdaq stocks are small compared to NYSE stocks.

changed over time in such a way that these portfolios are now composed of firms belonging to industries that bear less market risk. The first control that I perform is a within industry analysis. I construct the value and small stock portfolios using only stocks in one industry, and restrict the attention to industries that presumably did not experience major technological changes, so that I control for industry effects. For all the industries I consider (food, consumer products, clothing and oil), the betas of value and small stocks significantly decrease over time. An alternative control for industry effects consists of replacing the return of each stock in the portfolios with the return of the industry portfolio to which the stock belongs [5]. If the trend in beta is due to the B/M or size characteristics, as opposed to industry effects, we should expect that the beta of these new portfolios does not trend down. Consistent with this expectation, the resulting portfolios do not display the same decrease as the original value and small stock portfolios. In the case of value stocks, for example, the estimated trend in the portfolio constructed with industry returns is -0.03%, compared to the -0.10% of the original value portfolio. I interpret the fact that there is still some decrease in the betas of the new portfolios as due to the correlation between industries and the B/M characteristic.

The decrease in the market beta of value and small stocks could be the result of a decline in the leverage of these companies. Lower leverage should lead to a smaller beta. To assess whether this phenomenon is driving beta, Figure 4 plots the leverage series, defined as book value of debt over market value of equity, for the value stock portfolio and for the rest of the market [6]. The figure shows that, if anything, there was an increase in the leverage of value companies over time, so that leverage is not driving the decrease in beta. As leverage in the overall market is increasing, one might be concerned with the evolution of leverage for the portfolios of interest relative to the rest of the market. In fact, not even the ratio of value companies' leverage to the leverage of the rest of the market displays a decreasing

[5] I used the 17 industry portfolio classification that can be found on Ken French's web site.

[6] The accounting data come from the Compustat annual dataset and they start in 1950. Debt is defined as the sum of book value of current liabilities, long-term debt, convertible debt and preferred stocks. Portfolio leverage is computed as value weighted average of company leverage.

trend. Similar results rule out a leverage effect for small companies.

Other possible explanations of the observed decrease in the betas are linked to changes in the informational flows in the market. Lo and MacKinlay (1990) note that the positive autocorrelation of stock indices is mainly determined by cross-autocorrelations. In particular, large stocks tend to lead small stocks, possibly because of non-synchronous trading. As noted by Scholes and Williams (1977), if a stock is infrequently or non-synchronously traded, the standard estimate of beta is not representative of its true sensitivity to the market. Hence, it is possible that changes in the pattern of non-synchronous trading for small and value stocks determined the decrease in their beta. In order to control for this possibility, I compute a corrected version of the sensitivity to the market as the sum of the beta on the lagged monthly return and the standard beta (as suggested by Scholes and Williams, 1977). This correction does not affect the size of the estimated negative trend in the value and small stock portfolios' market sensitivity.

More generally, every explanation that relates to changes in the informational structure in the market should have different implications at different frequencies of the data. In low frequency data information has had more time to reveal itself than in higher frequency data. Hence, if the decrease in the beta is related to some informational story, it should be less pronounced at lower frequencies. Using quarterly and annual overlapping data, and extending the estimation window to ten years in order to have enough data points, does not seem to give different results from the ones obtained with monthly data. For values stocks, with all three data types the estimated beta drops from about two to below one. Similarly, for small stocks the beta drops as much with annual and quarterly data as with monthly data.

In summary, the drop in beta does not seem to depend on mechanical explanations relating to portfolio formation procedure, nor does it depend on changes in leverage over time. Moreover, changes in the patterns of non-synchronous trading do not seem to be relevant.

The next section, which relates the decrease in beta to macroeconomic conditions, is, I believe, the most convincing reply to most doubts that still linger about the economic relevance of the decline in beta of value and small stocks.

3 Relating beta to macroeconomic conditions

3.1 Time-varying betas and conditioning information

Several studies have produced evidence of time-varying betas for single stocks and for portfolios (e.g., Ferson and Harvey, 1991, Ferson and Korajczyk, 1995, Braun, Nelson, and Sunier, 1995). Shanken (1990) models the time variation of conditional betas as a linear function of predetermined state variables. Later studies apply this approach to testing multi-factor pricing models (Ferson and Korajczyk, 1995, Ferson and Harvey, 1999, Lewellen, 1999), and mutual fund performance evaluation (Ferson and Schadt, 1996).

In the context of this paper, modeling conditional betas as a function of state variables can help identify the macroeconomic factors, if any, that are driving the decrease in the beta of value and small stocks.

The rationale to believe that some economic state variables are related to the decrease in betas is that the value and small characteristics supposedly denote companies that are in a condition of relative distress [7]. Hence, it is reasonable to believe that changing macroeconomic conditions affect the severity of this condition of distress, and consequently the riskiness of these stocks's payoffs, as summarized by their market beta.

Suppose the following conditional one-factor model describes the excess portfolio return $R_{i,t+1}$

$$R_{i,t+1} = \alpha_i + \beta_{i,t} R_{m,t+1} + \varepsilon_{i,t+1}, \tag{5}$$

where $R_{m,t+1}$ is the market excess return, and $E_t(\varepsilon_{t+1}) = E_t(\varepsilon_{t+1} R_{m,t+1}) = 0$, which implies that the unconditional expectations of the same expressions are also zero.

[7] Chan and Chen (1991) show that small firms are more likely to have higher leverage, lower Returns-On-Equity, and have cut dividends in the recent past.

Following Shanken (1990), portfolio's betas are assumed to be a linear function of a vector of k state variables z_t

$$\beta_{i,t} = b_{0,i} + b'_{1,i} z_t + \eta_{i,t}. \tag{6}$$

While not imposing any constraint on the process of the market factor, the assumption that conditional betas depend linearly on some lagged variables allows the second moments of the conditional distribution of portfolio and market returns to change over time in a simple way. The variables used to predict conditional betas are public information, and summarize the state of the macroeconomy.

Using Equation (6) to replace for $\beta_{i,t+1}$, Equation (5) can be rewritten as

$$R_{i,t+1} = \alpha_i + b_{0,i} R_{m,t+1} + (b'_{1,i} z_t) R_{m,t+1} + \eta_{i,t} R_{m,t+1} + \varepsilon_{i,t+1}. \tag{7}$$

Providing that $\eta_{i,t}$ is regressively independent of all the information at time t, the sum $\eta_{i,t} R_{m,t+1} + \varepsilon_{i,t+1}$ can be considered as an orthogonal error term u_{t+1}, and the regression in Equation (7) yields consistent estimates.

The estimates of b_0 and b_1 from the time-series regression in Equation (7) allow us to obtain a fitted value for $\beta_{i,t}$

$$\widehat{\beta}_{i,t} = \widehat{b}_{0,i} + \widehat{b}'_{1,i} z_t, \tag{8}$$

which gives the benchmark series to which compare the observed decrease in the estimated betas of value and small stocks.

3.2 Empirical implementation

The state variables that I use in the analysis are the ones that in previous studies proved to be good predictors for expected returns and betas. They are: (1) the dividend yield on the S&P Composite Index (see, e.g., Fama and French, 1988, Ferson and Harvey, 1999); (2) the one-month T-bill rate (see, e.g., Shanken, 1990); (3) the growth rate of industrial production, computed as the first difference in the logarithm of the monthly seasonally adjusted index of industrial production provided by the Federal Reserve Board (see, e.g., Campbell and Mei, 1993); (4) the term spread defined as the end-of-month difference between the yield on Aaa corporate bonds and the annualized one-month T-bill rate (see, e.g., Fama and French, 1989, Ferson and Harvey, 1999); (5) the default spread, defined as the end-of-month difference between the yields on Baa and Aaa corporate bonds (see, e.g., Fama and French, 1989, Ferson and Harvey, 1999).

Panel B of Table **??** provides summary statistics for the state variables. Figures 5 and 6 graph them, along with NBER business cycle dates.

Fama and French (1989) give a thorough discussion of the cyclical behavior of the state variables. Here I summarize the main points. The default spread, although showing some negative correlation with the business cycle, displays major swings that go beyond the economic cycle (Figure 5). The spread is high during the thirties and the early years of World War II, a period characterized by major economic uncertainty. In the rest of the sample it is lower except for some blips in the periods of recession during the seventies and early eighties. A similar behavior characterizes the dividend yield (Figure 5), which is highly correlated with the default spread. What is peculiar about the dividend yield is the drop that occurred during the bull market of the second half of the nineties. The T-bill rate gravitates around zero in the 1933-1951 period that covers much of the Great Depression and the period after World War II, when the Fed fixed T-bill rates. Outside that interval the T-bill rate comes close to defining the business peaks and troughs identified by the NBER (Figure 6). Since the Aaa yield does not track the business cycle as closely as the T-bill rate, the term spread, except for the 1933-1951 period, follows more closely the business cycle (Figure 6) [8]. It is low at peaks, predicting recessions, and high at troughs, predicting recoveries. Finally, the growth rate of industrial production is strongly mean-reverting, so that high growth rates are soon followed by negative growth.

The estimation of the regression in Equation (7) for B/M and size portfolios produces estimates of b_0 and b_1 that can be replaced in Equation (8) along with the series of the state

[8] The T-bill series and the term series in Figure 6 appear to have different volatility. This is a result of using different scales for the two series. In reality they move together, being the term spread mainly driven by the T-bill rate component.

variables to fit the path of these stocks' beta. Figure 7 graphs the fitted beta for value stocks, along with the series resulting from the rolling regressions estimation. The fitted series in the graph has been constructed using two sets of estimates of b_0 and b_1 coming from the 1926-1962 and the 1963-2000 subsamples. The series of the estimated beta is aligned with the end date of the five-year estimation window. The tracking ability of the fitted beta (solid line) is striking. The estimated beta series appears smoother than the fitted series, because the effect of one month of data is not relevant over a five-year estimation horizon. However, the fitted beta follows closely all the main swings in the estimated beta. The correlation coefficient between the estimated and the fitted series is 0.84. The reader may be concerned that this high level of correlation is affected by a 'spurious regression' type of problem. To tackle this concern, I perform a test of unit root on the difference between the two series. In other words, I test whether the estimated and fitted beta are cointegrated with a (1 -1) cointegration vector. If the high correlation is spurious, the test should detect a unit root in the difference. In fact the correlation is authentic, as a Dickey-Fuller test on the difference in the two series produces a test statistic of -7.2, which rejects the null hypothesis of unit root at the 1% confidence level [9]. The picture is very similar if b_0 and b_1 are estimated over the whole 1926-2000 sample. The correlation is 0.78, and again the two series are cointegrated at the 1% confidence level.

Figure 8 plots the estimated and fitted beta series for small stocks. Although the fitted series does not track so closely the estimated one as in the case of value stocks, still it captures the major drop in the beta that occurred in the twenty years between the 1940 and 1960. The correlation coefficient is in this case 0.63, suggesting that perhaps some relevant state variable has been left out from the information set.

Table **??** reports the coefficients from the estimation of Equation (7) in the case of B/M portfolios. Looking at the column for the tenth decile, we notice that in the whole 1926-2000 sample (Panel A) the risk free interest rate has the highest predictive ability: a one-standard

[9]Notice that the Dickey-Fuller test does not reject the null hypothesis that the estimated beta series has a unit root

deviation increase (0.25%) in the monthly T-bill rate would cause a decrease of about 0.25 in the conditional beta. This coefficient decreases in absolute value as we move towards lower B/M deciles, consistent with the theoretical constraint that the weighted sum of the b_1 coefficients is zero (while the weighted sum of the b_0 coefficients is one). The default spread and the dividend yield have a similar predictive power for the conditional beta of value stocks: an increase in both variables causes the conditional beta to go up. For example, an increase of one percentage point in the annualized default spread causes the beta of the tenth decile portfolio to rise by 0.1. In the whole sample the term spread is generally not significant, while the growth rate of industrial production is significantly positively related to conditional betas only for the higher deciles.

The analysis by subsamples (Panels B and C of Table **??**) helps to further clarify the effect of each conditioning variable. As far as the tenth B/M decile portfolio is concerned, the default spread and the dividend yield take turns in explaining the conditional beta. The first variable is significant only between 1926 and 1962, while the second one is significant only between 1963 and 2000. The T-bill rate is always negative and significant, although more so in the first subsample. The term spread is significant with a negative coefficient in both subsamples. The impact of the growth rate of industrial production on the conditional beta changes from positive to negative. In general, as we move towards lower B/M deciles the predictive power of the state variables drops, suggesting that it is correct to focus the attention on the changes that affected value stocks.

The regression results for small stocks (first size portfolio in Table **??**) are similar to the case of value stocks. However, the predictive power of the state variables tends to drop in the second subsample. This fact is in line with the reduced tracking ability of the fitted series in Figure 8. Nevertheless, the major drop in small stocks' beta occurs before 1960, and that is mostly captured by the state variables.

Finally, other state variables turn out to be significant predictors of beta for both B/M and size portfolios. They have not been used for the plots in Figures 7 and 8, because their inclusion would have increased the high frequency volatility of the fitted series, and decreased its ability to track the smooth estimated series. The most important of these variables are the lagged excess market return and the volatility of the T-bill rate, constructed like in Shanken (1990). A positive market return predicts an increase in the beta of value and small stocks, whereas the effect of interest rate volatility is positive in the first subsample and negative in the second one. The purpose of my analysis was tracking the long run trend in the estimated beta series, but if the goal is predicting the future evolution of beta, then one may want to include these instruments, which capture the high frequency movements in the series of interest.

