Predicting Systematic Risk: Implications from Growth Options

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Abstract

In accordance with the well-known financial leverage effect, decreases in stock prices cause an increase in the levered equity beta for a given unlevered beta. However, as growth options are more volatile and have higher risk than assets in place, a price decrease may decrease the unlevered equity beta via an operating leverage effect. This is because price decreases are associated with a proportionately higher loss in growth options than in assets in place. Most of the existing literature focuses on the financial leverage effect: This paper examines both effects. We show, with a simple option pricing model, the opposing effects at work when the firm is a portfolio of assets in place and growth options. Our empirical results show that, contrary to common belief, the operating leverage effect largely dominates the financial leverage effect, even for initially highly levered firms with presumably few growth options. We then link variations in betas to measurable firm characteristics that proxy for the fraction of the firm invested in growth options. We show that these proxies jointly predict a large fraction of future cross-sectional differences in betas. These results have important implications on the predictability of equity betas, hence on empirical asset pricing and on portfolio optimization that controls for systematic risk.

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1 Introduction

The measurement of systematic risk (beta) is essential for portfolio and risk management, as well as for joint tests of asset pricing models and market efficiency. Consider, for example, DeBondt and Thaler (1985, 1987) who show that losers perform very well over the next three-to-five-year period. They conclude that these reversals support the hypothesis that stock prices tend to overreact to information. However, the well-known financial leverage hypothesis in Hamada (1972) and Rubinstein (1974) implies that losers, experiencing an increase in financial leverage, should also have increased levered equity beta. Indeed, Chan (1988) and Ball and Kothari (1989) argue that the higher subsequent returns of the losers simply reflect higher expected returns, due to this increase in systematic risk. However, this conclusion may change drastically if the betas of the losers have not changed, or even decreased. This example shows that to analyze performance, one must first agree on risk. For losers and winners, one should agree whether risk went up or down, before concluding for or against market efficiency.

This paper documents, with a simple model and empirically, the determinants of the variation of systematic risk. The empirical literature discusses the financial more than the operating leverage, even though the latter received some early attention, (see Rosenberg and McKibben (1973) and Rosenberg (1974, 1985)). Another segment of the literature mostly uses simple time series methods such as rolling windows or univariate filters to predict betas. In contrast, we show that operating leverage have a strong impact on betas, and that accounting for its variation can markedly improve their estimation. For example, we show that for a wide range of initial financial and operating conditions, the equity betas of the losers decrease. Therefore, an operating leverage effect counters and dominates the financial leverage effect. This possibility is not explored in the empirical literature, despite the intense debate on the nature of the well-known reversal results.

We illustrate the impact of operating leverage on betas with a simple model in which a firm with no debt has both growth options and assets in place. Growth options require more future discretionary investment expenditures than assets in place, and are akin to out-of-the money options, while assets in place are in-the-money options. It is easily shown that the betas of both options increase as moneyness decreases. Therefore, as is the case with the financial leverage effect, by this *"moneyness effect"*, negative returns are accompanied by increases in beta. However, we also show that since the firm is a portfolio of options of different moneyness, a second, opposite effect is at play. As moneyness decreases, options more out-of-the money lose more value than options more in-the-money. The beta of the firm is a value-weighted average of the two betas, growth options, and assets in place. Therefore, the beta of the firm tilts toward the lower of the two betas, and can actually decrease even though both betas increase. We denote this the *"change-in-mix effect"*. Our model shows that for a central range of firm value weights in growth options, the change-in-mix effect dominates the moneyness effect.

The financial leverage effect does offset the change-in-mix effect for levered betas. However, a lot of empirical evidence is at odds with the financial leverage hypothesis. For example, the equity betas of financially distressed firms decline as their condition deteriorates even though their unsystematic risk and total risk increase, (see Aharony, Jones, and Swary (1980) and Altman and Brenner (1981)).[1] Braun et al. (1995) incorporate financial leverage in a time series model for betas, without much success.

Our empirical analysis first seeks to discover how general the dominance of the change-in-mix effect over the combined moneyness and financial leverage effects is. We measure changes in levered betas for losers and winners, and imply out the unlevered beta by also measuring changes in financial leverage. The patterns are so strong that we do not need to assume a functional levering relationship to infer the sign of change in unlevered beta. The levered equity betas of losers decrease and those of winners increase, which is consistent with a dominance of the change-in-mix effect over both moneyness and leverage. The result is quite robust to the initial, low or high, financial leverage; losers with high initial debt still experience subsequent decreases in betas.

We conduct a similar analysis on industries with initially low and high growth options, to test the robustness of the change-in-mix effect to initial operating leverage. While somewhat weaker,

[1] They attribute the decline in betas to possible decreases in the systematic risk of earnings, but do not explain why this may happen. The empirical corporate finance literature also fails to vindicate the financial leverage hypothesis. The equity betas of firms that act to increase their financial leverage do not increase, see e.g., Healy and Palepu (1990), Dann, Masulis, and Mayers (1991), Denis and Kadlec (1994), or Kaplan and Stein (1990).

the change-in-mix effect often dominates the moneyness and the financial leverage effects. For this analysis, we need proxies for the weight of the firm's value in growth option. We use the ratios of market to book value of asset, earnings over price, and capital expenditures to assets, as well as the the dividend yield. These proxies have theoretical justification, and have been studied. With these proxies, we confirm that the change-in-mix effect dominates both the moneyness and financial leverage effects. Specifically, levered betas are positively related to growth options as measured by the proxy. Finally, we show, with cross-sectional and panel regressions, that the growth option proxies are reliable predictors of the cross-section of equity betas.

The paper proceeds as follows: Section 2 develops a simple option pricing model to illustrate the possible links between stock returns and betas; Section 3 describes the data, proxies, and the methodology; Section 4 contains the empirical results and analysis; and Section 5 concludes.

2 Growth Options and Unlevered Equity Betas

The simple option-pricing model below shows how unlevered betas may respond to changes in firm value. In the model, a firm has assets already in place and future growth options predicated on further discretionary investments. As the firm is not obligated to make the added investments, a growth option is viewed as a call option to acquire an asset at an exercise price equal to the added investment. Assets in place are far in-the-money options. Myers (1977) describes the firm as a portfolio of assets in place and growth options, a distinction more of degree than kind. All assets have a varying fraction of their value attributed to call options from discretionary decisions.

Before proceeding, we need to establish the relation between the beta of an option and moneyness. Consider an option G to undertake a project at an investment cost (exercise price) C_G. The project has an underlying value s and a beta β_s. Galai and Masulis (1976) show that the beta of the option is $\beta_G = \eta_G \beta_s$, where η_G is the elasticity of the option. We show in the appendix that η_G decreases as moneyness $\frac{s}{C_G}$ increases. Therefore, for two options A and G on s, with A deeper in the money than G, we have $\beta_G > \beta_A$. Growth options have higher betas than assets in place.[2]

[2]Skinner (1993) reports that firms with relatively more growth options tend to have higher asset betas.

We now consider a firm with these two options, its value is $V = V_A + V_G = AN_A + GN_G$. $A \equiv A(s), G \equiv G(s)$ are the option value of an asset in place and a growth option. $A(s)$ is deep in-the-money with investment cost $C_A \ll s$, $G(s)$ is out-of-the-money with $C_G > s$. N_A, N_G are the numbers of options held by the firm. The state variable s simultaneously affects the moneyness of both options. We can therefore distinguish between two types of news; first, possibly separate news about the number of options N_A, N_G held by the firm, second, news about moneyness driven by economy-wide state variables that jointly affect both options in the firm. The single underlying state variable s reflects this joint effect. For example, s may be related to the price of oil while A and G represent functioning oil wells and undeveloped oil property, or s could be the price of beef and A and G could be Mc Donald's operations in the US versus China.

More generally, one may think of a multivariate state vector s, of which not all elements affect all the options.[3] For our qualitative purpose, there would not be much gain to this generalization. It is already imbedded in the scale factors N_G, N_A, which main intuition here is not an actual number of options as to allow for independent news about each of the two options (see section 2.1). The unlevered beta of the firm is:

$$\beta_V = \frac{V_A\beta_A + V_G\beta_G}{V} = \frac{AN_A\beta_A + GN_G\beta_G}{V} \tag{1}$$

2.1 Separate news about assets in place and growth options

We first consider news about N_G and N_A, the scales of the growth options and assets in place. From (1), it follows that:

$$\frac{\partial \beta_V}{\partial N_G} = \frac{GV_A}{V^2}(\beta_G - \beta_A). \tag{2}$$

That is, an increase in N_G causes an increase in the firm's beta. $\frac{\partial \beta_V}{\partial N_A}$ follows by swapping indices $_A$ and $_G$ in (2); an increase in N_A causes a decrease in beta. Therefore, simultaneous news $\Delta N_A, \Delta N_G$

[3] Berk, Green and Naik (1999) model the firm value in terms of fundamental state variables, where growth options are explicit calls whose value is affected by state variables, as well as cash flows.

of the same sign have opposite effects on β_V. Their combined effect is given by the total derivative:

$$d\beta_V = \frac{\beta_G - \beta_A}{V^2}\,(GV_A \Delta N_G - AV_G \Delta N_A).$$

It follows that, for simultaneous increases in the numbers of options, $d\beta_V$ is positive if and only if:

$$\frac{\Delta N_G}{\Delta N_A} > \frac{N_G}{N_A} \qquad \text{or equivalently:} \;\; \frac{\Delta V_G}{\Delta V_A} > \frac{V_G}{V_A}. \tag{3}$$

That is, the ratio of the increases must be larger than the current ratio of growth options over assets in place. For simultaneous bad news, β_V decreases if the inequalities in (3) are true.

