# The Changing Nature Of Market Risk

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**ABSTRACT**

In the first three decades of CRSP data, value stocks have higher betas than growth stocks. Later on, the ranking is reversed and the gap in beta widens. What makes growth strategies nowadays bear more market risk than value strategies? What are the causes of the reversal in the ranking of betas? The paper argues that the negative link between beta and BM is due to growth options. The shift of listed firms towards more growth-oriented businesses has progressively changed the nature of market risk. The ultimate determinant of this evolution is conjectured to be financial market development, which has lowered the cost of capital. For this reason, the facts described in this paper resonate with other long-run phenomena, such as the rise in idiosyncratic risk and the R&D boom.

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Fama and French (2006b) produce clear-cut evidence on the relation between time-varying betas and the CAPM performance. First, they show that in the pre-1963 period the CAPM explains the value premium, because betas line up with book-to-market (BM). However, they also find that variation in beta that is independent of BM is not compensated in returns, irrespective of the sample. They argue that this is ominous evidence for the CAPM. Finally, in the post-1963 period, high-BM (value) stocks have lower betas and higher returns than low-BM (growth) stocks. So, the CAPM does not explain the value premium in the late sample.

Given these facts, identifying why the positive beta-BM link breaks down can shed some light on what causes CAPM to fail as a model for risk. Motivated by this observation, this paper explores the empirical determinants of the relation between beta and BM. In particular, the goal is to pin down the firm characteristics that cause high BM companies to have low betas, and vice versa. The answer to this question does not intend to be a direct solution to the value premium puzzle. The hope is that the evidence will provide some empirically founded directions to re-define risk in a successful way. From the practical point of view, the output of the analysis certainly helps to understand the risk properties of value and growth investment strategies. It also unveils the company characteristics that affect the CAPM-based estimates of the cost of capital.

To provide an accurate picture, one cannot neglect the temporal evolution in the beta-BM relation. Around the early sixties, beta becomes negatively related to BM. Afterwards, the gap in betas between growth and value portfolios widens. Then, as a second and related question, the papers investigates the causes of this evolution. The answer to this question does not merely have a historical interest. It turns out to disclose some of the forces that have contributed to shape the identity of today's financial markets.

The results point to an important role of a firm's growth potential in affecting the beta-BM relation. Growth boosts valuations (lowers BM) and, at the same time, it can raise betas. If these two effects are strong enough, they can even change the sign of the beta-BM link.

The first theoretical channel for an effect of growth on betas is the risk of growth options. Straightforward derivative pricing suggests that a call option is riskier than the underlying asset. Based on this intuition, it is possible to show that firms with a higher weight of growth options relative to assets in place have higher betas (see, e.g., Carlson, Fisher, and Giammarino (2004)). The second channel is duration risk. High growth stocks are long duration assets (see, e.g., Lettau and Wachter (2007) and Santos and Veronesi (2006)). As such, they are more sensitive to shocks to discount rates, which raises their beta. Some results in related literature (Campbell, Polk, and Vuolteenaho (2008)) suggest that the first mechanism is more likely to be at work. However, for the purposes of this work, I do not distinguish between the two alternatives, as they have similar implications for the unconditional beta.

Using a number of proxies for growth options, I show that the cross-sectional relation between beta and BM turns positive once growth is part of the regression. This evidence suggests that the ranking in the betas of BM-sorted portfolios is to a large extent determined by the growth characteristics of the individual stocks. Put simply, growth stocks have higher betas than value stocks, because growth is an important determinant of betas.

As for the long-run development that is the second focus of the paper, important insights come from the behavior of the variables that are used as proxies for growth opportunities. Cao, Simin, and Zhao (2006) argue that a trend in grow options explains the surge in idiosyncratic risk found by Campbell, Lettau, Malkiel, and Xu (2001). Moreover, Brown and Kapadia (2007) show that a new listing effect accounts for both the rise in both firm-specific risk and growth options.

Building on this evidence, I find that a new listing effect is also behind the decline in the cross-sectional link between beta and BM. That is, the beta-BM link is more and more negative for firms that list later. Then, I show that this effect disappears when the growth option proxies are included in the regression. The conclusion is that the arrival of new firms with inherently and persistently higher growth potential has progressively affected the cross-sectional link between beta and BM, which ultimately determines the spread in betas of value and growth portfolios.

As a last step, I suggest an economic story that places these facts in a broader context. Some authors argue that a positive trend in financial market development has favored the expansion of the supply of capital. As a consequence of a lower cost of funds, unprofitable growing firms, whose cash flows are more uncertain, manage to raise capital (Fama and French (2004)). Also, more R&D expenditures are funded through equity (Brown, Fazzari, and Petersen (2008)). In general, the identity of new lists changes towards riskier and growth oriented firms (Brown and Kapadia (2007)), which raises the amount of firm specific risk in the market.

I conjecture that the increasing importance of growth for listed firms has progressively changed the nature of market risk as well. For this reason, the evolution described in this paper can be placed alongside other trends that have recently been unveiled such as, for example, the increase in idiosyncratic risk (Campbell, Lettau, Malkiel, and Xu (2001)) and the R&D boom (Brown, Fazzari, and Petersen (2008)).

The determinants of betas of BM-sorted portfolios have not been widely studied. Besides some of the papers cited above, one notable exception is Campbell and Vuolteenaho (2004). These authors focus on the asset pricing ability of the two components of beta that they identify (cash flow and discount rate betas). Their finding that growth stock betas mostly derive from the sensitivity to discount rate news is consistent with both the growth option and the duration based explanations of the relevance of growth potential for betas. Moreover, the present findings lend support to their risk based explanation of the value premium, which is founded on the idea that investors require a low price for the risk originating from growth.

The paper by Campbell, Polk, and Vuolteenaho (2008) is more closely related to this one, because the authors investigate the sources of market risk of value and growth stocks. By breaking down the betas into components that are related to cash flow and discount rate news at the firm level, they study whether fundamentals or sentiment justifies the high risk loadings of growth stocks. Some of the intuitions in their paper potentially help to disentangle the growth option from the duration based story as determinants of beta (more on that in the conclusions). In this sense, their results are complementary to mine. Relative to that paper, the present focus is on firm characteristics, notably growth opportunities, that can explain the link between beta and BM. Also, I explore the time dimension by studying the evolution of the beta-BM relation in the context of broader stock market developments.

Bernardo, Chowdhry, and Goyal (2007) propose an empirical decomposition of the beta of industry portfolios into parts due to the risk of growth options and the risk of assets in place for the 1977-2004 sample. They use BM as a proxy for growth potential and find that the component of beta due to growth options is on average larger than the component due to assets in place. Their results are consistent with the evidence in the present paper relating to the importance of growth for listed firms. Here, rather than assuming BM as a proxy for growth options, I show that other company characteristics that are related to growth explain the negative link between beta and BM in the late sample.

Finally, like this paper, Polk, Thompson, and Vuolteenaho (2006) look at the time variation in the cross-sectional link between beta and valuation ratios. Their objective is to derive forecasts of the equity premium from the cyclical behavior of this relation. The present focus, instead, is on the long-run developments that have changed the ranking in the betas of BM-sorted portfolios.

The paper is organized as follows. Section I provides a statistical description of the evolution of the betas of BM-sorted portfolios. Section II delineates the theoretical background and develops the empirical strategy to study the cross-sectional link between beta and BM. In Section III, a number of proxies for growth options are introduced to explore the determinants of this relation. Section IV studies the dynamic evolution of the beta-BM link and explains it through the trend in growth options. Section V places these empirical findings in the context of broader economic trends. Section VI concludes. The Appendix provides details on variable construction and summary statistics.

# I. Long-Run Behavior Of The HML Beta

The work in cross-sectional asset pricing points out that value stocks have lower CAPM betas than growth stocks. This ranking causes CAPM to fail, as value strategies outperform on average (see, e.g., Fama and French (1993)). This evidence is specific to the samples that start in the early sixties. In the previous decades, value portfolios display larger market risk than growth portfolios, which nicely aligns with their higher average returns (see, e.g., Campbell and Vuolteenaho (2004)). For the present purposes, one can conclude that the ordering in betas along the dimension of valuation ratios changed at some point during the post-war period. What follows is a more detailed description of this evolution.

The analysis in this paper focuses on book-to-market (BM) as a valuation metric, because it is the most commonly used ratio in empirical asset pricing. Still, using other valuation ratios, such as the dividend yield or the earnings-to-price ratio, would not change the qualitative implications of the results. More details are available upon request.

Figure 1 plots the slope on the market factor for Fama and French's (1993) HML factor. The series of beta estimates are obtained using different data frequencies and lengths of the estimation windows in order to provide robust evidence. The data on the HML factor and on BM sorted portfolios at all frequencies come from Prof. Ken French's website. The monthly return series used in this study ranges from July of 1926 to December 2006. The daily series ranges from July 1, 1963 to December 31, 2006.

The estimates in Panel (a) of Figure 1 originate from time-series regressions of the HML return on the CRSP value-weighted index minus the risk free rate. The sample for each regression consists of sixty monthly observations and the estimation window rolls forward by one observation every month. I denote this series as the rolling-window estimates. Two adjacent estimation windows overlap by fifty-nine months. As a result, the series is fairly smooth.

The graph in Panel (a) confirms the cited evidence that growth stocks have higher market risk loadings than value stocks in the late sample. The HML beta is positive before the sixties and mostly negative afterwards. The striking feature, which does not emerge from the cross-sectional tests, is that this evolution occurred in a trending fashion.[1] Figure 2, which originates from the same methodology as Panel (a) of Figure 1, highlights the separate downward trend in the value beta (tenth BM deciles portfolio) and upward trend in the growth beta (first BM decile portfolio).[2]

In Panel (b) of Figure 1, the annual HML beta comes from regressions based on twelve monthly observations. Instead, the monthly betas in Panel (c) are computed using all the daily returns within a month. To correct for potential non-synchronous trading in daily data, following Dimson (1979), the regressions include the current market return along with its first two lags. The estimate

[1] The evidence of a trend in beta of value and growth portfolios is first pointed out by Franzoni (2002). This finding is then confirmed by other studies: Ang and Liu (2004), Ang and Chen (2006), Campbell and Vuolteenaho (2004), Fama and French (2006b), Lewellen and Nagel (2006), Polk, Thompson, and Vuolteenaho (2006).

[2] Furthermore, unreported evidence suggests that trend in the beta of the deciles portfolios moves uniformly from positive to negative as the decile ranking moves from 1 to 10.

of beta is the sum of the slopes on all lags.

Because of the non-overlapping estimation windows, the plots in Panels (b) and (c) reveal much larger high-frequency variation in betas than Panel (a). There are occasional spikes in the HML beta series in the late sample. The estimates turn temporarily positive in the seventies, the early nineties, and towards the end of the sample. Still, the overall picture is unchanged. The HML beta is mostly negative in the last four decades and the secular decrease resembles a negative trend.

One may wonder about the cyclical properties of the series in Figure 1. Regressions of the HML beta on a recession dummy built at monthly frequency provide mixed results. Using the monthly series in Panel (a), it seems that recessions cause temporary increases in the HML beta over this extended sample. However, this effect is not significant once the autocorrelation in the betas is taken into account. Instead, the impact of recessions is negative and insignificant for the monthly series built from daily data in the short sample (Panel (c)). Overall, there is no clear correlation between the HML beta and the business cycle.

Given the impression of a trend from Figures 1 and 2, the obvious question is whether the nature of this trend is stochastic or deterministic. The rolling-window estimation approach mechanically induces extremely high auto-correlation in the estimated slopes. In this case, one would not expect to reject a unit root in the series. Still, some persistence is present also in the other estimates, which calls for a statistical investigation.

Panel A of Table I reports the results from the augmented Dickey and Fuller (1979) $\rho$- and $t$-tests, which are conducted with and without a trend. The number of lagged differences to be included in the regressions is determined using standard $t$-tests on the last lagged difference, as recommended by Campbell and Perron (1991). Overall, the tests reject the null of a unit root in the different beta series at standard confidence levels. One exception is the $t$-test with no trend for the annual series estimated on monthly data (column I). In this case, the response is due the mis-specification of the test, as the inclusion of a trend causes a rejection at the 99% confidence level. As one would expect given the autocorrelation induced by the estimation approach, another failure to reject a unit root comes from the monthly estimates based on rolling-window regressions (column III, no trend). Again, adding a time trend to the specification causes a rejection of a unit root, although the significance is somewhat lower than the previous case.