3.3 Discussion

As mentioned above, the connection between variables that summarize the state of the macroeconomy and the beta of value and small stocks can be drawn because these companies are more likely to be in a situation of relative distress. The likelihood with which they actually are in distress can reasonably depend on the general state of the economy. Hence, their riskiness, as summarized by the market beta, can vary as a function of the business cycle and the general economic conditions.

In more detail, one can think of a model where distressed firms approach default, or move away from it, depending on the evolution of economic conditions. When a company is closer to the earnings cutoff point below which it defaults, the firm's payoff distribution can become more volatile, and so can its stock returns. Then, this model can yield the prediction that the beta of distressed firms decreases when economic conditions improve, and vice versa.

The relationship between the macro variables and the beta of value and small stocks, that was found in the previous subsection, seems to be in line with this model. Notice that the improvement in business conditions that I refer to, can take place both along the business cycle, and over the long run. In the first case the model describes the high frequency variation in beta. In the second case, the result is the long-term decrease in beta that is the main focus of the paper.

Fama and French (1989) interpret the power of the dividend yield and the default spread to predict increases in the expected return of stocks and bonds as related to the long-term evolution of business risk. These two variables track some components of expected returns that are high during periods like the Great Depression when business is persistently poor, and low otherwise. Consistent with their interpretation, I find that the measure of riskiness of some companies that are a priori believed to be more exposed to changes in business conditions, their beta, follows closely the evolution of these two variables. In particular, the decrease in the default spread and the dividend yield that occurred after the war explains a large part of the decline in beta in that period. Similarly, the drop in the dividend yield in the late nineties is responsible for the plunge in beta over those years.

The term spread tracks more closely the business cycle. It is low at the top of the expansion, and high at the end of a recession. I find that an increase in the lagged term premium predicts a decrease in the beta of value and small stocks. This result is in line with the above interpretation, because a high term premium predicts a recovery from a recession, from which distressed firms should benefit. The significance of the term spread in the subsamples, and not in the whole period, suggests that this variable captures the high frequency variation of beta, rather than the long run trend.

The interest rate is highly pro-cyclical. However, like the default spread and the dividend yield, it also tracks the long-term changes in business conditions that occurred starting from the early fifties. Therefore, its relevance as a predictor of beta is due to both its long-term swings and its cyclical movements. This fact is confirmed by the significance of the T-bill rate in whole sample and in the subsamples.

The reason behind the predictive power of the growth rate of industrial production is more dubious since its coefficient changes from positive to negative. The positive coefficient, that prevails when the estimation is performed on the whole sample, would suggest that due to the strong mean reversion of growth, a positive growth rate predicts a worsening of economic conditions in the future.

The interpretation of the relation of these macro variables to the decline in beta that is proposed here is also consistent with the evidence from the beta decomposition in Section 2.3.

The general improvement of macroeconomic conditions can have made these stocks, normally prone to distress, less risky, and their volatility smaller relative to the volatility of the rest of the market.

The above analysis suggests a relation between a conditional CAPM approach and the Fama-French three-factor model. The explanation of the link between these macroeconomic variables and the beta of value and small stocks involves changes in the sensitivity to the overall discount factor. The effect of these changes shows up in the beta of these companies because they are presumably more sensitive to business conditions. If this is the case, the loading on the market factor seems to capture some of the risk sources, like distress risk, that Fama and French (1993) use to justify the introduction of additional factors in the pricing model. Consequently, a conditional CAPM can be more appropriate than a three-factor model in pricing portfolios other than value and small stocks, for which the HML and SMB factors are bound to perform well.

Notice that the argument in favor of a conditional pricing model is consistent with the results in Lettau and Ludvigson (2001). Similar to the evidence in my paper, they find that the correlation value stocks' returns with fundamental factors increases when risk or risk aversion is high. This situation in turn occurs when economic conditions are poor, as signalled by their *cay* state variable.

Finally, it has to be acknowledged that the behavior of value stocks' beta in the second half of the nineties lends itself to a different interpretation from the one proposed so far. The drop in beta that occurs in that period is entirely driven by the decline in the dividend yield, which in turn depends on the surge of the price level during the bull market of the nineties. If a speculative bubble was behind that price increase, then the explanation for the decline in beta cannot hinge on the evolution of the stochastic discount factor. Hence, one may want to invoke a style investing argument (Barberis and Shleifer, 2001). In such a scenario, beta could have dropped because the returns of value and glamour stocks have become delinked, as a result of flows of funds moving from one style of investment to the other. The investigation of this explanation is left for future research.

4 A decomposition of market betas

4.1 Theoretical framework

If the interpretation of the link found in Section 3 between beta and the conditioning variables is correct, the decrease in the beta of value and small stocks should be associated with a reduction in the sensitivity of these companies' cashflows to the factors that cause movements in the market. The reason behind this prediction is that, according to the above interpretation, an improvement in the distress condition of these companies makes their cashflows less volatile in response to shocks. I use Campbell and Mei's (1993) beta decomposition to address this issue.

Campbell and Shiller's (1988) log-linearized present value relationship allows one to express unexpected excess returns, or excess return innovations, in terms of news about dividends, news about excess returns and news about real interest rates. Following Campbell (1991), $e_{i,t+1}$ is the (continuously compounded) excess return on portfolio i over the (continuously compounded) real return $r_{i,t+1}$ on a one-month T-bill, and $d_{i,t+1}$ is the (log) real dividend. Then, portfolio i's unexpected excess return $\tilde{e}_{i,t+1}$ can be expressed as

$$\begin{aligned} \tilde{e}_{i,t+1} &\simeq (E_{t+1} - E_t) \left\{ \sum_{j=0}^{\infty} \rho^j \Delta d_{i,t+1+j} - \sum_{j=0}^{\infty} \rho^j r_{t+1+j} - \sum_{j=1}^{\infty} \rho^j e_{i,t+1+j} \right\} \\ &= \tilde{e}_{di,t+1} - \tilde{e}_{r,t+1} - \tilde{e}_{ei,t+1}. \end{aligned} \tag{9}$$

The notation $(E_{t+1} - E_t)$ indicates a revision in the conditional expectation between times t and $t+1$. The constant ρ comes from the linearization process, and can be interpreted as a discount factor. The value of ρ is assumed to be the same for all portfolios [10]. The second equality in (9) introduces simpler notation for dividend news $\tilde{e}_{di,t+1}$, real interest rate news $\tilde{e}_{r,t+1}$ and excess return news $\tilde{e}_{ei,t+1}$.

[10] I refer to the Appendix in Campbell (1991) for the derivation of Equation (9) and to Campbell and Shiller (1988) for a discussion of its approximation accuracy. It turns out that $\rho = \frac{1}{1+e^{d-p}}$, where $d-p$ is set to the average log dividend price ratio. Campbell and Mei (1993) argue that the assumption of a unique value of ρ across all portfolios does not affect the results for plausible variations in ρ.

Equation (9) follows from an approximation of a present value identity after ruling out explosive behavior of stock prices, and can be thought of as a consistency condition for expectations. It simply states that, if unexpected returns are high today, then either there has been an upward revision in the expectation of future dividends, or a downward revision in the returns that the stock is expected to pay in the future, or both. The effect of future real returns is similar to that of future excess returns.

The Appendix describes in detail how to obtain each component of the return innovations. Briefly, the expected return on each portfolio is assumed to be a linear function of a vector of predetermined state variables, one of which is the real interest rate. The residuals in these predictive regressions represent the return innovations. The state variables are assumed to follow a VAR process. It is therefore possible to compute the revision in the expectation of every future value of the state variables, and take the discounted sum of these terms, which, combined with the parameters in the predictive regression, gives the expected return news component of returns. The real interest news component is also obtained from the parameters of the VAR. The cashflow news component is obtained residually using Equation (9) and the other two components.

As far as the cross-sectional aspects of the analysis are concerned, Campbell and Mei (1993) define a portfolio beta using unconditional variances and covariances of portfolio and market innovations. That is, beta is the unconditional covariance of the excess return innovation $\tilde{e}_i$ with the market innovation $\tilde{e}_m$, divided by the unconditional variance of the market innovation

$$\beta_{i,m} \equiv \frac{Cov(\tilde{e}_i, \tilde{e}_m)}{Var(\tilde{e}_m)}. \tag{10}$$

This beta is neither an unconditional beta (which would use returns themselves rather than innovations) nor a conditional beta (which would use conditional moments). However, it would coincide with a conditional beta if the conditional variance-covariance matrix of innovations had constant elements, or at least elements that changed in proportion to one another.

The definition in (10) has the advantage that the portfolio beta can be expressed as the sum of the market betas of the three news components. From Equations (9) and (10), it follows directly that

$$\begin{aligned}\beta_{i,m} &= \frac{Cov(\tilde{e}_{di}, \tilde{e}_m)}{Var(\tilde{e}_m)} - \frac{Cov(\tilde{e}_r, \tilde{e}_m)}{Var(\tilde{e}_m)} - \frac{Cov(\tilde{e}_{ei}, \tilde{e}_m)}{Var(\tilde{e}_m)} \\ &= \beta_{di,m} - \beta_{r,m} - \beta_{ei,m}, \end{aligned} \tag{11}$$

where $\beta_{di,m}$ is the market beta of news about portfolio i's cashflows, $\beta_{r,m}$ is the market beta of news about future real interest rates, and $\beta_{ei,m}$ is the market beta of news about portfolio i's future excess returns.

The assumption behind this analysis is that the vector of state variables represents entirely investors' information set. If this was not the case, the estimated dividend component of returns would contain a reaction to changes in expected returns, which would undermine the interpretation of the results.

4.2 Empirical Implementation

The first step in implementing the beta decomposition developed in Section 4.1 is to estimate the return components. To this purpose one needs to estimate the VAR system (19), along with the predictive regressions in (18), and to replace the estimated parameters in the expressions given in (21).

The VAR and the predictive regressions are estimated using OLS on each equation. In this case, where all the equations have the same right-hand-side variables, the estimates coincide with the ones obtained with a GMM procedure. Then, I combine the sample variances and covariances of the estimated return components to obtain the betas.

The purpose of this analysis is to find out the source of the observed decrease in market beta for value and small stock portfolios. Thus, I insert the beta decomposition methodology into the rolling regression framework that I adopted to document the fact under consideration. The use of annual data allows the state variables to have considerably higher predictive power in both the VAR equations and the portfolio predictive regressions. This finding is consistent, for example, with the results in Fama (1990), who argues that the predictive variables contain information that pertains to several months of return data, creating an error in variable problem that is attenuated in annual data.

However, the use of annual data reduces the number of available data points and this creates a problem for the convergence of the estimated parameters. Therefore, I construct the annual data from monthly data, so that two consecutive observations have a three quarter overlap. Each annual observation spans the period up to the end of a quarter. Moreover, I use twenty-five-year estimation windows, so that each regression is estimated using one-hundred overlapping annual data points. The estimation window advances by one data point at a time, which means that one quarter of new data is added to the right of the sample, and one quarter is lost on the left.

At this point a caveat is necessary. The Campbell and Mei (1993) procedure makes an implicit stationarity assumption. The parameters of the VAR, as well as the variance-covariance structure of the portfolio returns are assumed to be constant, not only throughout the estimation period, but, as far as the VAR is concerned, over an infinite horizon. The facts that beta changes over time, and that the estimated parameters of the VAR are not constant, might cast some doubt on the validity of the analysis. However, the assumption of a constant beta can be considered as a descriptive shortcut to look at the average beta over the estimation window, as it was the case in Section 2, when the rolling window procedure was first introduced. Moreover, the instability of the VAR should not considerably affect the results as long as the VAR coefficients vary at low frequencies, because in that case discounting should reduce the importance of the terms of the present value formulas that are distant in the future.

The returns of interest are the continuously compounded returns on B/M and size portfolios, from July 1926 to December 2000. For the definition of the vector of state variables I follow the previous literature. As said before, the first two variables have to be the market return and the real interest rate. Therefore I use the return on the CRSP value-weighted index, and the continuously compounded return on the one-month T-bill, deflated by the change in the (log of the) CPI index. Campbell and Mei (1993) also include the aggregate dividend yield, the inflation rate, and the growth rate of industrial production, defined in Section 3. I use the dividend yield on the S&P Composite Index, which turns out to have slightly more predictive power than the one constructed from the NYSE universe. The inflation rate is the change in the log of the CPI index. In addition to these variables I include the term spread, which is defined as in Section 3 (Table **??** provides summary statistics for portfolio returns and the state variables). For this sample, consistent with previous studies, a reasonable value for ρ is 0.96 in annual data and 0.9962 in monthly data.

I can provide some evidence on the increased predictive power allowed by the use of annual data rather than monthly data. In my sample the average R^2 over the ten predictive regressions for B/M portfolios in the whole 1926-2000 period is only 1.7% with monthly data (892 observations per regression). Instead it is considerably higher, 10.6%, with overlapping annual data (291 observations per regression).

The evidence on the sources of the decrease in beta comes from both a split of the main sample into two major subsamples, and a rolling regression analysis.