So what can this tell us about betas of winners and losers? Analysts regularly revise their assessment of N_A and N_G. Growth options are most likely harder to assess than assets in place. Therefore, revisions of N_G are likely of a larger magnitude than of N_A, and, for revisions in the same direction, condition (3) will hold. Consequently, we expect large negative returns to be followed by decreases in betas. This is a first aspect of what we refer to as the "change-in-mix" effect. The empirical section will show that it is almost always the case.

2.2 Common effect of news on the underlying asset

News about an underlying state variable can simultaneously affect both options. Consider news about s, with N_A and N_G unchanged.[4] This can be information about the price of oil, not the amount of oil in the ground owned by Texaco. Or, the wholesale price of beef goes down, moving both US and China operations for MacDonald's further in the money. Good news about s increases both A and G, as they both move more into the money. Then, as we already know, both β_A and β_G decrease. Yet, we now show that this does not always mean that β_V in (1) decreases. This is

[4] We model a single firm. A large change in s for a large fraction of the firms in the economy may lead them to redirect their efforts toward different growth options, in turn possibly affecting N_A, N_G. A full multi-period equilibrium model of the firm would have to account for this.

because A and G increase by different amounts, which affects their weight in V. We compute $\frac{d\beta_V}{ds}$:

$$\frac{d\beta_V}{ds} = \frac{GN_G}{V}\beta_G' + \frac{AN_A}{V}\beta_A' + N_G\frac{\beta_G - \beta_V}{V}G' + N_A\frac{\beta_A - \beta_V}{V}A',$$

where $G', A', \beta_G', \beta_A'$ are derivatives with respect to s. Recall that $\beta_i = \eta_i\beta_s$ for i equal to G or A. Replace β_V with (1), and it can be shown that :

$$\frac{V}{\beta_s}\frac{d\beta_V}{ds} = GN_G\eta_G' + AN_A\eta_A' + [\eta_G - \eta_A]^2\,\frac{N_A N_G A' G' s}{V}. \tag{4}$$

The first two terms are negative, the third is positive. A numerical example now shows that their sum can be positive for a central range of moneyness s/C_G and firm weight in growth options V_G/V. We assume $C_A = 1, C_G = 100, s \in [2, 90]$, and, without loss of generality, $N_A = 1$, a risk free rate of zero and a variance to maturity $\sigma^2 T = 1$. For this range of s, the asset in place is far into the money and the growth option deep out of the money. The weight of growth options V_G/V also matters. To cover a wide range we use three values of $N_G = 5, 10, 20$. The bottom panel in Figure 1 plots the weight of the firm in growth options, V_G/V versus moneyness s/C_G. The three curves, for $N_G = 5, 10, 20$ confirm that these values of N_G span a wide range for V_G/V. For example, for a moneyness s/C_G of 20%, V_G/V varies from 20% to 60%. The key is that this wide range of values has no effect on the pattern uncovered by the top plots, β_V versus s/C_G.

Figure 1 here

The three curves in the top panel have the same shape, with only minor variations in the location of the minimum and maximum. There are three regions. First, on the left, the growth options are very far out of the money, hence worth very little. There, an increase in s decreases β_V. Second, on the right, where the growth options are getting closer to the money and make a larger fraction V_G/V of the firm, an increase in s also decreases β_V. In both these regions, the firm is approximately homogeneous in the type of options held, nearly all in or nearly all out-of-the money. That is, the firm is approximately a one-option firm, the changes in weights $V_G/V, V_A/V$ do not play a role and the moneyness effect dominates. Hence, an increase in s increases moneyness, which causes the firm's beta to decrease. In the central region however, the firm is the most heterogeneous in G and A. So, even though both β_G, β_A decrease as s increases, the weight V_G/V increases enough so that β_V increases.

2.3 Implications for empirical analysis

The general implication of this model is that unlevered equity betas are more likely to be positively, rather than negatively, correlated with firm value. This was argued when changes in price came from news about the scales N_G, N_A, and about s that simultaneously affect both option values. Our empirical analysis will not separate news on scales from news on s, or the moneyness from the change-in-mix effects. Rather, it will document the dominance of the positive relationship between betas and returns (due to change-in-mix) over the negative relationship (due to financial leverage and moneyness).

We sort firms by performance deciles and show that, indeed, the unlevered betas of the winners (losers) increase (decrease), consistent with this positive association. The model in section 2 does not incorporate financial leverage which creates an negative association between returns and levered betas, and we only observe levered betas. But the observation of the levered betas and the debt-to-equity ratio will allow us to imply out the direction of the change in unlevered betas for losers and winners. This will allow us to conclude whether the change-in-mix effect dominates the moneyness effect. We will also document the robustness of the positive relationship between beta and firm value for subgroups of firms with initially high and low debt. The results depend on the initial weight in growth options, central versus lateral regions of Figure 1. We will use industries with high and low growth opportunities to explore these lateral regions of Figure 1.

Even this simple model shows that the relationship between unlevered beta and firm value may be inverse for extreme cases of initial weight in growth option. These are the left and right regions in the top plot of Figure 1. This begs the question of how wide the central region is in reality. To check this we study the relationship between beta and performance for industries argued to have high or low weight in growth opportunities. To characterize these industries as high or low growth, we introduce proxies for growth opportunities. We then directly check the cross-sectional relationship between these proxies and levered and unlevered betas.

3 Returns Data and Proxies for Growth Options

We collect monthly stock returns from CRSP, and annual financial statement data from the merged CRSP-Compustat database. Accounting data for fiscal years ending in calendar year t-1 are merged with monthly stock returns from July of year t to June of year t+1. That is, all our sorting presented in the empirical section is done from July to June. Our selection criteria and construction of firm-specific variables follow Fama and French (2001). We use NYSE, AMEX, and NASDAQ stocks with CRSP codes of 10 or 11, from June 1965 to June 2007. We exclude utilities, financial firms, and firms with book value of equity below K\$250 or assets below K\$500. We use a firm's market capitalization at the end of June of year t to calculate its book-to-market, leverage and earnings-to-price ratios, and dividend yield for that year.

As the weights of firms in growth options and assets in place are not observable, it is common practice to use proxy variables. These proxies all have some theoretical justification, and a number of studies evaluate their performance. For example, Goyal, Lehn and Racic (2002) show, with U.S. defense industry firms, that proxy variables track changes in investment opportunities. Any given proxy will potentially fail to measure the full extent of the investment opportunity set, and has its advantages and disadvantages. Erickson and Whited (2006) conclude that all the proxies for Tobin's q which they examine contain significant measurement errors. We use several proxies motivated in the literature and again below, each with its qualities and limitations.

Our first proxy for growth options is the ratio of market to book value of assets, **Mba**. The book value of assets is a proxy for assets in place. The market value of assets is a proxy for the sum of assets in place and growth options. The higher Mba is, the higher the proportion of growth options to firm value. As in Fama and French (2001), we define the market value of assets as the book value of assets minus the book value of equity plus the market value of equity. Adam and Goyal (2008) show that, among common proxies, the Mba ratio has the highest information content with respect to investment opportunities and is least affected by other confounding factors. It is also close to the Market to Book value of equity, often found to be a strong predictor of the cross-section of returns, since Fama and French (1992). Mba is similar to the reciprocal of the ratio of book value of assets to total firm value used by Smith and Watts (1992).

The second proxy is the ratio of earnings-to-price, **Ep**, used for example by Smith and Watts (1992). We use the earnings before extraordinary items minus preferred dividends plus income-statement deferred taxes if available. The larger Ep is, the larger the proportion of equity value attributable to earnings generated from assets in place rather than growth options. As this is only valid for firms with non-negative earnings, we allocate firms with negative earnings to a separate group when we sort by Ep. Ep and Mba are growth measures often used in the literature.

The third proxy is the dividend yield, **Div**. Dividends are linked to investment through the firm's cash flow identity. Jensen (1986) argues that firms with more growth options have lower free cash flows and pay lower dividends. When sorting firms based on the dividend yield, we put zero-dividend firms in a separate group.

The last proxy is the ratio of capital expenditures to net fixed assets, **Capex**. Capital expenditures are mostly seen as discretionary investment decisions. The higher capital expenditures are, the greater the investment made by a firm to create new products, and in turn the greater the growth options. However, capital expenditures are a pure accounting measure, and may be lumpy. Adam and Goyal (2008) suggest that Capex alone may not be a very good proxy for investment opportunities.

We also collect the debt-to-equity ratio, **Dtoe**. According to contracting theory, firms with high growth options may have lower financial leverage because equity financing controls the potential under-investment problem associated with risky debt, see Myers (1977). Here we do not use Dtoe as a proxy for growth options, but it allows us to infer changes in unlevered betas from changes in the measured equity betas. We will be able to derive unambiguous conclusion without resorting to specific levering formulas.

In summary, firms with high growth option should have higher Mba and Capex and lower

Ep, Div. Table 1 reports the aggregate values of the proxies for key years from 1965 to 2007, as well as summary statistics. To compute portfolio proxies, we sum the numerators and the denominators separately across firms. Capex ranges between 15 and 23% with quickly decaying autocorrelations. Mba is more persistent, and has a much larger coefficient of variation. From a low of 98% in 1982, it rises to 254% before the 2001 crash. The Dividend decreases steadily through the period, as discussed by Fama and French (2001). It is around 1.3% in 2007, from a high of 5% in 1982. Ep is at 4.8% in 2007, it has increased since its low of 1.2% in 2002. As expected, Dtoe varies a lot with the state of the economy and can jump dramatically during a crash year. It averages 33% for the period. Even in the aggregate, these proxies have high coefficients of variation despite their high autocorrelations.

