Equity Misvaluation and Default Options

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Abstract

We study whether default options are mispriced in equity values by employing a structural equity valuation model that explicitly takes into account the value of the option to default (or abandon the firm) and uses firm-specific inputs. We implement our model on the entire cross-section of stocks and identify both over- and underpriced equities. An investment strategy that buys stocks that are classified as undervalued by our model and shorts overvalued stocks generates an annual 4-factor alpha of about 11% for U.S. stocks. The model's performance is stronger for stocks with higher value of default option, such as distressed or highly volatile stocks. We find similar results in a sample of nine most highly-capitalized developed markets.

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1 Introduction

A large finance literature argues that equity securities are subject to potential misvaluation by investors (see Harvey, Liu, and Zhu (2016) for a recent survey), and that the extent of misvalaution impacts corporate decisions such as merger and acquisition activities, stock issuance and repurchases, and investment policy. The sources of equity misvaluations are attributed primarily to cognitive biases (see, for example, Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Baker and Wurgler (2006)).

In this paper we provide a new direction by arguing that equity misvaluation is, at least partly, driven by investors' failure to fully recognize and adequately price the optionality of equity. It has long been recognized in the finance literature that equity of a firm with debt in its capital structure is analogous to a call option written on the assets of the firm (see, for example, Merton (1974)). The title of the seminal paper by Black and Scholes (1973) reflects the applicability of their model to the valuation of corporate debt and equity. Today, nearly every corporate finance textbook (see, for example, Brealey, Myers, and Allen (2016)) discusses the option-based approach to value equity and debt. Our paper addresses the question of whether analysts and investors incorporate this option-based approach in their equity valuations, and whether their failure to do so gives rise to misvaluation.

While default option is clearly a key characteristic of equity, standard stock valuation techniques, such as multiples-valuation or discounted cash flow, do not explicitly account for the option to default. Using these techniques, therefore, can lead to mis- (under- or over-) valuation, especially among stocks with relatively high value of default option and higher prospects of default or exit. We build a structural equity valuation model that explicitly takes into account the value of the option to default (or abandon the firm). We then use our option-based valuation model to identify the potential misvaluation of equity by examining whether our model can predict future stock returns, and whether its predictive ability is driven by mispricing of default options.

Our model shares some common features with other structural valuation models of debt and equity such as endogenous default in Leland (1994) and a plethora of models that followed.[1] It also implicitly accommodates path-dependence of Brockman and Turtle (2003) (due to an additional financial distress cost in low cash flow states). Our model allows for endogenous default, different tranches of debt with different maturities, and additional

[1]For example, Goldstein, Ju, and Leland (2001) develop a model with dynamic refinancing, Hackbarth, Miao, and Morellec (2006) model the effect of time-varying macroeconomic conditions, Bharma, Keuhn, and Strebulaev (2010) embed a structural model of credit spreads in a consumption-based asset pricing model.

costs of financial distress. While our model does not incorporate some aspects that have received considerable attention in corporate finance literature like investments or managerial entrenchment (see Ozdagli (2010) for a more carefully calibrated model of default), it is specifically tailored to value the default option. Furthermore, we use firm-specific accounting inputs when implementing the model and are, therefore, able to generate firm-level valuations. To the best of our knowledge, our paper is the first to employ a structural option pricing model of default on a large cross-section of stocks to value equity and measure potential misvaluation at the firm level.

Leaving the details of our model for later, we start our analysis by sorting all stocks every month into decile portfolios according to the ratio of the model value to market value of equity.[2] We find that most misvalued stocks, either over- or undervalued, are smaller, more volatile, less liquid, have fewer analyst coverage with higher analysts' forecast dispersion, and have lower institutional ownership than more fairly-valued stocks, indicating that the former category of stocks is the most difficult to value. Excess returns on these categories of stocks show patterns consistent with our valuation model. Monthly excess return for overvalued decile of stocks is 0.51% (4-factor alpha of -0.24%) while that for undervalued decile stocks is 1.15% (4-factor alpha of 0.67%). The long-short strategy that buys stocks that are classified as undervalued by our model and shorts overvalued stocks, thus, generates a 4-factor annualized alpha of about 11%. These results are stronger for equal-weighted portfolios (4-factor annualized alpha of about 16%), robust to various sub-samples and return horizons, and are confirmed using Fama and MacBeth (1973) regressions.

To explore the role of the default option more directly, we investigate how the returns generated by the model vary across stocks with characteristics related to default option. We focus on four firm characteristics for this exercise: financial distress, size, volatility, and profitability. We sort all stocks into quintiles based on each of these characteristics and then double-sort all stocks within each quintile into quintiles according to the model/market value ratio. Calculating the fraction of the default option value in the total model-equity value shows a clear relation between the importance of the default option and each of the characteristics. Most notably, for the top distress quintile, the option to default accounts on average for 35.9% of equity value, compared to only 19.2% for the least distressed stock quintile (these numbers reflect also the value of the abandonment option, which is always positive in our model as long as fixed costs are non-zero). The difference in default option fraction between the two extreme size quintiles is 11%, between the two extreme volatility

[2]Sorts based on differences between model value and market value are used often in the literature. See, for example, D'Mello and Shroff (2000), Claus and Thomas (2001), Dong et al. (2006), and Pástor, Sinha, and Swaminathan (2008).

quintiles is 15%, and between the two extreme profitability quintiles is 7%. These relations justify the choice of these characteristics, and also support the reliability of our model.

The returns generated by the model also exhibit a clear pattern across these characteristics. For example, within the top distress quintile, undervalued stocks earn monthly 4-factor alpha higher by 1.19% than those earned by overvalued stocks. The equivalent difference within the bottom distress quintile is only 0.26%. The model's returns are also much higher among highly volatile stocks; 4-factor alpha of long-short strategy is 1.38% for the top volatility quintile, while is reduced to 0.39% among the least volatile stocks. The effect of firm size, however, is much weaker and not always monotonic. The model's 4-factor alpha is 0.75% for small firms and 0.43% for large firms. This is consistent with the fairly low difference between default option fractions of small and large stocks. For profitability sorted portfolios we see a reduction in the 4-factor alpha of the long-short strategy from 1.09% for least profitable stocks to 0.69% for most profitable.

The positive effect of firm characteristics, especially distress and volatility, on the model's performance strongly suggests that the option to default is the primary driver in the predictive ability of the model for future stock returns. To verify this finding we conduct the following test. We recalculate our model's equity values while shutting down the option to default, and we use these values to re-sort and calculate the returns within each characteristic-quintile. The model's performance is substantially weaker without the default option. The model's 4-factor alpha is reduced from 1.19% to 0.28% for most distressed stocks, and from 1.38% to 0.33% for most volatile stocks. These alpha reductions, thus, show that the option-to-default is hard to estimate and leads to stock mispricing.

While the return-based evidence already demonstrates our model's predictive ability, we zoom in further to explore the link between the model performance and mispricing by performing a battery of additional tests. First, we examine returns around earnings announcements. We expect a stronger model performance around earnings announcement days (EADs) as new information about firm fundamentals (and its default likelihood) is revealed to the market and leads to mispricing correction. Our results show strong support for this conjecture. For example, the daily return spread is 24 basis points around EADs, versus only 5 basis points on non-EADs.

Second, we explore proxies for information transparency (analyst coverage, institutional ownership, and availability of listed options). It is likely that the degree of mispricing is higher for firms with lower information transparency. We, therefore, expect the model to perform better for stocks with lower information transparency and we expect this difference in performance to be particularly high for stocks with high default option values. Our results are consistent with this argument. For example, the 4-factor monthly alpha of the long-short portfolio sorted on relative model value is higher by about 0.23% for low versus high analyst coverage stocks for the quintile of least distressed stocks while the same difference is 1.37% for the most distressed stocks.

Third, we analyze the time-series variation in mispricing. We use two measures to capture potential changes in misvaluation over time: NBER recession indicator and Baker and Wurgler (2006) sentiment index. We find that our long-short strategy performs better in recessions and during times of high sentiment supporting our conjecture that valuation difficulties are more pronounced during such times. For example, the 4-factor alpha of the hedge portfolio is 1.36% in high sentiment months but only 0.52% in low sentiment months.

Fourth, we examine a few post-formation variables (equity issuance, institutional ownership, insider trading, probability of mergers and acquisitions) of stocks classified as over- and undervalued by the model. We find that overvalued firms are more likely to issue equity, have lower institutional ownership, are sold more actively by insiders, and have lower probability of being acquired than do undervalued firms. Moreover, we find that the differences in these variables are much more strongly pronounced for smaller, more distressed, more volatile, and less profitable stocks. This evidence is consistent with our results being driven by the ability of the model to identify mispricing of default options.

Finally, as an out-of-sample test, we apply our methodology to the cross-section of stocks in a sample of nine most highly capitalized other developed markets. Sorting stocks on our model-based relative valuation, we find that, on average across the countries, the 4-factor alpha of a long-short value- (equal-) weighted strategy is 0.79% (1.19%). This alpha is significant for four (eight) of the countries in our sample. Fama and MacBeth (1973) regressions provide corroborating evidence; controlling for stock characteristics, the coefficient on relative model value is significant for six out of nine countries.

Our results suggest that default option values are not properly incorporated in equity prices in the U.S. or in the majority of other developed countries. It may seem that ignoring the optionality of equity will always lead to undervaluation of equity. While indeed, based on our model a median U.S. firm is undervalued by about 6.9% in our sample, we do not make the strong claim that investors are unaware of the possibility of default by equityholders. Our conjecture is only that the investors do not value the resulting option properly.[3] In other

[3] Anecdotal evidence suggests that even top equity analysts do not recognize the default-like features of equity. We studied analyst reports on Ford Motor around late 2008 to early 2009. Ford was in deep financial distress at that time and the option to default was in-the-money. Yet there is no evidence that analysts from top investment banks incorporated that option value in their analysis. For example, Société Générale based its price estimate on the long-term enterprise-value-to-sales ratio, while Deutsche Bank and JP Morgan used enterprise-value-to-EBITDA ratio. In addition, Deutsche Bank used a discount rate of 20%, and Crédit

words, standard valuation techniques, by employing more crude proxies for this optionality, lead to misvaluation (under and over) of equity.

An interesting question raised by our study is why do investors not use option-based valuation models to value stocks. One potential explanation is the complexity involved in implementing such models. We hypothesize that many investors, especially retail investors, do not possess the necessary skills to implement such a model. This conjecture is consistent with the evidence presented by Poteshman and Serbin (2003) who document that investors often exercise call options in a clearly irrational manner, suggesting that it is hard for certain types of investors to understand and value options correctly (Poteshman and Serbin find that this is particularly true for retail investors; traders at large investment houses do not exhibit irrational behavior). Benartzi and Thaler (2001) show that when faced with a portfolio optimization problem, many investors follow naïve and clearly suboptimal strategies suggesting that investors fail to fully understand more sophisticated models. Hirshleifer and Teoh (2003) argue that limited attention and processing power may lead investors to ignore or underweight information that is important for an option-based model to produce unbiased valuations.

Our paper features a real option model of default and is, therefore, indirectly related to the growing literature that examines how various properties of real options and their time-varying risk characteristics can affect expected stock returns in a rational framework.[4] There are two important differences between our approach and this strand of literature. First, we do not assume that stocks are rationally priced at all times. To the contrary, we build a model to gauge potential equity misvaluation. Second, by using firm-specific inputs, our model allows us to produce valuations at the firm level in every month.

Because our paper focuses on the importance of default options in equity valuations it is also indirectly related to papers that examine the performance of financially distressed stocks. Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008, henceforth CHS), amongst others, show that financially distressed stocks earn surprisingly low returns.[5] In this paper we do not contribute to the resolution of this puzzle. Unlike abovementioned papers, we study the entire cross-section of equities and do not focus on the subset of financially distressed

Suisse used a DCF model with a "big increase" in the discount rate. These different approaches result in very different values. For example, the JP Morgan target price for Ford in late October was $2.43 per share, while the Crédit Suisse target price was $1.00 per share.

[4]Fore example, Carlson, Fisher, and Giammarino (2004) model the role of growth option exercise in the dynamics of firm betas; Sagi and Seaholes (2007) focus on convexity in firm value arising from a mean-reverting price process; Garlappi and Yan (2011) examine how deviations from the absolute priority rule can affect the dynamics of risk of financially distressed stocks.

[5]Chava and Purnanandam (2010), Kapadia (2011), and Friewald, Wagner, and Zechner (2014) offer potential explanations.

stocks. We also note that for the distress risk puzzle to be explained from our misvaluation perspective, it must be that investors tend to consistently overvalue default options. This kind of persistent overvaluation would be hard to expect ex-ante and we do not see it in our results.[6] We merely argue that most commonly-used reduced-form valuation techniques have the potential of misvaluing (under and over) equity embedded with a default option. We apply our option-based valuation model to the entire cross-section of stocks and identify both over- and underpriced equity.

We reiterate that the power of our model is in the valuation of the option to default and/or shut down the firm. For stocks far from the default boundary (e.g., stocks with high cash flows, low volatility, and low leverage ratios), normal valuation techniques are still adequate and not much may be gained by using our model for such stocks. This is confirmed by our empirical results. The performance of the long-short strategy based on our valuation model deteriorates when applied to firms with low value of default option. Finally, while our model can also be used to price corporate debt, the objective of our study is only to use it to identify equity misvaluation.

2 Valuation model

A key characteristic of corporate equity is the default option. One source of difficulty in valuing equity, therefore, may come from the necessity of using an appropriate model to account for the value of the option to default. Any valuation model that fails to properly value this option is going to produce values that are further away from fundamental value than a model that accounts for this option.

Option pricing structural models have been employed in the literature to gauge the probability of default and to value corporate bonds *given* the value of equity. Our objective, instead, is to deploy an option pricing model to perform valuation of equity. As we explain in detail later in this section, our option-pricing based approach scores over the traditional approach on two fronts. First, we are better able to estimate future cash flows by explicitly accounting for the exercise of the default option by the equityholders. Thus, our model accounts for the truncation in cash flows—at very low states of demand when cash flows are sufficiently negative it is optimal to exercise the default option rather than to continue

[6] The fact that we do not see overvaluation of equity in our analysis suggests that some other aspects of distressed stocks like skewness (CHS (2008)) or reduced riskiness due to high shareholder advantage (Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011)) must be driving returns to distressed stocks. See also Eisdorfer, Goyal, and Zhdanov (2016) for an international study on the determinants of distressed stock returns.

to operate the firm. This optionality is missed by commonly employed valuation methods. Second, the estimation of time variation in discount rates is typically a difficult task; it becomes even more difficult for firms with high default risk where any small change in firm value can significantly change the risk of equity. The option-pricing approach bypasses this problem by conducting the valuation under a risk-neutral measure.[7]

Of course, the central insight that the equity of a firm with debt in its capital structure is analogous to a call option written on the assets of the firm dates back to Black and Scholes (1973). While nearly every corporate finance textbook discusses the option-based approach to value equity and debt, academic research on using these models to perform equity valuation is sparse. Most of the studies perform valuation of some specific types of companies, such as internet or oil companies, in a real options framework (see Moon and Schwartz (2000) for a an example).[8] By contrast, we implement our model on the entire cross-section of stocks.