Given these results, which tend to rule out a unit root in beta, one can legitimately analyze the beta series in levels. The summary statistics in Panel B of Table I confirm that the HML beta is on average larger in the early sample, irrespective of the frequency of the data and the date at which the sample starts. Also, the rolling-window beta estimates (column III) are by far the least volatile series, both before and after a linear trend is filtered out. For the detrended series computed on non-overlapping data, there is no apparent difference in volatility between annual (columns I and II) and monthly estimates (column IV).

Next, I test for the presence of a deterministic time trend in the beta of the HML factor. To this purpose, one should keep in mind that the high autocorrelation in the beta estimates is bound to bias the OLS estimates of the standard errors. Furthermore, except for the rolling-window estimates, there is no a priori indication on the autocorrelation structure. In this case, one can adopt the test statics in Vogelsang (1998), which are robust to general forms of serial correlation. The tests are valid also when the series are $I(1)$.

Panel C of Table I provides estimates of linear trends in the beta series and their 90% confidence intervals based on Vogelsang's $\mathrm{PS}^1$ and $\mathrm{PS}^2$ statistics. The first test is found to perform better with $I(0)$ errors, while the second one prevails with $I(1)$ errors. The HML beta in the annual series decreases by roughly the same amount (between 0.013 and 0.014 per year) whether the sample starts in 1927 or 1950. The shorter sample is the relevant one for most of this study because of the availability of Compustat data. It is therefore good news that a substantial decrease in beta is present also in this more recent period. Similar conclusions for the magnitude of the trend and its statistical significance apply to the monthly rolling-window series (column III). Instead, the trend in the non-overlapping monthly estimates (column IV) is somewhat smaller in absolute value (about -0.009 annually). This finding can be ascribed to the fact that the series starts in July 1963, when the HML beta has already substantially declined (see Figure 1). In this case, the statistical significance of the trend is established only by the $\mathrm{PS}^1$ test, which is the more powerful, given that a unit root has previously been rejected.

The statistical tests clearly conclude that a deterministic trend describes the evolution of the

HML beta. Still, simple economic wisdom suggests that one should not push the argument for a time trend in beta too far. Risk factor loadings are anchored by the economic characteristics of the firms, the market in which they operate, and the general economic environment. An explosive behavior in risk sensitivities would presuppose a similar development in some fundamental property of the economy. While these phenomena can exist for an extended period of time, they are unlikely to be a stable property of the economic environment, which is instead more suitably described by the property of mean reversion.

Accordingly, rather than contending the existence of a deterministic trend in the process governing the HML beta, the paper focuses on a conservative version of the evidence in this section. The following analysis will revolve around two hardly disputable facts. First, value stocks have lower betas than growth stocks. Second, this ranking is the result of a gradual development that occurred over the second half of the twentieth century. This evolution inverted the sign of the relationship between beta and book-to-market.

## II. The Link Between Beta And Book-To-Market

The empirical analysis of the paper intends to shed some light on the two stylized facts that emerge from the previous section. This section and the next are devoted to understanding the static relation between beta and BM. Without this step, one could not address the evolution of the link between the two variables, which is done in Section IV.

### *A. The Ranking of Betas for BM portfolios*

In what follows, I investigate the determinants of the CAPM beta of BM sorted portfolios. Given that the betas of the different BM portfolios average to one, the absolute level of beta is less interesting than the ranking of the portfolio betas. In other words, one would like to answer the question of which portfolios have high and low betas along the BM dimension.

At each annual sort, the portfolio beta is the average of the betas of the component stocks. Then, the relevant focus is on the cross-sectional relationship between beta and BM at firm level.

For the empirical analysis, I will make the simplifying assumption that beta and the log of BM, denoted by $bm$, are linearly related:

$$\beta_i = \gamma_0 + \gamma_1 bm_i + \varepsilon_i \tag{1}$$

where $i = 1, ..., N$ denotes the stocks in an annual cross-section. This assumption is not neutral, as it imposes a monotonic relationship between portfolio betas and the BM ranking. However, a simple empirical investigation based on BM decile portfolios supports this implication.[3] Further evidence, which I discuss below, is consistent with this assumption. In this framework, the sign of $\gamma_1$ in equation (1) determines the ranking of the betas of BM portfolios. If $\gamma_1$ is positive (negative) high BM portfolios have larger (smaller) betas than low BM portfolios.

Figure 3 plots the annual estimates of $\gamma_1$ from regressions of firm betas on $bm$. Betas are computed in December of year $t$ using at most sixty monthly observations on stock returns and at least twenty-four. Details on the construction of BM and the other variables that are used in the analysis are provided in the Appendix. The close resemblance between the profile of the series in this graph and the evolution of the betas in Figures 1 and 2 is striking. The HML beta turns negative at about the same time (the late fifties and early sixties) when $\gamma_1$ falls below zero. Similar spikes appear in both series in the seventies, late eighties/early nineties, and around the year two thousand. In the case of Figure 2, one should focus on the difference between value and growth betas for the comparison with $\gamma_1$. Overall, this evidence provides further testimony on the validity of the research design based on the linear relationship between beta and $bm$.

From now on, the analysis focuses on the cross-sectional relation between beta and BM. The goal is to understand which firm characteristics determine this link. Obviously, any factor that affects the connection between beta and BM is also considered relevant to explain the systematic risk of BM sorted portfolios.

[3] I compute portfolio betas for BM decile portfolios over different subsamples between 1926 and 2006. In most cases, the ordering of the portfolio betas follows monotonically the BM ranking. The details are available upon request.

*B. Economic Determinants of the Beta-BM Relation*

To understand the economic determinants of the link between beta and BM one needs to look for theoretical guidance. The asset pricing literature provides a number of useful insights. To begin, a simple present value identity positively relates book-to-market to the expected returns at which future cash flows are discounted. An example of this relation can be found in Fama and French (2006a). Vuolteenaho (2000) develops a log-linearization of the present value identity. Polk, Thompson, and Vuolteenaho (2006) push the log-linearization one step further and assume that the CAPM holds, so that a firm's discount rate is equal to beta times the equity premium. This linear relation between beta and the log of BM could serve as a basis for equation (1). Still, one does not need to assume that CAPM holds in order to draw useful implications from the present value identity. As long as the market factor is positively correlated with the set of factors in the correct asset pricing model, simple discounting arguments suggest that beta and BM are positively related.

A similar intuition motivates the positive link between beta and BM in the structural models of Berk, Green, and Naik (1999) and Gomes, Kogan, and Zhang (2003). Because the present value of future cash flows drops as risk increases, the ratio of current fundamentals (book) to the present value of future cash flows (market) is positively related to the risk of assets in place. The logic is somewhat different in Carlson, Fisher, and Giammarino (2004). In their model, BM proxies for operating leverage. Then, the positive relation between beta and BM emerges because operating leverage boosts beta.

In these three papers, however, beta is positively related to BM only in a multivariate relation that controls for size. Size is larger the lower the weight of growth options (GO) relative to assets in place. As GO are typically riskier than assets in place (see, e.g., Carlson, Fisher, and Giammarino (2004)), firms with more GO relative to assets in place (that is, smaller firms) tend to have higher beta. Also, as it is commonly believed, I postulate that BM is an inverse proxy for GO. That is, the larger the opportunities to grow, the larger is the market value of the firm relative to its installed capital (market-to-book ratio). Then, I conjecture that the positive link between BM and beta, which is suggested by the above arguments, may fail to emerge in empirical tests that do not control for GO.

To fix the ideas, imagine running the univariate regression in equation (1), while the true model is:

$$\beta_i = \delta_0 + \delta_1 bm_i + \delta_2 GO + u_i \tag{2}$$

where $\delta_1$ and $\delta_2$ are both positive. The OLS estimate of $\gamma_1$ in equation (1) contains an omitted variable bias:

$$\hat{\gamma}_1 = \delta_1 + \delta_2 \theta \tag{3}$$

where $\theta$ is the slope from a regression of GO on $bm$ and is typically negative. Hence, in spite of the theoretical arguments in favor of a positive link, the univariate relation between beta and BM may turn out to be negative, because BM correlates with GO. This simple intuition motivates much of the empirical analysis of the paper.

The models in Lettau and Wachter (2007) and Santos and Veronesi (2006) provide a different mechanism than the risk of GO that can generate a negative link between beta and BM. In these papers, growth stocks are long duration equity. Furthermore, beta can be decomposed into the sensitivities to cash flow shocks and discount rate shocks (as in Campbell and Vuolteenaho (2004)). Because shocks to discount rates hit more badly the firms whose cash flows are stretched out in the future, growth stocks may happen to have higher betas than value stocks. A similar intuition is used to justify the empirical results in Campbell and Vuolteenaho (2004).

From the empirical point of view, however, the duration effect can be tied to growth in a similar fashion as the risk of growth options. Indeed, the concept of cash flow duration is hardly distinguishable from growth potential. So, growth is still a factor that co-determines BM and betas. For this reason, the empirical analysis of the paper does not distinguish the predictions of the GO models from those of the duration based models. Still, because duration and GO affect different components of beta, one could actually try to disentangle the two theories. While I leave this analysis to future research, Section VI provides further insights on this issue.

*C. First Empirical Evidence on the Omitted Variable Bias*

As a first attack on the omitted variable problem, I follow closely the theoretical predictions of some of the above literature and control for size, which I measure as the log of market capitalization deflated by the CPI. Betas are regressed on $bm$ and other firm characteristics using pooled firm level observations. To account for the persistence in the dependent variable, the t-statistics are computed using robust standard errors that are clustered by firm.

The estimates in Table II reveal that the univariate slope of beta on $bm$ is significantly negative in both the extended sample (1928-2006) and the short sample (1950-2006). In the first case, however, the slope is much closer to zero, as in the early years the link between beta and BM is positive (see Figure 3). The control for size has no effect on the slope of $bm$ in the extended sample. In the short sample, the coefficient for $bm$ moves farther below zero once size is added to the regression. Overall, the simple addition of size to the regression does not explain the negative link between beta and BM.

Incidentally, the slope on size is negative in all specifications. This finding is apparently consistent with the models in Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and Carlson, Fisher, and Giammarino (2004). However, later results show that the negative sign on market capitalization hinges on the absence of other measures of the relative weight of GO and assets in place. Once these controls are included, the slope on size turns positive. The issue is discussed in Section III.

Another obvious candidate to explain a firm's beta is financial leverage. A correlation between leverage and BM could also induce an omitted variable bias in the slope on $bm$. The last two specifications in Table II control for leverage, which is measured as the ratio of debt to either book value or market value of assets. Book leverage does not substantially alter the coefficient on $bm$. Instead, the inclusion of market leverage is very effective in pushing upwards the slope on $bm$, whose distance from zero is cut by roughly two thirds. The reason for the different performance of the two leverage proxies is that the positive correlation with BM is much stronger for market leverage than for book leverage (see Table A-I).

Although leverage is successful in accounting for part of the omitted variable bias, the negative sign of its coefficient in Table II may appear puzzling. Simple logic suggests that, given the risk of the firm's assets, leverage should boost equity betas. Then, to reconcile the evidence of a negative estimate, one must conclude that asset betas are negatively correlated with leverage.

In search for an economic motivation to explain this conclusion, it is useful to remember that leverage is positively correlated with BM. Also, leverage is strongly negatively correlated with all the GO proxies that are introduced in the next section. For example, younger firms display lower financial leverage (see Table A-I). Then, one may contend that leverage itself is a measure of the relative importance of GO and assets in place. To support this conjecture, one could argue that firms whose value mostly derives from future cash flows are more subject to the financing constraints that arise from asymmetric information. Because they have lower collateral to pledge, they can attain lower leverage. Another explanation comes from Myers's (1977) debt overhang theory. Financing projects with equity rather than debt attenuates the underinvestment problem and leaves additional leeway for firms with abundant growth opportunities. Finally, excessive leverage might signal financial distress. Cao, Simin, and Zhao (2006) propose the last two motivations to justify leverage as an inverse proxy for GO. Similar arguments justify the adoption of financial constraints indices as a measure of GO in the next section.