Table 1 here.

4 Empirical Results

4.1 The betas of winners and losers

Every year, from June 1971 to june 2004, we assign firms to deciles on the basis of their total return for the past 3-year. We exclude firms with missing monthly returns or growth proxies in any period, or with share prices below $1 at the end of any period to remove illiquid stocks. We lost very few firms due to missing accounting data. This 3-year "ranking" period and the surrounding 3-year pre-ranking and post-ranking periods are labeled 0, -1, and 1 in the tables. We have 34 such windows of 9 years separated in 3 periods. Statistics are computed, and then averaged over these overlapping windows, separately for period -1, 0, and 1. We compute the value-weighted monthly returns of the ten decile portfolios. We estimate the value-weighted beta β_{VW} of each portfolio with the standard market model regression in excess-returns form. We use the value-weighted index of all NYSE, AMEX, and NASDAQ stocks as the market index. We subtract the 30-day U.S. Treasury bill to compute excess returns. We also compute betas for the 4-factor model with the usual regression in excess returns:

$$r_{it} = \alpha_i + \beta_{i,mkt}\, r_{mkt,t} + \beta_{i,smb}\, r_{smb,t} + \beta_{i,hml}\, r_{hml,t} + \beta_{i,umd}\, r_{umd,t} + \epsilon_{it}, \quad t = 1, ..., 36, \qquad (5)$$

where $r_{mkt}, r_{smb}, r_{hml}$ and r_{umd} are the returns on the market, size, and book-to-market factors. Finally, we compute the aggregate Dtoe for each decile, for periods -1, 0, 1.

We report averages, an analysis with medians gave similar results. We concentrate on changes in beta from period -1 to period 1, rather than 0 to 1, because it has been noted that the estimates of beta in period 0 could be biased if the ranking was done along a variable correlated with beta. Estimates of betas in period -1 are not related to the sorting effected in period 0. We also compute t-statistics for the null hypothesis that the mean difference in beta between periods -1 and 1 is zero. The basic OLS standard errors assume i.i.d. data and are therefore biased for our overlapping windows. This two-year overlap comes from the fact that the betas are estimated annually from three-year windows, this induces autocorrelation in the time series of $\widehat{\beta}$. Consequently, we compute heteroskedasticity and auto-correlation consistent (HAC) standard errors based on two lags of autocorrelation for the time series of 34 estimates $\widehat{\beta}_1 - \widehat{\beta}_{-1}$.

Table 2, panel A reports these estimates. Consider the total returns for periods -1, 0, 1; the typical loser decile experiences a 53% cumulative loss over the ranking period while the winner decile records a 264% return. In the following period 1, their returns are similar, 48% for the loser and 40% for the winner. Period 1 does not show any strong pattern in returns for the 10 deciles.

Table 2 here

Consider now β_{vw}: the loser β drops from 1.35 in period -1 to 1.26 in period 1 while the winner β increases from 1.21 to 1.27. To infer the changes on the unlevered betas, we look at the corresponding Dtoe ratios. As the β of the losers decreases, their Dtoe more than doubles, from 25% in period -1 to 58% in period 1. The Dtoe of winners is halved, from 46% to 23%, as their β increases. Consequently, we do not need a specific *"unlevering"* formula to draw unambiguous inference about the direction of the changes in unlevered betas. A specific formulas would allow us to quantify the magnitude of the change, but this would be limited to the validity of the hypotheses made. The changes in the levered betas of losers and winners contradict the predictions of the financial leverage hypothesis. If unlevered betas were constant, the loser (winner) levered betas should have increased (decreased) due to their large changes in financial leverage. Therefore, we conclude from Table 2A that a massive change in unlevered betas has taken place, in the opposite direction. This is consistent with large losses of growth options for the losers, implying a drop in their unlevered asset betas. Similarly, the winners exhibit large increases in their unlevered beta, consistent with gains in growth options.

These results show that the change-in-mix effect dominates both the moneyness and the financial leverage effect. If returns follow a factor model as in Fama-French (1992) or (5), β_{vw} gives an incomplete description of systematic risk. Consequently, Table 2 reports on the estimates of β_{mkt}, β_{hml} from (5). We do not report the size beta which is not clearly related to growth options. Small and young firms may be growth oriented. However, firms that have lost growth options may be smaller than average. We do not report on the momentum beta.

The HML factor portfolio is the difference between returns on high and low book to market equity stocks. Firms with higher growth options should have a lower β_{hml}. We can use β_{hml} to verify if losers (winners) have lost (gained) growth options. Table 2B shows that β_{hml} has an inverted U-shape pattern across deciles in period 0, and in period -1. Both winners and losers initially had lower β_{hml} than average. This means that extreme performers come from firms with high growth options. Their change in β_{hml} from period -1 to period 1 is then consistent with the expected changes in operating leverage. The losing decile β_{hml} increases from -0.61 to -0.07; consistent with losses in growth options. The winner β_{hml} decreases from -0.23 to -0.58, consistent with gains in growth options. In summary, the evolution of β_{hml} show that the losers are firms that fail to realize an initially high growth potential, while the winners are already growth oriented firms that further increase their growth options.

We now turn to the market beta β_{mkt}, it can be used as a robustness check on β_{vw}, to the extent that the four-factor model is more robust than the one-factor model. Table 2B shows that β_{mkt} is stable from period -1 to period 1, for both losers and winners, with a slight U-shaped distribution across the performance deciles. Both winners and losers have larger market betas than the average firm. Due to the change in Dtoe, we conclude that, as with β_{vw}, the unlevered market beta of losers (winners) has decreased (increased). The results are not as strong as with β_{vw}, but we can still conclude that the change-in-mix effect largely dominates the moneyness effect.

To conclude, we note that the total returns of losers or winners in the pre- or post-ranking periods are nothing out of the ordinary, unlike their returns in the ranking-period. The Dtoe ratio in the ranking period overstates the long-term change in financial leverage for extreme performers. The financial leverage of losers rises over time, but not as much as suggested in the ranking period.

4.1.1 Robustness to extreme initial financial leverage

The positive relationship between stock returns and unlevered betas is consistent with the change-in-mix effect dominating both the moneyness and the financial leverage effects. It is also consistent with the range of growth options in the middle region of Figure 1. We now ask how robust this result is to extreme initial growth options, the left and right regions of Figure 1. The financial leverage effect should be the strongest for the most highly levered firms, since contracting theory implies that such firms have low growth options. If these firms indeed have a low weight in growth options, they may be in the left region of Figure 1. There, the change-in-mix effect may be weaker, letting the inverse relationship between stock returns and betas appear. In brief, firms with very few growth options do not have much more to lose, and the moneyness and financial leverage effects may dominate.

We allocate stocks to three groups in period -1, along the 30^{th} and 70^{th} percentiles of Dtoe. We then form period 0 total return deciles within each Dtoe group, and perform the previous empirical analysis for these groups. Table 3 reports average returns, betas, and Dtoe for the winners and losers, deciles 1 and 10, among low and high Dtoe. We do not show the middle Dtoe group, as expected, their results are consistent with Table 2.

Table 3 here

The first two rows in each panel report on the groups with low initial debt. Their Dtoe shows that they are initially quasi debt-free. The loser β_{vw} decreases again, from 1.48 in period -1 to 1.29 in period 1, β_{mkt} decreases as well. The increase in Dtoe from 3% to 27% again implies that unlevered betas have decreased by large amounts. The loser β_{hml} increases from -0.95 to -0.39, also consistent with a decrease in weight in growth options. The winners' β_{vw} hardly changes, their β_{mkt} drops slightly from 1.04 to 0.96, and their Dtoe also hardly changes, from 5% to 7%. Consequently, the unlevered betas of the winners may have slightly decreased, if at all. This is consistent with a firm in the right region of Figure 1, where an increase in operating leverage comes with a small decrease in β. It may also be that for firms with an already very high weight in growth options, positive news are unlikely to be related to a further increase in this weight. Indeed the low-debt winners have a β_{hml} of -0.62 in period -1, already lower than the average winner β_{hml} in period 1 of -0.58 seen in Table 2. These results show that, while we do detect an effect similar to the right region in Figure 1, it is very weak.

We now turn to losers and winners with high initial Dtoe, 117% and 141%, respectively. For the winners, β_{vw} increases slightly and Dtoe decreases drastically, from 141% to 53%. This implies that the winners' unlevered betas must have increased, consistent with a dominating change-in-mix effect. The same conclusion follows from the decrease in β_{hml} from 0.17 to -0.08, which implies an increase in the weight of growth options. Winners with high initial financial leverage exhibit the same positive relationship between returns and unlevered betas as the general group. For the losers with high initial debt, β_{vw} decreases from 1.34 to 1.27, while Dtoe increases from 117% to 147%. This implies an even stronger decrease in unlevered beta, consistent with a loss of growth options and a dominance of the change-in-mix effect. The large increase in β_{hml} from 0.07 to 0.43 confirms this. So, even firms with initially few growth options, which then suffer a further reduction of their value, exhibit a dominating change-in-mix effect. This would imply that the central region of the top plot of Figure 1 extends far to the left.