2.1 Model

We assume that the cash flows of a firm i are driven by a variable x_{it} that reflects stochastic demand for the firm's products. The firm incurs fixed costs and uses debt and, therefore, has contractual obligations to make coupon and principal payments to its debtholders. We also assume that a firm with negative free cash flow incurs an additional proportional expense η. This extra cost reflects expenses that a financially distressed firm has to incur in order to maintain healthy relationship with suppliers, retain its customer base, deal with intensified agency costs like the under-investment problem, or the additional costs of raising new funds to cover for the short fall in cash flows. The free cash flow to equityholders of firm i is then given by:

$$\begin{aligned} CF_{it} &= [(1-\tau)(x_{it}-I_{it}-F_i)+\tau Dep_{it}-Capex_{it}] \times \\ &\qquad \left[1+\eta\mathbf{1}_{(1-\tau)(x_{it}-I_{it}-F_i)+\tau Dep_{it}-Capex_{it}<0}\right]-D_{it}, \end{aligned} \tag{1}$$

where x_{it} is the state variable of firm i at time t, I_{it} is the total interest payments to debtholders due at time t, D_{it} is the principal repayment due at time t, F_i is the total fixed cost that the company incurs per unit of time, τ is the tax rate, τDep_{it} is the tax shield due

[7]A necessary assumption for this approach to work is that there exists a tradeable asset in the economy whose price is perfectly correlated with the stochastic process that drives the dynamics of the cash flows.

[8]One notable exception is Hwang and Sohn (2010). They test predictability of returns using valuations derived from Black and Scholes (1973) model on a large cross-section of companies. However, the abandonment option is not explicitly modeled in their approach.

to depreciation expense, $Capex_{it}$ is capital expenditures, and $\mathbf{1}_{(\cdot)}$ is an indicator variable. Note that additional cost η is incurred only when the cash flow (before the repayment of principal) is negative, so the positive sign of η implies a negative effect on cash flows. We further assume that x_{it} follows a geometric Brownian motion under the physical measure with a drift parameter $\mu_{i,P}$ and volatility σ_i:

$$\frac{dx_{it}}{x_{it}} = \mu_{i,P}dt + \sigma_i dW_t. \tag{2}$$

Default is endogenous in our model similar to the majority of structural models (see, for example, Leland (1994)). The equity holders are endowed with an option to default which they exercise optimally; they default if continuing to operate the firm results in a negative value. In our model default occurs when cash flow to equity holders is sufficiently negative.[9] Note that the presence of the fixed cost component, F_i, means that the equityholders may decide to shut down operations and abandon the firm if the cash flow turns sufficiently negative even when the firm is debt-free. The option to exit is valuable even for an all-equity firm as long as F_i is positive.

We further assume that a firm that survives until its long-term debt is repaid refinances its assets by issuing new debt with a perpetual coupon rather than staying debt-free. At that moment (we assume that long-term debt matures in five years), the equityholders receive the proceeds from new debt issuance in exchange for a stream of subsequent coupon payments. Indeed, unless the fixed costs are too high, the firms may find it advantageous to issue new debt rather than staying debt-free due to tax shields on interest payments. We resort to the perpetual coupon assumption to get analytical solutions for post-refinancing values of debt and equity. Refinancing makes our model more realistic by capturing the additional tax benefits that would be otherwise forgone by an all-equity firm. In a previous version of the paper, we have also tried a model without refinancing with very similar results. See Appendix A for details on the refinancing procedure and pricing of new debt.

Stockholders maximize the value of equity (we abstract from any potential conflicts of interest between managers and stockholders). The value of equity, V_0, given the initial state variable x_0 is equal to the expected present value of future cash flows under the risk-neutral

[9] Note that we implicitly assume that the equity holders of a firm with negative free cash flow may continue to inject cash (issue new equity) into the firm (unless they decide to default), but it is costly do so and this cost is reflected in the parameter η. This assumption is common in structural credit risk and capital structure models. Setting η equal to infinity would result in immediate default as soon as the cash flow to equity holders turns negative.

measure discounted by the risk-free rate r:

$$E_{i0}(x_0) = \sup_{T_{x_d(t)}} \mathbf{E}^Q_{x_0} \int_0^{T_{x_d(t)}} e^{-rt} CF_{it} dt, \tag{3}$$

where $x_d(t)$ is the optimal default boundary and $T_{x_d(t)}$ is a first-passage time of the process x to the boundary $x_d(t)$.[10] The default boundary is a function of time because debt has final maturity and coupon and principal payments are allowed to vary over time. The equity value can be decomposed into the value that would accrue to equityholders should they be forced to operate the firm forever (the discounted cash flow component) and the value of the default (abandonment) option:

$$\text{Default option} = \sup_{T_{x_d(t)}} \mathbf{E}^Q_{x_0} \int_0^{T_{x_d(t)}} e^{-rt} CF_{it} dt - \mathbf{E}^Q_{x_0} \int_0^{\infty} e^{-rt} CF_{it} dt \geq 0. \tag{4}$$

Equation (4) shows two fundamental differences between our valuation approach and traditional valuation methods. First, we discount cash flows to equityholders only up until the stopping time $T_{x_d(t)}$. This stopping time is determined as the outcome of the optimization problem of the equityholders and results from the optimal exercise of the option to default. By contrast, the usual valuation methods implicitly assume an infinite discounting horizon and ignore that option (value only the second term on the right-hand side of equation (4)). Second, we use the risk-free rate and discount payouts to shareholders under the risk-neutral measure, while the standard valuation methods perform discounting under the physical measure. This also distorts valuations because risk and the appropriate discount rate under the physical measure varies significantly as the firm moves in and out of financial distress. In other words, as is well-known, one cannot price an option by expectation under the physical measure.

2.2 Implementation

We use both annual and quarterly COMPUSTAT data items as inputs to the model. Structural models typically use either earnings or the unlevered firm value as a state variable that drives valuation.[11] While both cash flows and earnings seem to be reasonable candidates, they pose implementation issues. Earnings is an accounting variable which may not be di-

[10] We assume that the absolute priority rule (APR) is enforced and the shareholders receive zero payoff upon default. Deviations from the absolute priority rule and non-zero value of equity in default would induce higher default option values and higher probability of default. See Garlappi and Yan (2011) for equity valuation when APR is violated.

[11] See Goldstein, Ju, and Leland (2001) for a criticism of the use of unlevered firm value.

rectly related to valuation. Cash flow data, on the other hand, is often missing from quarterly COMPUSTAT data making it difficult to compute cash flow volatility. Furthermore, cash flows are subject to one-time items such as lump-sum investments, and therefore the current value of cash flows may not necessarily be representative of its evolution in the future. To smooth out these potential short-term variations in cash flows, we use gross margin (defined as sales less costs of goods sold) as a proxy for the state variable x_{it}. Hence, our state variable for firm i in year t is defined as:

$$x_{it} = Sales_{it} - COGS_{it}, \tag{5}$$

where $Sales_{it}$ is the annual sales and $COGS_{it}$ is the cost of goods sold. There is a lot of short-term variation in capital expenditures and depreciation. In order to reduce this noise, we compute the average $Capex/Sales$ ratio for the 2-digit SIC industry over the last three years, $\overline{CSR}_{t-3,t}$, and use this ratio and current sales for firm i to proxy for firm i's capital expenditures:

$$Capex_{it} = Sales_{it} \times \overline{CSR}_{t-3,t}. \tag{6}$$

We model depreciation in a similar way:

$$Dep_{it} = Sales_{it} \times \overline{DSR}_{t-3,t}, \tag{7}$$

where $\overline{DSR}_{t-3,t}$ is the average depreciation to sales ratio for the 2-digit SIC industry over the last three years. We use selling, general, and administrative expenses (COMPUSTAT item $XSGA$) as a proxy for the fixed costs, F_i.

We assume that firms issue two types of debt: short-term and long-term debt (the model can incorporate any arbitrary maturity structure of debt). We use COMPUSTAT annual items DLT (long-term debt) and $DLCC$ (debt in current liabilities) as proxies for company's long and short-term debt. We further assume that the short-term debt matures in one year, while the long-term debt matures in five years. Since the coupon rate of debt presumably depends on a company's default likelihood, we model the coupon rate on the long-term debt as the sum of the risk-free rate and the actual yield on debt with a corresponding credit rating. We use the average of the T-bill rate and the 10-year T-note rate as the risk-free rate. For credit spread rating, we first divide the firms into quintiles based on CHS (2008) distress measure (details on these calculations are given in Appendix C). We then use AAA, BBB, and BBB+2% yields for distress quintiles 1-2, 3-4, and 5, respectively. We further assume that in year five, after the long term debt is paid off (if the firm has not defaulted before), the firm refinances its debt to match the industry average leverage ratio. Details on the refinancing procedure are provided in Appendix A.

We denote by GM_{it} the gross margin ratio:

$$GM_{it} = \frac{Sales_{it} - COGS_{it}}{Sales_{it}} = \frac{x_{it}}{Sales_{it}}.$$

To model the evolution of x_{it} we assume that the gross margin ratio stays constant in the future so future sales are proportional to the state variable x_{it} : $Sales_{is} = x_{is}/GM_{it}$ for $s \geq t$. We further assume that depreciation and Capex also remain proportional to sales (and, therefore, also proportional to x_{is}) in a similar way:

$$\begin{aligned} Capex_{is} &= Sales_{is} \times \overline{CSR}_{t-3,t} = \frac{x_{is} \times \overline{CSR}_{t-3,t}}{GM_{it}} \\ Dep_{is} &= Sales_{is} \times \overline{DSR}_{t-3,t} = \frac{x_{is} \times \overline{DSR}_{t-3,t}}{GM_{it}}. \end{aligned}$$

To model the growth rate of x_{it} under the physical measure we use the standard approach discussed in many corporate finance textbooks (see, for example, Brealey, Myers, and Allen (2016)). We model growth in capital expenditures in continuous time because our general setup is in continuous time. We first posit that capital expenditures generate growth. Thus, $Capex_{it}$ invested over a time interval $[t, t + dt]$ results in an expected (under P) increase in the operating cash flow by $Capex_{it} R_A dt$ over the next interval dt, where R_A is the after-tax return on assets and (instantaneous) operating cash flow, OCF, are defined as after-tax gross margin plus depreciation tax shield:

$$OCF_{it} dt = [(1 - \tau) x_{it} + \tau Dep_{it}]\, dt = x_{it} \left(1 - \tau + \tau \frac{\overline{DSR}_{t-3,t}}{GM_{it}} \right) dt. \tag{8}$$

Then, the expected growth rate in operating cash flows (under P) equals:

$$\frac{Capex_{it} R_A dt}{x_{it} \left(1 - \tau + \tau \frac{\overline{DSR}_{t-3,t}}{GM_{it}} \right) dt} = \frac{x_{it} \frac{\overline{CSR}_{t-3,t}}{GM_{it}} R_A}{x_{it} \left(1 - \tau + \tau \frac{\overline{DSR}_{t-3,t}}{GM_{it}} \right)} = \frac{\frac{\overline{CSR}_{t-3,t}}{GM_{it}} R_A}{\left(1 - \tau + \tau \frac{\overline{DSR}_{t-3,t}}{GM_{it}} \right)}. \tag{9}$$

Because operating cash flow in our setup is proportional to x_{it}, it follows that the drift parameter of the process x_{it} under the physical measure is given by:

$$\mu_{i,P} = \frac{\mathbb{E}_t^P (dx_{it})}{x_{it} dt} = \frac{\overline{CSR}_{t-3,t} R_A}{(1 - \tau) GM_{it} + \tau \overline{DSR}_{t-3,t}}, \tag{10}$$

where $\mathbb{E}_t^P$ is the conditional expectation under the physical measure P at time t.

We note that while the drift of x_{it} under the physical measure is given by $\mu_{i,P} = R_A - DY_{i,P}$, the growth rate under risk-neutral measure is given by $\mu_{i,Q} = r - DY_{i,Q}$, where DY is the dividend yield and r is the risk-free rate. Since the dividend yield is the same under both measures, $DY_{i,P} = DY_{i,Q}$, it follows that:

$$\mu_{i,Q} = r - R_A + \mu_{i,P}. \tag{11}$$

We use the risk-neutral growth $\mu_{i,Q}$ in the implementation of the model, in which the pricing is done under the risk-neutral measure Q. To measure the return on assets R_A, we calculate the cost of equity by using CAPM.[12] We estimate firms' betas over the past three-year period and then average across all firms in the same 2-digit SIC industry that fall in the same distress quintile based on the CHS (2008) measure of financial distress.[13] We model cost of debt using credit spread rating as described above. The return on assets, R_A, is then equal to the weighted average of the cost of equity capital and the cost of debt.

In Appendix B we allow for time-variation of the drift of x_{it} by modeling mean-reverting process in the return on capital R_A. The quality of investment projects available to managers may vary over time and they might have access to better or worse projects at different times. True return on investment is often hard to measure precisely ex-ante and can lead to the ex-post variation in the actual return. Furthermore, managers might have incentives to deliberately invest in negative NPV projects (those that generate return below R_A) due to the overinvestment/free cash flow problem of Jensen (1986). To account for these effects we assume a regime-shifting process that generates mean reversion in the growth rate. This alternative approach yields results that are qualitatively similar to our base case assumption of constant growth.

We proxy σ by the annualized quarterly volatility of sales over the last eight quarters. If quarterly sales values are not available in COMPUSTAT, we use the average quarterly volatility of sales of the firms in the same 2-digit SIC industry over the last eight-quarter period. We use volatility of sales as opposed to volatility of x_{it} in equation (2) because we believe it better reflects the volatility of the underlying demand-driven stochastic process, which drives valuation in structural models like ours. Using volatility of x_{it} instead would

[12]Note that the risk-neutral option-pricing approach of our model is consistent with the use of the CAPM to estimate the cost of capital R_A For example, if no cash flows are reinvested then the growth rate under Q is $r - R_A$, which makes put options on such firms more expensive and call options less expensive. This is consistent with call options having higher (positive) betas for such riskier firms and put options having lower (negative) betas. See also Rubinstein (1976) for a proof of the equivalence of the CAPM and the Black-Scholes option pricing framework.

[13]We differentiate between firms in different distress categories because expected returns to claimholders vary depending on the degree of distress.

capture some short-term variations in the costs of goods sold and capital expenditures which are not related to the underlying economic uncertainty and therefore should not affect the value of the option to default (nevertheless, we get similar results using volatility of $Sales - COGS$). We use 35% for the corporate tax rate, τ, while we set the distress costs, η, to 15%.[14] The inputs to the model are summarized in Table 1.

A potential minor issue with our approach is that a small percentage (on average 5%) of companies have negative current values of the gross margin, while we assume that x_{it} is a geometric process and, hence, always positive. We exclude these companies from our main set of tests. However, in robustness checks we follow an alternative approach. Since we cannot assume geometric growth for such companies, we assume that x_{it} follows an arithmetic Brownian motion until the moment it reaches the value equal to its annualized standard deviation (of course, before the company defaults), at which point we assume that x_{it} begins to grow geometrically. We obtain similar results using this alternative assumption. Finally, we employ a standard binomial numerical algorithm to determine both the optimal default boundary and the value of equity in equation (3). Further numerical details on the implementation of our procedure are provided in Appendix A.

3 Model performance

We perform our valuation on the entire universe of stocks obtained by merging annual and quarterly COMPUSTAT data with the return data from CRSP. Each month we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value. Decile one contains the most overvalued stocks while decile ten consists of the most undervalued stocks. This valuation sort is similar in spirit to scaling the market price in order to predict returns (Lewellen (2004)). While the most usual scaling variable is the book value, some studies use model implied valuation as a scaling variable. For example, Lee, Myers, and Swaminathan (1999) use the ratio of residual income value to market value to predict future returns. Some other papers that use the ratio of model value to market value to detect equity misvaluation are D'Mello and Shroff (2000), Claus and Thomas (2001), Dong et al. (2006), and Pástor, Sinha, and Swaminathan (2008). Our approach, while using a different valuation method, is similar in its use of the sorting variable.