To summarize, the theoretical arguments and empirical evidence in this section suggest that the negative unconditional link between beta and BM can be the outcome of an omitted variable bias. Growth options are a likely candidate for explaining this effect, as they inflate the market value of the firm relative to its installed capital and, at the same time, they boost betas. The following analysis explores this conjecture in more detail.

## III. Beta, Book-To-Market, and Growth Options

### *A. Direct Growth Option Proxies*

Growth opportunities are not observable. Hence, every attempt at measuring them is to some extent arbitrary. To circumvent this criticism, I will test a number of different candidate proxies for GO.

BM, or the closely related Tobin's Q, are typically considered an indicator of growth potential. However, because BM is the variable whose explanatory power for beta is under scrutiny, I need to look elsewhere. Table III contains estimates from pooled regressions of beta on the chosen GO proxies. The standard errors are clustered by firm.

Younger firms have more growth potential. Hence, age is an obvious candidate to measure GO. Using Jovanovic and Rousseau's (2001) data set, I construct the variable Age as the difference between the current year and the minimum among the founding year, the incorporation year, and the first year the firm appears in CRSP, in that order of availability. This variable does not use Compustat data and is therefore available over the entire long sample (1928-2006) with 172,368 firm-year observations. The first two columns of Table III suggest that Age pushes the negative coefficient on *bm* upwards by 30%. Also, the coefficient on Age is negative and significant, as one would expect from a variable that is inversely related to GO. In this light, there is some evidence that the negative coefficient on *bm* originates from its correlation with GO. Pastor and Veronesi (2003) find that Age is negatively related to valuation and propose a model where uncertainty about profitability raises valuations and stock volatility. This story is unlikely to be at work here, because it concerns the idiosyncratic part of risk and not the stock beta.[4]

At this point, it is worth stressing another result that emerges from these regression as well as from most of the following ones in this section. Once Age is included in the second specification of Table III, the coefficient on size turns significantly positive. Furthermore, the effect of Age on the slope on *bm* would not be that strong, if size was not in the regression (results not reported).

The finding of a positive coefficient on size seems to conflict with the models that predict a negative relation between beta and size (e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and Carlson, Fisher, and Giammarino (2004)). In these papers, the assumption that proportional growth becomes more difficult as market value increases causes size to be inversely related to the proportion of GO in total firm value.

However, regressions like the one in the second column of Table III contain another variable

[4]In fact, this story could be indirectly related to the estimated effect on beta to the extent that idiosyncratic volatility increases GO and, through this channel, it affects beta. See the discussion below about idiosyncratic volatility as a proxy for GO.

that can measure the relative importance of GO and assets in place, which in the specific case is Age. As a consequence, the orthogonal component of size is free to capture the unexplained part of GO. To exemplify, consider two firms with the same age. Without further information, we could conclude that the two firms face the same growth opportunities. Instead, we know that one firm has higher market value than the other. So, a plausible inference is that the more expensive company is expected by the market to have higher GO. In other words, age controls for the normal level of GO, and size measures the market's assessment of the additional growth potential. This story identifies the orthogonal component of size as a proxy for GO and justifies its positive impact on beta. The effectiveness of residual size to explain beta in conjunctions with the other GO proxies motivates its inclusion in the next specifications.

Firms that experience a larger realization of sales growth are more likely to have high growth opportunities. Hence, I adopt real sales growth over the current period (SG) as another proxy for GO. The estimates in Table III suggest that the intuition is correct. The effect of SG on beta is positive and highly significant. However, the slope on $bm$ is affected only slightly. Different definitions of sales growth have been tried, including growth over future periods, as in Grullon, Lyandres, and Zhdanov (2008), and the results are comparable.

In any model with frictions, internal cash flows are the preferred source of finance (see, e.g., Myers and Majluf (1984)). Hence, firms with abundant growth opportunities have an incentive not to pay dividends and save the money for positive NPV projects. For this reason, I use an indicator variable for firms that pay dividends (DIVPOS) as an inverse proxy for GO. The slope on DIVPOS in Table III is negative and significant, which is consistent with the positive impact of GO on beta. Also, the estimate for $bm$ falls substantially, providing support for the omitted variable conjecture. While the effect of DIVPOS on beta is consistent with a distress story, where firms in troubles do not pay dividends and are more risky, the positive correlation between $bm$ and DIVPOS suggests that non-dividend payers are typically not distressed.

For firms that exhaust their internal cash flows and still face valuable investment opportunities, the only alternative is to raise external finance. Brown, Fazzari, and Petersen (2008) show that the firms that mostly engage in research and development quite soon deplete internal resources, make negligible use of debt, and raise most of the necessary funds from equity issues. With this in mind, I use net equity issues relative to total assets (NEI) as an indicator of growth potential. In Table III, NEI operates in the expected direction. The effect on the slope on $bm$ is limited, as it drops in absolute value by about twenty percent. Other measures of financing activity, which include debt finance, have been tried without significant improvement in the results, suggesting that equity finance is preferred by growing firms.

Firm engage in research and development to generate growth potential. Hence, R&D intensity (that is, R&D divided by total assets, RD) is one of the most obvious proxies for GO (see, e.g., Grullon, Lyandres, and Zhdanov (2008)). Unfortunately, the data on R&D expenditures are sparse. So, the sample is substantially reduced relative to the previous proxies. Still, in Table III, RD performs remarkably well. The slope on $bm$ jumps from -0.15 to -0.06 and the regression $R^2$ almost triples. The effect of RD on beta is positive and significant, as expected.

A direct measure of the market expectations of a firm's growth potential is provided by analysts' forecasts of long term growth. These estimates, which come from IBES, span a three-to-five-year horizon. I construct a proxy for GO as the annual average up to December of year $t$ of the median analyst forecast of long term growth (Anfor). Unfortunately, IBES data start being available in 1981 and the sample is substantially reduced. However, this does not seem to be a problem because the negative link between beta and $bm$ that needs to be explained is even stronger in this sample (about -0.18), as it appears from Table III. Anfor does an outstanding job in filtering the downward bias in the coefficient on $bm$. In the multivariate regression that controls for Anfor, the slope on $bm$ is no longer distinguishable from zero, while the $R^2$ jumps to 15%.

The different economic motivations for the variables that have been used as GO proxies leave some hope that they have independent power in absorbing the omitted variable bias. So, the last specification in Table III is a multivariate regression of beta on $bm$, size, and the six GO proxies discussed so far. Because of the requirement that all variables be available, the sample is reduced to 25,401 firm-year observations over the 1981-2006 period. In this sample, the univariate coefficient on $bm$ is -0.17. Strikingly, in the multivariate regression, the slope turns significantly positive at about 0.07, while the $R^2$ grows to 21%. The controls retain statistical significance, although the coefficient on SG turns negative, confirming that this variable is a weak proxy for GO. The most significant controls are Anfor, RD, and DIVPOS, in that order.

As a final observation, all models that include GO proxies display a similar behavior to the one discussed when presenting the results for Age. The coefficient on size rises and often becomes positive and significant. Furthermore, unreported analysis suggests that the impact of the GO controls would not be as effective, if size was not in the regression. As explained above, the interpretation of this effect is that the orthogonal part of size acts as a measure of the GO unexplained by the other variables.

Overall, the results in Table III are quite supportive of the conjecture that the negative unconditional link between beta and *bm* results from a failure to control for GO. Next, I keep following this lead and explore other variables that may be related to growth options.

### *B. Idiosyncratic Volatility and Growth Options*

Campbell, Lettau, Malkiel, and Xu (2001) find an upward trend in idiosyncratic volatility that partly overlaps in time with the downward trend in the HML beta documented in Section I. Moreover, the trend in volatility starts to reverse at the beginning of the new century (see Brown and Kapadia (2007)), which is about the same time when the HML-beta stops decreasing.

At first, one may be tempted to dismiss the resemblance as pure chance and support this claim by arguing that idiosyncratic and systematic shocks to returns are orthogonal by construction. However, volatility and betas relate to the second moments of these shocks. So, they are not necessarily uncorrelated.

Another piece of evidence invites a careful reconsideration of the issue. Casual observations reveals that beta and firm-specific risk are highly correlated in the cross-section. I measure idiosyncratic volatility (Ivol) as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. The sample includes at least twenty-four and at most sixty monthly observations ending in December of year $t$.[5] In Table A-I, the correlation

[5]I use the three-factor model to measure Ivol to avoid the criticism that different approaches could leave the HML factor in the residuals and induce a mechanical correlation of Ivol with BM and the HML beta. However, similar results would hold with different measures, as all estimates of idiosyncratic volatility are highly correlated.

between beta and Ivol is about 50%. Hence, in the cross-section, firms with high systematic risk are likely to have high idiosyncratic risk as well.

A potential explanation that ties together beta and firm-specific risk once again attributes a role to GO. Cao, Simin, and Zhao (2006) show that the trend in idiosyncratic volatility is closely related to the increased importance of GO in the value of listed firms. In their story, thanks to the increased availability of investment opportunities, managers are able to choose projects with higher idiosyncratic risk. The goal is to increase the value of shareholders' call option at the expense of bondholders. One may argue that the causal link in this story could be reversed. That is, the value of the option to grow is a positive function of the volatility of the underlying assets. This argument motivates the study of the cross-sectional relation between returns and idiosyncratic risk in Grullon, Lyandres, and Zhdanov (2008). In either case, what matters for the present purposes is that Ivol and GO appear to correlate. Then, given the theoretical arguments and the empirical evidence from Table III, which suggest that GO boost beta, the link between Ivol and beta can be established.

One of the GO proxies that Cao, Simin, and Zhao (2006) use in their paper is the market-to-book ratio. Hence, there is also a tight link between Ivol and BM. The empirical question, then, is whether these two links are sufficiently strong to affect the unconditional relation between beta and BM.

Before addressing this issue, I should mention another theory that relates idiosyncratic risk to BM. Pastor and Veronesi (2003) argue that learning about profitability increases valuation ratios and idiosyncratic volatility of young firms. However, in their paper, learning does not affect systematic risk, that is, beta. Only if one goes beyond the scope of the theory and argues that young firms have more GO, can one reconcile their story with the evidence that Ivol is strongly correlated to beta. In the end, GO remain the main candidate for an explanation.

To provide robust evidence, I study two additional measures of volatility. Wei and Zhang (2006) show that the volatility of profitability is closely related to firm specific risk. Accordingly, I introduce the standard deviation of return-on-equity (VolROE) and the standard deviation of the

For example, Bekaert, Hodrick, and Zhang (2008) report a correlation of about 98% between the estimate obtained from the three-factor model and the Campbell, Lettau, Malkiel, and Xu (2001) original measure.

cash flow-to-assets ratio (VolCF). Both variables are computed on at most five and at least three annual observations including year $t$. Table IV shows that the two measures of fundamental risk operate in the expected direction. The negative link between beta and $bm$ is attenuated and they have a positive impact on beta. This evidence is consistent with the GO story.

Next, I directly consider Ivol. Because its construction does not require Compustat data, this variable is available in the extended sample. In these data, the addition of Ivol to the regression of beta on $bm$ turns the slope on $bm$ from negative to positive and significant. Given the relation between GO and Ivol, this effect is entirely consistent with the correction of the omitted variable bias due to GO.

The negative link between beta and $bm$ in the extended sample is not as strong as in the short sample, which may weaken the importance of the previous finding. Then, the last two specifications in Table IV focus on the Compustat sample where all three volatility variables are available. Again, the comparison between the univariate and multivariate regressions shows that the volatility measures are effective in changing the sign of the slope on $bm$. The most important contribution comes from Ivol.

As in the case of Table III, in the multivariate regressions in Table IV, the coefficient on size turns positive and often significant. The interpretation of this evidence conforms to what argued above. The residual component of size is itself an effective proxy for GO.

To summarize, the impact of idiosyncratic volatility on the relation between beta and $bm$ is similar to that of the GO proxies previously encountered. The proposed interpretation is that firm specific risk is tightly connected to the value of GO and, through this channel, to BM and beta. This story favors GO risk over duration risk as a determinant of betas.

### *C. Financial Constraints and Growth Options*

The early results from Table II point out a role for leverage in explaining the link between beta and BM. One interpretation of this effect is that growing firms have limited access to debt finance because of asymmetric information. This story traces a link between financial constraints and growth.