4.1.2 Robustness to initial operating leverage, industry analysis

We continue to investigate the robustness of the dominance of the change-in-mix effect. Consider firms with few growth options which incur losses: Does their unlevered beta still decrease markedly? Or, when firms with an initially high weight in growth options incur large wins, does their beta increase? In effect, we are still assessing the extent of the central region of Figure 1. To do this, we now use the growth option proxies.

We use Ken French's 30-industry classification, we obtained similar results with other industry groupings. We select 3 industries with the most and 3 with the least growth options. We compute each year the average aggregate value of the growth option proxies for each industry. We assign to each industry a rank for each proxy. We then build two indices; the first is equal to the average rank over the 4 proxies, and the second is equal to the average rank over Mba and Capex. We consider only Mba and Capex because of their documented strength as proxies for growth options. These two indices exhibit good consistencies in their ranking. We selected Business Equipment, Services, and Health Care as high growth industries, and Steel, Automobile, and Oil as low growth. The textile industry was ranked as low growth more often than the oil industry. We did not use it because its small number of firms made it difficult to break it down into performance groups.

We analyze these 6 industries as in Table 2. However, because of the smaller number of firms in each industry, we use the top and bottom quartiles of 3-year returns to select winners and losers. Then, as in Table 2, we allocate the firms of an industry into winner and loser portfolios during period 0. Table 4 reports the 3-year return, betas, and Dtoe over periods -1, 0, and 1. First, consider β_{hml} in period -1 shown in panel B. As they should, our 3 low (high) growth industries have strong positive (negative) β_{hml}. The spreads of returns in period 0, panel A, also show that high growth is associated with more volatile returns than low growth. High growth initial financial leverage is also lower than low growth.

Table 4 here

Consider first the winning low-growth firms. Their levered β_{vw}'s all increase, and their Dtoe's decrease. Therefore, their unlevered beta increases, which is consistent with a dominating change-in-mix effect. We cannot conclude as clearly for the Automobile firms that manages to increase their debt after winning periods. β_{hml} however decreases for all three industries, consistent with increased weights in growth options. But it is not be surprising that for firms with initially low weight in growth options, large positive returns are consistent with increases in that weight.

Now consider the low growth firms that experience large losses. Two of these industries see their levered beta decrease or remain basically constant, while their Dtoe increases. This again implies a decreased unlevered beta, and a dominating change-in-mix effect. We cannot conclude unequivocally for the Steel industry. But, with a levered β_{vw} rising 7.5% from 1.19 to 1.28 while the Dtoe jumps from 56% to 91%, it is most likely that the unlevered beta went down. In brief, Table 4 confirms that losing firms with initially low weight in growth options experience further decrease in growth options. Their β_{hml}'s all rising confirm this. The change-in-mix effect still dominates the moneyness effect, but is not always strong enough to overcome financial leverage.

Firms with initially high weight in growth options, Health, Services, and Business Equipments, see their levered beta decrease after losses. This, together with the rise in their Dtoe, implies unequivocally that their unlevered beta has decreased by an even larger amount. This is not surprising, since they had plenty of growth options to lose. More interesting is what happens to the high growth firms after large positive returns. Business equipments see their levered beta rise after wins. As their Dtoe also falls by more than 50%, it is certain that their unlevered beta increased a lot, consistent with a dominating change-in-mix effect. However, the levered betas of the Health and Services industries decrease by 11% and 6%, while their Dtoe's experience large decreases of 50% and 14%. So, again while not absolutely certain, it is extremely likely that unlevered betas have gone up. This is consistent with a further increase in their weight in growth options, confirmed by the decrease in their β_{hml}. While the change-in-mix effect does not always overcome the financial leverage effect, it still appears to dominate the moneyness effect

In summary, the effects uncovered in Table 2 are robust to initial operating leverage. The change-in-mix effect, although sometimes not strong enough to overcome the financial leverage effect, still dominates the moneyness effect.

4.2 Betas and growth options

These results are consistent with the hypotheses that gains and losses of firms are generally driven by a strong change-in-mix effect which in most situations dominates both the opposing moneyness and financial leverage effects. Also, growth options have higher betas and more volatile returns than assets in place. The previous analysis was akin to a time series study of changes in growth options. We now document the cross-sectional link between betas and proxies for growth options. This will also help gauge the quality of these variables as proxies of growth options.

At the end of every June from 1968 to 2004, we allocate firms to increasing growth option deciles on the basis of increasing Capex and Mba, and decreasing Div and Ep. Firms with zero dividends or non-positive earnings are grouped into an extra 11^{th} portfolio. For the following 3-year period, we compute for each group, its aggregate proxy value and Dtoe at the end of the period, and its β_{vw} and the four-factor model betas. Table 5 reports the average of these statistics over the 37 windows from 1968-1971 to 2004-2007.

Table 5 here

Panel A reports results on Capex based growth deciles. The average cross-sectional spread in Capex is 12% to 36%, from decile 1 to 10. This is much larger than the time series range of the market aggregate seen in Table 1, which was 15% to 24%. Recall that we allocate firms to portfolios based on ranking period values, but the values reported in Table 5 are computed in the following period. Consequently, the large spread is not induced by a selection bias. The monotone increase of Capex from decile 1 to 10 shows that the proxy persists over time, from period 0 to period 1. Deciles 1 and 10 have levered β_{vw}'s of 1.11 and 1.44, and Dtoe's of 62% and 18%. This means that the unlevered beta of low Capex stocks is even lower than that of high Capex stocks. Similar conclusions follow for β_{mkt}: although the relation is U-shaped, higher growth deciles have larger β_{mkt} than lower growth ones. The book-to-market risk factor β_{hml}, argued to be inversely related to growth options, is indeed inversely related to Capex. The size factor β_{smb} has a U-shaped relationship with Capex. This is consistent with the fact that both low and high growth option groups may include small firms. There is as strong relationship between the weight in growth option and returns standard deviation σ_R.

Panel B, with Mba results, leads to similar conclusions, although not as strong as for Capex. As expected by construction, there is a strong negative monotone relationship between Mba and β_{hml}. The size factor β_{smb} and Dtoe are also negatively related to Mba, suggesting that high growth firms, as proxied by Mba, tend to be smaller stocks with lower financial leverage than low growth firms. Again σ_R shows a strong link between growth as proxied by Mba and total variance

Panels C and D report the results based on Div and Ep. the conclusions are similar to those for Capex and Mba, with differences due to the nature of their group 11. Group 11 contains firms with zero dividends and non positive earnings in the ranking period. Decile 10, high growth in both panels, tends to have higher β_{vw} and β_{mkt}, and lower Dtoe than decile 1. These relationships are nearly monotonic from decile 1 to 10. Both div and Ep display an unambiguous positive relationship between proxy and beta and an inverse relationship between proxy and financial leverage. Therefore, unlevered betas must also have a positive relationship with the growth option proxies. The conclusion is robust to any reasonable levering relationship for betas, only requiring the levered beta to increase with financial leverage for a given unlevered beta. We can also infer that the positive relationship between growth options and unlevered betas is stronger than that reported with equity betas. The book-to-market risk factor β_{hml} is inversely related to both proxies, further supporting the view that unlevered betas are positively related to the growth option proxies. One difference with the first two proxies is that σ_R shows that the link between growth and return variance is quite tenuous for Div and Ep.

Zero-dividend firms, row *Div=0* in panel C, have the highest equity betas but not the lowest Dtoe. Their 40% Dtoe places them around deciles 4 of financial leverage, and their β_{hml} of -0.52 places them between deciles 9 and 10 of growth. So zero-dividend firms are mostly growth firms, with average debt. Firms with negative earnings, row $Ep \leq 0$ in panel D, are harder to interpret;

while lower Ep ratios can be related to higher growth options, it is hard to extend the reasoning to negative earnings, it might get you into a bubble burst as in 2001! Indeed, the β_{hml} of 0.11 and the Dtoe of 74% indicate that these firms have fewer growth options than average. Note that the positive Ep and Div in column 2 is measured at the end of the 3-year period following the portfolio formation. Some of these firms resume positive dividends or obtain positive earnings again. But both these Div and Ep are quite low.

In summary, the relations observed in Table 5 between growth proxies and, indirectly, unlevered betas are consistent with the hypothesis that higher growth options result in higher betas. As the firms are grouped in the ranking-period and systematic risk is measured in the post-ranking period in our analysis, the cross-sectional relationship between betas and proxies may have some predictive power on betas. We now show how this can be exploited.

4.3 Predicting cross-sectional variations in systematic risk with growth proxies

The above analysis uncovered strong univariate relationships between betas and the proxies. It also had a predictive aspect since portfolios were formed on the basis of the growth proxies, one period before the estimation of the betas. We now examine the joint ability of the growth option proxies to predict cross-sectional variations in asset betas. To do this, we estimate the cross-sectional regression:

$$\beta_{i,t} \; = \; \delta_{t-1} \, X_{i,t-1} \; + \; \gamma_t \, \Delta X_{i,t} + \epsilon_{i,t} \;\; i = 1 \ldots 25, \tag{6}$$

where X_{t-1} is the vector of proxies (Mba, Capex, Div, Ep, Dtoe) measured at $t-1$ and ΔX is the change in proxies from $t-1$ to t. The proxies at time $t-1$ are used to explain the cross-sectional distribution of β_t. The rational for including the changes in proxies from $t-1$ to t, is to check if recent changes in proxies have marginal power over the *long-run* values of the proxies, to predict the cross-section of betas. The literature documents low cross-correlations across proxies, e.g., Adam and Goyal (2008), which we verified. Using them jointly will not cause any multi-collinearity.