We report the characteristics of these portfolios in Table 2. In addition to size, market-to-book, market beta (calculated using past 60 months), past six-month return, and standard

[14] Weiss (1990) estimates the direct costs of financial distress to be of the order of 3% of firm value, Andrade and Kaplan (1998) provide estimates between 10% and 23%, while Elkamhi, Ericsson, and Parsons (2011) use 16.5% in their analysis. Our results are robust to different values of η.

deviation of daily stock returns, we also show the percentage of firms reporting negative earnings, number of analysts, the standard deviation of their forecasts, equity issuance, institutional ownership, and two proxies for liquidity, namely share turnover and Amihud's (2002) illiquidity measure. Accounting and stock return data are from CRSP and COMPUSTAT and all analyst data are from IBES. For each characteristic, we first calculate the cross-sectional mean and median of each portfolio. The table then reports the time-series averages of these means and medians. We exclude observations in the top and the bottom percentiles in calculating the means and medians. We include all common stocks, although our results are robust to the exclusion of financial stocks. The sample period for our study is 1983 to 2012 as the coverage of quarterly COMPUSTAT data is sparse before this date.

Table 2 shows that the most misvalued stocks (over- or undervalued) are smaller, more volatile, less liquid (especially undervalued stocks), have fewer analyst coverage with higher analysts' forecast dispersion, and have lower institutional ownership than more fairly valued stocks. While these observations are not especially surprising as these are presumably the characteristics of stocks that are the most difficult to value, these results do provide a first indication that our model successfully detects stocks whose market values move further away from fundamental values. The results further show that most overvalued stocks (decile one) have, unsurprisingly, higher market-to-book ratios than most undervalued stocks (decile ten), which also explain their higher market beta. Decile one stocks also show higher past returns and issue more equity than decile ten stocks. These equity issuance patterns are consistent with our valuation model under the additional assumption that managers of these firms understand true valuations and time the market in issuing equity.

We have conjectured that the stocks in the extreme deciles are the most misvalued by the market, apparently due to the market's inability to value the default option correctly. We check whether the stocks in these deciles do default more often than more fairly valued stocks. We calculate the fraction of stocks that default based on CRSP's delisting codes associated with poor performances, such as bankruptcy, liquidation, dropping due to bad performances, etc. In unreported results, we find that the average default rate of stocks in deciles one and ten is 6.6%, 11.0%, and 14.6% in one-, two-, and three-years after portfolio formation, respectively (cf. default rate of stocks in decile five is 1.1%, 2.2%, and 3.4%, respectively). These statistics provide further indication that the misvaluation picked up by our model is related to default option.

3.1 Portfolio returns of stocks sorted on model valuation

We proceed to check the efficacy of our valuation model by calculating returns of the decile portfolios. We form both value- and equal-weighted portfolios. While value-weighting is more common in the literature, Table 2 shows that more mispriced stocks are smaller on average. It is, thus, possible that equal-weighting leads to stronger performance of our sorts. Accordingly, we present most of results for value-weighted portfolios but also show equal-weighted portfolios for reference. Table 3 reports the monthly returns on each portfolio as well as the returns to the hedge portfolio that is long the most undervalued firm portfolio (decile ten) and short the most overvalued firm portfolio (decile one). In addition to reporting the average return in excess of the risk-free rate, we also report the alphas from one-, three-, and four-factor models. The one-factor model is the CAPM model. We use Fama and French (1993) factors in the three-factor model. These factors are augmented with a momentum factor in the four-factor model. All factor returns are downloaded from Ken French's website. All returns and alphas are in percent per month and numbers in parentheses denote the corresponding t-statistics.

Table 3 shows that returns and factor-model alphas are generally monotonically increasing when one moves from decile one (most overvalued stocks) to decile ten (most undervalued stocks, supporting our model's ability to detect stock mispricing. The hedge portfolio has excess returns of 0.65% per month (t-statistic=2.10). Factor model alphas display patterns consistent with excess returns and characteristics of stocks shown previously in Table 2. For example, since decile ten stocks are, on average, smaller and have lower market-to-book ratios than decile one stocks, the $10-1$ portfolio has lower 3-factor alpha at 0.49% than CAPM alpha at 0.82%. At the same time, since past returns for decile ten stocks are lower than those for decile one stocks, the 4-factor alpha of the long-short portfolio is higher at 0.91% (t-statistic=3.68). Regardless of the risk correction, the alphas of $10-1$ portfolio are economically large and mostly statistically significant.[15] The last column of Table 3 shows that, as suspected, the hedge portfolio returns on equal-weighted portfolios are even higher; the 4-factor alpha is 1.27% (t-statistic=6.65).

In a series of robustness checks, we calculate alphas from alternative factor models. These numbers are not reported in the table but we discuss the main results here. Since our holding

[15]Some readers have suggested that post-formation returns are not necessarily a sufficient test of the goodness of our valuation model, especially if market valuation drifts even further away from our 'fair' valuation. We check this by computing value gap, the difference between market valuation and our valuation. We calculate this value gap at portfolio formation and one quarter after portfolio formation (numbers not reported). We verify that the value gap does indeed shrink on average one quarter after portfolio formation. At the same time, the value gap does not decline to zero, suggesting that correction takes longer than one quarter (see also robustness checks on long horizon returns later in this section).

period is only one month, we include a short-term reversal factor in the asset pricing model. Alpha from this alternate five-factor model is similar to that from a four-factor model; the 5-factor alpha of the 10−1 portfolio is 0.86% (t-statistic=3.53). We calculate a five-factor model with an additional liquidity factor of Pástor and Stambaugh (2003). The alpha from this model is even higher than the 4-factor alpha at 0.95% (t-statistic=3.57). We check whether these returns can be explained by a volatility factor. We find that the loading of the 10−1 portfolio return on changes in VIX (proxy for volatility factor) is small and statistically insignificant. Finally, we calculate an alpha from a factor model that includes the five factors from Fama and French (2015) and the momentum factor and find similar statistically significant results, albeit slightly lower in magnitude.

We further examine the robustness of the results to different subsamples and return horizons in Table 4. To reduce the clutter in the table, we report only the 4-factor alphas for each portfolio. To facilitate comparison with the main results, we report the full-sample results in the first row of the table. We consider two different kinds of subsamples. The first subsample simply tabulates results for the months of January versus the rest of the months. It is well known that small stocks often tend to rally in January and stocks in both first and tenth deciles have lower market capitalization than that in mid-decile stocks. In the second subsample, we consider calendar patterns in our results by separately tabulating the results for the decades of 1980s, 1990s, and 2000s.

Hedge portfolio value-weighted alphas are higher in non-January months (0.80%) than those in January (0.56%), where the latter is not statistically significant, likely due to the small number of January observations. Returns are higher in the 1990s (1.00%) and this century (1.04%) than in the 1980s (0.69%). Patterns for equal-weighted alphas shown in the last column are different from those for value-weighted portfolios, yet the results remain significant for all sub-samples. Equal-weighted portfolios have a high alpha of 3.60% in January that is due to the small-firm January effect. While the alphas of value-weighted portfolios are similar across the three decades, equally weighted alphas are lower in this century than in the previous, suggesting that the contribution of small stocks to mispricing has declined.

We look at the horizon effects in Panel B of Table 4. Specifically, we consider holding periods of 3, 6, 12, and 18 months.[16] This implies that we have overlapping portfolios. We take equal-weighted average of these overlapping portfolios similar to the approach of Je-

[16]Whenever available from CRSP, we add delisting return to the last month traded return. If the delisting return is not available, we use the last full month return from CRSP. This could, in principle, impart an upward bias to portfolios returns (Shumway (1997)). This has no material impact on our results. Note that our procedure implies that the proceeds from sales of delisted stocks are reinvested in each portfolio in proportion to the weights of the remaining stocks in the portfolio.

gadeesh and Titman (1993). The table shows that 10−1 returns are strong and statistically significant for horizons up to 18 months, although they decline as we increase the horizon. In untabulated results, we look at month by month returns and find that most of the market value correction takes place in the first year after portfolio formation; there is almost no difference in returns between decile 1 and decile 10 in the 18th month after portfolio formation. We conclude that our valuation model does well across various subsamples and over longer horizons.

3.2 The importance of default option in model valuation

Our valuation model is inspired by the option-like characteristics of common stocks. The option value can be a significant fraction of the total value of equity for stocks with characteristics of financial distress, size, volatility, and profitability. In this section, we verify the importance of this default option in the ability of the model to value stocks and thereby predict returns amongst these subgroups of stocks.

Perhaps, the most natural characteristic that one can associate with the relevance of the option to default is the extent of financial distress. In fact, the terms 'financial distress' and 'high default risk' are often used interchangeably: firms experiencing financial distress have more uncertainty about their ability to generate sufficient future cash flows, thus making the option to default particularly relevant for them. Put differently, for highly distressed firms the option to default is likely to be in-the-money, and thus captures significant fraction of the total equity value. We expect that our model's ability to detect misvaluation will be higher amongst financially distressed stocks. We employ the model of CHS (2008) to measure financial distress.[17] CHS use logit regressions to predict failure probabilities while incorporating a large set of accounting variables. Detailed description of the estimation procedure of this measure is provided in Appendix C.

The second characteristic that we consider is firm size. Since firm size is one input in the CHS (2008) distress measure, one can view firm size as a reduced-form proxy for the likelihood of default. Also, in general, young and small firms face more competitive challenges and higher capital constraints and are therefore more likely to default or abandon their business. We measure firm size by equity market value and expect that our model will perform better for small-cap stocks.

The third firm characteristic is stock return volatility. The high uncertainty about the

[17] Another common measure of distress is from the Moody's KMV model, which is based on the structural default model of Merton (1974), and largely relies on leverage ratio and asset volatility. In unreported results, we find very similar results using this measure as those using the CHS (2008) measure.

future of firms facing the possibility of default is likely to be reflected in high stock return volatility. In particular, any news about future cash flows that affects the likelihood that the firm will default has a strong impact on the current price. In turn, as implied by option pricing theory, the value of an option increases with the volatility of the underlying asset. We use idiosyncratic volatility as our main volatility measure. We obtain similar results by using total volatility instead. We follow Ang et al. (2006) and calculate idiosyncratic volatility for each month by the standard deviation of the residuals of regression of daily stock returns on the daily Fama and French (1993) three factors augmented with the momentum factor. For each month, the idiosyncratic volatility is estimated during the previous month.[18] We expect better model performance for highly volatile stocks.

The fourth and last characteristic is profitability. We use the ratio of net income over total assets (ROA) as a proxy for profitability. We expect less profitable companies to be closer to default boundary and facing a higher default probability. Also, like size, this ratio is used as one of the inputs in the CHS (2008) model.

We proceed as follows. Each month we first sort all stocks into five quintiles according to each characteristic, using current market data and quarterly accounting data of the previous quarter. We use equal-sized quintiles for distress, volatility, and profitability and quintiles based on NYSE breakpoints for size. Then, within each characteristic quintile, we sort all stocks into five equal-sized portfolios according to the ratio of the model value to the market value. These second-sorted portfolios are labeled R1 (most overvalued) to R5 (most undervalued). Our double-sorted portfolios are well populated as the average number of stocks per portfolio is 123.

We report the mean fraction of default option value in the total equity value implied by our valuation model for value-weighted portfolios in the last column of each characteristic panel of Table 5. To compute this fraction, we run the model while shutting down the default option by disallowing default and exit and forcing equityholders to operate the firm indefinitely. The value of the option to default is then given by the difference in equity values with and without this option (see equation (4)). These mean fractions confirm our choice of characteristics, as they increase with distress and volatility, and decrease with firm size. For example, option value is, on average, 35.9% of the total value of equity for the most distressed stocks, but only 19.2% of the total value of equity for the least distressed stocks. Note that our model captures both the default and abandonment options and, therefore, implies positive option values for even zero-leveraged firms as long as fixed costs are nonzero. Mean fraction is increasing from 15.4% to 30.1% when moving from low- to

[18]The results remain similar taking the average idiosyncratic volatility during the prior three months and during the prior twelve months.

high-volatility stocks. Size and profitability have a weaker effect on default option. Mean fractions are 28.6% and 17.2% for the large and small size quintiles, respectively, and decrease from 27.6% for the least profitable firms to 20.5% for the most profitable. High profitability firms might optimally choose more debt financing that will make the default option more important. This effect might attenuate the relation between profitability and relative value of the option to default.

Table 5 also shows the 4-factor alphas on these double-sorted portfolios. For each characteristic sort we find that (a) the 4-factor alphas for R5 (most undervalued stocks) are always higher than those for R1 (most overvalued stocks), and (b) the hedge portfolio alphas are increasing with the value of default option. For example, Panel A shows that hedge portfolio alpha is only 0.26% (t-statistic=1.38) for least distressed stocks quintile and increases monotonically to 1.19% (t-statistic=2.10) for the top distress quintile. The effect of size in Panel B on the returns generated by the model's relative value portfolios is somewhat weaker than those of distress; the 4-factor alpha of the hedge portfolio is 0.75% for the small size quintile and 0.43% for the large size quintile. These return patterns are consistent with the weaker relation between size and the fraction of default option shown in the last column of Panel B. Panel C shows that the 4-factor alpha of the hedge portfolio is 1.38% for the high-volatility stocks (for which default option is more valuable), whereas it is only 0.39% for the low-volatility stocks (where default option is less valuable). Panel D shows that the hedge portfolio alpha goes down from 1.09% for the least profitable stocks to 0.69% for the most profitable stocks.

Reflecting the better performance of the model for small stocks, equal-weighted hedge portfolio returns in Table 5 show stronger support for our conjecture. The equal-weighted portfolio return difference between stocks with high and low default option is higher than those for value-weighted portfolios. For instance, Panel B shows that 4-factor alpha of the equal-weighted hedge portfolio is 1.19% for the small size quintile and only 0.43% for the large size quintile. The 4-factor alpha is 1.81% per month (t-statistic=6.12) for the most distressed D5 stocks in Panel A, 1.82% (t-statistic=6.66) for the most volatile IV5 stocks in Panel C, and 1.81% (t-statistic=6.38) for the least profitable PR1 stocks in Panel D, consistent with the highest fraction of default option amongst these categories of stocks.

The returns in Table 5 show that the strength of the model in valuing stocks is largely driven by the option to default. To provide a more direct test of the importance of default option in the total equity value, we recompute the returns to our double-sorted portfolios by shutting down the default option. Table 6 shows the 4-factor alphas to the long-short R5−R1 portfolios for each characteristic quintiles. The performance of the model in predicting returns deteriorates sharply without the option to default. For the top quintile of distressed stocks and idiosyncratic volatility stocks, the 4-factor alpha of the model without the default option is roughly a quarter of the magnitude of the alpha of the model with the default option. In particular, there is a reduction in 4-factor alpha from 1.19% to 0.28% for the most distressed stocks, and from 1.38% to 0.33% for the most volatile stocks. For the least profitable stocks the alpha of the long-short strategy drops from 1.09% with default option to 0.48% without default option. In contrast, the reduction in alpha is relatively modest for small stocks. The deterioration in model performance is relatively more modest for equal-weighted portfolio returns in Panel B.

3.3 Fama-MacBeth regressions on relative model value

The portfolio sorts provide a simple view of the relation between returns and our variables of interest. Another approach commonly used in the literature is Fama and MacBeth (1973) regressions. Beyond serving as an additional diagnostic check, these regressions offer the advantage of controlling for other well-known determinants of the cross-sectional patterns in returns and thus check for the marginal influence of relative model valuation on our results. Accordingly, we run these cross-sectional regressions and report the results in Table 7. The dependent variable is the excess stock return while the independent variables are (log) market capitalization, (log) market-to-book, past six-month return, relative model value (log of the ratio of the equity value implied by our valuation model to the actual equity value; higher numbers indicate undervaluation based on our model), CHS (2008) distress risk measure, volatility, profitability, and interaction terms between relative model value and the characteristics of interest. We winsorize all independent variables at the 1% and 99% levels to reduce the impact of outliers. All reported coefficients are multiplied by 100 and we report Newey-West (1987) corrected (with six lags) t-statistics in parentheses.