The analysis by subsamples is presented in Table 2 for B/M portfolios. Each beta estimate and the corresponding standard error have been obtained from OLS regressions of the appropriate return component on the market innovation.

In Panel A the estimation period coincides with the entire 1926-2000 sample. The plausible values of market betas in the first row testify that using innovations to define betas, as opposed to returns themselves, does not significantly affect the results. The betas of high decile portfolios (value stocks) are in general higher than those of low B/M deciles. This ranking differs from what reported in previous studies, such as Fama and French (1993), because my sample starts much earlier, in a time when value stocks used to have higher betas. The ranking in the overall betas seems to be determined entirely by the market sensitivity of the excess return news component $\beta_{ie,m}$, which, especially for value stocks, is the most sizeable part.

In Panel B the sample covers the 1926-1962 period. The spread in the betas of value over the beta of glamour stocks is even more pronounced than the one in the overall sample.

Again, the responsibility of the difference in the overall beta lies with the excess return betas, rather than the cashflow betas.

The results in Panel C (1963-2000 sample), where the ranking in the overall betas is inverted with respect to Panels A and B, reflect the empirical fact that has inspired this paper. The beta of value stocks has decreased considerably over the years, while the opposite happened for glamour stocks [11]. From the comparison of Panels B and C it is clear that the source of the decrease in the overall beta of value stocks is the decrease in $\beta_{id,m}$, namely the cashflow beta. The rolling regression analysis will make it even more clear that the reduction in cashflow beta plays the dominant role. The beta of real interest rates, which was not significant in Panels A and B, becomes negative and highly significant in Panel C.

In order to further define the source of the decreasing trend in the value stock beta, I now turn to the rolling regression analysis. A first graphic impression of the results is provided by Figure 9, that graphs the evolution of the estimated beta of the tenth decile, along with its cashflow component and the negative of its excess return component. It is evident from the picture that the responsibility of the decreasing trend in the overall beta lies with the cashflow beta, which drops from 1.11 in the twenty-five-year estimation window ending in June 1961, to -0.65 in the window ending in December 1995. The excess return beta does not seem to have any apparent trend. This impression is confirmed by the statistical tests that follow.

To quantify the evolution of the different beta components, I fit a trend line through each of the beta series obtained from the rolling regressions. The results are reported in Table **??**, Panel A. As said above, I use overlapping annual data, and the estimation window advances by one quarter per observation, so that the trend coefficients measure the change in the beta per quarter. The t-statistics are computed using Newey-West estimator of variance which corrects for the autocorrelation due to the use of overlapping windows in estimating beta. Equation (11) implies that the trend in $\beta_{id,m}$, minus the trend in $\beta_{ie,m}$, minus the trend in

[11]For market betas of innovations, as for normal betas, it holds that the weighted average of the population betas of the different partitions of the market (e.g., B/M or size portfolios) is equal to one.

$\beta_{r,m}$ (-0.001), equals the trend in the overall market $\beta_{i,m}$. The trend line is negatively sloped for the highest B/M deciles, and the slope gradually becomes positive as we approach the portfolios of glamour stocks.

Table **??** provides detailed evidence on the sources of the decrease in the overall betas. The cashflow betas of all portfolios trend down, and this effect is stronger for values stocks [12]. However, in the case of glamour stocks this trend does not affect the overall betas, given that the negative estimates of $\beta_{ie,m}$ become progressively bigger in absolute value. Instead, in the case of value stocks the negative trend in the cashflow beta is much stronger (-0.007 per quarter for decile ten), and it is not counterbalanced by a decrease in the excess return beta. Hence, I can conclude that the decrease in cashflow beta is the source of the observed decrease in the overall beta.

The fact that the results presented in this section hinge on the cashflow news component, which is estimated residually, might raise some concerns, which would be justified in case the VAR process was misspecified. To tackle this issue, I follow Campbell and Mei (1993) and form a direct measure of cashflow news by regressing annual log real dividend growth on the state variables, and using the VAR process for the state variables to form revisions in expectations of future dividends (details in the Appendix). Then, I can compute the cashflow beta series in the usual way, and fit a trend line through the series of estimates. The results, not reported, confirm the picture presented above. If anything, the decreasing trend in the cashflow beta for the value stock portfolio is stronger (-0.012, with t-stat. = -3.36). Hence, the use of residual cashflow news does not seem to affect the significance of the evidence presented in this section.

The picture for size portfolios largely resembles that for B/M portfolios, and small stocks play the role of value stocks. Over the entire sample the major drop in the overall beta is again imputable to a drop in the cashflow beta. However, after the beginning of the eighties the high frequency movements in the overall beta depend on the decrease in the excess return

[12]Notice that the beta components do not have to satisfy the constraint of adding to one across portfolios. Therefore it is possible that the cashflow betas of all portfolios decrease over time.

beta.

Table 3 confirms the decline in the beta of small stocks and the corresponding increase in the beta of large stocks. The market beta of the first decile portfolio, for example, is 1.60 between 1926 and 1962, and it drops to 1.36 in the 1963-2000 subsample.

The big drop in $\beta_{ie,m}$ that appears from the table, is not indicative of the global source of decrease in the overall beta, because it is affected by the last years of data. In fact Figure 10 shows that β_{ie} becomes very small in absolute value only around the end of the sample. Instead, the graph indicates that over the entire 1926-2000 period the drop in the cashflow beta is the main source of the decline in the market sensitivity of small stocks. Moreover, it is also evident from Figure 10 that after the beginning of the eighties the overall beta follows the path of $\beta_{ie,m}$, which declines in absolute value.

The analysis of the linear trends in the estimates from the rolling regressions procedure confirms that the source of the drop in the overall beta of small stocks is the decrease in the cashflow beta. Panel B of Table **??** shows that the overall beta of decile one portfolio, for example, has a linear trend of -0.005, which is entirely imputable to the -0.008 trend in $\beta_{id,m}$. Notice, however, that if the trend is computed using only the betas whose estimation window ends after January 1980, then the -0.004 (t-stat. = -10.96) trend in the overall beta depends on the decrease in the absolute value of the excess return beta (trend in $\beta_{ie,m}$ equal to 0.010, with t-stat. = 8.64). The use of direct, rather than residual, cashflow news, in the way described above, confirms entirely the results presented so far.

So, as in the case of value portfolios, the evidence suggests that the observed instability in the overall market betas of small stocks can be imputed to changes in the sensitivity of cashflow news to market returns.

Overall, the evidence from the beta decomposition is consistent with the conclusions from Section 3, which used conditional information to track the evolution of beta. That analysis suggested that the decrease in the beta occurred because the general improvement in the economic conditions has made the activities of these companies less risky. This section showed that, indeed, the decrease in the beta is imputable to the fact that the cashflows of these firms are less sensitive to market news.

5 Relation to mispricing

The previous sections have established that the beta of value and small stocks has experienced a major decline over the past sixty years. A question that arises naturally is how this fact relates to the debate surrounding the failure of the CAPM to price correctly these categories of stocks.

Figure 11 plots the beta and the intercept (i.e. the alpha) from time-series CAPM regressions for value stocks [13]. A one-tailed t-tests rejects the hypothesis that the intercept is equal to zero at 5% level in most of the estimation windows from the early seventies to the mid-nineties. It is evident from the picture that the occurrence of mispricing starting from the seventies goes side by side with the decrease in beta. Alpha started to rise in the early sixties, when beta was experiencing a major drop, and its growth is always accompanied by a decline in beta. The correlation between the two series is about -50%. The graph for small stocks (not reported) also shows that alpha rises when beta declines, although for this portfolio the mispricing disappears in the late eighties.

The decrease in beta can be related to mispricing in at least two ways. First, if the correct pricing model is a conditional CAPM, and the estimated model is an unconditional CAPM, the premium estimated by the econometrician contains a bias due to correlated omitted variables. Secondly, the drastic changes in beta can have caused investors to formulate the wrong expectations on the riskiness of these stocks. The next subsections examine these two explanations.

[13] The series are produced using rolling regressions with a ten-year estimation window. I extended the estimation window from five to ten years to obtain smoother series, and to have more power in the t-tests on the intercept.

5.1 The omitted variable bias

The time-series tests of the CAPM, like the ones in Fama and French (1993), which rely on the significance of the intercept to decide if the market value-weighted portfolio is on the mean-variance efficient frontier, fail to incorporate the time variation in beta. So, for example, Fama and French (1993, Table 9a) find that the portfolio of small high B/M stocks has a monthly premium of 0.54% (t-stat. = 2.53) in the 1963-1991 sample.

However, even if the CAPM holds conditionally, it does not necessarily hold unconditionally. For it to be the case the relevant moments of the joint conditional distribution of returns would have to be constant over time, or change proportionally. The evidence of a decreasing beta does not depose in favor of this possibility. In fact, the analysis of Section 3 showed that beta can be closely tracked by a number of state variables summarizing the state of the economy. Hence, there are reasons to believe that part of the premium found for these categories of stocks in the time-series tests can be explained by time variation in beta, in the form of a correlated omitted variable bias.

Suppose one estimates the following unconditional CAPM regression

$$R_{i,t+1} = \alpha_i + \beta_i R_{m,t+1} + u_{i,t+1}, \tag{12}$$

but the correct model is a conditional CAPM

$$E_t R_{i,t+1} = \beta_{i,t} E_t R_{m,t+1}, \tag{13}$$

where the conditional beta is a linear function of some state variables, as in Equation (6). Then, solely because of the omission of the time variation in beta from the unconditional regression, the estimated intercept turns out to be different from zero. In particular, the probability limit of $\widehat{\alpha}_i$ is

$$\text{Plim } \widehat{\alpha}_i = b'_{1,i}(E\widetilde{z} - \gamma E R_m), \tag{14}$$

where $\widetilde{z} = z_t R_{m,t+1}$, and γ is the linear projection coefficient of $\widetilde{z}_t$ on the market return $R_{m,t+1}$. So, when beta is a non-trivial function of the state variables, and the term in parenthesis is also not zero [14], part of the premium in the time-series unconditional CAPM regressions can be explained on the basis of Equation (14).

From Panel C of Tables **??** and **??** it appears that the tenth B/M portfolio and the first size portfolios are those that in the 1963-2000 subsample have the highest absolute values of the coefficients in the vector $b_{1,i}$. This fact makes it more likely for the estimated intercept from an unconditional CAPM regression to be different from zero, as it can be seen from Equation (14).

In order to assess what part of the premium of value and small stocks is accounted for by the omission of the time variation in beta, one can compute the sample equivalent of the expression in Equation (14) and compare it with the intercept from the regression in Equation (12). An equivalent, and more simple, way to do that is estimating Equation (7), and comparing the intercept from that regression with the intercept from the unconditional regression in Equation (12). In the case of value stocks, about 30% of the 0.44% monthly premium in the 1963-2000 sample can be accounted for when beta is allowed to vary. For small stocks this share is 66%, but the premium in the 1963-2000 sample is just 0.10%, and it is not significant. In shorter samples, like the 1963-1980 one, this procedure does not seem to account for any sizeable part of the premium to small stocks.

Besides shedding some light on the sources of the value premium, the results from this analysis suggest that the conditional version of the CAPM should be preferred to the unconditional one in most applications. The time variation in portfolio betas and the ability to track it with state variables, which have been documented in this paper, make the stationarity assumption behind the unconditional CAPM not realistic.

5.2 Exaggerated perception of risk

Daniel and Titman (1997) argue that characteristics, as opposed to covariation with risk factors, generate the observed premium of small and value stocks. In their view, the market

[14]Notice that the term in parentheses in Equation (14) is trivially zero if the state variables are constant over time. It is also zero if the market return is independent of the state variables.

dislikes these categories of stocks, so that a premium is required for investors to hold them. This negative attitude towards small and value stocks might depend on the fact that investors overestimated their systematic risk. As more powerful computing resources become publicly available, these anomalies should disappear. The size effect actually disappeared in the early 80's, as well as the B/M effect in the late nineties.

Consistent with this argument, I argue that the large decline that the beta of value and small stocks experienced starting from the early forties can be the reason why investors made mistakes in the assessment of risk. The observation that these assets used to bear a great deal of market risk in the years of the Great Depression and World War II can have convinced investors that the value and small characteristics were associated with higher risk. Consequently, these stocks had to pay a premium, even when the amount of systematic risk they were bearing had declined.

Suppose the return that the market expects in the next period for the portfolios of interest is based on the unconditional CAPM

$$ER_{i,t+1} = \beta_i^e ER_{m,t+1}, \tag{15}$$

where β_i^e is the expectation of beta. This assumption implies that the probability limit of the estimated intercept in a time-series unconditional CAPM regression is

$$\alpha_i = (\beta_i^e - \beta_i) ER_{m,t+1}. \tag{16}$$

To keep things simple, suppose for now that the expectation of beta is identically equal to the value of beta estimated from all past return realizations. More complicated setups in which the market learns from the path of realized betas will be discussed later.

From Equation (16) it is evident that whenever the expectation of beta exceeds the true beta, the portfolio pays a premium relative to the CAPM, and the estimate of alpha from the time-series regression tends to a positive value. Hence, in the case of value and small stocks, the decreasing path of estimated betas and the assumption of adaptive expectations can actually explain part of the premium.