Every year, from July 68 to June 04, we allocate firms to 25 portfolios on the basis of past

3-year returns. Aggregate portfolio growth proxies for this period $t-1$ and the following 3-year period t are calculated. We estimate factor betas with thirty-six monthly value weighted portfolio returns over period t. We first run (6) as thirty-seven cross-sectional regressions. To facilitate an economic interpretation of δ and γ, we standardize the proxies by their cross-sectional mean and variance, recomputed annually. That is, δ measures the change in β for a one cross-sectional standard deviation change in the proxy. This standardization may also be preferable if proxies exhibit strong time trends or changes through the sample period.

Table 6A, reports results for the dependent variables β_{vw} and β_{mkt}. Subscripts $({}_{-1})$ refer to the estimates of δ_{t-1} in (6). The column "mean" shows the average of the 37 estimates, Q_1 and Q_3 are the first and third quartiles of the distribution of the 37 estimates, "#" is the number of estimates with the expected sign, next to it is the the HAC corrected t-statistics for the mean of the time series of estimates, accounting for two lags of autocorrelation. Finally, $\bar{R}^2$ and $\bar{R}^2_{-1}$ report on the adjusted R-squares of the regressions, with all the independent variables and with only the lagged, $({}_{-1})$, variables.

Table 6 here

The fit, shown by the R-squares is clearly high. The proxies jointly explain a large fraction of the future cross-section of systematic risk. For β_{vw}, the R-square averages 72%, with three quarters above 65%. For β_{mkt}, the average R-square is around 44%. We can verify the validity of each proxy individually. We expect positive coefficients for Capex and Mba, negative for Div and Ep. Capital expenditures and dividends are significant and with the correct sign about every year. However, for both β_{vw} and β_{mkt}, the slope estimate for Mba_{-1} is contradictory to what we would expect. The coefficient of Ep_{-1} for β_{vw} has a similar pattern. The coefficient of Dtoe_{-1} is insignificant, but with the correct sign about two-thirds of the time. This shows that one can recover the sign expected by the financial leverage hypothesis, once growth proxies are also accounted for.

The recent changes in proxies, from $t-1$ to t, add to the explanatory power, but do not explain as much as the lagged proxies themselves. This is seen clearly by comparing the R-squares of the full regression in (6) with $\bar{R}^2_{-1}$ shown below, the R-square of a regression without ΔX.

The coefficient estimates for the change variables ΔX confirm this result: the coefficient for ΔDiv is significant but of the right sign most of the time, the other coefficients for changes in proxies are mostly insignificant, and about half the time of the correct sign, as expected under the null hypothesis.

One use of the regression (6) is to assess to what extent we can filter out estimation error in beta through the use of growth option proxies. As has been known since Fama-MacBeth (1973), the larger the portfolio, the smaller the estimation error for beta. Indeed regressions as in Table 6A, but with 50 or 100 portfolios have similar results albeit with lower R-squares of 59% and 46%, due to the higher noise in $\hat{\beta}$.

While convenient and robust, the time averaging of cross-sectional regressions is not the most powerful estimation technique. We report in Panel B the results of a panel data regression, pooling the time series and cross-sections. The R-squares are lower, 39% for β_{vw}, as expected since the coefficients are constrained to be constant through 40 years. The panel data approach brings up the issue of the autocorrelation in errors, due to the overlap in the returns used to compute β, and the autocorrelation of the regressors. Appropriate corrections of the standard error in these regressions has gotten renewed attention in the finance literature, (See Petersen (2009)). We also estimated a feasible GLS with very similar results. See also Bauer et al. (2009) for a bayesian approach combining time series and cross-sectional estimation. Given multiple observations for the same portfolio (or firm), and persistent regressors (here the proxies), there can be strong residual autocorrelation within portfolios over time. In addition, since variables like stock returns pick up systematic changes in value, there can also be strong residual correlation across portfolios for a given time period. This "within" and "between" portfolio residual correlation creates a bias in traditional OLS standard errors. We use the method in Thompson (2009) which allows for time and cross-sectional clustering. We do not report the basic OLS errors which are much lower. The results of the panel data regression are not very different from those in panel A, apart for the inevitably lower fit, from the cross-sectional analysis.

To summarize, the lagged growth option proxies predict a large fraction of cross-sectional differences in systematic risk. The relationship between betas and each proxy most often has the desired sign given that growth options have higher betas. Recent changes in the proxies have limited marginal explanatory power over and above the lagged values of the proxies.

5 Conclusions

The empirical literature still makes much more of acase of the financial than of the operating leverage effect. This is somewhat surprising given that the predictions of the financial leverage are often at odds with the evidence. In particular, as we emphasize in this paper, betas of stocks that have had high returns do not decline, while betas of stocks with large negative returns decline significantly, facts that are inconsistent with the pure financial leverage hypothesis. This evidence means that another, more important, effect opposes it. This paper shows that indeed, operating leverage in most situations opposes and dominates the financial leverage. This is consistent with a strong change-in-mix effect, whereby good news is associated with an increase in the weight of the firm in growth options. This causes the unlevered beta of the winning firm to increase.

Several recent papers link growth options to systematic risk. For instance, Berk, Green and Naik (1999), Anderson and Garcia-Feijoo (2006) and Carlson, Fisher and Giammarino (2004) show that the exercise of growth options changes a firm's systematic risk. Cao, Simin and Zhao (2008) argue that a significant portion of the upward trend in idiosyncratic risk can be explained by changes in the level and variance of growth options, as well as in the capital structure of firms; subsiding the profitability-based explanations in the literature. Recent general equilibrium models link the evolution of betas to latent state variables that include measures of growth options. These structural models of betas are however difficult to implement. Our cross-sectional regressions can be justified as practical and robust reduced forms for these models.

Using Myers's (1977) view of the firm as a portfolio of assets in place and growth options, we show that even a simple option pricing model can yield subtle implications on the link between positive news and unlevered betas. Two effects counter each other: by the moneyness effect, good news moves each of the firm's projects more in the money, and their betas decrease; by the change-in-mix effect, good news causes the weight of the projects more out-of-the money to increase, so the beta should increase. Our empirical analysis shows that the change-in-mix effect almost always dominates the moneyness effect, and very often dominates the financial leverage effect as well.

We analyze the links between betas and growth opportunities by examining the changes in betas of losers and winners. We show the robustness of this link to extreme initial financial and operational leverage. In these extremes, there are only a few instances where the change-in-mix effect does not overcome the financial leverage effect. We, then, study directly the link between growth option proxies and betas. We show that, together, these proxies and their recent changes predict a large fraction of the future cross-section of betas. Because they are predictive, these cross-sectional regressions have important implications. They can be used as a tool to reduce predictive error in betas, resulting in improved estimation of expected returns in asset pricing models. They can also help portfolio optimization, which is often performed conditional on constraints on systematic risk. Finally, these results, together with similar work on unsystematic risk as in Cao et al. (2008), can be a starting point for a study of the joint evolution of the parameters of the basic market or factor model; total, systematic, and idiosyncratic risks, and factor variance.

APPENDIX: Partial derivative of $\eta_G = \frac{\beta_G}{\beta_S}$ with respect to moneyness.

Consider $N(d_1), N(d_2), r_f, T$ as in the standard Black-Scholes notation. Denote S the underlying value, C the strike price, and $m = S/C$ the moneyness ratio. The elasticity of the option G with respect to the underlying S is

$$\eta_G = \frac{SN(d_1)}{G} = \frac{SN(d_1)}{SN(d_1) - Ce^{-r_f T}N(d_2)} = \left[1 - \frac{1}{m}e^{-r_f T}\frac{N(d_2)}{N(d_1)}\right]^{-1} \geq 1.$$

The partial derivative of η_G with respect to the moneyness ratio m is

$$\begin{aligned} \frac{\partial \eta_G}{\partial m} &= e^{-r_f T}\ \eta_S^2\ \frac{\partial\left(\frac{N(d_2)}{mN(d_1)}\right)}{\partial m} \\ &= e^{-r_f T}\ \eta_S^2\ \left[-\frac{N(d_2)}{m^2 N(d_1)} + \frac{1}{mN^2(d_1)}(N(d_1)Z(d_2)\frac{\partial d_2}{\partial m} - N(d_2)Z(d_1)\frac{\partial d_1}{\partial m})\right] \end{aligned} \tag{7}$$

where Z$(\cdot)$ is the standard normal density function, $d_1 = \frac{ln(m)+(r_f+0.5\sigma^2)T}{\sigma\sqrt{T}}$, and $d_2 = d_1 - \sigma\sqrt{T}$.

Note that $\frac{\partial d_1}{\partial m} = \frac{\partial d_2}{\partial m} = \frac{1}{m\sigma\sqrt{T}}$, recall that $\eta_G = SN(d_1)/G$, and replace m with $\frac{S}{C}$. Equation

(7) simplifies as

$$\frac{\partial \eta_G}{\partial m} = -\frac{C^2 e^{-r_f T}}{S^2 \sigma \sqrt{T}} N(d_2) N(d_1) \left(\sigma\sqrt{T} - \frac{Z(d_2)}{N(d_2)} + \frac{Z(d_1)}{N(d_1)} \right).$$

Galai and Masulis (1976, p. 76-77) show that $\sigma\sqrt{T} > \frac{Z(d_2)}{N(d_2)} - \frac{Z(d_1)}{N(d_1)}$. Hence, $\frac{\partial \eta_G}{\partial m}$ is negative.