The first regression shows the usual patterns; returns are related to size, market-to-book, and past return. The second specification is the regression version of the univariate sorts in Table 3 showing that our valuation measure is able to predict returns. Regression (3) shows that distress and idiosyncratic volatility are negatively related to returns, while profitability is positively related, although the statistical significance of the volatility measure is not high for our sample period. Specifications (4) and (5) show that relative model value is positively associated with future returns even after inclusion of standard stock characteristics. These regressions, thus, provide robust multivariate evidence of the efficacy of our valuation measure that corroborates the portfolio-sort results.

Next, we interact our valuation measure with the stock characteristics to gauge whether our model works better for stocks with a high value of default option. Specifications (6) through (10) are regression counterparts of Table 5. Regressions (6)-(8) show that the interaction terms between relative model value and size, distress, and idiosyncratic volatility are statistically significant. This implies that our relative model value does particularly well for the subset of small stocks, distressed stocks, and more volatile stocks. It is important to note that the effect of the interaction term on size in specification (6) is highly statistically significant in contrast to the somewhat weaker results from portfolio sorts. The coefficient on the interaction term with profitability has the expected negative sign though is statistically insignificant. As discussed above, the effect of profitability might be subdued by the endogeneity of financial leverage – more profitable firms might optimally choose higher leverage and therefore increase the likelihood of default. Finally, including all variables and interaction terms in regression (10), we find that the coefficients on relative model value and the interaction term with size are significant although the coefficients on other interaction terms lose their significance.

To summarize, the cross-sectional regressions of Table 7 coupled with the portfolio sort results provided in Tables 5 and 6 demonstrate the importance of the default option in the model valuation. Both portfolio sort results and regression based evidence suggest that the power of the model is stronger for stocks with higher values of default options and characteristics closely associated with financial distress and default.

3.4 Double sort on relative valuation and market-to-book

As a final robustness test, we check whether our results are not just a manifestation of the value effect in stock returns. This concern is warranted as both our relative value measure and market-to-book ratio compare a fundamental value to actual market value. The results in Table 3 already show that the alpha of the long-short relative value portfolio remains significant in the presence of the HML factor, which indicates that our measure goes deeper than the simple value effect. Likewise, we report positive and significant coefficients on the relative valuation measure while controlling for market-to-book ratio in the Fama-MacBeth regressions in Table 7. To provide additional evidence, we examine the model performance separately in portfolios sorted by market-to-book ratio. Each month we first sort all stocks into five quintiles according to the market-to-book ratio, using current market value and book value of the previous quarter. Then, within each market-to-book quintile, we sort all stocks into five equal-sized portfolios by the ratio of model value to market value. These second-sorted portfolios are labeled R1 (most overvalued) to R5 (most undervalued). Similar to our analysis in Table 5, we also compute the mean fraction of default option value in the total equity value implied by our valuation model.

Table 8 reports the results of this exercise. There is no clear relation between the relative default option value and market-to-book, although firms in mid market-to-book quintiles tend to have slightly lower default option values. More importantly, while there is some variation in the 4-factor alphas produced by the long-short strategy, the performance is strong and significant in all market-to-book quintiles. This demonstrates that our valuation measure is not subsumed by market-to-book and goes beyond the simple value effect.

4 Additional Tests for Mispricing

As mentioned earlier in Section 3, there is extant literature that explores equity misvaluation by comparing market values to the values derived from equity valuation models, such as dividend-discount model or residual-income model. We follow in the footsteps of these papers using a relatively more sophisticated model (albeit a relatively standard model from real options literature). Along the way, we have to make a number of assumptions in order to implement the model empirically. This might raise concerns about our model. The fact that we see large spreads in future returns (and factor model alphas) to over- versus undervalued stocks conveys to us that our model does a good job of identifying mispriced stocks, especially stocks that are hard to value. If the market prices were mostly correct and our model had a lot of noise, we would not see these spreads. In this section we undertake additional tests to demonstrate that it is indeed market mispricing that is driving our results and that a richer rational model would not likely overturn them.

4.1 Earnings announcements

We follow the literature in examining what might be the triggers for market learning that eventually correct the mispricing. In particular, we examine stock returns around earnings announcements after portfolio formation (see, for example, Lakonishok, Shleifer, and Vishny (1994), La Porta et al. (1997), and Cooper, Gulen, and Schill (2008)). If mispricing drives our results, then return spreads around EADs should be higher than those around non-EADs.

We obtain EADs from quarterly Compustat (data item RDQE). In the first test, we partition the sample into firm-months with and without EADs. Panel A of Table 9 shows 4-factor alphas to deciles sorted on relative model value for these subsamples. While long-short $10-1$ portfolio alphas in both samples are statistically significant, the magnitude of 1.32% in months where firms had EADs is almost twice that of 0.67% in months with no EADs. To gain even more precision, in Panel B we look at daily returns in a three-day window around EADs. Once again, the $10-1$ portfolio 4-factor alphas are 0.24% per day around EADs but only 0.05% around non-EADs. Equal-weighted portfolios show even larger differences in alphas in both panels. These results suggest that subsequent earnings announcements impart valuable information to the market and are consistent with expectational errors in stock pricing.

4.2 Information transparency

Market mispricing is likely to be stronger among stocks with less information transparency. To examine the potential effect of mispricing on the long-short portfolio returns, we use three proxies for the degree of information transparency. Our first proxy is analyst coverage. Existing literature has argued that analyst coverage is associated with information production (see, for example, Chang, Dasgupta, and Hilary (2006), Kelly and Ljungqvist (2012), and Derrien and Kecskés (2013)). We obtain analyst coverage from IBES.

Our second proxy for information transparency is institutional ownership. We follow the literature that shows that greater institutional ownership enhances information transparency. See, for example, Bushee and Noe (2000), Ajinkya, Bhojraj, and Sengupta (2005), and Boon and White (2015) for evidence of an association between institutional ownership and management disclosure, information asymmetry, as well as quality and frequency of management forecasts. Institutional ownership is taken from Thomson 13F institutional holding database.

Our third and last proxy for information transparency is the availability of listed options for a given stock. Jennings and Starks (1986) and Senchack and Starks (1993) show that the prices of stocks with listed options adjust much faster to new information than the prices of stocks without options. In addition, there is large evidence in the literature that information in option prices has predictive ability for subsequent stock returns, suggesting that the options market produces additional information and contributes to price discovery.[19] We identify the availability of traded options from 1996 onwards using Optionmetrics.

Since we argue that the potential for mispricing is stronger among stocks with low information transparency, we not only expect our model-based investment strategy returns to be higher for stocks with more important default options (as evidenced in Section 3.2 and Table 5), but we also expect the improvement in performance to be particularly pronounced among low information transparency stocks. To test this hypothesis, we double sort all stocks into quintiles based on characteristics related to default options used in Table 5 (CHS (2008) distress score, size, idiosyncratic volatility, and profitability) and into two groups based on the

[19] See, for example, Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing, Zhang, and Zhao (2010).

three proxies of information transparency discussed above. For each of these double sorts, we further triple sort on relative model value and report the value-weighted 4-factor alphas of these R5−R1 relative value portfolios in Table 10. To reduce clutter, we only report the result for quintile portfolios with the most/least important default options.

Results in Table 10 provide strong support for our conjecture. The effect of default options on improvement in alphas is greater for stocks with less information transparency, across all proxies for default options and measures of information transparency. For example, as one moves from the least to the most distressed stocks, the strategy's 4-factor alpha increases from 0.48% to 2.21% (an improvement of 1.73%) for stocks with low analyst coverage, but only from 0.25% to 0.84% (an improvement of 0.59%) for stocks with high analyst coverage. The corresponding improvement is 2.25% (0.73%) for low (high) institutional ownership and 0.51% (0.29%) for stocks without (with) listed options. The differences in 4-factor alphas for the other three proxies of default options (size, volatility, and profitability) exhibit a similar pattern.

4.3 Time-series variation in model performance

We next analyze model performance in different states of the economy. Our hypothesis is that valuation difficulties are more pronounced during bad, more turbulent times and times of high investor sentiment. We divide the sample into two parts based on either NBER recession dummy or the Baker and Wurgler (2006) sentiment index.

Table 11 shows the 4-factor alphas of the 10−1 portfolio in these two sub-samples. Panel A shows that our valuation model produces a hedge portfolio alpha of 1.61% in recessions and 0.89% in expansions. Note that most overvalued stocks in decile one have particularly poor performance in recessions (4-factor alpha of −0.90%). Most undervalued stocks in decile ten, however, perform similarly well in terms of 4-factor alphas in both recessions and expansions.

Panel B shows even bigger differences for the sample split by the sentiment index. The 10−1 portfolio alpha is 1.36% in high sentiment months but only 0.52% in low sentiment months. The fact that sentiment plays an important role in mispricing is also consistent with the evidence in Stambaugh, Yu, and Yuan (2012). Overall, these time-series results are suggestive of market mispricing.

4.4 Characteristics of undervalued and overvalued stocks

The tests so far in this section have focused on the relation between hedge portfolio returns and proxies for potential mispricing. As an additional validation of the model's ability to identify mispricing, and in particular misvaluation of default options, we take a closer look at characteristics of the stocks classified as over- or undervalued by our model. If our model does a reasonable job in detecting mispricng, then such stocks are likely to exhibit characteristics commonly associated with over-/undervaluation. Furthermore, since the model derives its power from incorporating default options explicitly, this association is expected to be stronger for firms with more important default options.

We focus on the following characteristics associated with over-/undervaluation: equity issuance, institutional ownership, insider trading, and the likelihood of becoming an acquisition target. There is a large body of evidence (see, for example, Spiess and Affleck-Graves (1995), Loughran and Ritter (1997), and Dong, Hirshleifer, and Teoh (2012)), including survey evidence (Graham and Harvey (2001)) that shows that overvalued firms tend to issue more equity. Institutional investors are commonly viewed as more sophisticated and, therefore, are less likely to hold overvalued stocks. For example, CHS (2008) report that institutional investors tend to sell financially distressed stocks (such stocks exhibit low subsequent returns and are potentially overvalued). It is likely that insiders have superior information about the fundamental value of their firm and it is easier for them to identify potential mispricing and time their trades accordingly. Empirical evidence on insider trading is consistent with this argument (see, for example, Rozeff and Zaman (1998), Jenter (2005), and Cohen, Malloy, and Pomorski (2012)). Finally, undervalued firms become potentially attractive acquisition targets (see, for example, Rhodes-Kropf, Robinson, and Viswanathan (2005), Dong et al. (2006), and Malmendier, Opp, and Saidi (2016)).

We obtain information on insider trades from Thomson's Insiders. Net insider buys are calculated as the difference between the number of shares bought and sold by insiders during the portfolio formation month, scaled by total number of shares outstanding. We estimate the likelihood of becoming an acquisition target as the percentage of firms that were acquired during the following year. The data on mergers is from SDC Platinum database.

Table 12 summarizes the results from this exercise. We double sort all stocks into quintiles based on a stock characteristic related to default options (distress, size, volatility, and profitability) and relative model value the same way as in Table 5. We then look at the mispricing-related characteristics among firms with high and low default option values separately for most undervalued and most overvalued stocks. As before, we argue that the power of the model hinges on incorporating default option values. Therefore, we expect the difference in characteristics chosen in this section to be stronger for firms with high values of default option.

The results in Table 12 are strongly supportive of our hypothesis. Overvalued stocks (quintile R1) are different from undervalued stocks (quintile R5) with respect to their characteristics in the expected direction. While these results are generally consistent with the descriptive statistics of Table 2, the novelty of the analysis in this section is that the difference in characteristics is larger for those firms where the default option is more important. For example, the difference in equity issuance between most overvalued and most undervalued firms is 4.3% for the most distressed firms while the same difference is only 1.6% for the least distressed firms. For institutional ownership, insider buys, and takeovers the corresponding differences are 3.6%, 4.2%, and 2.2%, respectively, for the most distressed firms versus −9.8%, 2.3%, and 0.1%, respectively, for the least distressed firms. The results are qualitatively similar for three other proxies of default options.

Overall, the evidence in this section strongly suggests that the performance of the long-short strategy is driven to a large extent by market mispricing of default options. First, portfolio returns are stronger for stocks that are likely subject to more mispricing; at times when mispricing is likely to be high; and this effect is amplified by the presence of default options. Second, misvalued stocks exhibit characteristics typically associated with over- and undervaluation and this association is much stronger for firms with more important default options.

5 International evidence

As an out-of-sample exercise, we check the efficacy of our model for a sample of nine developed markets, namely Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Switzerland, and the U.K. We obtain stock returns and accounting data for international firms from Datastream and Worldscope. The availability of data varies across countries and is very scarce before early 1990s, so we start our sample in 1994. We follow standard filters in cleaning up the data (see, for example, İnce and Porter (2006) and Griffin, Kelly, and Nardari (2010)). To ensure that we have a reasonable number of stocks for our tests, we also drop country-years with less than 100 firms with available data. As we use factor-model alphas in some of our tests, we build factors separately for each country following the approach of Fama and French (1993).

For each country, we first perform valuation on the entire cross-section of stocks in the same way as detailed in Section 2. We make two adjustments to the procedure to account for data availability issues. First, we estimate the volatility of sales using annual data (based on the past eight years) as quarterly accounting data is sparse for international firms. As for the U.S. sample, in cases where firm-specific volatility cannot be computed, we use the average annual volatility of sales of the firms in the same industry. For robustness we also report the results using quarterly sales, acknowledging that for a large proportion of the sample, the quarterly volatility of sales represents the industry average. Second, we use distance-to-default from Merton's (1974) model instead of CHS (2008) to construct industry-distress peer groups and cost of debt. This is because Merton model uses only equity value, equity volatility, and the face value of debt, as opposed to CHS and other models that rely on a large set of accounting variables.

Table 13 shows country-specific descriptive statistics. Our summary statistics are consistent with other international studies (see Fama and French (1998) and Fan, Titman, and Twite (2012)), despite some differences in the sample periods. There is a substantial variation in the number of firms with available data across countries, from only 175 firms (12,701 firm-months) in Switzerland to 4,305 (551,830 firm-months) in Japan. Market-to-book ratio exhibits two regimes; Hong Kong, Italy, and Japan have fairly low ratios (means of 1.19 to 1.67), where the other seven countries show higher ratios (2.14 to 2.80). Italy and Japan also show relatively high levels of market leverage (mean ratios of 0.40 and 0.36), which is consistent with the low market-to-book ratios in these countries. In the rest of the countries the mean market leverage ranges between 0.21 and 0.30, which is more comparable to the level of U.S. firms. Finally, monthly stock returns also vary significantly across countries, from an average of 0.12% in Italy to 1.37% in Australia. This suggests that our exercise captures different states of the economy across countries. We view all these differences in firm characteristics as an advantage because they allow us to examine whether our model can be successful in predicting returns for different types of samples and conditions.

Using the model valuation, we sort stocks into deciles and calculate value- and equal-weighted returns. The returns and alphas of the hedge portfolio that is long in undervalued stocks and short in overvalued stocks are reported in Panel A of Table 14. For value-weighted portfolios, the excess returns range from 0.07% for Italy to 1.51% for Hong Kong. For the most part, alphas are similar to excess returns. Focusing on 4-factor alphas, we find positive alphas in eight countries with Italy being an exception; four of these alphas are statistically significant (two more are significant at 10% significance level). As was the case for the U.S., equal-weighted portfolios generate a bigger spread in returns. This suggests that small stocks are typically more mispriced than large stocks in other developed markets as well. With the exception of Italy again, 4-factor alphas are positive and statistically significant for all other eight countries; the 4-factor alpha is highest at 1.99% for Australia and lowest at 0.82% for

Germany, with t-statistics of 2.48 to 4.62. Panel B shows fairly similar results when using quarterly data in calculating volatility of sales; the means of the 4-factor alphas on the value- and equal-weighted hedge portfolios are 0.95% and 1.00% per month, compared to 0.79% and 1.19% using annual data.