The financial constraints literature suggests another potential relation between the two concepts. Hennessy and Whited (2007) distinguish two dimensions of financial constraints. The first dimension is the firm's need for external funds, as measured by the ratio of first best investment to internal resources. The second dimension is the cost of external funds, which is the additional cost the firm would incur if it used external rather internal finance. In the first case, financing constraints are also determined by growth opportunities. In a similar spirit, Kaplan and Zingales (1997) find that, keeping profitability constant, a firm with higher Tobin's Q, that is, better investment opportunities, is more likely to be financially constrained.

I follow the lead coming from this literature and test financial constraints as a proxy for GO. One of the most successful measures of financing constraints in the literature is the Whited and Wu (2006) index (WW). These authors fit the shadow value of external funds from a structural model of investment onto a number of observable variables. Firms ranking high with the WW index are small, rely heavily on equity financing, have low cash flow, and are slow-growing firms in fast-growing industries (see the Appendix for the exact definition).[6]

In Table V, the inclusion of the WW index in the regression of beta on *bm* turns the slope on *bm* significantly positive from significantly negative. The effect is consistent with the conjecture that financial constraints may act as a proxy for GO. Incidentally, the coefficient on size also turns positive and significant, confirming the importance of residual size in explaining beta. The third specification reveals that the contribution of WW is partly independent from the effect of volatility and of a direct GO proxy such as Age.

The effect of WW may appear as a black box at first. To provide further insight, I break down WW into its components. As expected, the unconstrained explanatory power of the individual components of the index is stronger (column four of Table V). In particular, cash flows (CF), the dummy for dividend-payers (DIVPOS), and the size of the company assets (LNTA) play the most important roles. The sign of their coefficients is the same as the one in the WW index. Instead, sales growth takes on the opposite sign relative to its negative sign in the WW index. As seen before, growing firms have higher betas and valuations. When Ivol and Age are added to the regression

[6]Other financing constraints indices have been tested, such as the Kaplan and Zingales (1997) and Cleary (1999) scores. These variables do not prove as effective as the WW index.

(last specification), the coefficient on *bm* reaches the highest magnitude of all specifications that have been tested so far. Incidentally, the link between beta and leverage is positive, as one would expect from simple theoretical arguments. This confirms that the negative relation between the two variables in Table II results from the fact that leverage also proxies for GO. As other controls for growth are included in Table V, the positive effect of leverage on beta is re-established.

The positive and strongly significant link between beta and *bm* once controls for GO are present in the regression is a convincing sign that the unconditional relation between *bm* and beta is largely determined by the impact of growth opportunities on both beta and valuation. With this evidence in mind, the following analysis investigates whether the evolution of GO is sufficient to explain the change from positive to negative in the univariate relation between beta and BM, that is to say, the fall in the HML beta.

## IV. The Evolution In The Beta-BM Link

The question is whether GO play some role in the decrease of the coefficient that ties beta to BM. Figure 4 gives a graphical answer. The dashed line is the slope from annual cross-sectional regressions of beta on *bm* and exhibits the usual decline. Instead, the solid line depicts the coefficient on *bm* once the GO proxies are added to the regressions. For this graph, the controls are size, Age, Ivol, and WW. The visual impression is that the controls absorb a large part of the decrease.

Table VI provides a statistical validation of the graphical inference. For different specifications of the annual regressions of beta on *bm* and GO controls, the table reports the time-series mean of the coefficient on *bm*, the *t*-test (corrected for serial correlation) for the null that the mean is zero, and the trend in the series of *bm* slopes, along with its confidence interval based on Vogelsang's (1998) $PS^1$ statistic. The first specification includes no controls for GO and corresponds to the dashed line in Figure 4. The slopes are significantly below zero and the negative trend is also significant. In the next column, controlling for Age and size slightly increases the average slope, which stays significantly negative. The trend is still negative but no longer significant. Adding WW to the controls turns the average slope positive. Finally, the last specification also includes

Ivol and corresponds to the solid line in Figure 4. The average slope is significantly positive and the trend is no longer present, which confirms the graphical impression.

In summary, not only are GO relevant to understand the cross-sectional slope of beta on BM, but also they are effective in explaining at least part of the decline in the link between the two variables. Because this link is what determines the allocation of stocks into BM sorted portfolios, the evolution of GO seems to be behind the decrease in the HML beta. For the GO controls to be able to absorb the trend, they must also be characterized by some non-stationarity. The next analysis investigates this dimension.

### *A. New Listing Effect and Growth Options*

The confirmation of the last conjecture comes from Cao, Simin, and Zhao (2006), who find that different measures of GO trend up in a way that explains the increase in idiosyncratic volatility.

Further insight is provided by Brown and Kapadia (2007), who show that the trend in firm-specific risk originates from a new listing effect. The cohorts of firms that list later are persistently more risky than the earlier lists. Also, these firms are more strongly characterized by those properties that previous studies have related to the increase in idiosyncratic risk. In particular, the new comers face more growth opportunities. So, the stratification of increasingly more risky and more growth oriented firms causes the average level of idiosyncratic risk and GO in the public market to trend up. The conclusion concerning growth opportunities is consistent with the evidence in Fama and French (2004), who argue that the distribution of growth rates for new lists has become progressively more right skewed.

Given these findings, the question is whether the new listing effect in GO determines a similar behavior in the relation between beta and BM. The first step in addressing this issue is to look for evidence that the decline in the slope of beta on *bm* exhibits a new listing effect.

To this purpose I follow Brown and Kapadia (2007) and construct dummy variables for firms that list in different periods (before 1965, 1965-1974, 1975-1984, 1985-1994, after 1994). The sample is limited to the years between 1950 and 2006, because of the availability of Compustat data. I run pooled regressions of beta on the interactions between *bm* and the listing group dummies. The group dummies are also part of the regression.[7]

The impression from the first column of Table VII is that a new listing effect characterizes the beta-BM link. The slope on *bm* uniformly decreases as we move from early to late listing groups. Unreported results from annual cross-sectional regressions, reveal that, in each year, the estimates of the coefficient on *bm* for later groups are lower than the estimates for earlier groups. This implies that the ranking of coefficients in Table VII is not merely the result of averaging slopes over different time periods.

Next, I investigate whether the new listing effect is related to GO. To begin with, I use size and the WW index as GO controls. Including the level of size and WW in the regressions has no relevant impact. Then, I interact size and WW with the listing group dummies, in order to allow for a different effect of the GO proxy in each group. This strategy is successful, as the initial ranking in the slopes on *bm* disappears (second specification in Table VII). Although the ordering is not monotonic, later lists tend to have larger coefficients than early lists. Remarkably, the effect WW is uniformly stronger for later listing groups, which explains why constraining WW to have a unique slope is not effective. The coefficients on size (not reported to save space) follow a similar pattern (they are all positive and increase in the listing year).

The remaining specifications in Table VII include more GO controls (Ivol, Age, and RD). Interacting these variables with the listing group dummies does not substantially affect the results. So, I enter them in levels for the sake of parsimony. Strikingly, with the richest set of controls (last column), the slopes on *bm* are all significantly positive and monotonically increasing in the listing year. Arguably, after one controls for the effect of GO, the remaining link between beta and BM is likely to derive from the systematic risk of assets in place. The last finding, then, suggests that companies that entered the market at a later stage bear more systematic risk than early lists, which seems a plausible conclusion. As I discuss below, this inference mirrors similar conjectures advanced by some studies of the trend in idiosyncratic risk.

To summarize, the decline in the link between beta and BM contains a new listing effect. Late comers have betas that are more negatively related to BM than early lists. This effect disappears

[7]In practice, it is as if a different regression was estimated for each listing group. The only difference is that the standard errors are computed from pooling all observations together and clustering by firm.

if GO controls are added to the regression. Then, it must be the case that GO proxies are also characterized by a new listing effect.

As argued above, Brown and Kapadia (2007) confirm this conjecture for some of the variables that I use as proxies of growth opportunities (DIVPOS, Ivol, VolROE, LNTA). To complete the picture, Table VIII and Figure 5 show that a new listing effect is present in all the GO proxies used in this study. The table reports estimates from regressions of the GO proxies on the listing group dummies. In practice, the coefficients are means of the different variables within each listing group. Almost in a monotonic fashion, late lists have higher growth options than early lists. The figure is even more informative, as it shows that the ordering tends to be preserved over the entire sample. For example, throughout the sample, firms listing in the 1965-1974 period remain substantially more likely to be non-dividend payers than firms listing before 1965. As observed by Brown and Kapadia (2007) new public companies are really of a different nature than pre-existing ones as far as risk and growth are concerned. This is the essence of the new listing effect.

### *B. Industry and Exchange Effects*

A legitimate question is whether the new listing effect in GO overlaps with a change of industry composition in the stock market. It could be the case that new firms are listed in growth oriented sectors, where the relationship between beta and *bm* is negative. In this case, the decline in the HML beta would originate from the evolution of the output mix in the economy. The alternative possibility is that, for some other reason, growth options have become more important within each industry.

To separate the two hypotheses, I run the annual cross-sectional regressions of beta on *bm* at industry level. That is, each observation is the average beta and *bm* in one of the thirty Fama and French industries. Because it annihilates the change in industry composition of the stock market, this procedure rules out the possibility of finding a decline in the slope on *bm* deriving from more and more firms listing in high growth industries. The results are in Figure 6, where the thin solid line is the slope on *bm* from the usual firm-level regressions, while the short-dashed line originates from the industry-level regressions. The industry-based slopes are necessarily more volatile, because only thirty observations are used each year. Still, it is evident that the industry slopes exhibit a similar downward trend as the original series.

Perhaps, focusing on a broad industry classification does not provide enough power to distinguish between the two alternatives. Brown, Fazzari, and Petersen (2008) argue that much of the R&D boom in the last two decades of the twentieth century takes place in a restricted number of high-tech industries. It is possible that the increasing number of firms listing in these seven high-GO industries causes the reversal of the beta-BM relation. To verify this conjecture, starting in 1980, I run the annual firm-level regressions of beta on $bm$ excluding the firms in these seven industries. The slopes are graphed with the thick solid line in Figure 6. The comparison with the original series (thin solid line), which for most of the period lies below, suggests that the high-tech industries may play some role. However, these element is far from explaining the negative relation between beta and BM over this horizon.

In a similar spirit, one may conjecture that the addition of Nasdaq stocks starting in 1973 changes the nature of the link between beta and valuation. The companies listing on this exchange are typically smaller and operate in sectors with high growth potential. I follow the same approach as for high-tech industries and run the annual firm-level regressions excluding Nasdaq firms. The series of slopes is captured by the long-dashed line in Figure 6. Once again, the comparison with the original series suggests that Nasdaq stocks contribute somewhat to the decline in the beta-BM link, but are by no means the main culprit.

Given the last set of results, it seems fair to conclude that the decline in the beta-BM link is far from being the outcome of a change in industry composition or the result of a high-tech/Nasdaq boom. Rather, the relevant development occurred within each industry irrespective of the listing exchange, where high beta companies have increasingly been characterized by high growth opportunities and, therefore, high valuations.

## V. Discussion

The goal of this section is to delineate an economic story behind the findings of the paper.

Before doing that, it is useful to reiterate the logical direction followed by the empirical analysis. The observation that growth stocks have progressively exhibited larger CAPM betas than value stocks has motivated the study of the cross-sectional link between beta and BM. Backed by the theoretical prediction that growth options increase the systematic risk of a company and, at the same time, they raise the valuation of future cash flows relative to installed capital, the focus has shifted onto the impact of GO proxies on the beta-BM relation. Consistent with the priors, direct proxies of growth opportunities as well as less obvious ones, such as financial constraints and idiosyncratic volatility, prove to be crucial determinants of the cross-sectional link between systematic risk and valuations. Once GO are controlled for, beta is positively linked to BM, as it should be the case if only the systematic risk of assets in place determined valuations. The next logical step has been to relate the evolution of GO to the decline in the beta-BM link. Consistent with other studies, I find that the amount of growth opportunities that characterize listed companies has progressively increased. This phenomenon is the result of a new listing effect, where the new companies that come to the market are inherently and persistently more growth oriented than the old ones. As a result, new lists exhibit a progressively stronger link between high betas and high valuations. In the end, the analysis identifies the culprit of the drop in the HML beta in the increased importance of growth for listed companies.