References

Adam T, Goyal V.K., 2008, The Investment Opportunity Set and its Proxy Variables: Theory and Evidence, Journal of Financial Research, Volume 31, No 1, pp 41-63, Spring 2008.

Aharony J., Jones C.P. and Swary, I., 1980, An Analysis of Risk and Return Characteristics of Corporate Bankruptcy Using Capital Market Data, Journal of Finance, 1001-1016.

Altman E. and Brenner M., 1981, Information Effects and Stock Market Response to Signs of Firm Deterioration, Journal of Financial and Quantitative Analysis, 35-51.

Anderson C. and Garcia-Feijo, L., 2006. Empirical evidence on capital investment, growth options, and security returns. Journal of Finance 61, No. 1, 171-194.

Ball R. and Kothari S.P., 1989, Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns, Journal of Financial Economics 25, 51-74.

Bauer R., Cosemans M., Frehen R., and P. Schotman, 2009 Efficient Estimation of Firm-Specific Betas and its Benefits for Asset Pricing and Portfolio Choice, working paper, Maastricht University.

Berk J.B., C.G. Green and V. Naik, 1999, Optimal Investment, Growth Options, and Security Returns, Journal of Finance 54, 1553-1607.

Braun P.A., Nelson D. and Sunier A., 1995, Good news, Bad news, Volatility and Betas, Journal of Finance 50, 1575-1603.

Brown G. and Kapadia N., 2007, Firm-specific risk and equity market development, Journal of Financial Economics, 84, pp 358-388.

Campbell J. and J Mei, 1993, Where Do Betas Come From? Asset Price Dynamics and the Sources of Systematic Risk, Review of Financial Studies 6, 567-592.

Cao C., Simin T., and J. Zhao, 2008, Can Growth options explain the trend in firm specific risk? Review of Financial Studies 21: 2599 - 2633.

Carlson M., Fisher A., and R. Giammarino, 2004, Corporate Investment and Asset Price Dynamics: Implications for the Cross Section of Returns, Journal of Finance, Vol. 59, 2577-2603.

Chan K.C., 1988, On the Contrarian Investment Strategy, *Journal of Business* 61, 147-163.

Dann L.Y., Masulis R.W. and Mayers D., 1991, Repurchase Tender Offers and Earnings Information, Journal of Accounting and Economics 14, 217-251.

DeBondt W. and Thaler R., 1985, Does the Stock Market Overreact?, Journal of Finance 40, 793-805.

DeBondt W. and Thaler R., 1987, Further evidence on investor overreaction and stock market seasonality, Journal of Finance 42, 557-581.

Denis D.J. and Kadlec G.B., 1994, Corporate Events, Trading Activity, and the Estimation of Systematic Risk: Evidence From Equity Offerings and Share Repurchases, Journal of Finance 49, 1787-1811.

Erickson T. and Whited T, 2006, On the Accuracy of Different Measures of Q, Financial Management, 35.

Fama E. and French K., 1992, The Cross-Section of Expected Stock Returns, Journal of Finance, 47, 427-465.

Fama, E. and French K., 2001, Disappearing Dividends: Changing Firm Characteristics or lower propensity to pay?, Journal of Financial Economics, 60, 3-43.

Galai D. and Masulis R.W., 1976, The Option Pricing Model and the Risk Factor of Stock, Journal of Financial Economics 3, 53-81.

Goyal V.K., Lehn K. and Racic S., 2002, Growth Opportunities and Corporate Debt Policy: The Case of the U.S. Defense Industry, Journal of Financial Economics 64, 35-59.

Hamada R.S., 1972, The Effects of the Firm's Capital Structure on the Systematic Risk of Common Stocks, Journal of Finance 27, 435-452.

Healy P.M. and Palepu K. , 1990, Earnings and Risk Changes Surrounding Primary Stock Offers, Journal of Accounting Research 28, 25-48.

Jagannathan R. and Z. Wang, 1996, The Conditional CAPM and the Cross-Section of Expected Returns, *Journal of Finance* 51 (1), 3-53.

Jones S.L., 1993, Another look at time-varying risk and return in a long-horizon contrarian strategy, Journal of Financial Economics 33, 119-144.

Kaplan S.N. and Stein J.C., 1990, How risky is the debt in highly leveraged transactions?, Journal of Financial Economics 27, 215-245.

Myers S., 1977, Determinants of Corporate Borrowing, Journal of Financial Economics 5, 147-175.

Petersen M., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, Review of Financial Studies 22, 435-480.

Rosenberg B. and McKibben W., 1973, The Prediction of Systematic and Specific Risk in Common Stocks, Journal of Financial and Quantitative Analysis, 317-333.

Rosenberg B., 1974, Extra-Market Components of Covariance in Security Returns, Journal of Financial and Quantitative Analysis, 263-274.

Rosenberg B., 1985, Prediction of Common Stock Betas, Journal of Portfolio Management, Winter, 5-14.

Rubinstein, M.E., 1973, A mean-Variance Synthesis of Corporate Financial Theory, Journal of Finance 28, 167-181.

Smith W.S., Watts R.L., 1992, The Investment Opportunity Set and Corporate Financing, Dividend and Compensation Policies, Journal of Financial Economics 32, 263-292.

Skinner D.J., 1993, The Investment Opportunity Set and Accounting Procedure Choice, Journal of Accounting and Economics 16, 407-445.

Thompson S., 2009, Simple Formulas for Standard Errors that Cluster by Both Firm and Time. SSRN working paper, forthcoming Journal of Financial Economics.

Table 1
Descriptive statistics of growth proxies and financial leverage

Year	Count	Capex	Mba	Div	Ep	Dtoe
1968	943	19.6	173	2.60	5.20	19.4
1969	1056	18.6	161	2.79	5.86	23.1
1975	1693	21.6	120	3.30	10.09	41.2
1976	2317	19.9	123	3.06	8.48	38.1
2001	3119	21.6	202	0.99	3.51	20.9
2002	2835	20.0	171	1.20	1.22	27.1
2006	2691	17.8	178	1.68	4.77	23.1
2007	2528	18.3	192	1.31	4.76	18.3
Mean		19.4	153	2.54	6.44	32.5
Std. Dev.		2.0	37	1.12	3.49	9.5
Min.		15.0	98	0.76	1.22	16.9
Year(Min)		2004	1982	2000	2002	2000
Max.		23.7	254	5.22	15.38	53.7
Year(Max)		1982	2000	1982	1982	1982
$\rho(1)$		0.69	0.88	0.85	0.84	0.73
$\rho(2)$		0.22	0.74	0.81	0.76	0.57
$\rho(3)$		-0.01	0.64	0.73	0.70	0.43

The table reports averages for some selected years, and summary statistics for the number of firms, aggregate growth option proxies, and financial leverage from 1968 to 2007. The proxies are the ratios of aggregate capital expenditures to fixed assets (Capex), of market to book value of assets (Mba), and of earnings to price ratio (Ep), as well as the dividend yield (Div). Financial leverage is measured by the debt to equity ratio (Dtoe). All are reported in percent. The statistics include the autocorrelation functions up to 3 lags.

Table 2
Systematic risks of portfolios sorted by total returns

Panel A: Total period return, leverage and β_{VW}

	% Return			% Dtoe			β_{VW}			
	-1	0	1	-1	0	1	-1	0	1	t_diff
Loser	75	-53	48	25	82	58	1.35	1.34	1.26	(-1.76)
2	58	-28	48	28	60	45	1.21	1.17	1.12	(-2.11)
3	53	-10	52	27	51	43	1.07	1.07	1.01	(-1.96)
4	40	7	47	36	48	45	1.03	0.98	0.95	(-2.62)
5	41	23	48	38	47	43	0.99	0.91	0.93	(-1.92)
6	47	40	47	37	37	36	0.96	0.95	0.95	(-0.35)
7	39	61	45	36	32	34	0.96	0.93	0.95	(-0.17)
8	38	89	45	43	29	30	0.98	0.96	0.99	(0.15)
9	41	134	49	42	24	28	1.04	1.04	1.07	(0.58)
Winner	40	264	40	46	16	23	1.21	1.20	1.27	(1.13)

Panel B: Four-factor model market and book-to-market betas

	β_{MKT}				β_{HML}			
	-1	0	1	t_diff	-1	0	1	t_diff
Loser	1.12	1.17	1.13	(0.40)	-0.61	-0.26	-0.07	(5.63)
2	1.06	1.10	1.11	(1.14)	-0.34	-0.15	0.04	(4.44)
3	1.01	1.06	1.05	(1.22)	-0.18	-0.05	0.06	(3.42)
4	1.02	0.99	1.00	(-0.45)	-0.12	0.01	0.17	(4.30)
5	0.99	0.94	0.99	(-0.14)	-0.06	0.07	0.17	(3.82)
6	1.00	0.96	0.98	(-0.64)	-0.01	0.02	0.07	(1.22)
7	0.99	0.94	0.96	(-0.83)	-0.01	0.04	-0.01	(0.00)
8	0.98	0.99	0.97	(-0.37)	-0.04	0.07	-0.11	(-0.97)
9	1.02	1.01	0.97	(-1.29)	-0.10	-0.07	-0.29	(-2.55)
Winner	1.07	1.02	1.04	(-0.50)	-0.23	-0.42	-0.58	(-3.83)

Firms are allocated to deciles on the basis of cumulative returns, over 34 overlapping 3-year periods ending June 71 to June 04. We compute the cumulative returns, the Debt to equity ratio, Dtoe, the market beta β_{vw}, and two of the four-factor model betas, β_{MKT} and β_{HML}, for this period, and the previous and following 3-year periods. We average these values over the the 34 windows. They are reported under columns 0, -1, and 1 for the allocation period and the two surrounding periods. The t-statistic t-diff is that of the mean difference in the 34 changes in beta from period -1 to 1, it uses HAC standard errors with two lags.