To implement the model empirically, I split the sample of realized returns in two subsamples, from 1926 to 1962 and from 1963 to 2000. The second subsample more or less coincides with the time period when the CAPM was known to financial markets. Further, I assume that the market expected return for the portfolio of interest in the second subsample is formed according to Equation (15), and the expectation of beta is equal to the estimate of beta from the first subsample. Finally, I assume that these expectations are not revised until the end of the second subsample. Although these assumptions are obviously unrealistic, they capture the idea that the high level of market risk born by value and small stocks in the years of the Great Depression and World War II affected the market expectations of how risky these stocks would be later on.

By replacing sample estimates in Equation (16), I can compute the fraction of the estimated intercept in the CAPM regression in the 1963-2000 subsample that is explained by the model above. For value stocks the intercept is 0.44% (t-stat. = 2.9) between January 1963 and December 2000, while beta is 1.64 in the first subsample, and 0.97 in the second subsample. The product of the difference in these betas and the mean excess market return between 1963 and 2000 (0.52% monthly) is equal to 0.35%, which is the sample equivalent of the expression in Equation (16). Hence, under these assumptions, the misperception of the riskiness of value stocks can have caused about 80% of the premium that they paid in the 1963-2000 subsample.

Small stocks did not have much of a premium in the whole 1963-2000 subsample (only 0.10%). Therefore, the above method would imply an intercept that is almost three times as big as the actual intercept. Instead, when I restrict the second subsample to end in 1980, which was approximately when the size effect disappeared, the estimated premium is 0.59% (t-stat. = 2.1). Beta in the 1926-1962 subsample is 1.65, and in the 1963-1980 subsample is 1.29, while in the same period the mean monthly market excess return is 0.34%. Hence, misperception of risk, as defined above, generates a 0.12% monthly premium, which is about 20% of the realized premium for small stocks.

More complicated setups than the one described above can be thought, where the market revises its adaptive expectations on the basis of realized returns. Suppose, for example, that investors form their expectations of beta by combining the corresponding expectation in the previous period and the last estimate of beta, as in the following equation

$$\beta_t^e = \delta\widehat{\beta}_t + (1-\delta)\beta_{t-1}^e, \tag{17}$$

where β_t^e is the beta expected to apply to time $t+1$, $\widehat{\beta}_t$ is the estimated beta at time t, and δ is a weighting coefficient.

To make this model operational, I insert it in a ten-year rolling regression framework, starting from 1963. So, $\widehat{\beta}_t$ corresponds to the estimate of beta in the last ten-year window. In some estimation windows the mean value of the market excess return is negative and I cannot use it as an estimate of the market premium, because it would be inconsistent with CAPM. Hence, I estimate $E_t R_{m,t+1}$ using the mean excess market return from the beginning of month $t+1$ to December 2000. The estimates obtained with this procedure are consistently positive. So, for each window I can compute an estimate of the α in Equation (16) using the expectation of beta from Equation (17), the estimate of beta in the window, and the estimate of the market excess return. I calibrate δ to minimize the sum of the squared differences between the estimates of α and the estimated intercepts in the CAPM rolling-regressions. Finally, I set the initial condition for β_t^e to equal the estimate of beta in the 1926-1962 subsample.

When this model is applied to the value portfolio, the optimal δ is around 0.002. This small number is consistent with the idea that one additional month of data is not very informative about beta. The distribution of the share of the premia in the CAPM rolling regressions explained by the estimates of α has mean equal to 104%, median equal to 70%, maximum equal to 487%, minimum equal to 32%, and standard deviation equal to 94%.

Again in the case of small stocks I restrict the sample to the years up to 1980. Further, I consider only the estimation windows for which the intercept in the CAPM regressions is positive, namely the ones in which there is actually a premium. The optimal value of δ is then 0.06. For these windows, the distribution of the share of the premia that is explained by the estimate of α has mean equal to 75%, median equal to 66%, maximum equal to 331%, minimum equal to 22%, and standard deviation equal to 54%.

Notice that these exercises do not account for the effect on returns of the revision in the expectation of future discount rates. Investors' realization that beta is lower than they thought causes a positive surprise in returns, because future payoffs are discounted at a lower rate. To the extent that these surprises are correlated across periods, this effect shows up as a positive premium in the CAPM regression. Therefore, the distributions of premia that were computed above represent a lower bound on the premia that can be generated under the assumption that investors slowly learn about beta. A non-arbitrary assessment of the impact of the revision in discount rates on the premium can be provided within an equilibrium model of learning on beta, which is developed in Adrian and Franzoni (2002).

Although the assumptions underlying the above models are certainly restrictive, the results presented in this subsection suggest that misperception of risk based on the higher values of beta characterizing value and small stocks in the early years of the sample can play a big role in explaining the premia of these portfolios. This hypothesis is pursued in further research (Adrian and Franzoni, 2002), which develops a formal models of learning on beta, and assesses the relevance of the decrease in beta for the estimated premium of value and small stocks.

6 Conclusions

This paper found a striking decrease in the market beta for portfolios of value and small stocks. In the course of sixty years the beta of each of these portfolios decreased by about 75%. The maximum estimated beta for value stocks was 2.2 in the early forties, and the minimum was 0.55 in the late nineties. The situation for small stocks evolved similarly.

The fact that the path of beta can be closely tracked using state variables that are related to business conditions, such as the nominal interest rate, the default spread, the term spread, the dividend yield, and the growth rate of industrial production, suggested the interpretation that a change occurred in the structure of these companies' cashflows. According to this argument, the improvement of business conditions reduced payoff uncertainty for all firms, and especially for value and small companies, which are believed to be more prone to distress, and therefore more sensitive to the status of the economy. Support for this intuition came from the result that the source of the decrease in the beta is the decline in the sensitivity of cashflow news to market news. This interpretation generates the out-of-sample prediction that we should observe a rise in the beta of these portfolios in conjunction we the recent economic downturn and the interest rate cuts.

This evidence is relevant for the debate on the premium to value and small stocks in the CAPM regressions. The amount of market risk born by these stocks went down contemporaneously to the appearance of the premium. The paper found some evidence that a part of the premium, which can be as high as 80% for value stocks, originates from investor beliefs that a high level of market risk would characterize these stocks even when, due to the decrease in beta, this was no longer the case. This argument is in line with some behavioral explanations of the anomaly (e.g., Daniel and Titman, 1997) that suggest that the market may have misperceived the riskiness of these portfolios.

Finally, the paper provided further evidence in favor of the adoption of a conditional version of the CAPM in place of the unconditional one. The sizeable changes in the beta of these portfolios, the close relationship between these changes and the evolution of some state variable, the ability to explain 30% of the value premium once the time variation of beta is taken into account, are all elements that motivate a model that lets beta depend on some conditioning information.

These findings can have applications in the areas of portfolio selection and performance evaluation. Mutual funds that adopt value or small cap strategies should know that the amount of market risk born by their portfolios is subject to variation over time. For example, the fund manager should expect value and small stock portfolios to become more risky during recessions. The good news is that this evolution can be predicted on the basis of information that is easily available, and using a simple linear relationship. Also, when evaluating performance of mutual fund managers, one needs to take into account the fact that the manager can predict changes in the portfolio beta, especially for these categories of stocks. Hence, the manager should not be rewarded for portfolio returns that can be anticipated using conditioning information. Ferson and Schadt (1996) develop this idea by assessing what part of mutual fund performance is imputable to changes in beta that were predictable using a conditional CAPM.

Further research should extend different aspects of this paper. The interpretation of the link between beta and the state variables was not tested directly, and it was not supported by some economic model. Possibly, one should look into the evolution of the accounting and financial figures of the companies in the portfolios of interest, and assess whether they conform with the change-in-distress interpretation that was provided in the paper. Preliminary evidence suggests that a measure of distress, such as the ratio of interest expenses to operating income, is not only higher in the case of value and small companies, but it is also more positively related to recessions. Moreover, the gap between the level of this ratio for the companies of interest and for the rest of the market has been shrinking, consistent with the negative trend in the beta.

Another promising direction of research concerns the implications of the decrease in beta for the misperception of the riskiness of these stocks, and the premium that they pay. More sophisticated models of learning on beta than the ones used in the paper can be developed to fit these data. In order to feature a slow learning process, necessary to generate the premium, these models can either assume that investors learn about the default risk of these stocks from infrequent events like recessions, or they can be founded on some psychological bias in probability assessment and expectation formation.

A Obtaining the news components of returns

This Appendix describes how the different components of excess return innovations in Equation (9) are obtained. In this I follow, with some minor modifications, Campbell and Mei (1993), who assume that expectations of portfolio excess returns are linear in a vector x_t of state variables $x_{t,l}$, $l = 1, ..., L$, which represent investor information set. The first element of this vector is the excess return on the market, and the second one is the real return on a one-month T-bill, while the other elements are variables known at the end of period t. Thus, the excess return on portfolio i can be written as

$$e_{i,t+1} = a_i' x_t + \tilde{e}_{i,t+1} \tag{18}$$

for some portfolio specific L-element column vector of coefficients. The expected return on the portfolio is thus $a_i' x_t$, while the unexpected return is $\tilde{e}_{i,t+1} = e_{i,t+1} - a_i' x_t$.

Next it is assumed that the state vector follows a first-order VAR process

$$x_{t+1} = \Pi x_t + \tilde{x}_{t+1}, \tag{19}$$

where the $\tilde{x}_{t+1}$ denotes the innovation in the state variables. The assumption of a first-order VAR is not restrictive since a higher-order VAR can always be rewritten in first-order form (see, e.g., Campbell and Shiller, 1988). The $L \times L$ matrix Π is known as the companion matrix of the VAR. Given the VAR model, revisions in long-horizon expectations of x_{t+1} are

$$(E_{t+1} - E_t) x_{t+1+j} = \Pi^j \tilde{x}_{t+1}. \tag{20}$$

Further, I define the L-elements vectors ι_1 and ι_2 to have a one in first and second position, respectively, and zeros in all other positions. These vectors pick the excess return on the market and the real interest rate out of the VAR. Thus, Equation (20) and the definitions of $\tilde{e}_{di,t+1}$ and $\tilde{e}_{ei,t+1}$ in (9) imply that the components of portfolio i return and of the market return can be written as follows

$$
\begin{aligned}
\tilde{e}_{ei,t+1} &= \rho a_i'(I-\rho\Pi)^{-1}\tilde{x}_{t+1}, \\
\tilde{e}_{r,t+1} &= \iota_2'(I-\rho\Pi)^{-1}\tilde{x}_{t+1}, \\
\tilde{e}_{di,t+1} &= \tilde{e}_{i,t+1} + (\iota_2' + \rho a_i')(I-\rho\Pi)^{-1}\tilde{x}_{t+1}, \\
\tilde{e}_{em,t+1} &= \rho\iota_1'\Pi(I-\rho\Pi)^{-1}\tilde{x}_{t+1}, \\
\tilde{e}_{dm,t+1} &= \tilde{e}_{m,t+1} + (\iota_2' + \rho\iota_1'\Pi)(I-\rho\Pi)^{-1}\tilde{x}_{t+1}. \qquad (21)
\end{aligned}
$$

The discounted sum of the revisions in expectations for the vector of state variables at $t+1$ is $(I-\rho\Pi)^{-1}\tilde{x}_{t+1}$, where I is the $L \times L$ identity matrix. This term is translated into revisions of forecast portfolio returns through the vector a_i, which links the state variables to expected returns. Finally, the revision in expected cashflows is determined residually from Equation (9).

The cashflow news component can also be computed directly under the assumption that the state variables predict dividends as well. In particular, if c is the vector of regression coefficients of dividend growth on the state variables, and μ_{t+1} are the residuals from this regression, the direct cashflow news is

$$\widetilde{e}_{id,t+1} = \mu_{t+1} + \rho c'(I-\rho\Pi)^{-1}\widetilde{x}_{t+1}. \qquad (22)$$

Panel B: State Variables								
	Mean	Std. Dev.	ρ_1	ρ_2	ρ_3	ρ_4	ρ_{12}	ρ_{24}
T-bill	.31	.25	.97	.95	.94	.93	.87	.78
Div. Yield	.042	.015	.98	.96	.93	.91	.73	.56
Growth I.P.	.003	.019	.53	.24	.08	-.02	-.15	-.11
Term spr.	2.11	1.36	.84	.77	.74	.69	.47	.21
Default spr.	1.13	.73	.97	.94	.91	.90	.75	.55

Panel C: Correlation matrix of State Variables					
	T-bill	Term	Def.	DY	Gr. I.P.
T-bill	1				
Term	-0.39	1			
Def.	-0.07	0.41	1		
DY	-0.29	0.09	0.56	1	
Gr. I.P.	-0.07	0.05	-0.11	-0.11	1

Table 1: Linear trends in the estimated betas. The table reports OLS estimates from the model $\log \beta_t = \gamma_0 + \gamma_1 trend_t + \varepsilon_t$. The variable β_t is the series of estimates from five-year rolling regressions in which the dependent variable is the portfolio monthly excess return, and the independent variable is the market excess return. The variable $trend_t$ is a time trend. The estimation sample refers to the window over which betas are estimated. The data are at monthly frequency, and the first month is July in both the the 1926-2000 and the 1963-2000 samples. The T-statistic (in paretheses) is computed using the Newey-West estimator with 59 lags of autocorrelation.