This inference begs for an explanation that relates to broader developments in the economy. To this purpose, I draw on the conclusions of a number of previous studies. Brown and Kapadia (2007) suggest that the listing of increasingly more risky stocks is the desirable outcome of financial market development. They show that the profile of idiosyncratic volatility closely correlates with Rajan and Zingales's (2003) indices of financial development. In their story, the access of a larger public to financial markets has improved risk sharing and allowed riskier enterprises to obtain finance. Also, they suggest that their results have a relation to Morck, Yeung, and Yu (2000). These authors find that the average $R^2$ of the market model, a measure of stock price synchronicity, is related to per-capita GDP and investor protection.

These arguments strongly resonate with Fama and French's (2004) explanation of the fact that new lists are increasingly more growth oriented and less profitable. Fama and French argue that a shift in the supply of capital has induced a decrease in the cost of equity. So, business ventures whose cash flows are stretched out in the future obtain funding.

In a similar spirit, Brown, Fazzari, and Petersen (2008) suggest that the recent boom in R&D is also the result of a positive shift in the supply of equity finance. They conjecture that more abundant equity finance has caused a release of financial constraints for young high-growth firms.

All these studies argue that long-run developments in financial markets have lowered the cost of capital and allowed riskier and more growth-oriented firms to access equity markets. This story also fits the facts that are described in the present work. Because growth options raise market risk, growth firms' betas have progressively risen above value firms' betas.

In the end, the same factors that potentially explain a number of previously documented trends (the rise in idiosyncratic risk, the fall in the market model $R^2$, and the boom in R&D) can also account for the decline in the CAPM beta of the HML portfolio. The common thread linking all these facts could be financial markets development and the decrease in the cost of capital.

## VI. Conclusions

The focus of this paper is complementary to the literature on the value premium. While much research has been devoted to understanding what other factors besides market risk may explain the spread in returns between value and growth stocks, the question that I address here is: why do value stocks have lower market betas than growth stocks?

This issue is made more interesting by the consideration that the ranking in market risk has not always been the same. From the beginning of the CRSP dataset up to the early sixties, value stocks load more heavily than growth stocks on the market factor. At that point, the ordering changes and the spread in betas increases. As a consequence of this development, the CAPM stops explaining the value premium.

The beta of BM-sorted portfolios depends on the empirical link between beta and BM. The primary result of the paper is that the relation between the two variables is largely determined by the firm's growth opportunities. Growth options are typically riskier than assets in place. This fact raises the beta of firms with high growth potential. At the same time, the valuation of growth firms tends to originate from future cash flows rather than assets in place, that is, they have low BM ratios. This logic suggests that, if growth is an important characteristic of listed firms, a negative connection between beta and BM can emerge. The empirical analysis proves this point by showing that a number of controls for growth options are successful in re-establishing a positive link between beta and BM. The positive sign is what one would expect, if the risk of assets in place was the only determinant of the relation between the two variables.

It is worth mentioning a distinct theoretical mechanism that could be generating this evidence. Growth stocks pay cash flows that are stretched out in the distant future. In this sense, they are comparable to long-duration equity (see Lettau and Wachter (2007) and Santos and Veronesi (2006)). Hence, they are more sensitive to discount rate shocks than short-duration/value stocks. Like the effect described above, this channel also boosts the beta of firms with high growth potential. Yet, the two stories are inherently different, because duration risk originates from shocks to the denominator of a present value formula. Instead, the risk of growth options relates to whether future cash flows (the numerator) will be realized or not. Some results in Campbell, Polk, and Vuolteenaho (2008) suggest that duration is not likely to be the relevant determinant of the beta of growth stocks. By breaking down a firm's beta into components related to cash flow and discount rate news, they show that it is really the risk of cash flow shocks that qualifies the beta of growth portfolios. Future research should try to further disentangle the two explanations. For the purposes of the present paper, I generally refer to the effect of growth opportunities on the total unconditional beta. From this point of view, the two explanations are observationally equivalent.

As far as the evolution of the beta-BM link is concerned, the paper shows that the relation has been made progressively more negative by the increase in the average level of growth options in the market. This phenomenon occurs as newly listed firms are more growth oriented than pre-existing companies. So, the paper reveals a new listing effect in the cross-sectional link between market risk and valuation. The arrival on the market of inherently different firms changes the nature of systematic risk. The new listing effect relates this work to Brown and Kapadia (2007), who find a similar stratification in the idiosyncratic risk of public companies.

Like these authors, and others in the literature, I conjecture that the shift of newly listed companies towards more growth oriented and riskier ventures originates from broader economic events. In particular, an increase in the supply of capital may have reduced the cost of funds, so that projects whose cash flows are more uncertain have become viable. This logic inspires Brown and Kapadia (2007) to draw a potential link among a number of long-run developments in financial markets. Following their lead, I am inclined to place the change in the nature of systematic that this paper points out alongside: (1) the increase in idiosyncratic volatility (Campbell, Lettau, Malkiel, and Xu (2001)); (2) the decrease in the $R^2$ of the market model in the U.S. (Morck, Yeung, and Yu (2000)); (3) the boom in R&D (Brown, Fazzari, and Petersen (2008)); (4) the trend towards higher growth and lower profitability of new lists (Fama and French (2004)); (5) the increase in U.S. financial market development in second half of the twentieth century (Rajan and Zingales (2003)).

To conclude, one feels compelled to relate the findings of the paper to the debate on the value premium, given its proximity to the topic of this study. From the combination of the present evidence and previous results concerning expected returns, such as Fama and French (2006b), one can certainly infer that the sources of beta that originate from growth do not command a premium. One potential explanation could be that the growth-related component of beta measures the sensitivity to discount rate shocks, which are not as costly as cash flow shocks for long-lived investors. This is the conjecture in Campbell and Vuolteenaho (2004) and Lettau and Wachter (2007). In a somewhat different vein, Zhang (2005) suggests that growth stocks may have unconditionally high betas, but value stocks are riskier in recessions, when the price of risk is higher. To the disappointment of the believers in rational markets, however, the current evidence is not fit to rule out Lakonishok, Shleifer, and Vishny's (1994) conjecture that investors overprice growth options. This hypothesis is also able to explain why high-growth/high-beta stocks earn low realized returns. Hopefully, the results in the paper will help future research to disentangle the different explanations.

# Appendix

This appendix provides definitions for the variables that are used in the empirical analysis. The data come mostly from Compustat, CRSP, and IBES.

**Firm Beta** is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations).

**Book-to-Market** (as in Fama and French (1993)) is book value of equity at the end of the fiscal year (BE) divided by market capitalization in December. BE is stockholders' equity, plus balance sheet deferred taxes (Compustat item 74) and investment tax credit (item 208) (if available), plus post-retirement benefit liabilities (item 330) (if available), minus the book value of preferred stock. Depending on availability, I use redemption (item 56), liquidation (item 10), or par value (item 130) (in that order) for the book value of preferred stock. I calculate stockholders' equity used in the above formula as follows. I prefer the stockholders' equity number reported by Moody's (data on Ken French's website), or Compustat (item 216). If neither one is available, we measure stockholders' equity as the book value of common equity (item 60), plus the book value of preferred stock. If common equity is not available, I compute stockholders' equity as the book value of assets (item 6) minus total liabilities (item 181). Values of BM below 0.01 and above 100 are set to missing.

**Size** is the logarithm of market capitalization in December of year $t$ divided by the CPI.

**Book Leverage** is the logarithm of total debt (item 9) divided by the book value of total assets (item 6).

**Market leverage** is the logarithm of total debt divided by the market value of the firm (that is, total assets minus stockholders' equity plus market capitalization in December).

**CF** is the ratio of cash flow (data 18 + data 14) to total assets (item 6).

**DIVPOS** is an indicator that equals one if the firm pays dividends (item 19 + item 21), and zero otherwise.

**SG** is growth in firm real sales (item 12 divided by the CPI).

**ISG** is three-digit industry sales growth, and $LNTA$ is the natural log of total assets (item 6).

**Whited-Wu Index**. The index is:

$$0.938407 - 0.091CF - 0.062DIVPOS + 0.021Book\_Lvg - 0.044LNTA + 0.102ISG - 0.035SG$$

**Age** is the number of years since the minimum available observation among the founding, incorporation, and listing year. Founding and incorporation years are taken from Jovanovic and Rousseau (2001), while the listing year is the first year when the stock appeared in the CRSP monthly file.

**NEI** is net equity issuance, defined as the sale of common and preferred stock (item 108) minus the purchase of common and preferred stock (item 115) divided by total assets.

**RD** is the amount of research and development (item 46) divided by total assets in the previous year.

**Anfor** is the annual average of the median analyst forecasts of long term growth from IBES. The data start being available in 1981.

**VolROE** is the sample standard deviation of the return-on-equity (ROE), where ROE is net income (item 72) divided by stockholders' equity.

**VolCF** is the sample standard deviation of CF. The standard deviation is computed using at least three and at most five annual observations including year $t$.

**Ivol** is idiosyncratic return volatility computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations).

All the variables, except for BM, Size, Age, and Anfor, are winsorized at the first and ninety-ninth percentile. Table A-I provides summary statistics.

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**Table I: Tests for Unit Root, Summary Statistics, and Linear Trends.** Panel A reports unit-root tests for annual and monthly series of market beta estimates for the return on Fama and French's (1993) HML factor. The the Dickey-Fuller $\rho$- and $t$-tests are based on regressions that include a constant, or a constant and a time trend. *, **, and *** denote 10%, 5%, and 1% significance, respectively, for the rejection of the null hypothesis of a unit root. Panel B reports means (for the whole sample and subperiods), standard deviation, and first-order autocorrelation for different series of beta estimates. The standard deviation is also computed for the detrended beta series. Panel C contains (annualized) estimates of a linear trend in the annual and monthly series of the HML beta. The panel also reports the 90% confidence intervals (C.I.) for the trend based on Vogelsang's (1998) $PS^1$ and $PS^2$ statistics. The annual beta series (columns I and II) is obtained using twelve monthly observations of HML returns within a year in OLS regressions. The monthly rolling-window (r.w.) series (column III) is obtained using a sixty-month rolling window for the regressions. Hence, the estimation windows for two consecutive estimates overlap by fifty-nine observations. The monthly series in column IV is obtained using all the available daily observations for each month.

| | | | | |
|---|---|---|---|---|
| Panel A: Unit Root Tests | | | | |
| | (I) | (II) | (III) | (IV) |
| | 1927-2006 | 1950-2006 | 6:1931-12:2006 (r.w.) | 7:1963-12:2006 |
| Constant | | | | |
| $\rho$-test | -17.20** | -22.15*** | -2.50 | -107.59*** |
| $t$-test | -2.20 | -2.61* | -1.30 | -3.71*** |
| Lags | 2 | 2 | 5 | 9 |
| Constant & trend | | | | |
| $\rho$-test | -58.03*** | -45.56*** | -18.31* | -120.73*** |
| $t$-test | -6.65*** | -6.02*** | -3.46** | -3.87** |
| Lags | 0 | 0 | 5 | 9 |
| Panel B: Summary Statistics | | | | |
| | (I) | (II) | (III) | (IV) |
| | 1927-2006 | 1950-2006 | 6:1931-12:2006 (r.w.) | 7:1963-12:2006 |
| Mean (overall) | 0.010 | -0.130 | -0.020 | -0.240 |
| Mean (before 1963) | 0.270 | 0.090 | 0.300 | |
| Mean (after 1962) | -0.200 | -0.200 | -0.250 | -0.240 |
| St. Dev. | 0.400 | 0.350 | 0.320 | 0.300 |
| St. Dev. (detrended) | 0.290 | 0.290 | 0.120 | 0.290 |
| Autocorr. | 0.610 | 0.450 | 0.990 | 0.410 |
| Panel C: Linear Trend | | | | |
| | (I) | (II) | (III) | (IV) |
| | 1927-2006 | 1950-2006 | 6:1931-12:2006 (r.w.) | 7:1963-12:2006 |
| Trend (annualized) | -0.013 | -0.014 | -0.014 | -0.009 |
| C.I. ($PS^1$) | [-0.016, -0.010] | [-0.018, -0.010] | [-0.026, -0.002] | [-0.016, -0.001] |
| C.I. ($PS^2$) | [-0.017, -0.009] | [-0.018, -0.010] | [-0.018, -0.010] | [-0.133, 0.116] |