We show the results of Fama-MacBeth regressions in Table 15. We run regressions separately for each country. The dependent variable is the monthly excess stock return. The independent variables are (log) market capitalization, (log) market-to-book, past six-month return, and relative model value. The coefficients on size, market-to-book, and past returns are mostly consistent with the extant evidence. The coefficient of interest to us is the one on relative model value. Since the magnitudes of the coefficients are difficult to compare across countries, we focus on the statistical significance. The coefficient is positive for all nine countries we analyze and significant for six of these countries (t-statistics from 2.32 to 3.18). The coefficient is also significant at a 10% level for Switzerland (t-statistic of 1.82).

To conclude, the evidence from the sample of developed countries is consistent with that for the U.S., providing further evidence that our model is able to identify stocks that are mispriced.

6 Conclusion

Equities are embedded with an option to default. We believe that a meaningful equity valuation model should take this optionality into account. An important question is whether investors recognize this insight and account for default option when valuing equity. To address this question we build such a model by accounting for the value of the option to default or to abandon the firm. Our model is capable in separating over- and undervalued stocks. The long-short strategy that buys stocks that are classified as undervalued by our model and shorts overvalued stocks generates an annualized 4-factor alpha of about 11%. This performance is robust to various sample splits and holding periods. Furthermore, a similar investment strategy produces significantly higher returns for stocks with a relatively high value of default option, namely distressed, highly volatile, and low profitability stocks, articulating the importance of the option to default as the key ingredient of our model. International evidence from nine of the largest developed markets reinforces our U.S.-based results. This suggests that default options are mispriced by the market and, in general, investors do not fully recognize the option-like nature of equities and do not value them accordingly.

Appendix A: Numerical details on the valuation model

The first step is to find a value of the firm that survives until year five and pays off its long-term debt. We assume that at the end of year five, the firm refinances by issuing perpetual coupon debt in an amount to match the average 2-digit SIC market leverage ratio. We assume refinancing to average industry leverage, as opposed to inferring the optimal leverage from the model due to the known tendency of structural contingent claim models to predict optimal leverage ratios that appear too high compared with their empirical counterparts.

The net instantaneous post-refinancing cash flow to equityholders is:

$$\begin{aligned} CF_{it} &= [(1-\tau)(x_{it}-c_i-F_i)+\tau Dep_{it}-Capex_{it}]\times \\ &\qquad \left[1+\eta\mathbf{1}_{(1-\tau)(x_{it}-c_i-F_i)+\tau Dep_{it}-Capex_{it}<0}\right]dt, \end{aligned} \tag{A1}$$

where the coupon amount is c_i. The cash flow to bondholders is $c_i dt$. Note that the additional cost of financial distress η is incurred if $x_{it} < x^*$, where:

$$(x^*-c_i-F_i)(1-\tau)+\tau Dep_{it}-Capex_{it}=0.$$

Because we assume that the gross margin ratio, GM_{it}, as well as the depreciation-to-sales and capex-to-sales ratios stay constant over time, x^* is given by:

$$x^*=\frac{(c_i+F_i)(1-\tau)}{1-\tau+\left(\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}\right)/GM_{it}}. \tag{A2}$$

The cash flows to equityholders and, therefore, the value of equity depend on whether the current value of x_{it} is above or below the threshold x^*. The cash flows in equation (A1) above can be rewritten as:

$$\begin{aligned} CF_{it} &= \Bigg[x_{it}\left(\frac{\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}}{GM_{it}}+(1-\tau)\right)\times \\ &\qquad \left(1+\eta\mathbf{1}_{x_{it}\left(\frac{\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}}{GM_{it}}+(1-\tau)\right)-(c_i+F_i)(1-\tau)<0}\right) \\ &\qquad -(c_i+F_i)(1-\tau)\Bigg]dt. \end{aligned} \tag{A3}$$

Then standard arguments show that the value of equity is given by:

$$E(x_{it})=\begin{cases} Ax_{it}^{\beta_1}+Bx_{it}^{\beta_2}+\left[\frac{\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}}{GM_{it}}+(1-\tau)\right]\frac{x_{it}}{r-\mu}-(1-\tau)\frac{c_i+F_i}{r} & \text{if } x_{it}\geq x^* \\ Cx_{it}^{\beta_1}+Dx_{it}^{\beta_2}+(1+\eta)\left\{\left[\frac{\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}}{GM_{it}}+(1-\tau)\right]\frac{x_{it}}{r-\mu}-(1-\tau)\frac{c_i+F_i}{r}\right\} & \text{otherwise,} \end{cases} \tag{A4}$$

where β_1 and β_2 are the positive and the negative root of the quadratic equation $\frac{1}{2}\sigma^2\beta(\beta - 1) + \mu_Q\beta - r = 0$, and A, B, C, and D are constants. Equation (A4) must be solved subject to the following boundary conditions:

$$
\begin{aligned}
&A = 0 \\
&Bx^{*\beta_2} + \left[\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right]\frac{x^*}{r-\mu_Q} - (1-\tau)\frac{c_i + F_i}{r} = \\
&\qquad Cx^{*\beta_1} + Dx^{*\beta_2} + (1+\eta)\left\{\left[\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right]\frac{x^*}{r-\mu_Q} - (1-\tau)\frac{c_i + F_i}{r}\right\} \\
&\beta_2 Bx^{*\beta_2 - 1} + \left[\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right]\frac{1}{r-\mu_Q} = \\
&\qquad \beta_1 Cx^{*\beta_1 - 1} + \beta_2 Dx^{*\beta_2 - 1} + (1+\eta)\left\{\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right\}\frac{1}{r-\mu_Q} \\
&Cx_d^{\beta_1} + Dx_d^{\beta_2} + (1+\eta)\left\{\left[\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right]\frac{x_d}{r-\mu_Q} - (1-\tau)\frac{c_i + F_i}{r}\right\} = 0 \\
&\beta_1 Cx_d^{\beta_1 - 1} + \beta_2 Dx_d^{\beta_2 - 1} + (1+\eta)\left[\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right]\frac{1}{r-\mu_Q} = 0.
\end{aligned} \tag{A5}
$$

The first boundary condition precludes bubbles as x increases, the second and third conditions ensure that the value functions and their first derivatives match at x^*, and the fourth and fifth conditions are the value-matching and smooth-pasting conditions that ensure optimality of the default threshold x_d. Together, these conditions comprise a system of four non-linear equations with four unknowns (B, C, D, and x_d) that must be solved numerically. By solving this system we find the post-refinancing value of equity in year five, $E(x_{i5})$.

The value of debt is given by:

$$
D(x_{i5}) = \frac{c_i}{r} + \left(\frac{x_{i5}}{x_d}\right)^{\beta_2}\left[(1-\alpha)(V_U(x_d) - \frac{c_i}{r})\right], \tag{A6}
$$

where $V_U(x_d)$ is the value of the unlevered firm and α is the bankruptcy costs (upon default debtholders get this unlevered value, net of bankruptcy costs). Note that $V_U(x_d)$ is always positive because the value of equity is decreasing in the total fixed cash outflow $c_i + F_i$, and so is the optimal default/ exit boundary. This implies that for $c_i > 0$ the optimal default threshold x_d is greater than the optimal exit threshold of the same firm with no debt and hence the value of that firm at x_d is positive. When implementing this procedure, we set $\alpha = \eta = 15\%$.

For a given x_{i5} (we assume that the long-term debt is repaid in five years) we find the value of c_i such that $\frac{D(x_{i5})}{E(x_{i5})+D(x_{i5})}$ is equal to the average 2-digit SIC leverage ratio in the last three years. If we are unable to find this solution (e.g. for high enough values of fixed costs), we assume that the firm remains unlevered throughout the rest of its life. The pre-refinancing equity value (after repayment of the initial debt) equals the sum of the post-refinancing value and the proceeds from issuing debt:

$$E'(x_{i5}) = E(x_{i5}) + D(x_{i5}). \tag{A7}$$

Once we find the terminal value of equity in year five, $E'(x_{i5})$, we solve the model numerically and compute the optimal default boundary and equity values for all $t \le T = 5$. For that purpose, we introduce a new variable $y_t = \log(x_t)$, that follows an arithmetic Brownian motion under the risk-neutral measure:

$$dy_t = \left(\mu_Q - \frac{\sigma^2}{2}\right) dt + \sigma dW_t. \tag{A8}$$

We then discretize the problem by using a two-dimensional grid $N_y \times N_t$ with the corresponding increments of y and t given by dy and dt, where $dy = (y_{\max} - y_{\min})/N_y$ and $dt = T/N_t$, where $T = 5$. To get a reasonable balance between execution speed and accuracy we set $dt = 0.1$, $y_{\min} = -5$, and $y_{\max} = 10$ when implementing this algorithm.

We iterate valuations backwards using a binomial approximation of the Brownian motion (see, for example, Dixit and Pindyck (1994)). At each node the equityholders have an option to default. They will default if the present value (under Q) of running the firm for one more period is negative:

$$\begin{aligned} E(ndy, mdt) \;=\; \max\Bigg\{ & e^{-rdt}\left[p_u E((n+1)dy, (m+1)dt) + p_d E((n-1)dy, (m+1)dt\right] \\ & + \Bigg[e^{n\times dy}\left(\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right) \times \\ & \left(1 + \eta \mathbf{1}_{x_{it}\left(\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right) - (I_i + F_i)(1-\tau) < 0}\right) \\ & - (I_{it} + F_i)(1-\tau)\Bigg] dt - D_{it}, 0 \Bigg\}, \end{aligned} \tag{A9}$$

where

$$p_u = 0.5 + \left(\mu_Q - \frac{\sigma^2}{2}\right)\frac{\sqrt{dt}}{2\sigma}, \quad p_d = 1 - p_u, \text{ and } dy = \sigma\sqrt{dt}.$$

Equation (B9) shows that at each node the value of equity is given by the discounted present value of equity the next time period plus the cash flows that equityholders receive over the time period dt. If this value is negative, then the firm is below the optimal default boundary so it is optimal for equityholders to default, in which case the value of equity is zero. (We assume that the absolute priority rule is enforced if bankruptcy occurs and the residual payout to equityholders is zero.)

Appendix B: Modeling mean-reversion in growth rates

For robustness, we allow for time-variation of the drift of x_{it} by modeling a mean-reverting process in the return on capital R_A. In particular, we assume that the return on capital that the managers of firm i are able to generate at time t is $R_A \times y_{it}$, where $y_{it} \in \{L, M, H\}$ (low, medium, and high) is a three-state Markov chain, whose transition follows a Poisson law. The transition probabilities between the three states over a time interval dt are given by:

	L	M	H
L	$1 - \lambda_{lm} dt$	$\lambda_{lm} dt$	0
M	$\lambda_{ml} dt$	$1 - \lambda_{ml} dt - \lambda_{mh} dt$	$\lambda_{mh} dt$
H	0	$\lambda_{hm} dt$	$1 - \lambda_{hm} dt$

We further assume that $L = 1 - f$, $M = 1$, and $H = 1 + f$, where f is the magnitude of the jump from one state to an adjacent state and that the processes y_{it} and x_{it} are uncorrelated. To make sure that the jumps of y_t are symmetric we set $\lambda_{lm} = \lambda_{ml} = \lambda_{mh} = \lambda_{hm} = \lambda$. This ensures that the long run average of the processes y_{it} is 1 and the long-run average growth rate of x_{it} is the same as in our base-case scenario.

This set of assumptions results in time variation of the growth rate of x_{it}. There are times when the managers deliver the rate of return equal to R_A, just like in our base case version of the model. In those times, the growth rate of x_{it} (under P) is given by equation (10) in the paper:

$$\mu_{i,P} = \frac{\mathbb{E}_t^P(dx_{it})}{x_{it} dt} = \frac{\overline{CSR}_{t-3,t} R_A}{(1-\tau) GM_{it} + \tau \overline{DSR}_{t-3,t}}. \tag{B1}$$

However, there is always a possibility that the rate of return will degrade to $R_A(1 - f)$ when the growth rate of x will slow down to $\mu_{i,P}(1 - f)$. Likewise, it is possible that the managers temporarily get access to investment projects that generate return of $R_A(1+f)$ and growth rate of $\mu_{i,P}(1 + f)$. However, these superior projects are in limited supply and there is a probability of jumping back to the mean rate of return equal to R_A. This mechanism results in a mean-reverting growth rate of the process x_{it}.

To account for these mean-reversion features of the stochastic shock, we modify our numerical procedure in the following way. We first determine the terminal values at the end of the five year period, when the long term debt is due, and then roll valuations backwards on the same valuation grid. However, the value of equity at every node now becomes also a function of the state of y_{it}. Therefore the formula for the value of equity in the intermediate state becomes:

$$
\begin{aligned}
&E^M(ndy, mdt) = \\
&\quad \max\Bigg\{e^{-rdt}\Big\{\ \big[(p_u^M E^M((n+1)dy,(m+1)dt) + p_d^M E^M((n-1)dy,(m+1)dt)(1-2\lambda dt)\big] \\
&\qquad + \big[(p_u^L E^L((n+1)dy,(m+1)dt) + p_d^L E^L((n-1)dy,(m+1)dt)\lambda dt)\big] \\
&\qquad + \big[(p_u^H E^H((n+1)dy,(m+1)dt) + p_d^H E^H((n-1)dy,(m+1)dt)\lambda dt)\big]\ \Big\} \\
&\qquad\quad + \Bigg[e^{n\times dy}\left(\frac{\tau\overline{DSR}_{t-3,t} - \overline{CSR}_{t-3,t}}{GM_{it}} + (1-\tau)\right)\times \\
&\qquad\qquad \left(1+\eta\mathbf{1}_{x_{it}\left(\frac{\tau\overline{DSR}_{t-3,t}-\overline{CSR}_{t-3,t}}{GM_{it}}+(1-\tau)\right)-(I_{it}+F_i)(1-\tau)<0}\right) \\
&\qquad\qquad\quad -(I_{it}+F_i)(1-\tau)\Bigg]dt - D_{it}, 0\Bigg\},
\end{aligned}
\tag{B2}
$$

where

$$
\begin{aligned}
p_u^Z &= 0.5 + \left(\mu_Q^Z - \frac{\sigma^2}{2}\right)\frac{\sqrt{dt}}{2\sigma}, \quad p_d^Z = 1 - p_u^Z \\
\mu_Q^Z &= r - R_A + \mu_P^Z \\
Z &\in \{L, M, H\} \\
\mu_P^H &= \kappa R_A(1+f), \quad \mu_P^L = \kappa R_A(1-f), \quad \mu_P^M = \kappa R_A \\
\kappa &= \frac{\overline{CSR}_{t-3,t}}{(1-\tau)GM_{it} + \tau\overline{DSR}_{t-3,t}}.
\end{aligned}
$$

Expressions for the values of equity in the low and high states are obtained similarly.

Table B1 replicates our main results in Table 3 when the growth rate of x_{it} follows the mean-reverting regime shifting process described above for the following values of parameters: $f = 0.5$ and $\lambda = 0.5$. The value-weighted results in Table B1 suggest that the performance of the long-short strategy deteriorates very slightly due to introduction of time variation in growth. For example, the spread in excess returns narrows from 0.65% a month to 0.59% and is now marginally significant. The 4-factor alpha drops from 0.91% to 0.83%. The 3-factor alpha is essentially unchanged, however, and both the CAPM and the 4-factor alphas are statistically significant at a 5% level. Results from equally weighted returns are stronger and consistent with patterns in Table 3. This evidence demonstrates the robustness of our modeling approach to the introduction of alternative time-varying dynamics of the drift parameter of the process x_{it}.