Decile	1	2	3	4	5	6	7	8	9	10
Panel A: B/M Portfolios										
Sample: 1926-2000										
$\gamma_1(\times 100)$	0.029	0.015	0.023	-0.009	-0.006	-0.034	-0.056	-0.068	-0.091	-0.103
	(5.67)	(3.15)	(4.55)	(-1.10)	(-0.76)	(-4.45)	(-6.23)	(-8.71)	(-7.02)	(-7.58)
Sample: 1963-2000										
$\gamma_1(\times 100)$	0.034	0.004	0.027	-0.004	0.010	0.003	-0.022	-0.067	-0.092	-0.130
	(3.56)	(0.46)	(1.52)	(-0.27)	(0.64)	(0.24)	(-1.16)	(-4.66)	(-3.11)	(-4.11)
Panel B: Size Portfolios										
Sample: 1926-2000										
$\gamma_1(\times 100)$	-0.086	-0.048	-0.030	-0.020	-0.023	-0.022	-0.018	-0.006	-0.010	0.003
	(-6.10)	(-3.83)	(-3.27)	(-2.13)	(-2.57)	(-3.26)	(-2.72)	(-1.59)	(-1.86)	(1.04)
Sample: 1963-2000										
$\gamma_1(\times 100)$	-0.166	-0.093	-0.076	-0.067	-0.037	-0.048	-0.046	-0.022	0.007	0.032
	(-8.47)	(-5.93)	(-4.99)	(-4.48)	(-3.17)	(-3.73)	(-7.65)	(-3.06)	(0.83)	(8.64)

Table 2: Beta decomposition (B/M portfolios). Estimates from the following decomposition of beta for B/M decile portfolios: $\beta_{i,m} = \beta_{di,m} - \beta_{r,m} - \beta_{ei,m}$. $\beta_{i,m}$ is the portfolio beta computed using portfolio and market excess return innovations. $\beta_{id,m}$ is the dividend news component of beta. $\beta_{ie,m}$ is the expected return news component of beta. $\beta_{r,m}$ is the real interest rate news component of beta. T-statistics in parentheses.

Decile	1	4	7	10
	Panel A: 1926-2000			
$\beta_{i,m}$	1.04	1.06	1.10	1.29
	(52.06)	(55.72)	(40.61)	(27.93)
$\beta_{id,m}$	0.56	0.17	0.18	-0.10
	(21.21)	(4.36)	(4.01)	(-1.27)
$\beta_{ie,m}$	-0.49	-0.89	-0.93	-1.39
	(-17.17)	(-17.68)	(-19.63)	(-20.69)
$\beta_{r,m}$	0.01			
	(0.39)			
	Panel B: 1926-1962			
$\beta_{i,m}$	0.95	1.14	1.20	1.44
	(46.14)	(51.50)	(33.93)	(22.65)
$\beta_{id,m}$	0.37	0.57	0.43	0.21
	(8.00)	(15.17)	(7.59)	(2.13)
$\beta_{ie,m}$	-0.64	-0.63	-0.83	-1.28
	(-10.61)	(-10.38)	(-12.33)	(-13.89)
$\beta_{r,m}$	0.06			
	(1.74)			
	Panel C: 1963-2000			
$\beta_{i,m}$	1.15	0.98	0.89	0.85
	(27.50)	(27.35)	(20.29)	(14.38)
$\beta_{id,m}$	1.15	-0.80	-0.32	-0.92
	(12.59)	(-6.98)	(-4.10)	(-7.46)
$\beta_{ie,m}$	0.28	-1.50	-0.94	-1.49
	(3.47)	(-14.81)	(-18.15)	(-16.81)
$\beta_{r,m}$	-0.28			
	(-16.68)			

Table 3: Beta decomposition (Size portfolios). Estimates from the following decomposition of beta for Size decile portfolios: $\beta_{i,m} = \beta_{di,m} - \beta_{r,m} - \beta_{ei,m}$. $\beta_{i,m}$ is the portfolio beta computed using portfolio and market excess return innovations. $\beta_{id,m}$ is the dividend news component of beta. $\beta_{ie,m}$ is the expected return news component of beta. $\beta_{r,m}$ is the real interest rate news component of beta. T-statistics in parentheses.

Decile	1	4	7	10
	Panel A: 1926-2000			
$\beta_{i,m}$	1.50	1.23	1.14	0.94
	(29.05)	(44.07)	(64.74)	(105.13)
$\beta_{id,m}$	0.26	0.14	0.23	0.40
	(3.47)	(2.59)	(5.94)	(18.47)
$\beta_{ie,m}$	-1.25	-1.10	-0.92	-0.55
	(-20.25)	(-20.20)	(-20.30)	(-17.61)
$\beta_{r,m}$	0.01			
	(0.39)			
	Panel B: 1926-1962			
$\beta_{i,m}$	1.60	1.27	1.14	0.93
	(23.69)	(39.67)	(54.18)	(136.41)
$\beta_{id,m}$	0.48	0.45	0.41	0.45
	(4.57)	(6.96)	(8.12)	(13.69)
$\beta_{ie,m}$	-1.18	-0.88	-0.80	-0.54
	(-12.59)	(-12.39)	(-12.60)	(-10.32)
$\beta_{r,m}$	0.06			
	(1.74)			
	Panel C: 1963-2000			
$\beta_{i,m}$	1.36	1.23	1.14	0.93
	(15.09)	(22.58)	(34.31)	(44.62)
$\beta_{id,m}$	0.39	-0.33	0.06	0.08
	(3.48)	(-2.89)	(0.94)	(2.69)
$\beta_{ie,m}$	-0.69	-1.28	-0.80	-0.57
	(-18.44)	(-17.22)	(-26.07)	(-31.46)
$\beta_{r,m}$	-0.28			
	(-16.68)			

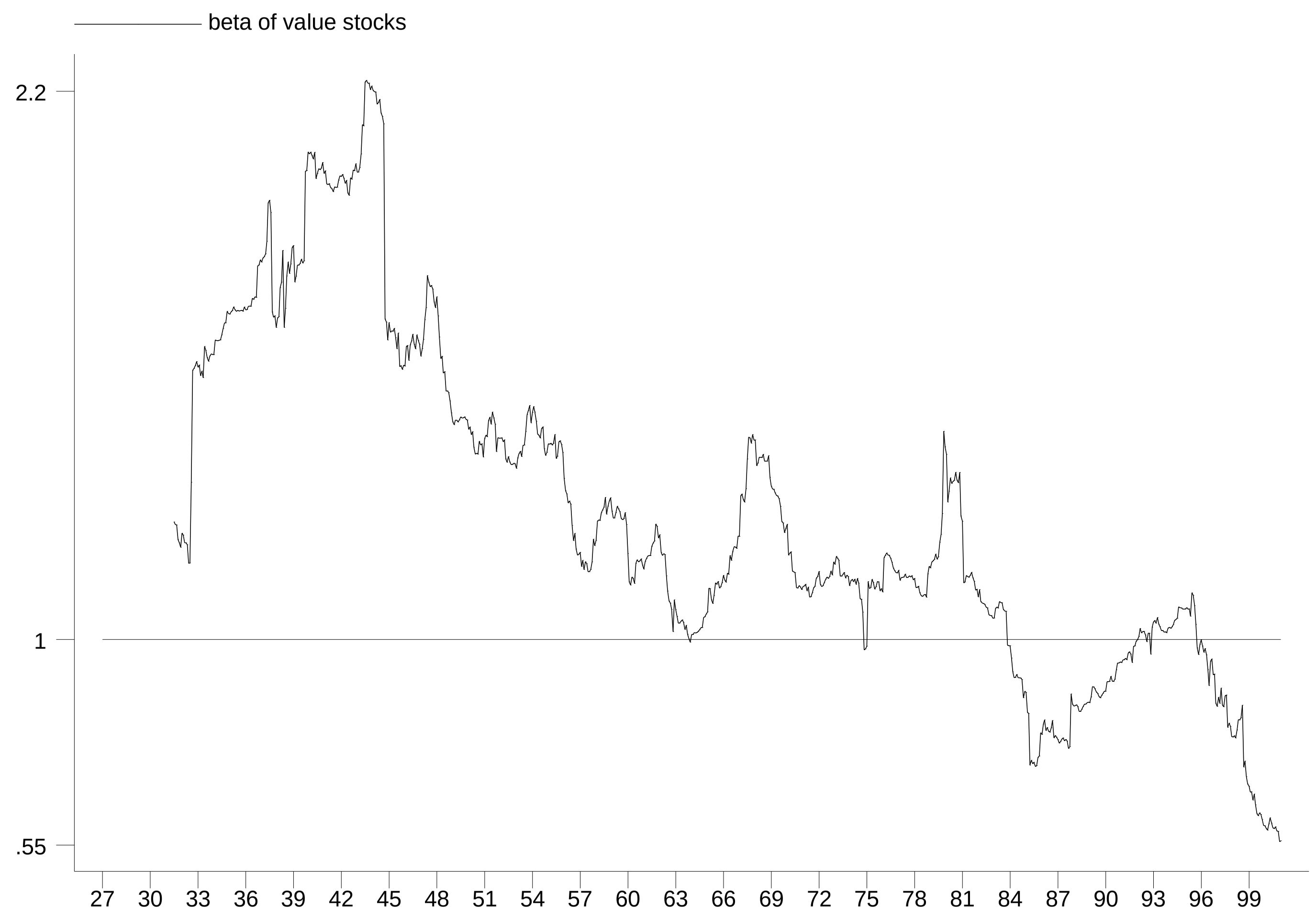

Figure 1: Beta of value stocks. The figure plots the estimates from 5-year rolling window regressions. The series originates from time-series regressions where the dependent variable is the the return on B/M decile 10 portfolio, and the independent variable is the excess return on the market value-weighted portfolio.

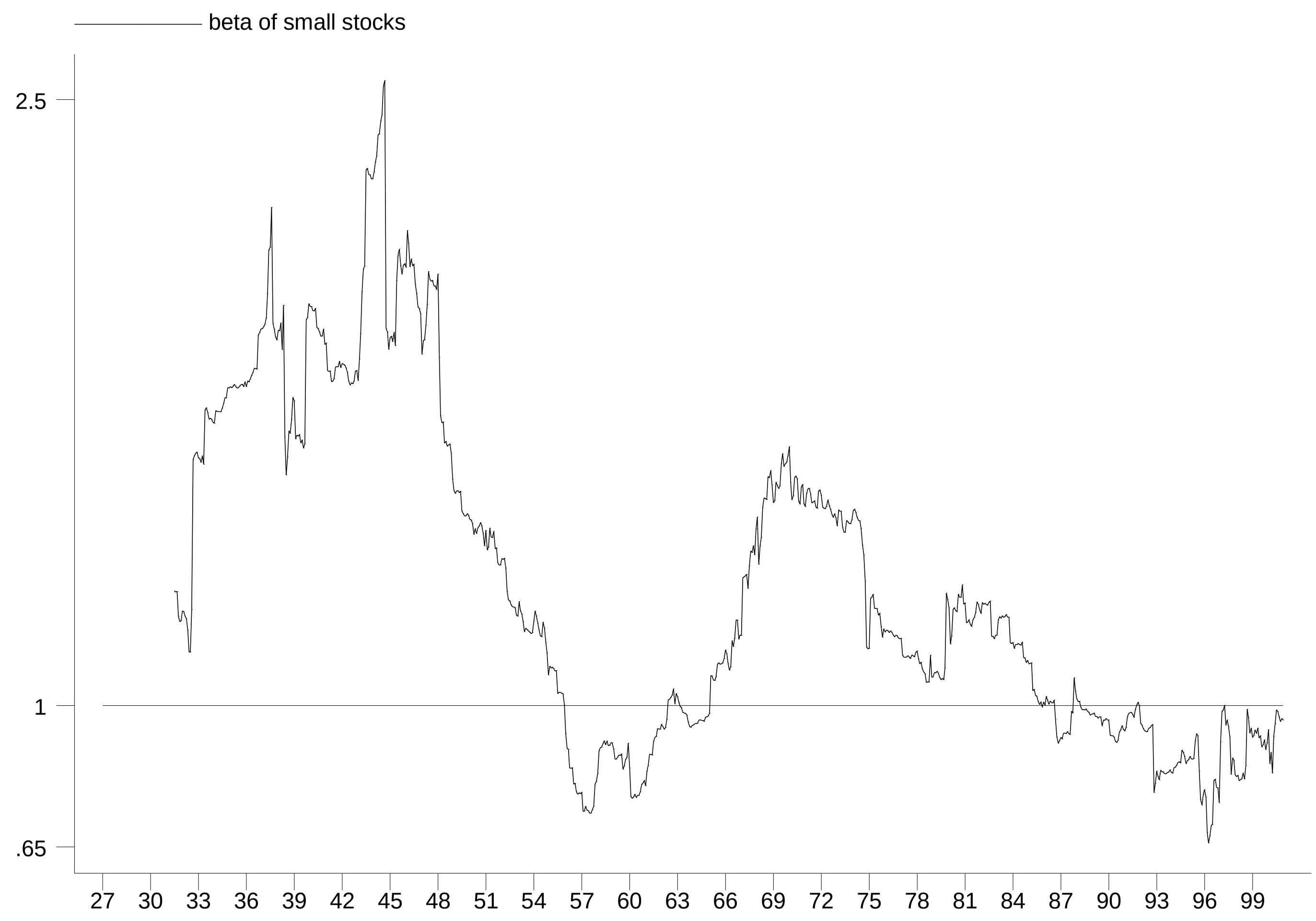

Figure 2: Beta of small stocks. The figure plots the estimates from 5-year rolling window regressions. The series originates from regressions where the dependent variable is the return on size decile 1 portfolio, and the independent variable is the excess return on the market value-weighted portfolio.