**Table II: Beta on Book-To-Market, Size, and Leverage.** The table reports estimates from regressions of firm-level betas on different combinations of (the log of) book-to-market (bm), (the log of) market capitalization in December (size), and (the log of) leverage. Size is expressed in real terms. Book leverage (book_lvg) is total debt divided by the book value of total assets. Market leverage (market_lvg) is total debt divided by the market value of the firm (total assets minus book equity plus market capitalization in December). The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The adjusted $R^2$ and the number of firm-year observations are also provided. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | Dep. Var.: beta | | | | | |
|---|---|---|---|---|---|---|
| | 1928-2006 | | 1950-2006 | | | |
| bm | -0.060 | -0.061 | -0.117 | -0.132 | -0.122 | -0.044 |
| | (-12.525) | (-11.730) | (-23.821) | (-23.908) | (-22.758) | (-6.687) |
| size | | -0.001 | | -0.016 | -0.016 | -0.016 |
| | | (-0.462) | | (-5.950) | (-5.989) | (-5.910) |
| book_lvg | | | | | -0.297 | |
| | | | | | (-15.642) | |
| market_lvg | | | | | | -0.149 |
| | | | | | | (-19.706) |
| Adj. $R^2$ | 0.006 | 0.006 | 0.019 | 0.020 | 0.031 | 0.043 |
| Obs. | 186,670 | 186,670 | 148,273 | 148,273 | 148,273 | 148,273 |

**Table III: Beta on Book-To-Market and Growth Options Proxies.** The table reports estimates from regressions of firm-level betas on (the log of) book-to-market (bm), (the log of) market capitalization in December divided by the CPI deflator (size), and different proxies for growth options. Age is the number of years since the minimum available observation among the founding, incorporation, or listing year. Real sales growth (SG) is computed relative to previous year sales. DIVPOS is an indicator variable for whether the firm pays dividends. NEI is net equity issuance. RD is the amount of research and development divided by total assets in the previous year. Anfor is the average over the year of the median analyst forecasts of long term growth. The specifications denoted by All include all of the above variables. The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The adjusted $R^2$ and the number of firm-year observations in each specification are also provided. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | Dep. Var.: beta | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Age | | SG | | DIVPOS | | NEI | |
| bm | -0.103 | -0.071 | -0.133 | -0.125 | -0.130 | -0.078 | -0.099 | -0.082 |
| | (-21.456) | (-14.067) | (-23.959) | (-22.361) | (-23.669) | (-14.484) | (-18.722) | (-15.685) |
| size | 0.001 | 0.029 | -0.017 | -0.017 | -0.016 | 0.021 | 0.004 | 0.008 |
| | (0.350) | (10.180) | (-6.427) | (-6.138) | (-5.859) | (7.387) | (1.576) | (2.954) |
| Age | | -0.003 | | | | | | |
| | | (-16.831) | | | | | | |
| SG | | | | 0.071 | | | | |
| | | | | (10.127) | | | | |
| DIVPOS | | | | | | -0.335 | | |
| | | | | | | (-32.549) | | |
| NEI | | | | | | | | 0.406 |
| | | | | | | | | (15.819) |
| Adj. $R^2$ | 0.016 | 0.033 | 0.021 | 0.022 | 0.020 | 0.062 | 0.016 | 0.022 |
| Obs. | 172,368 | 172,368 | 145,933 | 145,933 | 148,579 | 148,579 | 121,700 | 121,700 |
| | RD | | Anfor | | All | | | |
| bm | -0.154 | -0.056 | -0.177 | -0.006 | -0.174 | 0.071 | | |
| | (-22.000) | (-8.105) | (-21.177) | (-0.777) | (-14.812) | (6.078) | | |
| size | -0.020 | -0.003 | -0.057 | 0.003 | -0.066 | 0.050 | | |
| | (-5.235) | (-0.869) | (-14.129) | (0.730) | (-11.098) | (7.608) | | |
| Age | | | | | | -0.002 | | |
| | | | | | | (-8.486) | | |
| SG | | | | | | -0.118 | | |
| | | | | | | (-6.477) | | |
| DIVPOS | | | | | | -0.225 | | |
| | | | | | | (-11.580) | | |
| NEI | | | | | | 0.160 | | |
| | | | | | | (3.242) | | |
| RD | | 1.885 | | | | 1.917 | | |
| | | (26.702) | | | | (15.000) | | |
| Anfor | | | | 0.032 | | 0.018 | | |
| | | | | (38.950) | | (16.049) | | |
| Adj. $R^2$ | 0.028 | 0.083 | 0.034 | 0.150 | 0.032 | 0.207 | | |
| Obs. | 71,270 | 71,270 | 55,094 | 55,094 | 25,401 | 25,401 | | |

**Table IV: Beta on Book-To-Market and Volatility.** The table reports estimates from regressions of firm-level betas on (the log of) book-to-market (bm), (the log of) market capitalization in December divided by the CPI deflator (size), and different volatility measures. VolROE is the sample standard deviation of the return-on-equity. VolCF is the sample standard deviation of cash flows to assets. Both volatility measures are computed using at least three and at most five annual observations including year $t$. Ivol is idiosyncratic return volatility computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The adjusted $R^2$ and the number of firm-year observations in each specification are also provided. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | Dep. Var.: beta | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | VolROE | | VolCF | | Ivol | | All | |
| bm | -0.124 | -0.070 | -0.133 | -0.055 | -0.101 | 0.036 | -0.123 | 0.031 |
| | (-20.353) | (-11.821) | (-22.723) | (-9.583) | (-20.960) | (7.546) | (-20.221) | (5.673) |
| size | -0.017 | 0.004 | -0.019 | 0.015 | 0.002 | 0.090 | -0.017 | 0.080 |
| | (-6.251) | (1.460) | (-6.859) | (5.085) | (0.731) | (32.844) | (-6.064) | (26.568) |
| VolROE | | 0.778 | | | | | | -0.130 |
| | | (22.078) | | | | | | (-4.390) |
| VolCF | | | | 2.638 | | | | 1.283 |
| | | | | (26.285) | | | | (12.808) |
| Ivol | | | | | | 0.043 | | 0.046 |
| | | | | | | (44.631) | | (37.098) |
| Adj. $R^2$ | 0.018 | 0.052 | 0.020 | 0.096 | 0.015 | 0.137 | 0.018 | 0.195 |
| Obs. | 127,937 | 127,937 | 139,209 | 139,209 | 172,098 | 172,098 | 127,870 | 127,870 |

**Table V: Beta on Book-To-Market and Financial Constraints Proxies.** The table reports estimates from regressions of firm-level betas on (the log of) book-to-market (bm), (the log of) market capitalization in December divided by the CPI deflator (size), the Whited and Wu (2006) index of financial constraints (WW), and its components. The components of the WW index are: the logarithm of real total assets (LNTA), total debt divided by total assets (book_lvg), cash flows divided by total assets in the previous year (CF), an indicator variable for firms that pay dividends in the current year (DIVPOS), three-digit industry real sales growth (ISG), firm real sales growth (SG). The last specification also includes idiosyncratic return volatility (Ivol), computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). Finally, age is the number of years since the minimum available observation among the founding, incorporation, or listing year. The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The adjusted $R^2$ and the number of firm-year observations in each specification are also provided. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | Dep. Var.: beta | | | | |
|---|---|---|---|---|---|
| bm | -0.133 | 0.056 | 0.105 | 0.092 | 0.162 |
| | (-23.409) | (8.604) | (16.952) | (10.036) | (19.034) |
| size | -0.017 | 0.174 | 0.175 | 0.197 | 0.235 |
| | (-6.003) | (32.424) | (35.428) | (22.643) | (29.163) |
| WW | | 3.788 | 1.765 | | |
| | | (40.339) | (20.782) | | |
| LNTA | | | | -0.176 | -0.144 |
| | | | | (-20.627) | (-18.587) |
| book_lvg | | | | 0.028 | 0.044 |
| | | | | (1.087) | (1.939) |
| CF | | | | -0.961 | -0.447 |
| | | | | (-27.592) | (-13.732) |
| DIVPOS | | | | -0.251 | -0.027 |
| | | | | (-24.675) | (-2.736) |
| ISG | | | | 0.016 | 0.051 |
| | | | | (1.129) | (3.836) |
| SG | | | | 0.085 | 0.005 |
| | | | | (9.780) | (0.656) |
| Ivol | | | 0.045 | | 0.044 |
| | | | (41.221) | | (38.723) |
| Age | | | -0.002 | | -0.002 |
| | | | (-10.743) | | (-11.713) |
| Adj. $R^2$ | 0.020 | 0.082 | 0.203 | 0.107 | 0.210 |
| Obs. | 139,801 | 139,801 | 139,801 | 139,801 | 139,801 |

**Table VI: Annual Slopes on Book-to-Market: Level and Trend.** The table reports statistics on the time series of slopes on (the log of) book-to-market resulting from annual cross-sectional regressions where the dependent variable is the firm's beta. In specification the first column, no other controls are included. In the second column, (the log of) market capitalization in December divided by the CPI deflator (size) and firm age are included. Age is the number of years since the minimum available observation among the founding, incorporation, or listing year. In the third column, size, age, and the Whited and Wu (2006) index of financial constraints (WW) are included. Finally, in the fourth column, size, age, WW, and idiosyncratic volatility (Ivol) are included. Ivol is computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The time-series mean of the annual slopes is provided along with the t-statistic for the hypothesis that the mean is zero (in parentheses). The t-statistic is computed using Newey and West (1987) standard errors with four lags of autocorrelation. The table also provides the slope on a linear trend (Trend) along with its 90% confidence interval (in brackets) computed using Vogelsang's (1998) $PS^1$ statistic.

| Controls: | none | size, age | size, age, WW | size, age, WW, Ivol |
|---|---|---|---|---|
| Mean | -0.105 | -0.093 | 0.034 | 0.072 |
| | (-3.559) | (-2.782) | (1.125) | (2.694) |
| Trend | -0.006 | -0.006 | -0.004 | -0.004 |
| | [-0.008, -0.003] | [-0.020, 0.008] | [-0.056, 0.049] | [-0.180, 0.173] |

**Table VII: New Listings Effect.** The table reports estimates from regressions of firm-level betas on (the log of) book-to-market (bm) interacted with listing year dummies, and the same set of listing year dummies (coefficients not reported). The second specification controls for (the log of) market capitalization (size, coefficients not reported) and the Whited and Wu (2006) index of financial constraints (WW). These two variables are also interacted with listing year dummies. The third specification also includes firm age and idiosyncratic return volatility (Ivol), computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). Age is the number of years since the minimum available observation among the founding, incorporation, or listing year. The last specification also includes research and development divided by total assets in the previous period (RD). The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations). The adjusted $R^2$ and the number of firm-year observations in each specification are also provided. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | Dep. Var.: beta | | | |
|---|---|---|---|---|
| bm* pre 1965 listing dummy | -0.003 | -0.038 | 0.007 | 0.075 |
| | (-0.380) | (-2.900) | (0.620) | (4.850) |
| bm* 1965-1974 listing dummy | -0.065 | 0.003 | 0.062 | 0.083 |
| | (-6.930) | (0.200) | (5.190) | (5.440) |
| bm* 1975-1984 listing dummy | -0.139 | -0.012 | 0.073 | 0.096 |
| | (-11.210) | (-0.720) | (4.780) | (4.610) |
| bm* 1985-1994 listing dummy | -0.182 | 0.050 | 0.088 | 0.128 |
| | (-18.520) | (4.030) | (7.630) | (7.450) |
| bm* 1995-2004 listing dummy | -0.233 | 0.159 | 0.135 | 0.217 |
| | (-16.060) | (8.650) | (8.480) | (8.710) |
| WW* pre 1965 listing dummy | | 1.120 | 0.398 | 0.149 |
| | | (4.610) | (1.850) | (0.520) |
| WW* 1965-1974 listing dummy | | 1.990 | 0.888 | 0.266 |
| | | (11.050) | (5.520) | (1.190) |
| WW* 1975-1984 listing dummy | | 2.700 | 1.410 | 0.748 |
| | | (12.660) | (7.530) | (2.600) |
| WW* 1985-1994 listing dummy | | 4.310 | 2.210 | 1.820 |
| | | (28.940) | (16.250) | (7.480) |
| WW* 1995-2004 listing dummy | | 8.180 | 4.530 | 3.890 |
| | | (38.010) | (23.070) | (10.280) |
| Ivol | | | 0.050 | 0.049 |
| | | | (42.910) | (30.250) |
| Age | | | -0.003 | -0.003 |
| | | | (-16.550) | (-13.270) |
| RD | | | | 1.080 |
| | | | | (15.560) |
| Adj. $R^2$ | 0.037 | 0.127 | 0.257 | 0.266 |
| Obs. | 139,887 | 139,887 | 139,801 | 68,460 |