Table 3
Systematic risk of portfolios sorted by total return and financial leverage

Panel A: Total period return, leverage and CAPM beta

		% Return			% Dtoe			β_{VW}			
Leverage	Return	-1	0	1	-1	0	1	-1	0	1	t_diff
Low	Loser	143	-57	47	3	26	27	1.48	1.49	1.29	(-2.96)
Low	Winner	80	259	45	5	4	7	1.26	1.24	1.28	(0.16)
High	Loser	19	-47	52	117	253	147	1.34	1.28	1.23	(-1.37)
High	Winner	10	304	42	141	39	53	1.23	1.21	1.27	(0.71)

Panel B: Four-factor model market and book-to-market betas

		β_{MKT}				β_{HML}			
Leverage	Return	-1	0	1	t_diff	-1	0	1	t_diff
Low	Loser	1.12	1.22	1.06	(-0.74)	-0.95	-0.59	-0.39	(4.15)
Low	Winner	1.04	0.98	0.96	(-0.76)	-0.62	-0.71	-0.88	(-1.91)
High	Loser	1.22	1.22	1.17	(-0.90)	0.07	0.44	0.43	(2.42)
High	Winner	1.13	1.10	1.14	(0.34)	0.17	0.10	-0.08	(-1.65)

Panel C: Four-factor model size and momentum betas

		β_{SMB}				β_{UMD}			
Leverage	Return	-1	0	1	t_diff	-1	0	1	t_diff
Low	Loser	0.38	0.30	0.55	(1.63)	0.05	-0.55	-0.21	(-2.68)
Low	Winner	0.24	0.13	-0.01	(-1.97)	0.02	0.27	-0.02	(-0.54)
High	Loser	0.55	0.86	0.85	(3.14)	-0.19	-0.41	-0.21	(-0.22)
High	Winner	0.69	0.51	0.40	(-2.38)	-0.12	0.22	0.09	(2.29)

Firms are allocated to Low, Medium, and High financial leverage groups every June at the end of each of 34 pre-ranking periods, ending June 68 to July 2001, based on 30^{th} and 70^{th} percentiles of Dtoe. Within each leverage group, firms are allocated to deciles of total returns in the following three-year ranking period. We report on the High and Low Dtoe groups, and deciles 1 and 10 of total returns. Columns -1, 0, 1, denote the pre-ranking, ranking, and post-ranking (July 71-June 74 to July 04-June 07) periods. We then follow the same procedure as in Table 1.

Table 4
Systematic Risks of Portfolios sorted by return and industry

Panel A: Total period return, leverage and CAPM beta

		% Return			Dtoe in %			β_{VW}			
Industry	Return	-1	0	1	-1	0	1	-1	0	1	t_diff
Steel	Loser	35	-26	28	56	104	91	1.19	1.17	1.28	(0.93)
Autos	Loser	55	-18	37	56	131	123	1.21	1.15	1.23	(0.16)
Oil	Loser	59	-17	50	37	66	56	1.04	1.02	0.94	(-0.99)
Steel	Winner	32	103	40	71	38	44	1.10	1.20	1.27	(1.60)
Autos	Winner	31	141	47	99	72	127	1.10	1.16	1.20	(1.21)
Oil	Winner	33	123	56	50	30	39	0.85	0.91	0.92	(0.66)
Health	Loser	63	-30	71	16	40	26	1.16	1.09	1.05	(-1.40)
Services	Loser	101	-35	67	20	50	35	1.55	1.45	1.42	(-1.35)
Bus. Equip.	Loser	83	-37	50	18	49	38	1.42	1.42	1.39	(-0.37)
Health	Winner	46	181	53	28	14	14	1.08	0.98	0.96	(-1.28)
Services	Winner	55	205	47	28	17	24	1.33	1.35	1.27	(-0.63)
Bus. Equip.	Winner	49	185	54	31	14	15	1.38	1.37	1.42	(0.61)

Panel B: size and book-to-market betas

		β_{SMB}				β_{HML}			
Industry	Return	-1	0	1	t_diff	-1	0	1	t_diff
Steel	Loser	0.37	0.56	0.61	(1.48)	0.43	0.49	0.65	(1.07)
Autos	Loser	0.36	0.43	0.66	(1.89)	0.20	0.42	0.75	(3.05)
Oil	Loser	0.16	0.19	0.26	(0.45)	0.21	0.30	0.66	(2.05)
Steel	Winner	0.52	0.49	0.32	(-1.78)	0.42	0.51	0.35	(-0.38)
Autos	Winner	0.31	0.14	0.19	(-0.70)	0.42	0.15	0.29	(-0.66)
Oil	Winner	-0.11	-0.09	-0.03	(0.47)	0.53	0.41	0.35	(-1.14)
Health	Loser	0.41	0.21	0.44	(0.21)	-0.64	-0.34	-0.34	(1.89)
Services	Loser	0.52	0.49	0.72	(1.13)	-0.84	-0.37	-0.35	(2.84)
Bus. Equip.	Loser	0.29	0.23	0.40	(0.53)	-0.93	-0.64	-0.40	(2.35)
Health	Winner	0.01	0.00	-0.16	(-1.92)	-0.37	-0.65	-0.70	(-1.88)
Services	Winner	0.44	0.26	0.23	(-1.39)	-0.54	-0.67	-0.69	(-1.00)
Bus. Equip.	Winner	0.42	0.26	0.24	(-1.26)	-0.54	-0.59	-0.76	(-0.83)

We study firms in 6 industries from the 30 industry groups defined in Ken French's data library. Steel, Auto, and Oil are deemed low growth options, while Health, Services, and Business Equipment are high growth. For these 6 industries, we then follow the same procedure as in Table 1, with the following difference: We allocate firms to loser and winner portfolios on the basis of the 25^{th} and 75^{th} percentiles of total returns.

Table 5
Systematic risk characteristics versus growth proxies

Panel A: Capex, proxy increasing in growth

Growth	Capex	σ	σ_R	β_{VW}	β_{MKT}	β_{HML}	β_{SMB}	Dtoe
Low	11.7	2.9	31	1.11	1.09	0.27	0.37	62
2	14.4	2.9	32	0.92	0.94	0.18	0.01	45
3	16.1	2.1	30	0.87	0.93	0.15	-0.07	41
4	17.7	2.4	34	0.93	1.01	0.08	-0.16	33
5	19.4	2.9	38	0.92	0.97	-0.02	-0.19	32
6	21.2	3.0	39	0.96	0.99	-0.09	-0.13	32
7	23.8	4.0	46	1.09	1.03	-0.25	-0.11	30
8	25.2	4.1	37	1.12	1.02	-0.31	0.00	33
9	28.5	3.4	66	1.24	1.03	-0.52	0.08	24
High	36.3	6.9	69	1.44	1.13	-0.73	0.27	18

Panel B: Mba, proxy increasing in growth

Growth	Mba	σ	σ_R	β_{VW}	β_{MKT}	β_{HML}	β_{SMB}	Dtoe
Low	92	16	39	1.05	1.08	0.53	0.41	72
2	102	17	38	1.06	1.11	0.52	0.24	87
3	106	14	33	0.99	1.09	0.51	0.08	89
4	119	25	37	1.00	1.06	0.34	0.04	59
5	130	28	33	0.95	1.02	0.21	-0.02	48
6	141	34	31	1.00	1.03	0.08	-0.08	39
7	158	45	36	1.02	1.01	-0.01	-0.05	34
8	182	55	31	1.02	0.99	-0.15	-0.06	22
9	233	86	44	1.01	0.95	-0.36	-0.09	13
High	365	180	54	1.09	0.93	-0.70	-0.11	6

Panel C: Div, proxy decreasing in growth

Growth	Div	σ	σ_R	β_{VW}	β_{MKT}	β_{HML}	β_{SMB}	Dtoe
Low	4.94	1.74	30	0.80	0.94	0.56	-0.09	65
2	4.19	1.48	35	0.84	0.97	0.34	-0.17	56
3	3.71	1.38	37	0.88	0.99	0.22	-0.16	48
4	3.22	1.11	32	0.88	0.96	0.11	-0.16	35
5	2.96	1.19	37	0.92	0.97	0.03	-0.14	34
6	2.52	1.04	34	0.93	0.96	-0.05	-0.12	28
7	2.22	0.95	35	0.98	0.95	-0.23	-0.12	24
8	1.72	0.75	37	1.01	0.96	-0.31	-0.06	22
9	1.33	0.71	37	1.09	1.03	-0.37	0.03	22
High	0.68	0.39	44	1.20	1.05	-0.54	0.07	16
Div=0	0.31	0.32	57	1.50	1.18	-0.52	0.47	40

Panel D: EP, proxy decreasing in growth

Growth	Ep	σ	σ_R	β_{VW}	β_{MKT}	β_{HML}	β_{SMB}	Dtoe
Low	7.59	7.72	41	1.07	1.15	0.56	0.23	102
2	8.34	5.32	45	0.96	1.03	0.33	0.04	62
3	8.48	4.79	34	0.92	0.99	0.24	-0.04	48
4	8.03	4.68	32	0.93	0.98	0.16	-0.06	37
5	8.09	4.35	34	0.94	0.96	0.07	-0.14	40
6	7.12	3.78	37	0.98	0.96	-0.05	-0.09	28
7	6.52	3.51	33	0.97	0.94	-0.21	-0.11	26
8	5.80	3.22	35	1.01	0.95	-0.30	-0.11	19
9	4.83	2.68	40	1.07	0.96	-0.48	-0.01	18
High	3.57	3.07	48	1.27	1.11	-0.56	0.08	19
EP ≤ 0	4.91	5.91	46	1.35	1.18	0.11	0.56	74

Every end of June from 1968 to 2004, we allocate firms to deciles of growth options on the basis of Capex, Mba, Div, or Ep. Firms with zero dividends or non-positive earnings are in separate portfolios. For the following three-year period, we compute the aggregate proxy, Dtoe, betas, and standard deviation for each portfolio. This is repeated annually for 37 overlapping 3-year reanking periods until June 07. The table reports the average proxy and its standard deviation, the returns standard deviation, the portfolio's average betas, standard deviation, and Dtoe. σ is the time-series standard deviations of proxy values. σ_R is the time-series standard deviation of the 36-month portfolio holding period return.