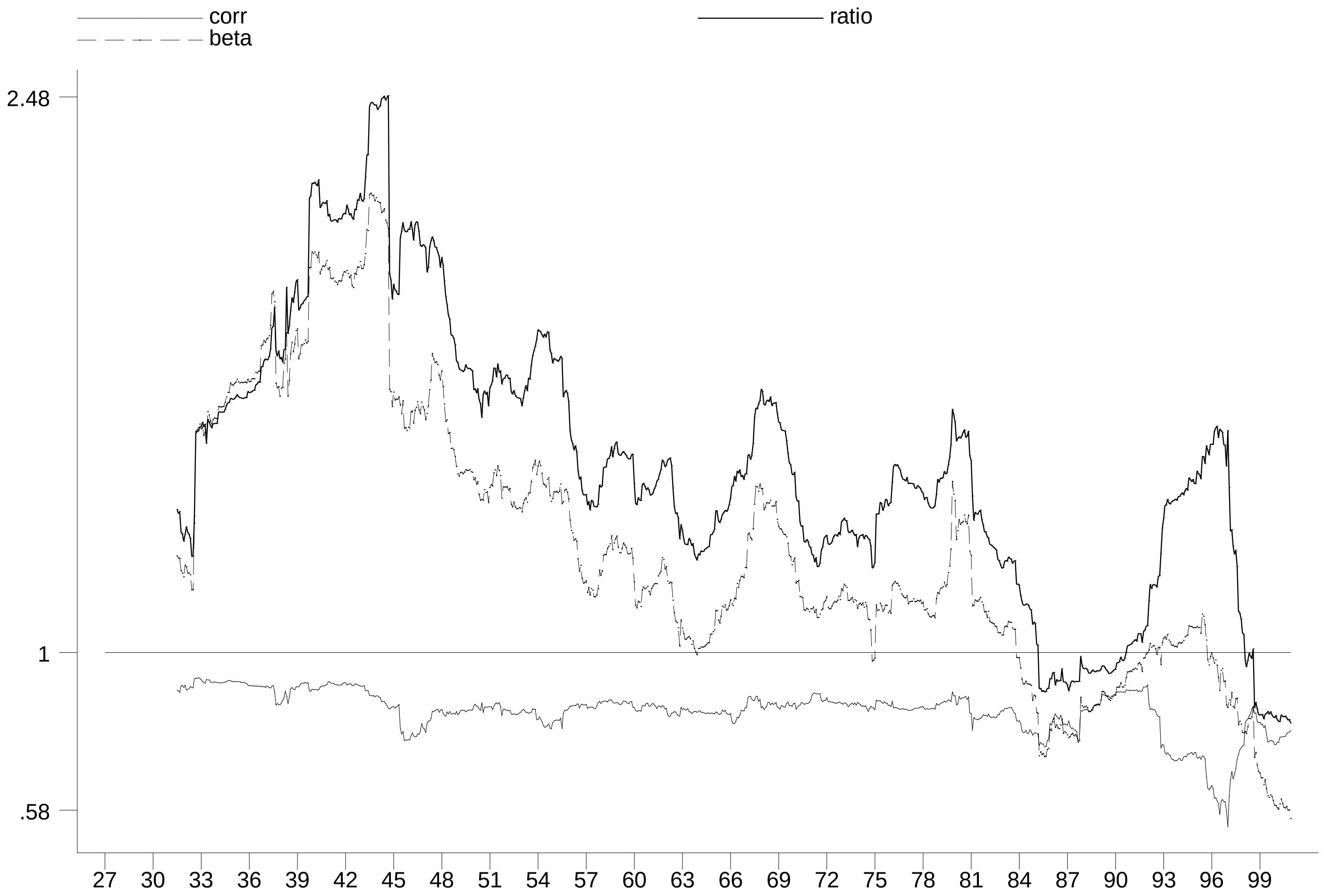

Figure 3: Decomposition of the beta of value stocks. The figure plots series of estimates from 5-year rolling window regressions. The series *beta* (dashed line) originates from CAPM time-series regressions where the dependent variable is the the return on B/M decile 10 portfolio. The series *corr* (thinner solid line) consists of correlation coefficient between the decile 10 portfolio return and the return on the rest of the market in the estimation window. The series *ratio* (thicker solid line) consists of the ratio of the standard deviation of the the decile 10 portfolio return to the standard deviation of the return on the rest of the market in the estimation window.

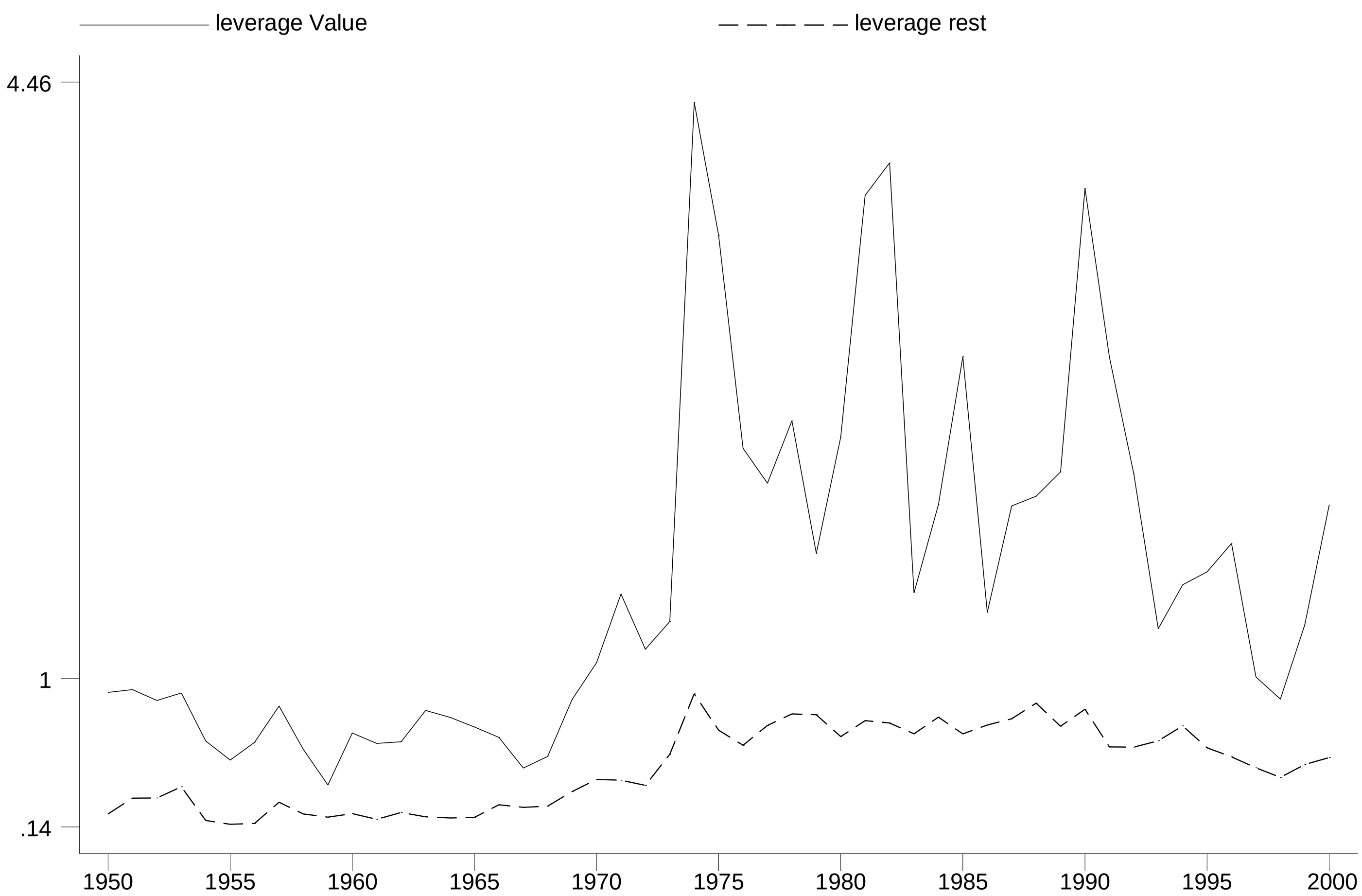

Figure 4: Leverage of value companies and the rest of the market. The figure plots the leverage series for the tenth B/M decile (solid line) and for the rest of the market (dashed line). For each company leverage is defined as the ratio of book value of debt to market value of equity. Portfolio average is the value weighted average of company leverage. Debt is defined as the sum of book value of current liabilities, long-term debt, convertible debt and preferred stocks. Accounting data is from the Compustat annual dataset.

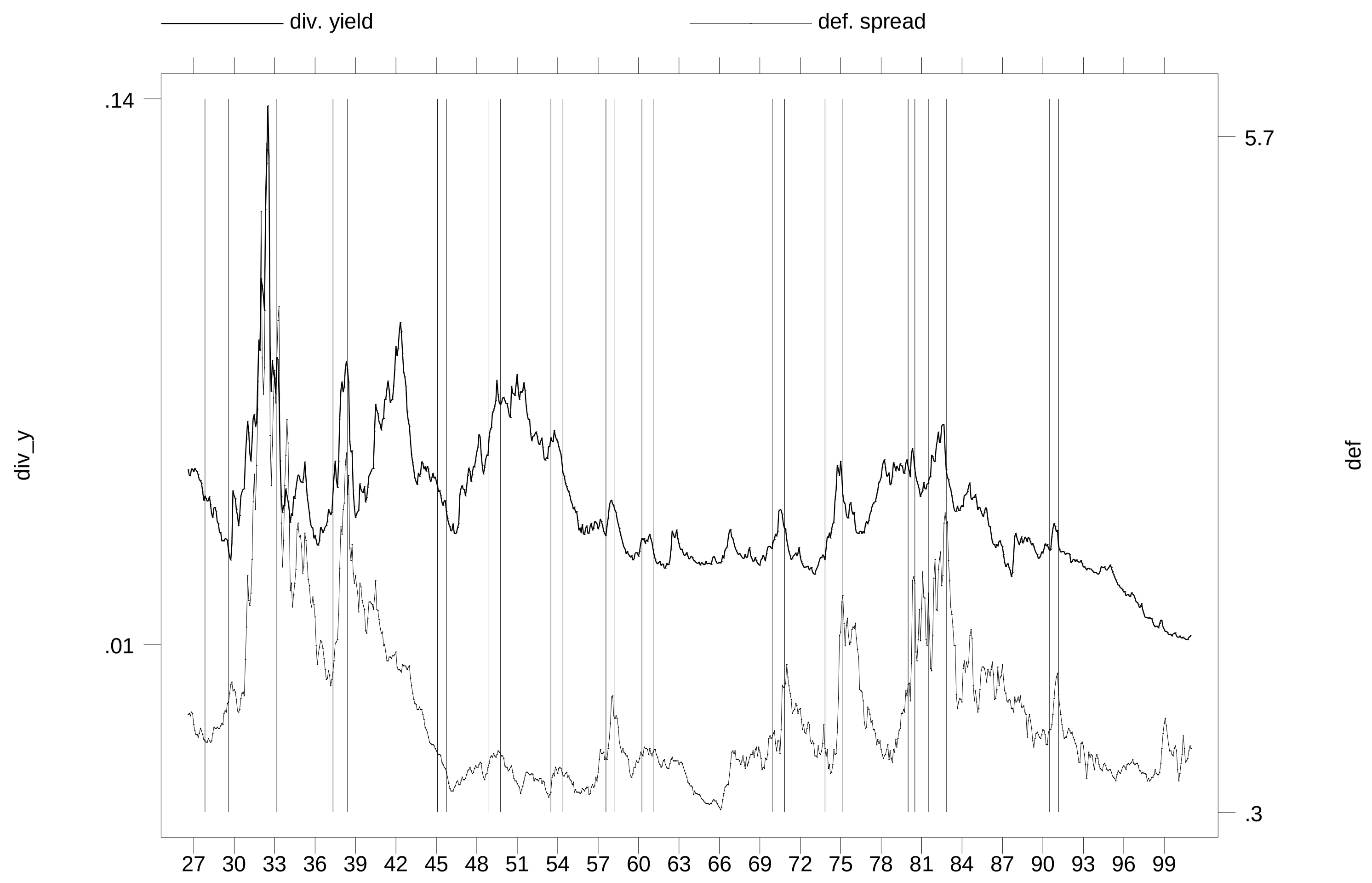

Figure 5: Dividend yield and default spread. The figure plots the series of the dividend yield on the S&P Composite Index (thicker line) and the default spread. The default spread is the end-of-month difference between the annualized yields on Aaa and Baa corporate bonds. The scale is different for the two series. The dividend yield is measured on the left vertical axis, and the default spread is measured on the right vertical axis. The vertical grid lines are the NBER business cycle peaks (P) and troughs (T). The dates are: 11/27(T), 8/29(P), 3/33(T), 5/37(P), 6/38(T), 2/45(P), 10/45(T), 11/48(P), 10/49(T), 7/53(P), 5/54(T), 8/57(P), 4/58(T), 4/60(P), 2/61(T), 12/69(P), 11/70(T), 11/73(P), 3/75(T), 1/80(P), 7/80(T), 7/81(P), 11/82(T), 7/90(P), 3/91(T).