**Table VIII: Firm Characteristics by Listing Group.** The table reports estimates from regressions of firm-level characteristics on listing year group dummies. DIVPOS is an indicator variable for whether the firm pays dividends. NEI is net equity issuance. Real sales growth (SG) is computed relative to previous year sales. RD is the amount of research and development divided by total assets in the previous year. Anfor is the average over the year of the median analyst forecasts of long term growth. WW is the Whited and Wu (2006) index of financial constraints. VolCF is the sample standard deviation of the ratio of cash flows to total assets in the previous year. The sample consists of the current and the past four years of data (with at least three annual observations). Ivol idiosyncratic return volatility computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). The sample for these regressions ranges from 1950 to 2006, except for Anfor that starts becoming available in 1981. The t-statistics (in parentheses) are computed using robust standard errors clustered by firm.

| | DIVPOS | NEI | SG | RD |
|---|---|---|---|---|
| pre 1965 listing dummy | 0.886 | 0.004 | 0.059 | 0.025 |
| | (151.070) | (8.370) | (43.690) | (22.000) |
| 1965-1974 listing dummy | 0.741 | 0.009 | 0.072 | 0.027 |
| | (98.800) | (16.810) | (37.720) | (22.490) |
| 1975-1984 listing dummy | 0.418 | 0.048 | 0.166 | 0.073 |
| | (36.380) | (28.190) | (33.030) | (25.260) |
| 1985-1994 listing dummy | 0.381 | 0.062 | 0.195 | 0.097 |
| | (49.070) | (31.830) | (47.700) | (31.250) |
| 1995-2004 listing dummy | 0.317 | 0.060 | 0.190 | 0.127 |
| | (38.790) | (21.690) | (37.080) | (34.960) |
| Obs. | 148,579 | 121,700 | 145,933 | 71,270 |
| | Anfor | WW | volCF | Ivol |
| pre 1965 listing dummy | 11.405 | 0.811 | 0.022 | 8.288 |
| | (74.570) | (368.870) | (53.470) | (118.280) |
| 1965-1974 listing dummy | 13.882 | 0.868 | 0.029 | 10.967 |
| | (98.920) | (453.770) | (55.570) | (124.160) |
| 1975-1984 listing dummy | 17.859 | 0.917 | 0.055 | 15.417 |
| | (82.420) | (358.630) | (39.050) | (103.660) |
| 1985-1994 listing dummy | 18.545 | 0.910 | 0.063 | 15.297 |
| | (116.540) | (551.790) | (48.770) | (131.230) |
| 1995-2004 listing dummy | 21.558 | 0.908 | 0.098 | 17.687 |
| | (103.200) | (518.810) | (35.820) | (108.260) |
| Obs. | 55,094 | 139,887 | 139,209 | 186,368 |

**Table A-I: Summary Statistics.** The table provides means, standard deviations, number of available observations, and correlations for the variables that are defined in the Appendix. *bm* is the log of book-to-market.

| | Mean | St. Dev. | Obs. | Correlations | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Beta | bm | Size | B_lvg | M_lvg | CF | DIVPOS | SG | ISG | WW | Age | NEI | RD | Anfor | VolROE | VolCF |
| Beta | 1.11 | 0.73 | 186670 | 1.00 | | | | | | | | | | | | | | | |
| bm | -0.32 | 0.92 | 186670 | -0.11 | 1.00 | | | | | | | | | | | | | | |
| Size | -0.14 | 2.07 | 186670 | -0.07 | -0.45 | 1.00 | | | | | | | | | | | | | |
| Book_lvg | 0.35 | 0.25 | 148311 | -0.20 | 0.14 | 0.05 | 1.00 | | | | | | | | | | | | |
| Market_lvg | -1.04 | 0.88 | 148833 | -0.22 | 0.61 | -0.19 | 0.69 | 1.00 | | | | | | | | | | | |
| CF | 0.06 | 0.14 | 148723 | -0.23 | -0.15 | 0.29 | -0.12 | -0.19 | 1.00 | | | | | | | | | | |
| DIVPOS | 0.62 | 0.49 | 148579 | -0.32 | 0.08 | 0.31 | 0.19 | 0.24 | 0.20 | 1.00 | | | | | | | | | |
| SG | 0.12 | 0.44 | 145933 | 0.09 | -0.25 | 0.08 | -0.04 | -0.20 | 0.14 | -0.14 | 1.00 | | | | | | | | |
| ISG | 0.06 | 0.18 | 148492 | 0.01 | -0.09 | 0.01 | -0.04 | -0.07 | 0.07 | -0.07 | 0.22 | 1.00 | | | | | | | |
| WW | 0.67 | 0.10 | 139887 | 0.24 | 0.06 | -0.84 | -0.26 | -0.19 | -0.33 | -0.63 | -0.01 | 0.16 | 1.00 | | | | | | |
| Age | 34.80 | 34.70 | 186670 | -0.28 | 0.06 | 0.41 | 0.23 | 0.24 | 0.14 | 0.49 | -0.15 | -0.07 | -0.56 | 1.00 | | | | | |
| NEI | 0.03 | 0.15 | 121700 | 0.15 | -0.10 | -0.08 | -0.11 | -0.19 | -0.14 | -0.15 | 0.25 | 0.07 | 0.17 | -0.15 | 1.00 | | | | |
| RD | 0.06 | 0.10 | 71270 | 0.36 | -0.28 | -0.06 | -0.30 | -0.36 | -0.25 | -0.34 | 0.17 | 0.04 | 0.30 | -0.26 | 0.27 | 1.00 | | | |
| Anfor | 16.70 | 8.99 | 55094 | 0.34 | -0.32 | -0.18 | -0.26 | -0.43 | -0.17 | -0.42 | 0.28 | 0.09 | 0.43 | -0.41 | 0.27 | 0.37 | 1.00 | | |
| VolROE | 0.12 | 0.17 | 127937 | 0.24 | -0.17 | -0.11 | 0.11 | 0.00 | -0.29 | -0.26 | 0.08 | 0.00 | 0.20 | -0.16 | 0.16 | 0.25 | 0.22 | 1.00 | |
| VolCF | 0.04 | 0.08 | 139209 | 0.40 | -0.12 | -0.19 | -0.13 | -0.13 | -0.49 | -0.30 | 0.02 | -0.01 | 0.34 | -0.23 | 0.15 | 0.37 | 0.28 | 0.54 | 1.00 |
| Ivol | 12.00 | 7.34 | 186368 | 0.50 | -0.10 | -0.37 | -0.19 | -0.22 | -0.37 | -0.56 | 0.12 | 0.03 | 0.54 | -0.46 | 0.23 | 0.39 | 0.50 | 0.42 | 0.53 |

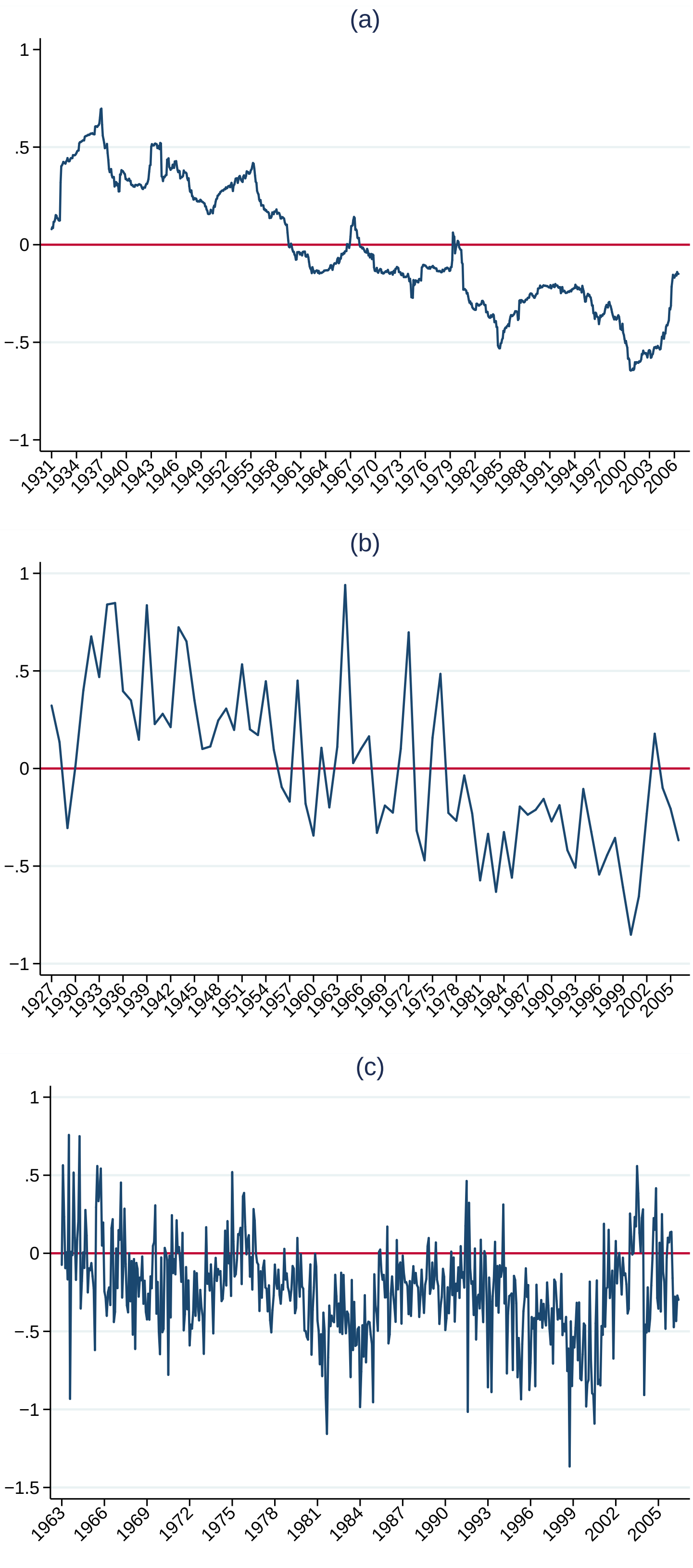


**Figure 1: Beta of HML Factor.** The figure plots the market beta of Fama and French's (1993) HML factor over time. The monthly series in plot (a) is obtained using monthly returns in sixty-month rolling-window regressions. The annual series in plot (b) is obtained using monthly returns in twelve-month non-overlapping window (January to December) regressions. The monthly series in plot (c) is obtained from regressions that use all the available daily observations in each month.

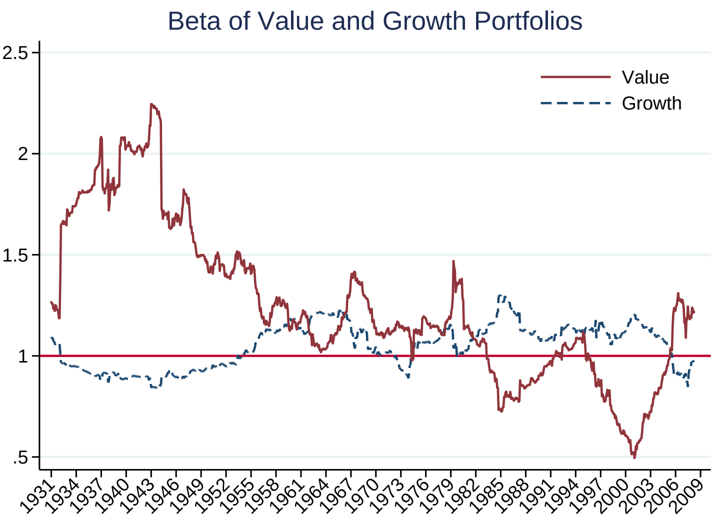


**Figure 2: Beta of Value and Growth Portfolios.** The figure plots the market betas of value (solid line) and growth (dashed line) portfolios. Value and growth denote the value-weighted portfolios formed from the tenth and first deciles of the book-to-market distribution, respectively. The monthly beta series are obtained using monthly returns in sixty-month rolling-window regressions.