Appendix C: Distress measure

Campbell, Hilscher, and Szilagyi (2008) use logit regressions to predict failure probabilities. We use their model for predicting bankruptcy over the next year (model with lag 12 in their Table IV) as our baseline model. This model, which is repeated below, gives the probability of bankruptcy/failure from a logit model as:

$$\begin{aligned} CHS_t &= -9.16 - 20.26\, NIMTAAVG_t + 1.42\, TLMTA_t - 7.13\, EXRETAVG_t \\ &\quad +1.41\, SIGMA_t - 0.045\, RSIZE_t - 2.13\, CASHMTA_t + 0.075\, MB_t \\ &\quad -0.058\, PRICE_t, \end{aligned} \tag{C1}$$

where $NIMTA$ is the net income divided by the market value of total assets (the sum of market value of equity and book value of total liabilities), $TLMTA$ is the book value of total liabilities divided by market value of total assets, $EXRET$ is the log of the ratio of the gross returns on the firm's stock and on the S&P500 index, $SIGMA$ is the standard deviation of the firm's daily stock return over the past three months, $RSIZE$ is ratio of the log of firm's equity market capitalization to that of the S&P500 index, $CASHMTA$ is the ratio of the firm's cash and short-term investments to the market value of total assets, MB is the market-to-book ratio of the firm's equity, and $PRICE$ is the log price per share. $NIMTAAVG$ and $EXRETAVG$ are moving averages of $NIMTA$ and $EXRET$, respectively, constructed as (with $\phi = 2^{-\frac{1}{3}}$):

$$\begin{aligned} NIMTAAVG_{t-1,t-12} &= \frac{1-\phi^3}{1-\phi^{12}} \left(NIMTA_{t-1,t-3} + \ldots + \phi^9 NIMTA_{t-10,t-12} \right), \\ EXRETAVG_{t-1,t-12} &= \frac{1-\phi}{1-\phi^{12}} \left(EXRET_{t-1} + \ldots + \phi^{11} EXRET_{t-12} \right). \end{aligned} \tag{C2}$$

The source of accounting data is COMPUSTAT while all market level data are from CRSP. All accounting data are taken with a lag of three months for quarterly data and a lag of six months for annual data. All market data used in calculating the distress measure of equation (A1) are the most current data. We winsorize all inputs at the 5th and 95th percentiles of their pooled distributions across all firm-months (winsorizing at the 2nd and 98th percentiles has no material impact on our results), and $PRICE$ is truncated above at \$15. Further details on the data construction are provided by CHS (2008) and we refer the interested reader to their paper.[20] We include all common stocks, although our results are robust to the exclusion of financial stocks. The sample period for our study is 1983 to 2012 as the coverage of quarterly COMPUSTAT data is sparse before this date.

[20] There are two minor differences between CHS's (2008) approach and ours. First, CHS eliminate stocks with fewer than five nonzero daily observations during the last three months; and then replace missing $SIGMA$ observations with the cross-sectional mean $SIGMA$ in estimating their bankruptcy prediction regressions. We do not make this adjustment. Second, CHS treat firms that fail as equivalent to delisted firms, even if CRSP continues to report returns for these firms. We do not make this adjustment either.

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Table 1: Inputs to the Valuation Model

This table reports the input parameters used in our valuation model for all CRSP/COMPUSTAT firm population. The categories of parameters include values that are kept constant for all firms and months, firm-month specific values, and values based on 2-digit SIC industry code and CHS (2008) distress-risk quintile. The sample period is 1983 to 2012.

Input variable	Value used in the model	Mean	Median	StDev
Coupon rate	AAA, BBB and BBB+2% yields for distress quintiles 1-2, 3-4, and 5, respectively	8.35%	8.04%	2.36%
Distress costs, η	15%			
Corporate tax rate, τ	35%			
Risk-free rate, r	Avg. of 3-month and 10-year treasury yields	5.22%	5.25%	2.56%
R_{WACC}	Avg. industry-distress WACC in the last three years	9.39%	9.56%	2.49%
CAPEX to sales ratio, CSR	Avg. industry-distress CSR in the last three years	0.108	0.066	0.122
Depreciation to sales ratio, DSR	Avg. industry-distress DSR in the last three years	0.079	0.048	0.079
Volatility, σ (annualized)	Quarterly volatility of sales	0.396	0.260	0.440
Short term debt/Total assets	Annual COMPUSTAT items DLC/AT	0.057	0.020	0.114
Long term debt/Total assets	Annual COMPUSTAT items DLTT/AT	0.169	0.110	0.203
Market leverage ratio	(DLC+DLTT)/(DLC+DLTT+Equity value)	0.265	0.191	0.258
Fixed costs/Sales	Annual COMPUSTAT items XSGA/SALE	0.351	0.244	0.466
Gross margin/Sales	Annual COMPUSTAT items (SALE−COGS)/SALE	0.253	0.346	0.874

Table 2: Descriptives of Portfolios Sorted on Relative Model Value

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table presents descriptive statistics for each portfolio, where for all variables, observations outside the top and the bottom percentiles are excluded. For each variable, we first calculate the cross-sectional mean and median across stocks for each portfolio. The table then reports the time-series averages of these means/medians. Size is equity value (in millions of dollars). Market-to-book ratio is equity market value divided by equity book value. Market beta is measured by regression of stock return on market return over the past 60 months. Past return is cumulative return over the past six months. Standard deviation of daily stock returns (reported in percent) is based on market-adjusted returns in the past year. Share turnover is trading volume scaled by total shares outstanding. Amihud illiquidity is the monthly average of daily ratios of absolute return to dollar trading volume (in millions). Percent of firms with negative earnings is based on the net income in the previous calendar year. Number of analysts covering the firm is measured by the number of forecasts appearing in IBES. Standard deviation of analysts' forecasts is also calculated from IBES data. Equity issuance (reported in percent) is measured by the difference between the sale and purchase of common and preferred stocks during the year, scaled by equity market value at the beginning of the year. Institutional ownership (reported in percent) is the sum of all shares held by institutions divided by total shares outstanding. The sample period is 1983 to 2012.

		1	2	3	4	5	6	7	8	9	10
Size	Mean	833.4	1,757.0	2,197.9	2,057.0	2,034.1	1,822.5	1,605.7	1,313.5	1,037.9	435.7
	Median	113.6	260.1	384.1	390.0	357.8	308.9	275.4	220.3	156.8	55.4
Market-to-book ratio	Mean	2.69	2.57	2.40	2.16	1.96	1.79	1.64	1.51	1.34	1.04
	Median	2.11	2.24	2.18	1.96	1.76	1.60	1.46	1.32	1.15	0.80
Market beta	Mean	1.31	1.28	1.15	1.04	0.98	0.94	0.93	0.95	0.95	1.01
	Median	1.19	1.17	1.05	0.93	0.88	0.84	0.83	0.86	0.87	0.94
Past return	Mean	15.9	17.7	15.3	12.6	10.3	8.3	6.6	4.4	1.1	−7.2
	Median	6.6	9.0	9.0	7.7	5.9	4.5	2.7	0.2	−3.3	−12.2
Stdev of stock returns	Mean	4.2	3.6	3.2	3.0	2.9	2.9	3.0	3.2	3.7	4.9
	Median	3.7	3.1	2.7	2.5	2.4	2.4	2.5	2.7	3.1	4.2
Share turnover	Mean	0.12	0.13	0.12	0.11	0.10	0.09	0.09	0.09	0.08	0.08
	Median	0.07	0.08	0.08	0.07	0.07	0.06	0.06	0.06	0.06	0.05
Amihud's illiquidity	Mean	5.15	3.28	2.54	2.37	2.49	2.73	3.28	4.55	6.95	14.83
	Median	0.21	0.07	0.05	0.06	0.06	0.07	0.11	0.26	0.63	2.19
% of negative earnings	Mean	60.9	33.6	23.0	17.7	15.7	15.1	15.6	17.8	22.0	35.9
	Median	86.0	10.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.5
Number of analysts	Mean	3.54	4.01	4.22	4.11	3.87	3.79	3.63	3.30	3.19	2.60
	Median	2.80	3.27	3.51	3.47	3.25	3.14	3.00	2.71	2.65	2.15
Stdev of analysts' forecasts	Mean	0.06	0.04	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.08
	Median	0.04	0.03	0.03	0.03	0.03	0.04	0.05	0.04	0.05	0.06
Equity issuance	Mean	5.9	3.1	1.9	1.3	1.0	1.0	1.0	1.0	1.3	3.0
	Median	0.7	0.2	0.2	0.1	0.0	0.1	0.1	0.0	0.0	0.0
Institutional ownership	Mean	31.5	40.7	44.4	44.3	43.0	41.1	40.0	38.6	35.2	29.5
	Median	25.7	38.9	45.6	45.8	43.6	40.9	38.9	37.4	33.1	25.5

Table 3: Returns of Portfolios Sorted on Relative Model Value

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table shows the portfolios' mean excess monthly returns (in excess of the risk-free rate) and alphas from factor models. The CAPM one-factor model uses the market factor. The three factors in the three-factor model are the Fama and French (1993) factors. The four factors in the four-factor model are the Fama-French factors augmented with a momentum factor. We also show the equal-weighted (ew) returns/alphas on the long-short 10−1 portfolio in the last column. All returns and alphas are in percent per month and the corresponding t-statistics are in parentheses. The sample period is 1983 to 2012.

	1	2	3	4	5	6	7	8	9	10	10−1	ew 10−1
Excess return	0.51	0.39	0.69	0.66	0.56	0.73	0.78	0.83	1.11	1.15	0.65	1.11
	(1.36)	(1.24)	(2.54)	(2.59)	(2.32)	(2.96)	(3.12)	(3.31)	(4.01)	(3.34)	(2.10)	(4.59)
CAPM alpha	−0.31	−0.33	0.08	0.08	0.03	0.20	0.26	0.30	0.55	0.51	0.82	1.16
	(−1.76)	(−2.73)	(0.69)	(0.81)	(0.24)	(1.65)	(1.92)	(2.29)	(3.49)	(2.23)	(2.68)	(4.77)
3-factor alpha	−0.21	−0.26	0.10	0.02	−0.11	0.06	0.07	0.13	0.33	0.28	0.49	0.90
	(−1.32)	(−2.21)	(0.89)	(0.18)	(−1.14)	(0.56)	(0.66)	(1.17)	(2.52)	(1.37)	(1.76)	(4.14)
4-factor alpha	−0.24	−0.29	0.08	0.02	−0.07	0.13	0.18	0.26	0.48	0.67	0.91	1.27
	(−1.54)	(−2.43)	(0.67)	(0.16)	(−0.75)	(1.29)	(1.68)	(2.34)	(3.74)	(3.95)	(3.68)	(6.65)

Table 4: 4-Factor Alphas of Portfolios Sorted on Relative Model Value in Different Samples and Over Different Horizons

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table reports 4-factor alphas where the factors are market, size, book-to-market, and momentum. We also show the alpha on the equal-weighted (ew) long-short 10−1 portfolio in the last column. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The full sample period is 1983 to 2012. The full sample period is broken up two different ways into subsamples in Panel A. The holding period is increased to 3, 6, 12, and 18 months in Panel B.

	1	2	3	4	5	6	7	8	9	10	10−1	ew 10−1
Full sample	−0.24	−0.29	0.08	0.02	−0.07	0.13	0.18	0.26	0.48	0.67	0.91	1.27
	(−1.54)	(−2.43)	(0.67)	(0.16)	(−0.75)	(1.29)	(1.68)	(2.34)	(3.74)	(3.95)	(3.68)	(6.65)
Panel A: Sub-samples												
January	0.35	−0.57	0.76	−0.05	0.11	0.00	0.09	−0.06	0.01	0.91	0.56	3.60
	(0.39)	(−1.20)	(1.98)	(−0.11)	(0.28)	(0.00)	(0.35)	(−0.12)	(0.02)	(1.04)	(0.37)	(3.29)
Non-January	−0.30	−0.27	0.02	0.01	−0.06	0.10	0.12	0.23	0.45	0.50	0.80	0.89
	(−1.87)	(−2.18)	(0.15)	(0.10)	(−0.62)	(0.90)	(1.08)	(2.04)	(3.43)	(3.05)	(3.32)	(5.02)
1980s	−0.62	−0.40	−0.11	0.04	−0.09	−0.38	0.04	0.12	0.29	0.07	0.69	1.44
	(−1.84)	(−1.46)	(−0.33)	(0.26)	(−0.41)	(−1.79)	(0.18)	(0.56)	(1.26)	(0.17)	(1.34)	(4.17)
1990s	−0.33	−0.13	0.04	0.04	−0.15	0.04	0.19	0.06	0.49	0.68	1.00	1.80
	(−1.41)	(−0.84)	(0.29)	(0.25)	(−1.03)	(0.21)	(1.28)	(0.39)	(2.21)	(2.87)	(2.89)	(5.92)
2000s	−0.21	−0.32	0.20	0.15	0.10	0.47	0.34	0.54	0.63	0.83	1.04	0.78
	(−0.84)	(−1.67)	(1.13)	(1.04)	(0.70)	(3.00)	(1.92)	(3.11)	(3.32)	(3.05)	(2.59)	(2.55)
Panel B: Longer Horizon												
3 months	−0.25	−0.22	0.07	0.02	−0.08	0.14	0.12	0.32	0.46	0.52	0.77	1.09
	(−1.60)	(−1.92)	(0.69)	(0.21)	(−0.89)	(1.52)	(1.28)	(3.32)	(3.96)	(3.51)	(3.36)	(6.37)
6 months	−0.25	−0.17	0.05	0.06	−0.05	0.12	0.14	0.30	0.45	0.51	0.76	1.03
	(−1.73)	(−1.56)	(0.56)	(0.70)	(−0.60)	(1.40)	(1.49)	(3.31)	(4.17)	(3.62)	(3.45)	(6.39)
12 months	−0.29	−0.10	0.08	0.05	−0.02	0.10	0.16	0.25	0.38	0.40	0.69	0.90
	(−2.09)	(−1.04)	(0.94)	(0.58)	(−0.24)	(1.19)	(1.80)	(2.94)	(3.79)	(2.97)	(3.30)	(6.07)
18 months	−0.28	−0.08	0.06	0.07	−0.02	0.09	0.15	0.23	0.30	0.33	0.61	0.80
	(−2.10)	(−0.82)	(0.79)	(0.83)	(−0.22)	(1.05)	(1.76)	(2.83)	(3.04)	(2.51)	(3.03)	(5.78)

Table 5: 4-Factor Alphas of Portfolios Double Sorted on Relative Model Value and Characteristics Related to Default Option

Each month, we first sort all stocks into quintiles based on a stock characteristic related to default option. The stocks are then further sorted into quintiles according to the ratio of the equity value implied by our valuation model to the actual equity value (R1=most overvalued, R5=most undervalued). The variable for the first sort is distress in Panel A, size in Panel B, stock return idiosyncratic volatility in Panel C, and profitability in Panel D. Distress is calculated based on CHS (2008) using current market data and quarterly accounting data of the most recent available quarter. Size is the market capitalization. Idiosyncratic volatility is calculated as the standard deviation of the residuals of regression of daily stock returns on the daily four factors over the last month. Profitability is defined as the ratio of net income to total assets, calculated using quarterly data. The holding period for all portfolios is one month. For each distress quintile we report value-weighted alphas of all relative value portfolios, and equal-weighted alpha of only the hedge portfolio. The table reports 4-factor alphas where the factors are market, size, book-to-market, and momentum. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The last column within each panel gives the fraction of value coming from the default option (in percent). To compute this fraction we run the model while shutting down the default option (i.e. imposing a restriction that the firm is run by equityholders indefinitely). The value of the option to default is then given by the difference in equity values with and without this option. The sample period is 1983 to 2012.