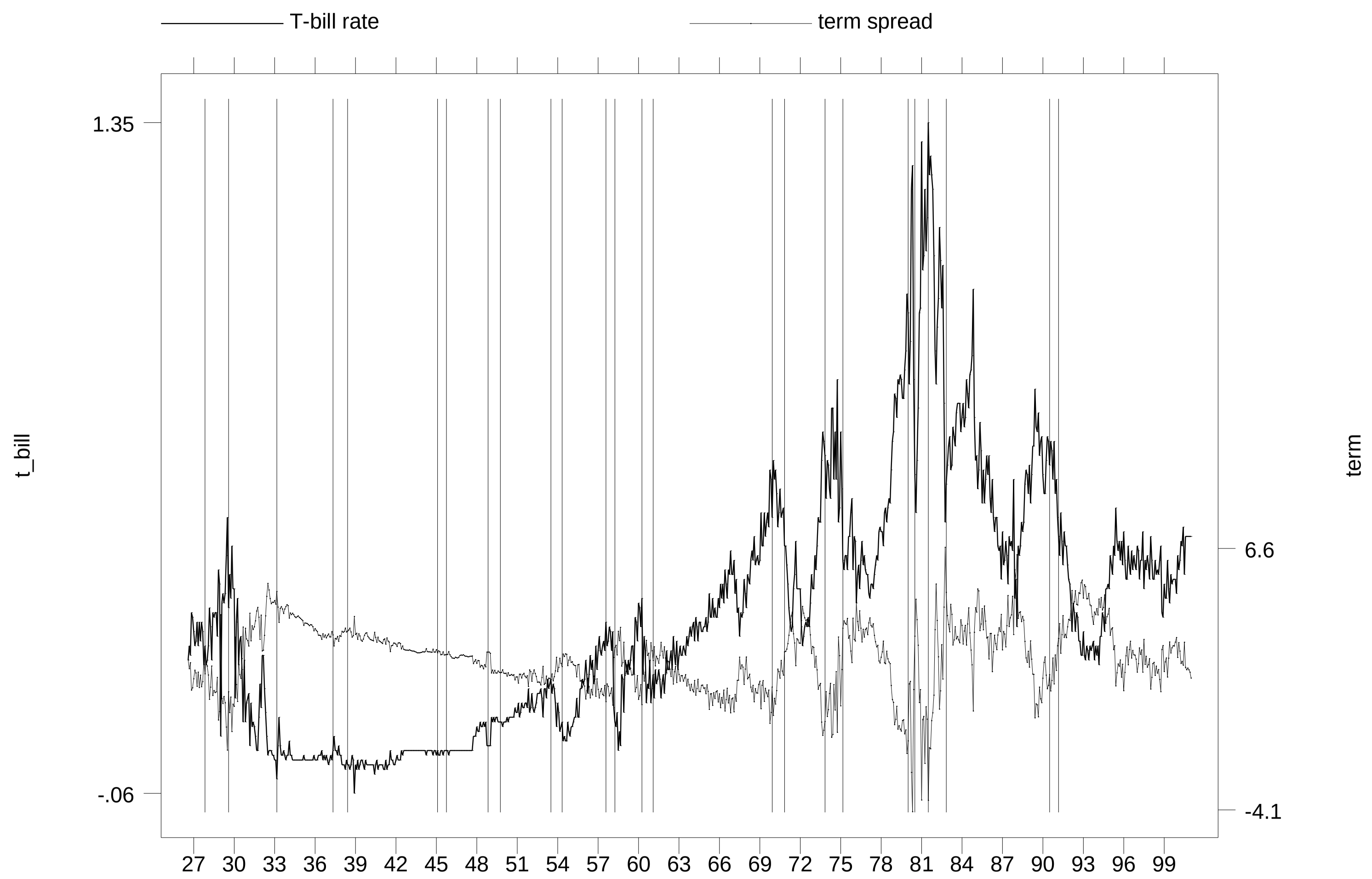

Figure 6: T-bill rate and term spread. The figure plots the series of the one-month T-bill rate (thick line) and the term spread (thin line). The term spread is the end-of-month difference between the annualized yields on Aaa corporate bonds and the one-month T-bill rate. The scale is different for the two series. The T-bill rate is measured on the left vertical axis, and the term spread is measured on the right vertical axis. The vertical grid lines are the NBER business cycle peaks (P) and troughs (T). The dates are: 11/27(T), 8/29(P), 3/33(T), 5/37(P), 6/38(T), 2/45(P), 10/45(T), 11/48(P), 10/49(T), 7/53(P), 5/54(T), 8/57(P), 4/58(T), 4/60(P), 2/61(T), 12/69(P), 11/70(T), 11/73(P), 3/75(T), 1/80(P), 7/80(T), 7/81(P), 11/82(T), 7/90(P), 3/91(T).

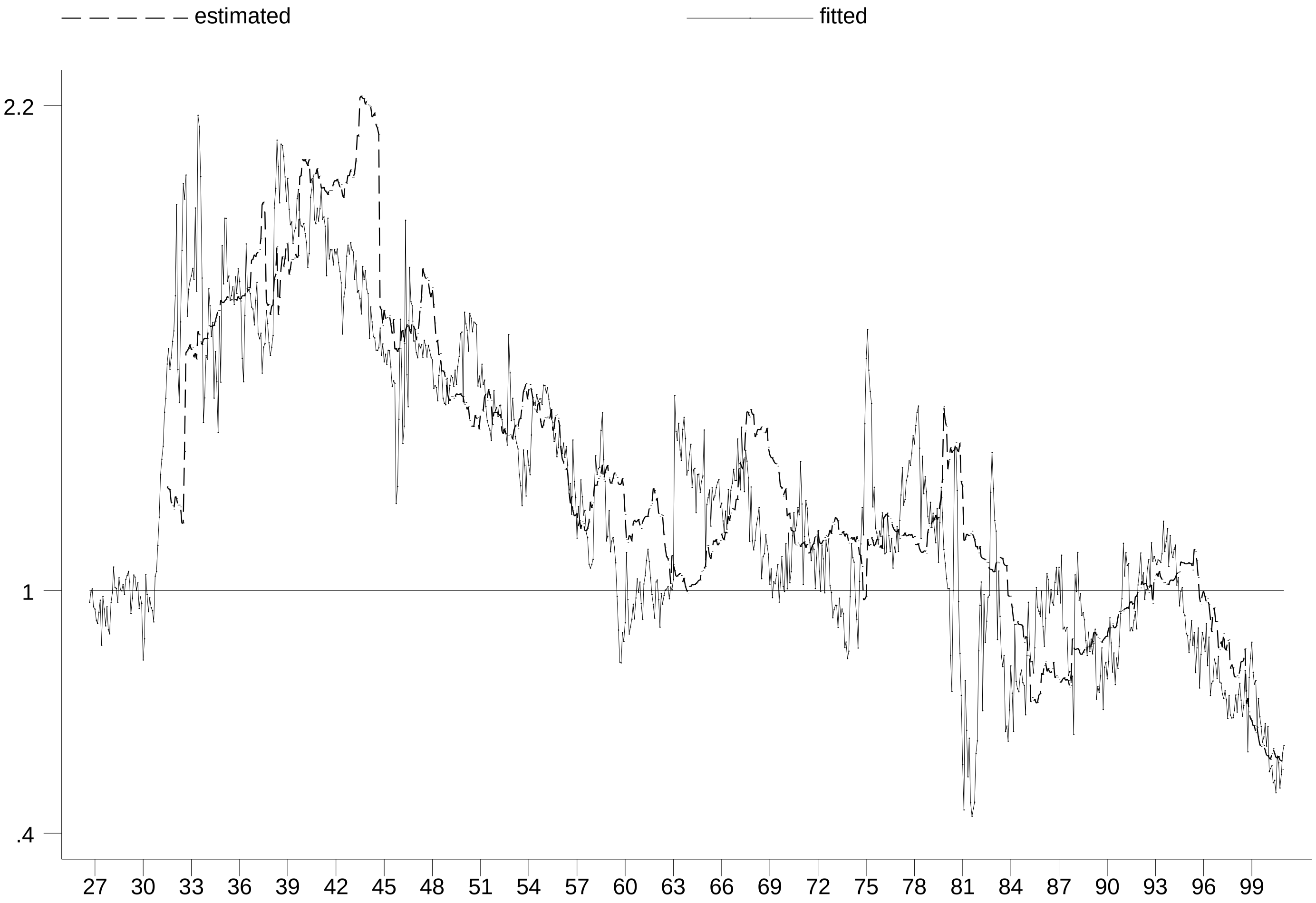

Figure 7: Tracking the beta of value stocks with state variables. The figure plots the time-series of the fitted beta (solid line) of the tenth B/M decile portfolio. The series has been generated according to Equation 8 in the text using monthly data from 7/1926 to 12/2000. The state variables are the t-bill rate, the dividend yield on the S&P Composite Inded, the default spread, the term spread, the growth rate of industrial production. The other series is the estimated beta (dashed line) for the same portfolio using 5-year rolling window regressions.

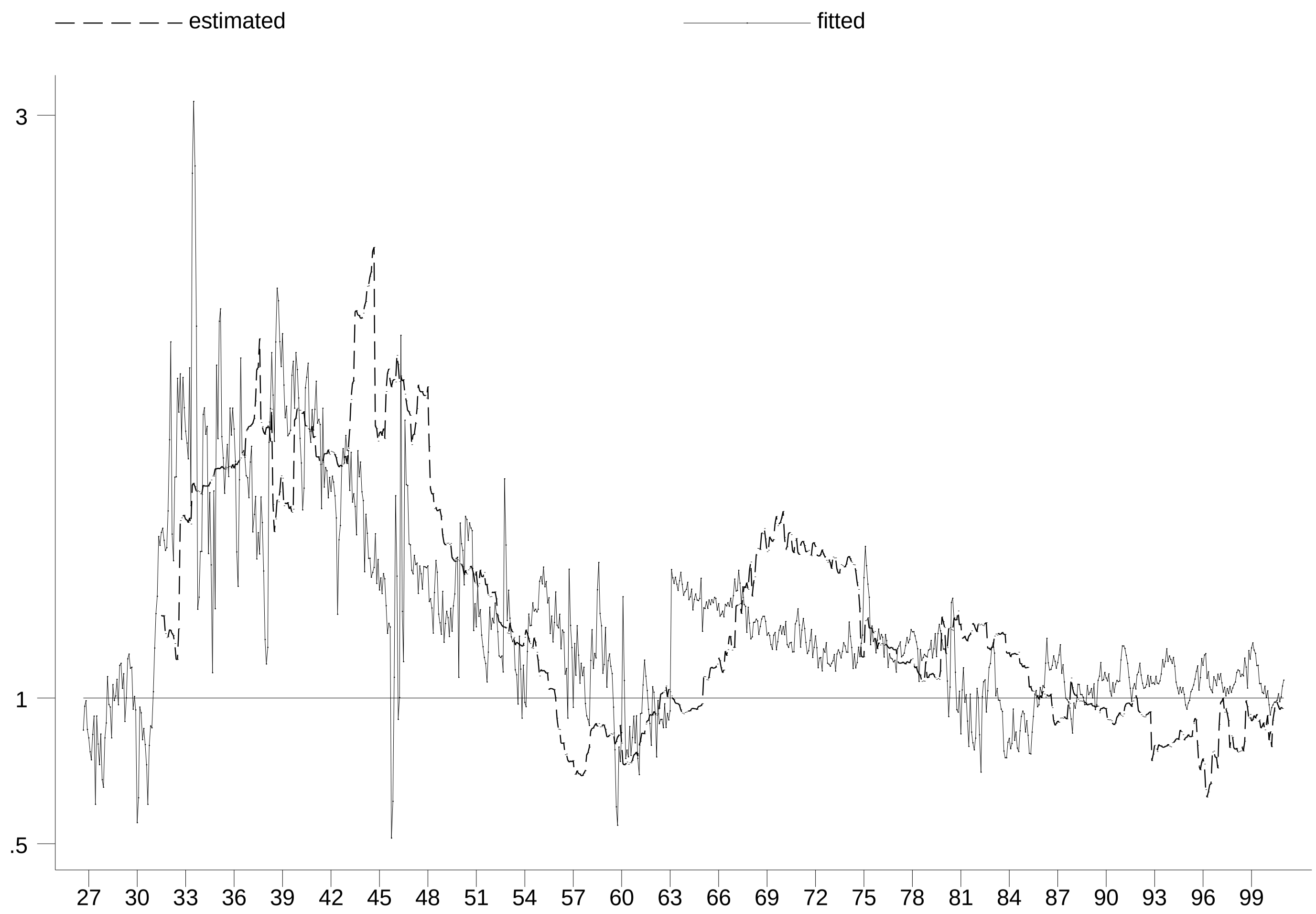

Figure 8: Tracking the beta of small stocks with state variables. The figure plots the time-series of the fitted beta (solid line) of the first size decile portfolio. The series has been generated according to Equation 8 in the text using monthly data from 7/1926 to 12/2000. The state variables are the t-bill rate, the dividend yield on the S&P Composite Inded, the default spread, the term spread, the growth rate of industrial production. The other series is the estimated beta (dashed line) for the same portfolio using 5-year rolling window regressions.