Table 6
Cross-sectional variation in systematic risk

Panel A: Individual cross-sectional regressions

	β_{VW}					β_{MKT}				
	Mean	Q_1	Q_3	#	t	Mean	Q_1	Q_3	#	t
Intercept	1.100	1.056	1.142	37	64.11	1.045	1.022	1.067	37	83.16
Capex_{-1}	0.032	-0.012	0.074	26	2.16	0.009	-0.041	0.050	21	0.64
Div_{-1}	-0.190	-0.260	-0.143	36	-13.73	-0.102	-0.178	-0.026	32	-5.41
Mba_{-1}	-0.080	-0.153	0.025	13	-1.89	-0.114	-0.176	0.023	13	-2.64
Ep_{-1}	-0.002	-0.100	0.095	15	-0.04	0.051	-0.050	0.108	15	1.99
Dtoe_{-1}	0.013	-0.052	0.051	21	0.66	0.011	-0.081	0.051	17	0.42
ΔCapex	0.013	-0.021	0.043	24	1.28	-0.007	-0.043	0.026	18	-0.79
ΔDiv	-0.101	-0.126	-0.052	35	-5.04	-0.064	-0.111	-0.020	32	-4.68
ΔMba	-0.077	-0.143	0.028	13	-1.98	-0.088	-0.134	0.026	13	-2.24
ΔEp	0.021	-0.073	0.092	16	0.84	0.039	-0.015	0.085	14	2.06
ΔDtoe	0.005	-0.044	0.068	20	0.27	0.006	-0.057	0.086	22	0.27
$\bar{R}^2$	0.72	0.65	0.84			0.44	0.27	0.62		
$\bar{R}^2_{-1}$	0.61	0.51	0.75			0.33	0.18	0.47		

Panel B: Panel Data regressions

	β_{VW}	t	β_{MKT}	t
Intercept	1.100	71.40	1.045	100.23
Capex_{-1}	0.068	4.08	0.033	2.62
Div_{-1}	-0.193	-8.50	-0.074	-5.68
Mba_{-1}	-0.042	-0.95	-0.060	-2.47
Ep_{-1}	0.028	0.92	0.008	0.41
Dtoe_{-1}	0.058	2.57	0.033	1.89
ΔCapex	0.010	0.86	-0.010	-1.03
ΔDiv	-0.099	-5.28	-0.048	-5.04
ΔMba	-0.026	-0.82	-0.040	-2.74
ΔEp	0.044	1.81	0.016	1.05
ΔDtoe	0.011	0.55	0.005	0.46
$\bar{R}^2$	0.39		0.18	
$\bar{R}^2_{-1}$	0.33		0.14	

The table reports the cross-sectional regression of β_{VW} and β_{MKT} on growth proxies Capex, Mba, Div, and Ep, and financial leverage Dtoe. For each of the 37 overlapping 3-year periods ending from June 68 to June 04, firms are grouped into 25 portfolios on the basis of total returns. Portfolio growth proxies are computed at the end of this ranking period, and of the following, post-ranking, 3-year period. Portfolio betas are calculated using the 36 value weighted monthly portfolio returns of the post-ranking period. We regress the betas on the ranking period proxies, subscripted $_{-1}$, and on their changes from ranking to post-ranking period, denoted Δ. These variables are cross-sectionally standardized for each of the thirty-seven periods. Panel A shows the results from the 37 individual cross-sectional regressions, namely the time-series average and first and third quartile values of parameter estimates, the number of estimates with the expected sign (#), and t-statistics based upon HAC standard errors with two lags. We also report the average of the 37 adjusted R-squares with all the independent variables, $\bar{R}^2$, and with only the lagged variables, $\bar{R}^2_{-1}$. Panel B shows the results of a pooled time-series and cross-section regression with two-way clustered standard errors robust to time (cross-correlation) and group (auto-correlation) effects.

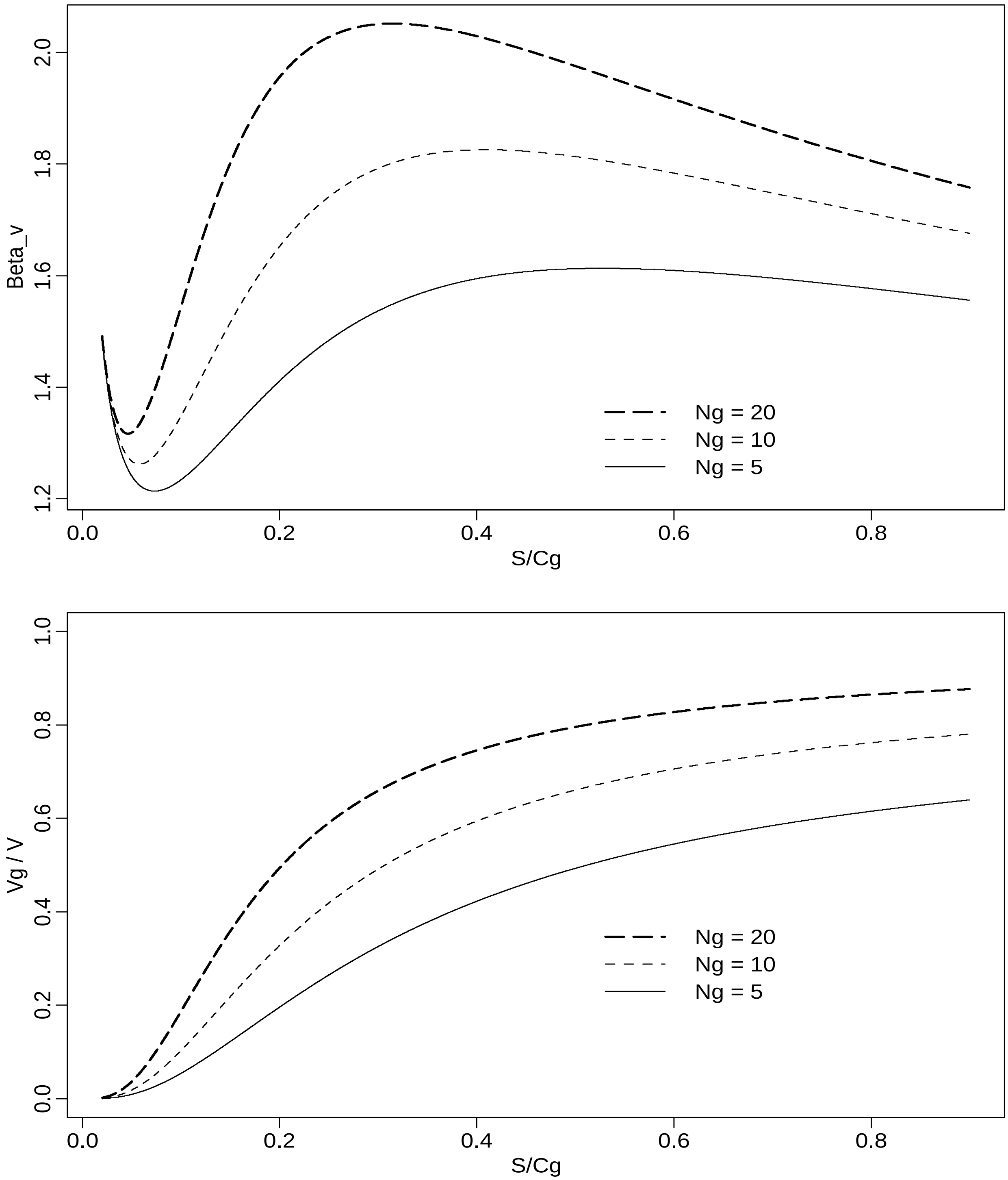

Figure 1: Firm β and weight in growth options versus moneyness
Top panel: $\beta_V = (AN_A\beta_A + GN_G\beta_G)/V$ vs s/C_G, where $V = AN_A + GN_G = V_A + V_G$. A and G are calls on s with exercise prices $C_A = 1, C_G = 100$. $r_f = 0, \sigma^2 T = 1, N_A = 1,\ N_G = 5, 10, 20$.
Bottom panel: weight in growth options V_G/V vs moneyness s/C_G.