	R1	R2	R3	R4	R5	R5−R1	ew R5−R1	DefOpt
				Panel A: Distress				
D1	0.18	0.14	0.14	0.04	0.43	0.26	0.39	19.2
	(1.41)	(1.21)	(1.18)	(0.27)	(2.81)	(1.38)	(2.92)	
D2	−0.26	0.02	0.20	0.30	0.37	0.63	0.52	16.6
	(−2.07)	(0.22)	(1.80)	(2.40)	(2.95)	(3.45)	(3.68)	
D3	−0.26	−0.01	0.00	0.50	0.53	0.78	0.81	19.2
	(−1.60)	(−0.08)	(0.01)	(4.06)	(3.40)	(3.27)	(5.36)	
D4	−0.45	−0.53	−0.30	0.11	0.36	0.81	1.04	22.3
	(−1.83)	(−2.75)	(−1.81)	(0.57)	(1.67)	(2.49)	(5.42)	
D5	−0.85	−1.19	−0.21	0.65	0.34	1.19	1.81	35.9
	(−2.39)	(−3.69)	(−0.62)	(1.98)	(0.69)	(2.10)	(6.12)	

	R1	R2	R3	R4	R5	R5−R1	ew R5−R1	DefOpt
				Panel B: Size				
S1	−0.44	0.14	0.15	0.35	0.31	0.75	1.19	28.7
	(−2.95)	(1.21)	(1.54)	(3.21)	(2.09)	(4.31)	(7.08)	
S2	−0.11	0.03	0.17	0.26	0.22	0.34	0.33	22.6
	(−0.90)	(0.33)	(1.78)	(2.81)	(1.95)	(1.84)	(1.82)	
S3	−0.22	−0.19	−0.06	0.21	0.47	0.69	0.66	19.8
	(−1.72)	(−1.98)	(−0.66)	(2.06)	(4.07)	(3.80)	(3.64)	
S4	−0.10	0.10	−0.06	0.17	0.42	0.52	0.55	17.4
	(−0.73)	(0.91)	(−0.60)	(1.69)	(3.50)	(2.85)	(2.96)	
S5	−0.10	−0.01	0.05	−0.03	0.33	0.43	0.43	17.2
	(−0.80)	(−0.13)	(0.55)	(−0.34)	(2.90)	(2.30)	(2.42)	

				Panel C: Idiosyncratic Volatility				
IV1	−0.05	0.03	0.13	0.20	0.34	0.39	0.29	15.4
	(−0.41)	(0.28)	(1.36)	(2.01)	(2.80)	(2.31)	(2.47)	
IV2	−0.11	0.11	−0.03	0.09	0.48	0.59	0.59	19.4
	(−0.80)	(0.86)	(−0.25)	(0.61)	(3.21)	(2.78)	(4.25)	
IV3	−0.01	−0.06	0.06	0.24	0.85	0.86	0.73	22.0
	(−0.06)	(−0.31)	(0.36)	(1.35)	(4.20)	(2.96)	(4.29)	
IV4	−0.52	−0.35	0.13	0.45	0.23	0.75	1.23	25.9
	(−1.96)	(−1.50)	(0.56)	(2.01)	(0.94)	(2.12)	(5.94)	
IV5	−1.08	−0.11	−0.65	−0.31	0.30	1.38	1.82	30.1
	(−2.91)	(−0.34)	(−2.59)	(−1.03)	(0.80)	(2.80)	(6.66)	

				Panel D: Profitability				
PR1	−0.87	−0.31	0.10	−0.10	0.21	1.09	1.81	27.6
	(−2.96)	(−1.09)	(0.38)	(−0.42)	(0.75)	(2.72)	(6.38)	
PR2	−0.17	−0.53	−0.11	0.13	0.36	0.54	0.66	21.3
	(−0.93)	(−3.31)	(−0.82)	(0.85)	(1.70)	(1.79)	(2.84)	
PR3	−0.17	−0.17	0.07	0.35	0.41	0.58	0.79	15.0
	(−1.25)	(−1.44)	(0.66)	(2.82)	(2.73)	(2.90)	(4.99)	
PR4	−0.19	−0.02	−0.06	0.14	0.41	0.60	1.05	16.5
	(−1.45)	(−0.15)	(−0.51)	(1.05)	(2.82)	(3.06)	(6.73)	
PR5	0.05	0.33	0.22	0.44	0.74	0.69	0.86	20.5
	(0.36)	(2.46)	(1.70)	(2.92)	(4.24)	(3.12)	(4.78)	

Table 6: 4-Factor Alphas of Portfolios Double Sorted on Relative Model Value (without the default option) and Characteristics Related to Default Option

Each month, we first sort all stocks into quintiles based on a stock characteristic related to default option. The stocks are then further sorted into quintiles according to the ratio of the equity value implied by our valuation model to the actual equity value (R1=most overvalued, R5=most undervalued). The variable for the first sort is distress, size, stock return idiosyncratic volatility, or profitability. Distress is calculated based on CHS (2008) using current market data and quarterly accounting data of the previous quarter. Size is the market capitalization. Idiosyncratic volatility is calculated as the standard deviation of the residuals of regression of daily stock returns on the daily four factors over the last month. Profitability is defined as the ratio of net income to total assets, calculated using quarterly data. We run the model two times, one time with default option and another time without the default option. The shutting down of the default option is accomplished by imposing a restriction that the firm is always run by equityholders. The holding period for all portfolios is one month and the portfolios are value-weighted in Panel A and equal-weighted in Panel B. For each characteristic, the left column shows the 4-factor alpha of the long-short relative value portfolio R5−R1 as in Table 5. The right column shows the equivalent alphas based on model values without the option to default. The factors are market, size, book-to-market, and momentum. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The sample period is 1983 to 2012.

	Distress		Size		Volatility		Profitability	
	with option	without option	with option	without option	with option	without option	with option	without option
	Panel A: Value-weighted returns							
Q1	0.26	0.19	0.75	0.54	0.39	0.43	1.09	0.48
	(1.38)	(0.87)	(4.31)	(2.98)	(2.31)	(2.37)	(2.72)	(0.78)
Q2	0.63	0.55	0.34	0.42	0.59	0.24	0.54	0.73
	(3.45)	(2.69)	(1.84)	(2.20)	(2.78)	(1.06)	(1.79)	(2.28)
Q3	0.78	0.75	0.69	0.91	0.86	0.67	0.58	0.67
	(3.27)	(3.09)	(3.80)	(4.93)	(2.96)	(2.12)	(2.90)	(3.38)
Q4	0.81	0.22	0.52	0.37	0.75	0.45	0.60	0.83
	(2.49)	(0.60)	(2.85)	(1.91)	(2.12)	(1.06)	(3.06)	(3.91)
Q5	1.19	0.28	0.43	0.34	1.38	0.33	0.69	0.16
	(2.10)	(0.41)	(2.30)	(1.76)	(2.80)	(0.54)	(3.12)	(0.62)
	Panel B: Equal-weighted returns							
Q1	0.39	0.22	1.19	0.87	0.29	0.48	1.81	1.12
	(2.92)	(1.33)	(7.08)	(4.71)	(2.47)	(4.19)	(6.38)	(2.65)
Q2	0.52	0.51	0.33	0.42	0.59	0.40	0.66	0.95
	(3.68)	(3.25)	(1.82)	(2.25)	(4.25)	(2.96)	(2.84)	(4.29)
Q3	0.81	1.01	0.66	0.90	0.73	0.70	0.79	0.94
	(5.36)	(6.40)	(3.64)	(4.93)	(4.29)	(3.66)	(4.99)	(5.74)
Q4	1.04	0.99	0.55	0.39	1.23	1.07	1.05	0.94
	(5.42)	(4.42)	(2.96)	(2.03)	(5.94)	(3.71)	(6.73)	(6.22)
Q5	1.81	1.30	0.43	0.26	1.82	1.26	0.86	0.71
	(6.12)	(3.18)	(2.42)	(1.28)	(6.66)	(3.19)	(4.78)	(3.53)

Table 7: Fama-MacBeth Regressions on Relative Model Value

We run cross-sectional Fama and MacBeth (1973) regressions each month of excess stock returns. The independent variables are (log) market capitalization, (log) market-to-book, past six-month return, distress-risk measure, idiosyncratic volatility, profitability, and relative model value (RelModVal). Market-to-book ratio is calculated as the ratio of current market value divided by book value of the previous quarter. We skip one month in calculating the six-month returns. Distress is calculated based on CHS (2008) using current market data and quarterly accounting data of the previous quarter. Idiosyncratic volatility is calculated as the standard deviation of the residuals of regression of daily stock returns on the daily four factors over the last month. Profitability is defined as the ratio of net income to total assets, calculated using quarterly data. Relative model value is the log of the ratio of the equity value implied by our valuation model to the actual equity value. All coefficients are multiplied by 100 and Newey-West corrected t-statistics (with six lags) are in parentheses. The sample period is 1983 to 2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cnst	1.575	0.858	1.298	1.631	1.378	1.660	0.576	2.459	1.962	1.421
	(1.95)	(2.66)	(1.68)	(2.01)	(1.82)	(2.04)	(0.50)	(5.15)	(2.64)	(1.92)
Log(size)	−0.068		−0.156	−0.072	−0.147	−0.076	−0.133	−0.119	−0.097	−0.154
	(−1.35)		(−5.19)	(−1.41)	(−4.85)	(−1.47)	(−3.89)	(−3.53)	(−2.14)	(−5.22)
Log(MB)	−0.166		−0.212	−0.097	−0.151	−0.097	−0.163	−0.091	−0.127	−0.152
	(−2.64)		(−3.79)	(−1.75)	(−3.22)	(−1.75)	(−3.11)	(−1.84)	(−2.34)	(−3.27)
Past return	0.278		0.137	0.306	0.180	0.292	0.146	0.337	0.250	0.166
	(1.46)		(0.76)	(1.64)	(1.02)	(1.58)	(0.82)	(1.90)	(1.35)	(0.95)
RelModVal		0.217		0.194	0.153	0.710	0.599	0.046	0.144	0.684
		(4.46)		(4.41)	(4.35)	(3.95)	(4.86)	(0.76)	(3.60)	(2.41)
Log(size) × RelModVal						−0.048				−0.036
						(−2.85)				(−2.15)
Distress			−0.198		−0.171		−0.238			−0.174
			(−2.83)		(−2.55)		(−2.46)			(−2.62)
Distress × RelModVal							0.069			0.029
							(4.13)			(1.50)
IdioVol			−6.282		−5.858			−12.598		−5.940
			(−1.15)		(−1.07)			(−1.78)		(−1.10)
IdioVol × RelModVal								3.498		0.461
								(2.38)		(0.25)
Profitability			2.022		1.484				3.014	1.031
			(2.24)		(1.74)				(2.28)	(1.05)
Profitability × RelModVal									−0.359	−0.003
									(−1.44)	(−0.01)

Table 8: 4-Factor Alphas of Portfolios Double Sorted on Relative Model Value and Market-to-book ratio

Each month, we first sort all stocks into quintiles based on market-to-book. Market-to-book ratio is calculated as the ratio of current market value divided by book value of the previous quarter. The stocks are then further sorted into quintiles according to the ratio of the equity value implied by our valuation model to the actual equity value (R1=most overvalued, R5=most undervalued). The holding period for all portfolios is one month. For each distress quintile we report value-weighted alphas of all relative value portfolios, and equal-weighted alpha of only the hedge portfolio. The table reports 4-factor alphas where the factors are market, size, book-to-market, and momentum. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The last column within each panel gives the fraction of value coming from the default option (in percent). To compute this fraction we run the model while shutting down the default option (i.e. imposing a restriction that the firm is run by equityholders indefinitely). The value of the option to default is then given by the difference in equity values with and without this option. The sample period is 1983 to 2012.

	R1	R2	R3	R4	R5	R5−R1	ew R5−R1	DefOpt
MB1	−0.24	0.16	0.45	0.33	0.85	1.08	0.73	19.3
	(−0.98)	(0.86)	(2.41)	(1.59)	(2.83)	(2.79)	(2.77)	
MB2	−0.03	0.31	0.16	0.64	0.62	0.65	0.41	14.2
	(−0.19)	(2.31)	(1.07)	(5.43)	(3.48)	(2.53)	(2.50)	
MB3	−0.12	−0.07	0.08	0.31	0.51	0.63	0.44	14.8
	(−0.76)	(−0.53)	(0.63)	(2.50)	(3.22)	(2.81)	(2.85)	
MB4	−0.30	−0.04	0.03	0.03	0.26	0.57	0.60	18.1
	(−1.92)	(−0.35)	(0.23)	(0.26)	(1.83)	(2.83)	(3.72)	
MB5	−0.39	−0.07	0.11	0.12	0.23	0.62	0.80	21.7
	(−1.75)	(−0.43)	(0.95)	(1.04)	(1.80)	(2.25)	(3.84)	

Table 9: 4-Factor Alphas of Portfolios Sorted on Relative Model on Earnings Announcement Days

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table shows 4-factor alphas where the factors are market, size, book-to-market, and momentum. We also show the equal-weighted (ew) alphas on the long-short 10−1 portfolio in the last column. Panel A divides the sample into months where the firms had earnings announcement or not. Alphas in this panel are in percent per month. Panel B divides the sample into a three-day window around earnings announcement or not. Alphas in this panel are in percent per day. The corresponding t-statistics are in parentheses. The sample period is 1983 to 2012.

	1	2	3	4	5	6	7	8	9	10	10−1	ew 10−1
Full sample	−0.24	−0.29	0.08	0.02	−0.07	0.13	0.18	0.26	0.48	0.67	0.91	1.27
	(−1.54)	(−2.43)	(0.67)	(0.16)	(−0.75)	(1.29)	(1.68)	(2.34)	(3.74)	(3.95)	(3.68)	(6.65)
Panel A: Firm-months with and without earnings announcement												
With	−0.38	−0.15	−0.11	0.17	0.28	0.20	0.28	0.65	0.63	0.94	1.32	1.92
	(−1.08)	(−0.51)	(−0.31)	(0.65)	(0.83)	(0.76)	(1.07)	(2.05)	(1.94)	(3.34)	(2.85)	(5.04)
Without	−0.44	−0.48	−0.34	−0.32	−0.51	−0.19	−0.09	−0.02	0.42	0.22	0.67	0.97
	(−2.36)	(−3.38)	(−3.13)	(−2.79)	(−4.05)	(−1.71)	(−0.68)	(−0.18)	(2.85)	(1.17)	(2.53)	(4.45)
Panel B: Firm-days with and without earnings announcement												
With	−0.12	0.02	0.03	0.01	0.17	0.07	0.05	0.10	0.09	0.12	0.24	0.40
	(−2.37)	(0.36)	(0.70)	(0.19)	(3.43)	(1.81)	(1.03)	(1.91)	(1.74)	(2.03)	(3.07)	(5.02)
Without	0.00	−0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.05	0.11
	(−0.58)	(−2.02)	(−0.35)	(−0.28)	(−0.56)	(0.97)	(1.27)	(2.40)	(3.82)	(4.47)	(3.61)	(11.87)

Table 10: 4-Factor Alphas of Portfolios Triple Sorted on Relative Model Value, Characteristics Related to Default Option, and Characteristics Related to Information Transparency

Each month, we first sort all stocks into quintiles based on a stock characteristic related to default option. These characteristics are the same as those in Table 5, namely distress, size, stock return idiosyncratic volatility, and profitability. Distress is calculated based on CHS (2008) using current market data and quarterly accounting data of the most recent available quarter. Size is the market capitalization. Idiosyncratic volatility is calculated as the standard deviation of the residuals of regression of daily stock returns on the daily four factors over the last month. Profitability is defined as the ratio of net income to total assets, calculated using quarterly data. The stocks are then further divided into two groups related to information transparency. The characteristics for the second sort are analyst coverage, institutional ownership (IO), and whether the stocks have traded options. Finally, the stocks are sorted into quintiles according to the ratio of the equity value implied by our valuation model to the actual equity value (R1=most overvalued, R5=most undervalued). The holding period for all portfolios is one month. For each of the first two sorts, we report value-weighted 4-factor alphas of R5−R1 relative value portfolios. The factors are market, size, book-to-market, and momentum. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The sample period is 1983 to 2012.