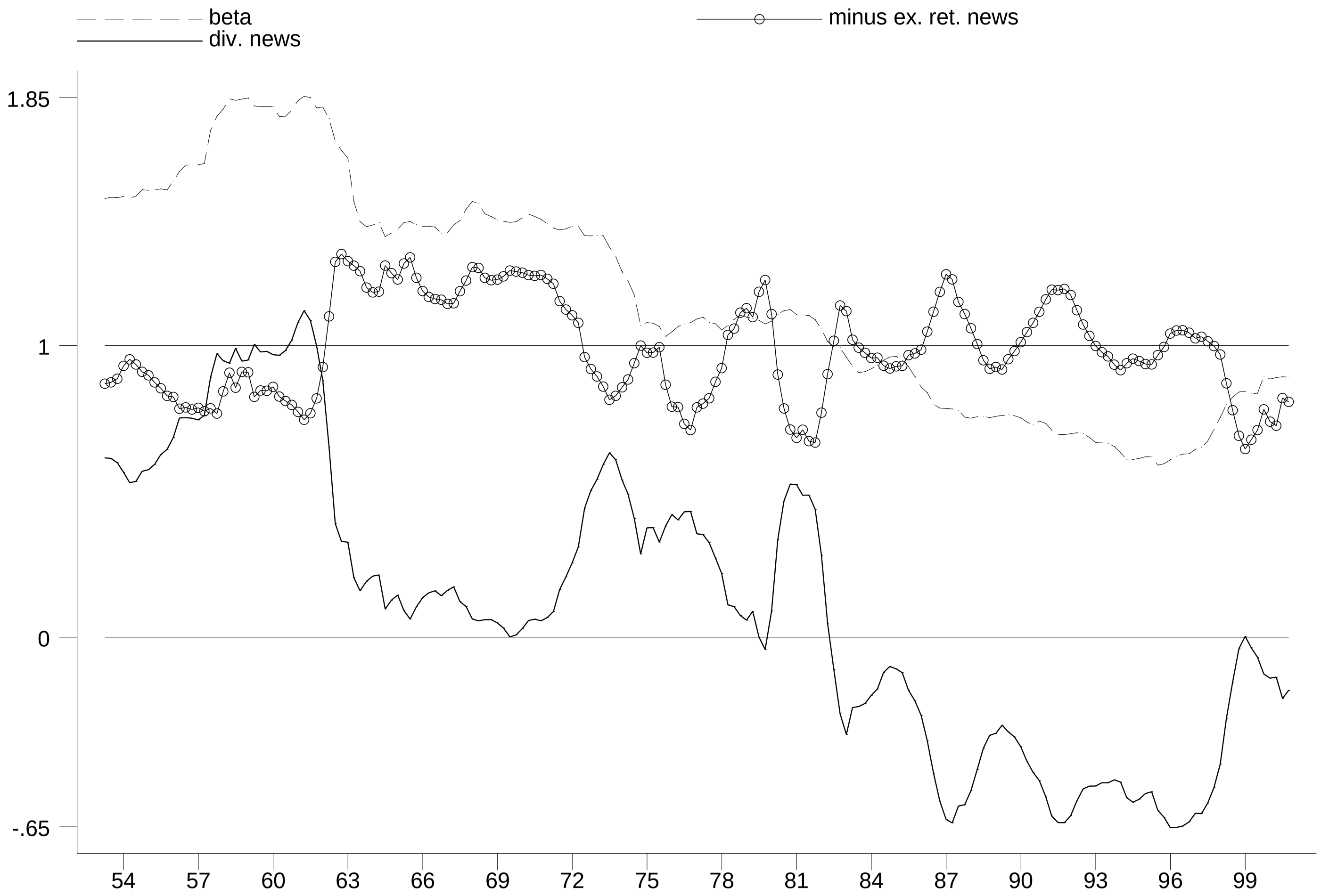

Figure 9: Beta of value stocks and its components. The figure plots the estimates from 25-year rolling window regressions where the independent variable is the innovation in the market return. The series *beta* (dashed line) originates from regressions where the dependent variable is the innovation in the return on B/M decile 10 portfolio. The series *div. news* (solid line) originates from regressions where the dependent variable is the dividend news component of the return on B/M decile 10 portfolio. The series *minus ex. ret. news* (circles) is the opposite of a series of estimates originating from regressions where the dependent variable is the excess returns news component of the return on B/M decile 10 portfolio.

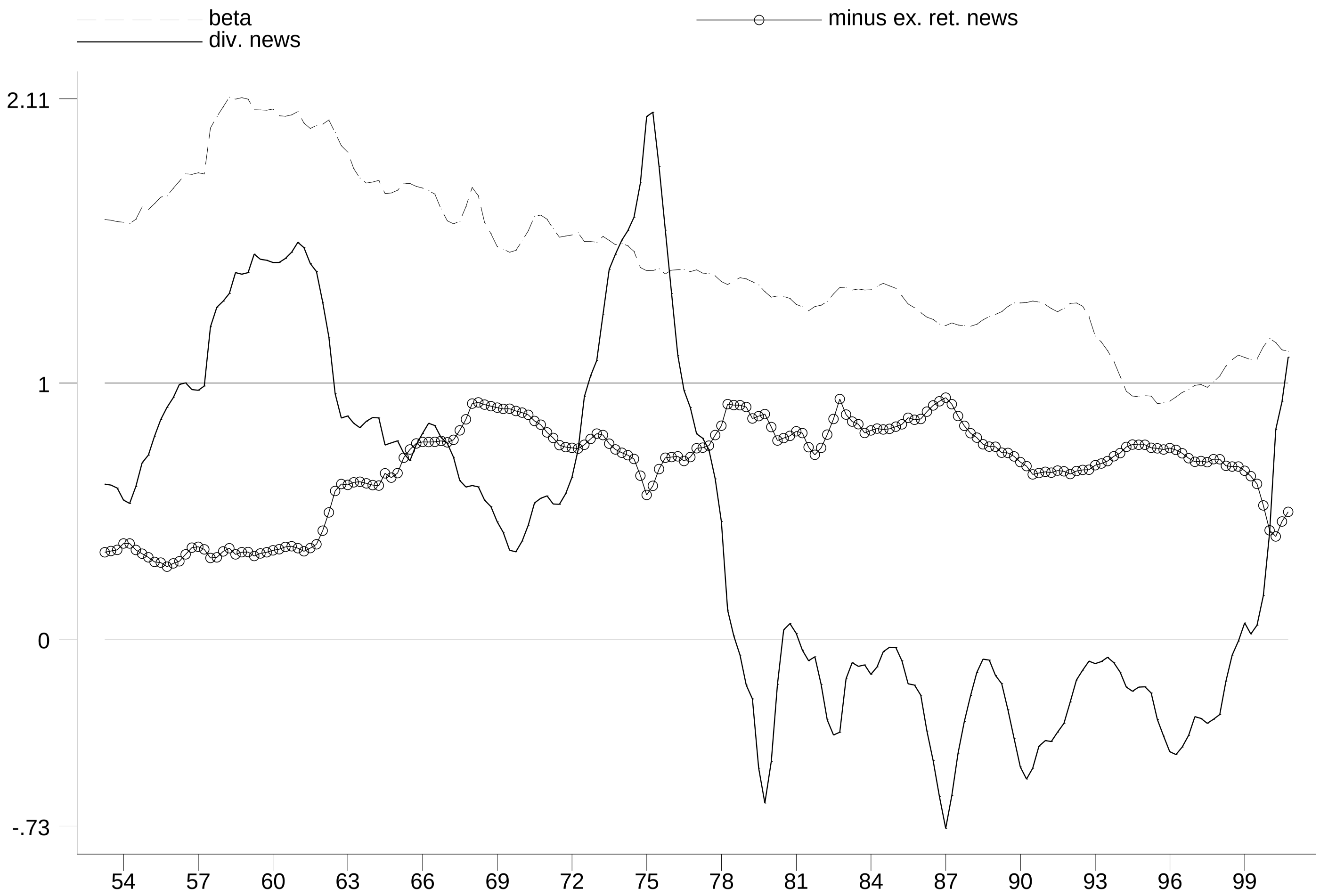

Figure 10: Beta of small stocks and its components. The figure plots the estimates from 25-year rolling window regressions where the independent variable is the innovation in the market return. The series *beta* (dashed line) originates from regressions where the dependent variable is the innovation in the return on size decile 1 portfolio. The series *div. news* (solid line) originates from regressions where the dependent variable is the dividend news component of the return on size decile 1 portfolio. The series *minus ex. ret. news* (circles) is the opposite of a series of estimates originating from regressions where the dependent variable is the excess returns news component of the return on size decile 1 portfolio.

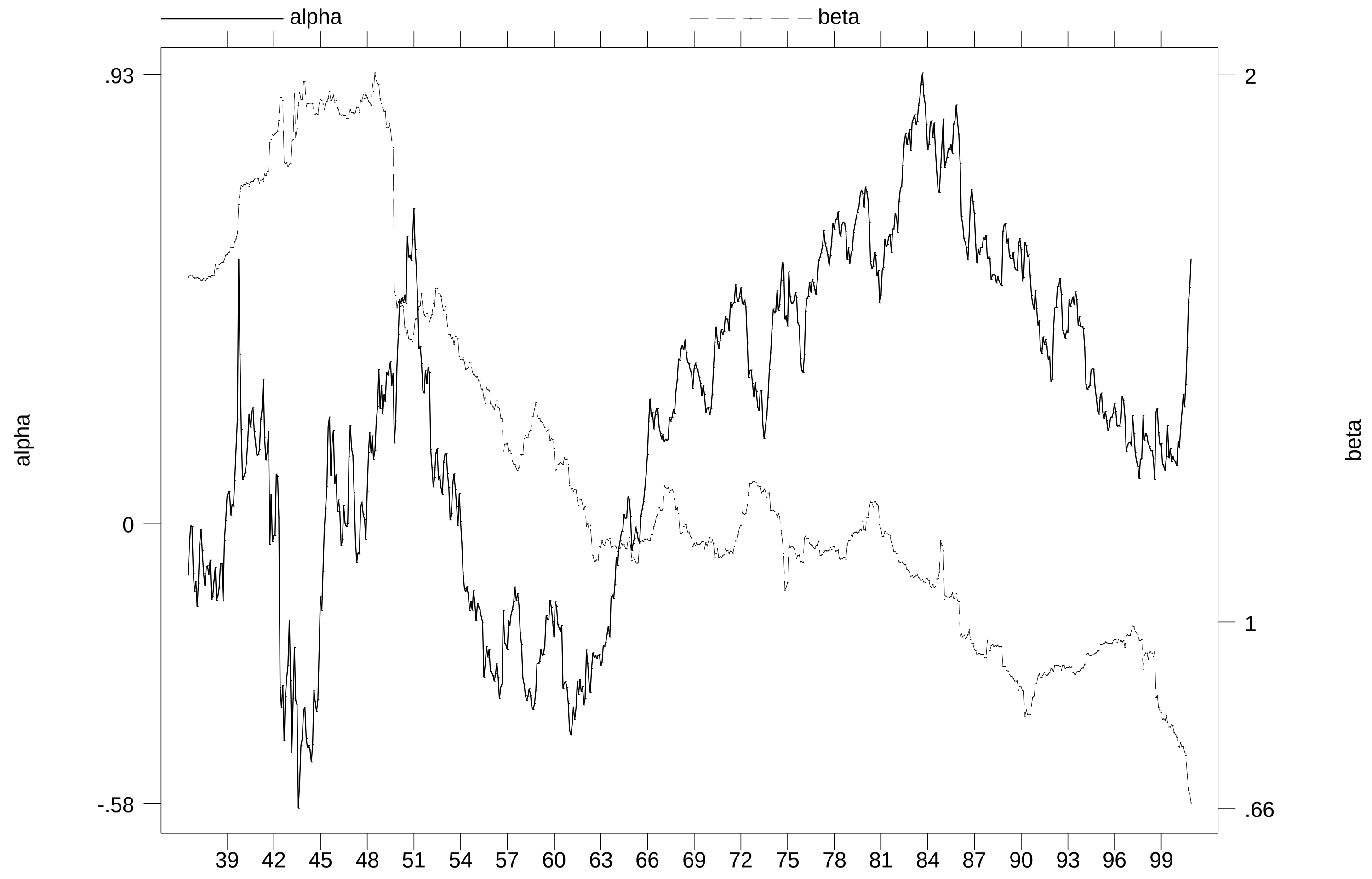

Figure 11: Alpha and Beta. The figure plots series of estimates from 10-year rolling window CAPM regressions where the dependent variable is the excess return on B/M decile 10 portfolio. The series *alpha* (solid line, left scale) is the intercept in the CAPM regression. The series *beta* (dashed line, and right scale) is the beta in the CAPM regression.

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