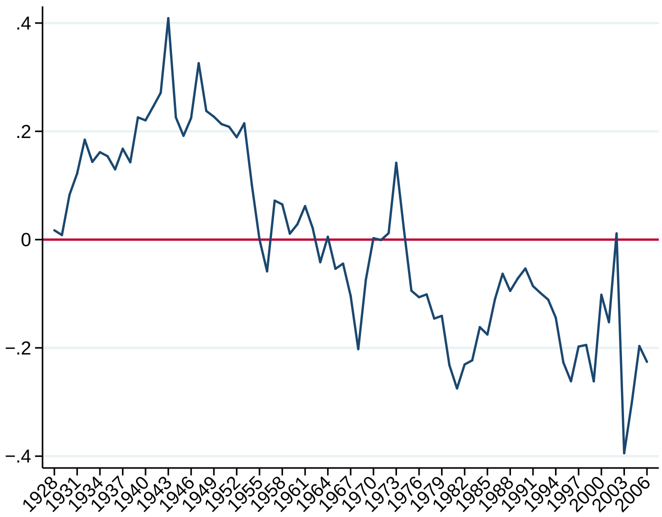


**Figure 3: Slope of Beta on Book-to-Market.** The figure plots the slope coefficients from annual cross-sectional regressions of firm level betas on (the log of) book-to-market. Betas are obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations).

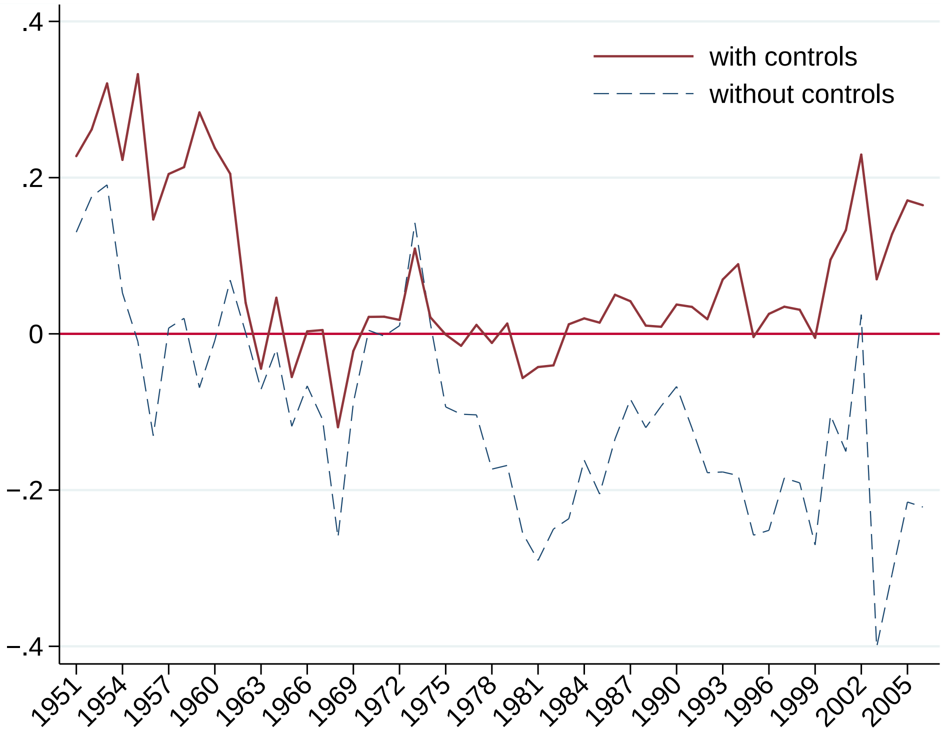


**Figure 4: Slope of Beta on Book-to-Market and Controls.** The figure plots the slope coefficients from annual cross-sectional regressions of firm level betas on (the log of) book-to-market. The dashed line is produced without any further controls in the regressions. The solid line comes from regression that also include (the log of) market capitalization in December divided by the CPI deflator (size), firm age, the Whited and Wu (2006) index, and idiosyncratic volatility (Ivol). Age is the number of years since the minimum available observation among the founding, incorporation, or listing year. Ivol is computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations). The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations).

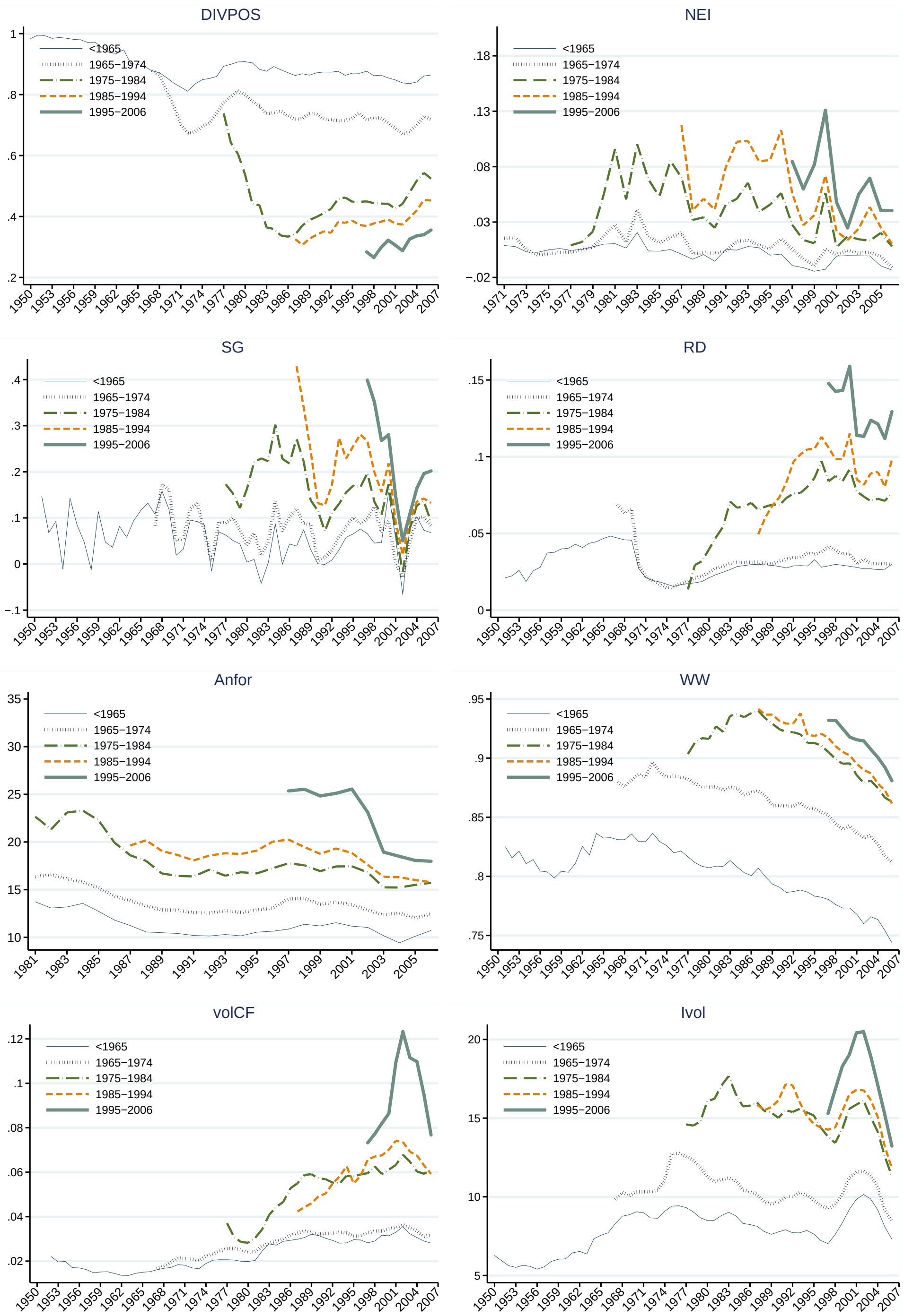


**Figure 5: New Listing Effect in Firm Characteristics.** The figure plots the annual average of firm characteristics by listing year groups. The groups are: before 1965 (thin solid line), 1965-1974 (dotted line), 1975-1984 (dashed-dotted line), 1985-1994 (dashed line), 1995-2006 (thick solid line). DIVPOS is an indicator variable for whether the firm pays dividends. NEI is net equity issuance. Real sales growth (SG) is computed relative to previous year sales. RD is the amount of research and development divided by total assets in the previous year. Anfor is the average over the year of the median analyst forecasts of long term growth. WW is the Whited and Wu (2006) index of financial constraints. VolCF is the sample standard deviation of the ratio of cash flows to total assets in the previous year. The sample consists of the current and the past four years of data (with at least three annual observations). Ivol idiosyncratic return volatility computed as the standard deviation of the residuals from the regression of stock returns on the Fama and French (1993) three factors. For the computation of Ivol, the sample consists of the sixty monthly observations ending in December of year $t$ (with at least twenty-four available observations).

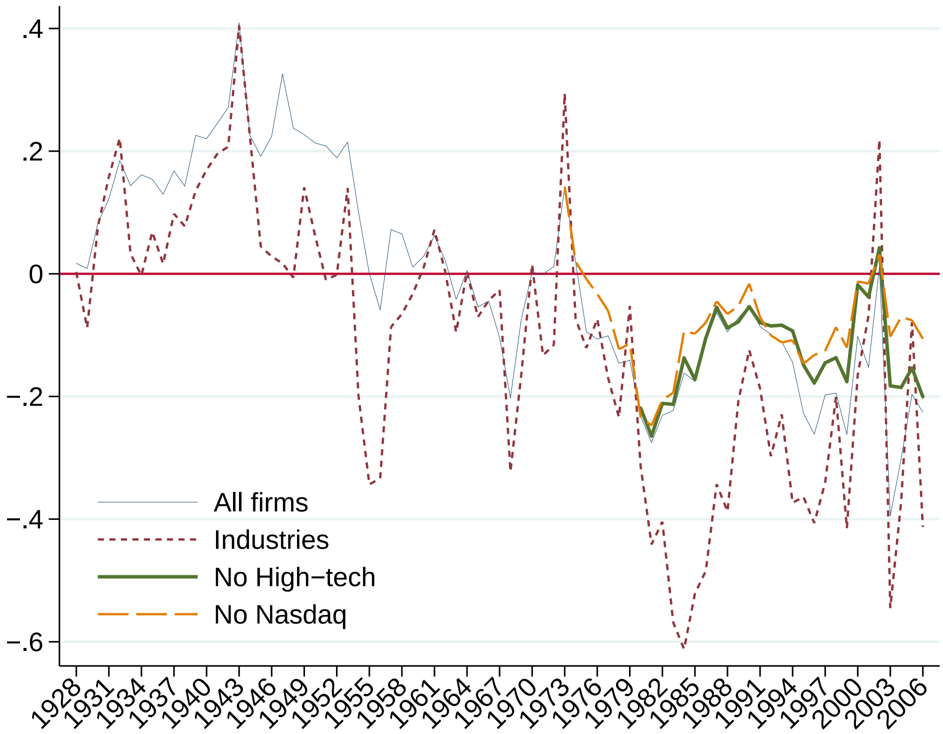


**Figure 6: Slope of Beta on Book-to-Market: Industry and Exchange Controls.** The figure plots the slope coefficients from annual cross-sectional regressions of betas on (the log of) book-to-market. The thin solid line is produced without any restriction on the firm-year observations. The short-dashed line comes from a regression where the dependent and independent variable have been averaged at industry level using the Fama and French thirty industry classification. For the long-dashed line, the sample is restricted to non-Nasdaq stocks (after 1972). For the thick solid line, the sample is restricted to firms that are not in the high-tech sectors (after 1979). High tech sectors are industries with SIC codes 283, 357, 366, 367, 382, 384, and 737. The dependent variable, a firm's market beta, is obtained from regressing monthly stock returns on the value-weighted market index in the sixty-month sample ending in December of year $t$ (with at least twenty-four available observations).