		Distress		Size		Volatility		Profitability	
		D1	D5	S1	S5	IV1	IV5	PR1	PR5
Analyst	Low	0.48	2.21	1.35	0.66	0.20	2.17	1.87	0.84
		(1.91)	(4.44)	(6.61)	(3.10)	(0.92)	(4.80)	(4.07)	(3.00)
	High	0.25	0.84	0.49	0.44	0.40	1.20	0.88	0.33
		(1.24)	(1.36)	(2.57)	(2.14)	(2.33)	(2.03)	(2.15)	(1.53)
IO	Low	0.44	2.69	1.51	0.62	0.18	2.59	2.39	0.73
		(1.57)	(3.98)	(6.14)	(2.76)	(0.66)	(4.65)	(4.18)	(2.44)
	High	0.29	1.02	0.37	0.26	0.48	1.37	0.74	0.40
		(1.35)	(1.60)	(1.93)	(1.18)	(2.56)	(2.40)	(1.65)	(1.74)
Options	No	0.65	1.16	0.51	0.79	0.19	1.89	2.02	0.74
		(1.80)	(1.92)	(2.09)	(1.12)	(0.56)	(3.07)	(3.53)	(2.13)
	Yes	0.42	0.71	0.63	0.51	0.61	−0.49	0.59	0.32
		(1.38)	(0.65)	(1.51)	(1.74)	(2.49)	(−0.48)	(0.86)	(0.90)

Table 11: 4-Factor Alphas of Portfolios Sorted on Relative Model Value in Different Time Periods

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table reports 4-factor alphas where the factors are market, size, book-to-market, and momentum. All alphas are in percent per month and the corresponding t-statistics are in parentheses. The full sample period is 1983 to 2012. The sample period is broken up into recession and expansion periods based on NBER recession dummy in Panel A. The sample period is broken up into high and low sentiment months based on Baker and Wurgler (2006) sentiment index in Panel B.

	1	2	3	4	5	6	7	8	9	10	10−1
Full sample	−0.24	−0.29	0.08	0.02	−0.07	0.13	0.18	0.26	0.48	0.67	0.91
	(−1.54)	(−2.43)	(0.67)	(0.16)	(−0.75)	(1.29)	(1.68)	(2.34)	(3.74)	(3.95)	(3.68)
Panel A: Expansions and recessions											
Recession	−0.90	−0.27	0.07	0.20	0.14	0.43	0.46	0.59	1.15	0.71	1.61
	(−1.70)	(−0.69)	(0.22)	(0.69)	(0.37)	(1.11)	(0.99)	(1.31)	(2.43)	(1.04)	(1.74)
Expansion	−0.19	−0.24	0.06	0.02	−0.11	0.06	0.13	0.21	0.41	0.70	0.89
	(−1.12)	(−1.88)	(0.46)	(0.17)	(−1.07)	(0.58)	(1.27)	(1.93)	(3.06)	(3.98)	(3.42)
Panel B: High and low sentiment											
High	−0.63	−0.39	0.08	0.00	−0.05	0.20	0.22	0.29	0.57	0.74	1.36
	(−2.46)	(−1.95)	(0.39)	(0.01)	(−0.29)	(1.02)	(1.22)	(1.53)	(2.83)	(2.52)	(3.29)
Low	0.10	−0.12	0.03	0.06	−0.13	0.11	0.16	0.25	0.35	0.63	0.52
	(0.47)	(−0.73)	(0.21)	(0.54)	(−1.12)	(0.93)	(1.24)	(1.74)	(1.95)	(2.87)	(1.57)

Table 12: Mispricing-Related Characteristics of Portfolios Double Sorted on Relative Model Value and Characteristics Related to Default Option

Each month, we first sort all stocks into quintiles based on a stock characteristic relayed to default option. The stocks are then further sorted into quintiles according to the ratio of the equity value implied by our valuation model to the actual equity value (R1=most overvalued, R5=most undervalued). The variable for the first sort are the same as those in Table 5, namely distress, size, stock return idiosyncratic volatility, and profitability. Distress is calculated based on CHS (2008) using current market data and quarterly accounting data of the most recent available quarter. Size is the market capitalization. Idiosyncratic volatility is calculated as the standard deviation of the residuals of regression of daily stock returns on the daily four factors over the last month. Profitability is defined as the ratio of net income to total assets, calculated using quarterly data. The portfolios are value-weighted and held for one subsequent month. The table presents descriptive statistics for each portfolio, where for all variables, observations outside the top and the bottom percentiles are excluded. For each variable, we first calculate the cross-sectional mean across stocks for each portfolio. The table then reports the time-series averages of these means. Equity issuance (reported in percent) is measured by the difference between the sale and purchase of common and preferred stocks during the year, scaled by equity market value at the beginning of the year. Institutional ownership (IO, reported in percent) is the sum of all shares held by institutions divided by total shares outstanding. Net insider buys are calculated as the difference between the numbers of shares bought and sold by insiders during the portfolio formation month, scaled by total number of shares outstanding (reported in basis points). Merger targets is the percentage of firms that were acquired during the following year. The sample period is 1983 to 2012.

		Equity issuance		IO		Net Insider buys		Merger Targets	
		R1	R5	R1	R5	R1	R5	R1	R5
Distress	D1	0.7	−0.9	54.8	45.0	−16.7	−14.4	1.4	1.5
	D5	10.4	6.1	15.8	19.4	−6.5	−2.3	1.2	3.4
Size	S1	5.9	2.9	19.1	23.2	−16.0	−9.2	1.0	2.2
	S5	0.3	−0.9	62.2	59.3	−5.5	−2.2	1.0	1.3
IdioiVol	IV1	0.6	−0.2	44.4	43.5	−5.4	−6.5	1.0	1.7
	IV5	8.7	5.3	16.5	17.2	−18.7	−9.0	1.1	2.9
Profitability	PR1	9.0	6.0	21.5	23.1	−10.5	−5.4	1.0	3.1
	PR5	2.0	0.8	40.4	34.4	−15.6	−6.9	0.6	1.1

Table 13: Descriptive Statistics by Country

The table presents descriptive statistics separately for nine countries. All variables are winsorized at the 1st and 99th percentiles. Size is market equity value (in millions of dollars). Book-to-market is book equity value divided by market equity value. Monthly stock return is presented in percent. Market leverage is the ratio of total debt book value to the sum of total debt book value and market equity value. For each characteristic, we first calculate the cross-sectional mean and median in each country. The table then reports the time-series averages of these means/medians. The sample period is 1994 to 2012.

	# of	# of	Size		Market-to-book		Monthly returns		Market leverage	
	firms	firm-months	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Australia	1,176	64,663	694.5	97.0	2.57	1.56	1.37	0.60	0.21	0.14
Canada	1,456	80,972	1,159.3	178.8	2.14	1.53	0.74	0.30	0.25	0.19
France	1,041	82,902	1,387.0	122.4	2.25	1.57	0.99	0.50	0.30	0.26
Germany	975	78,056	733.0	82.5	2.80	1.74	0.65	0.20	0.26	0.19
Hong Kong	174	19,871	1,901.3	260.9	1.19	0.73	1.33	0.20	0.27	0.22
Italy	280	17,062	1,043.8	215.9	1.67	1.23	0.12	−0.20	0.40	0.38
Japan	4,305	551,830	752.6	134.2	1.38	0.96	0.39	−0.30	0.36	0.34
Switzerland	175	12,701	1,789.1	390.5	2.29	1.55	0.94	0.90	0.24	0.19
U.K.	2,059	139,095	962.0	98.8	2.43	1.45	0.63	0.30	0.23	0.17

Table 14: Returns of Portfolios Sorted on Relative Model Value: International Sample

For each country listed below, each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The portfolios are value-weighted and held for one subsequent month. The table shows the portfolios' mean excess monthly returns (in excess of the risk-free rate) and alphas from factor models. The CAPM one-factor model uses the market factor. The three factors in the three-factor model are the Fama and French (1993) factors. The four factors in the four-factor model are the Fama-French factors augmented with a momentum factor. All factors are calculated separately for each country. We also show the equal-weighted (ew) alpha of the long short 10−1 portfolio in the last column. All returns and alphas are in percent per month and the corresponding t-statistics are in parentheses. Panel A (B) uses annual (quarerly) sales for calculating volatility in the model implementation. The sample period is 1994 to 2012.

	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	ew 4-factor alpha
Panel A: Volatility calculated using annual sales					
Australia	1.23	1.29	1.11	1.44	1.99
	(2.15)	(2.22)	(1.89)	(2.34)	(4.60)
Canada	0.87	1.20	1.02	1.19	1.57
	(1.35)	(1.89)	(1.65)	(1.90)	(3.67)
France	0.41	0.46	0.21	0.40	0.95
	(1.02)	(1.12)	(0.54)	(0.98)	(3.57)
Germany	0.92	0.93	0.71	1.10	0.82
	(2.20)	(2.21)	(1.72)	(2.57)	(3.03)
Hong Kong	1.51	1.65	1.58	1.89	1.87
	(2.40)	(2.60)	(2.53)	(2.96)	(3.12)
Italy	0.07	0.02	−0.25	−0.65	0.25
	(0.12)	(0.03)	(−0.44)	(−1.10)	(0.53)
Japan	0.75	0.73	0.38	0.59	0.92
	(1.86)	(1.89)	(1.15)	(1.96)	(4.62)
Switzerland	0.85	0.62	0.42	0.15	1.27
	(1.26)	(0.94)	(0.67)	(0.23)	(2.48)
U.K.	0.57	0.53	−0.02	1.03	1.04
	(0.90)	(0.83)	(−0.03)	(1.77)	(3.92)

	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	ew 4-factor alpha
Panel B: Volatility calculated using quarterly sales					
Australia	1.71	1.72	1.57	1.94	1.74
	(2.68)	(2.67)	(2.39)	(2.88)	(3.30)
Canada	0.70	1.11	0.94	1.01	1.52
	(1.04)	(1.72)	(1.51)	(1.61)	(3.78)
France	0.34	0.42	0.15	0.27	0.86
	(0.82)	(1.02)	(0.36)	(0.66)	(2.79)
Germany	0.84	0.88	0.47	0.86	0.61
	(1.84)	(1.90)	(1.06)	(1.91)	(2.18)
Hong Kong	2.12	2.29	2.29	2.31	1.14
	(2.65)	(2.83)	(2.92)	(2.82)	(1.80)
Italy	−0.06	−0.20	−0.19	−0.47	0.08
	(−0.10)	(−0.34)	(−0.34)	(−0.83)	(0.19)
Japan	1.04	1.03	0.69	0.79	0.96
	(2.84)	(2.88)	(2.25)	(2.62)	(4.87)
Switzerland	1.16	0.98	0.91	0.93	1.28
	(1.99)	(1.70)	(1.61)	(1.57)	(2.34)
U.K.	0.69	0.67	0.21	0.88	0.84
	(1.23)	(1.18)	(0.40)	(1.69)	(3.10)

Table 15: Fama-MacBeth Regressions on Relative Model Value: International Sample

We run cross-sectional Fama and MacBeth (1973) regressions each month of excess stock returns separately for each country listed below. The independent variables are (log) market capitalization, (log) market-to-book, past six-month return, and relative model value. Market-to-book ratio is calculated as the ratio of current market value divided by book value of the previous quarter. We skip one month in calculating the six-month returns. Relative model value is the log of the ratio of the equity value implied by our valuation model to the actual equity value. All coefficients are multiplied by 100 and Newey-West corrected t-statistics (with six lags) are in parentheses. The sample period is 1994 to 2012.

	Australia	Canada	France	Germany	Hong Kong	Italy	Japan	Switzerland	U.K.
Cnst	1.075	0.668	0.410	0.565	0.943	−0.157	−0.383	0.365	0.952
	(1.28)	(0.96)	(1.01)	(0.76)	(1.00)	(−0.27)	(−0.35)	(0.58)	(1.15)
Log(size)	0.129	−0.012	−0.021	0.067	−0.015	0.101	0.018	−0.011	−0.109
	(0.49)	(−0.13)	(−0.42)	(0.64)	(−0.14)	(1.53)	(0.08)	(−0.13)	(−1.02)
Log(MB)	−0.234	−0.019	0.041	−0.140	−0.005	−0.506	−0.254	0.171	0.072
	(−1.75)	(−0.20)	(0.31)	(−1.80)	(−0.02)	(−3.27)	(−3.34)	(0.79)	(0.88)
Past return	2.942	1.439	1.015	1.048	−0.114	1.755	−0.325	2.177	1.633
	(3.81)	(4.28)	(2.24)	(2.59)	(−0.13)	(2.66)	(−0.60)	(2.37)	(3.84)
Relative	0.201	0.187	0.257	0.148	0.100	0.035	0.142	0.198	0.125
model value	(2.78)	(2.32)	(3.18)	(3.11)	(0.85)	(0.41)	(2.50)	(1.82)	(2.39)

Table B1: Returns of Portfolios Sorted on Relative Model Value (with Mean Reversion in Growth Rates)

Each month, we sort all stocks into deciles according to the ratio of the equity value implied by our valuation model to the actual equity value (Decile 1=most overvalued, Decile 10=most undervalued). The model includes a mean reverting process for the growth rate as described in Appendix B. The portfolios are value-weighted and held for one subsequent month. The table shows the portfolios' mean excess monthly returns (in excess of the risk-free rate) and alphas from factor models. The CAPM one-factor model uses the market factor. The three factors in the three-factor model are the Fama and French (1993) factors. The four factors in the four-factor model are the Fama-French factors augmented with a momentum factor. We also show the equal-weighted (ew) returns/alphas on the long-short 10−1 portfolio in the last column. All returns and alphas are in percent per month and the corresponding t-statistics are in parentheses. The sample period is 1983 to 2012.

	1	2	3	4	5	6	7	8	9	10	10−1	ew 10−1
Excess return	0.48	0.41	0.63	0.67	0.64	0.71	0.79	0.77	1.05	1.06	0.59	1.04
	(1.25)	(1.34)	(2.36)	(2.63)	(2.73)	(2.79)	(3.19)	(3.01)	(3.92)	(3.14)	(1.90)	(4.36)
CAPM alpha	−0.35	−0.29	0.03	0.08	0.12	0.16	0.27	0.23	0.51	0.43	0.78	1.11
	(−1.96)	(−2.53)	(0.25)	(0.90)	(1.17)	(1.29)	(2.05)	(1.72)	(3.30)	(1.93)	(2.59)	(4.62)
3-factor alpha	−0.24	−0.24	0.06	0.02	0.01	0.02	0.09	0.04	0.31	0.23	0.47	0.85
	(−1.51)	(−2.06)	(0.53)	(0.22)	(0.08)	(0.15)	(0.83)	(0.39)	(2.33)	(1.13)	(1.70)	(4.01)
4-factor alpha	−0.27	−0.24	0.02	0.04	0.02	0.11	0.19	0.14	0.43	0.56	0.83	1.20
	(−1.69)	(−2.08)	(0.23)	(0.42)	(0.19)	(1.03)	(1.81)	(1.32)	(3.37)	(3.12)	(3.23)	(6.46)