Valuing high technology growth firms*

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Abstract

For the valuation of fast growing innovative firms Schwartz/Moon (2000, 2001) develop a fundamental valuation model where key parameters follow stochastic processes. While prior research shows promising potential for this model, it has never been tested on a large scale dataset. Thus, guided by economic theory, this paper is the first to design a large-scale applicable implementation on around 30,000 technology firm quarter observations from 1992 to 2009 for the US to assess this model. Evaluating the feasibility and performance of the Schwartz-Moon model reveals that it is comparably accurate to the traditional sales multiple with key advantages in valuing small and non-listed firms. Most importantly, however, the model is able to indicate severe market over- or undervaluation from a fundamental perspective. We demonstrate that a trading strategy based on our implementation has significant investment value. Consequently, the model seems suitable for detecting misvaluations as the dot-com bubble.

JEL classification: G11, G12, G17, G33
Keywords: Schwartz-Moon model, market mispricing, empirical test, company valuation, trading strategy

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1. Introduction

Web based social networks like Facebook, Twitter and so forth are currently one of the fastest growing industries and therefore attracting investors' attention. Recently, Facebook went public as the second-largest U.S. IPO of all time, implicitly valuing this company at around $100 billion. The result was a market capitalization higher than for mature internet firms as Ebay or Amazon.[1] While Facebook's IPO currently dominates the media, its social network game development company Zynga, the deal-of-the-day website Groupon and the music recommendation service Pandora went public last year with corresponding firm values of $13 billion, $7 billion and $2 billion, respectively, although still making losses.[2] Hence, the challenging exercise of valuing fast growing technology firms is becoming popular again despite the recent financial crisis.

In response to the demand for a valuation model suitable for such firms, Schwartz/Moon (2000) and Schwartz/Moon (2001) develop and extend a theoretical model explicitly focusing on the value generating process in high technology growth stocks. It is based on fundamental assumptions about the expected growth rate of revenues and the company's cost structure to derive a value for technology firms. Using simple Monte Carlo techniques and short term historical accounting data, the Schwartz-Moon model simulates a growing technology firm's possible paths of development. As next step, it calculates a fundamental firm value by averaging all discounted, risk-adjusted outcomes of the simulated enterprise values. Additionally, throughout the growth process firms may default. Therefore, the model provides investors not only with a value estimate but also with a long term probability of bankruptcy, which is not the case for the standard valuation procedures such as multiples. Another major advantage is that it does not require market data which makes it applicable for the large number of non-listed firms. Finally, given that high technology firms often experience losses and do not have analyst coverage, one has to take into account that the most accurate valuation methods, as Discounted Cash Flow (DCF) models or price earnings multiples, are not applicable. Due to its theoretical appeal, the model has been used and extended by other studies like Pástor/Veronesi (2003, 2006). A first important attempt to operationalize the model is presented by Keiber et al. (2002), who apply it to 46 German technology firms during the dot-com bubble.[3]

Based on these thoughts, the issue arises whether the Schwartz-Moon model can fill this gap in the valuation literature, despite the difficulty that many of the model's input parameters need to be estimated ex-ante. Specifically, we ask the following three research questions: First, given the theoretical advantages but challenging input parameter estimation of the Schwartz-Moon model, how does an economic reasonable, but at the same time feasible implementation look like? Second, how does the proposed model implementation perform in terms of valuation accuracy? Third, given that the model is based on fundamental accounting information, is it possible to indicate market misvaluation in the technology sector?

Answering these questions yields the following key results: First, building on economic theory regarding the development of key accounting and cash flow figures in a competitive market environment, we present an easily applicable configuration of the Schwartz-Moon model. It is developed for large scale valuation purposes on a sample of around 30,000 technology firm quarter observations from 1992 to 2009 using realized accounting data. Second, although this model is especially suited for non-listed firms, we need the market environment to test its feasibility. Therefore, we compare the fundamentals based Schwartz-Moon model to the Enterprise-Value-Sales method and find that it performs comparably accurate with regard to deviations from market values. Moreover, there are clearly smaller deviations for firms in the chemicals and computer industries and for smaller companies. Note that this perspective assumes that markets are on average efficient considering the complete time period and are not influenced by market sentiment. Finally and most importantly, leaving this accuracy perspective and turning to the last question of potential misvaluation, the Schwartz-Moon model shows the ability to indicate severe market over- or undervaluation in each quarter from 1992 until 2009 and to produce reasonable estimates for the probability of default. Given these findings, we demonstrate that a trading strategy based on the Schwartz-Moon model has significant investment value, both before and after transaction costs.

By providing and testing an applicable implementation of the Schwartz-Moon model, we contribute to the literature on company valuation. Our findings offer promising results on how to accurately value especially small firms, which often exhibit losses and are therefore excluded in other studies.[4] Furthermore, these firms are often not covered by analysts; consequently, other fundamental valuation models as the Discounted Cash Flow model are not applicable. Including analyst forecasts would lead to an important sample selection bias as demonstrated in Pástor/Veronesi (2003).[5] Moreover, even if analyst forecasts are available, they are frequently overoptimistic as demonstrated in Easterwood/Nutt (1999). This would then contradict the effort to detect misvaluation. In contrast, the Schwartz-Moon model only relies on a short history of eight quarters of firm-specific accounting data. Although it contains more than 20 parameters, we introduce a sensible implementation, which is only based on major items from the income statement and the balance sheet and information about firms in the same industry, thereby significantly reducing the model's complexity. Furthermore, it is also applicable to non-publicly traded firms and does not rely on market prices. This can be of special interest during times of inefficient markets and for investors who target unlisted firms and in particular for venture capital and private equity investors who invest in small to medium technology enterprises as documented in Cumming/MacIntosh (2003).

One could argue that the Schwartz-Moon model is only applicable for loss making firms, because it was tailored to firms characteristic for the dot-com era (1999-2001). However, the Schwarz-Moon model is based on the key idea to forecast future balance sheets and income statements which is similar to "traditional" Discounted Cash Flow models. Consequently, this technique and therefore the Schwartz-Moon model is generally applicable for profitable firms as well, since the time series properties of the stochastic processes, for example for a firm's sales, are capable to capture any pattern. While the model is certainly applicable for profitable firms, we acknowledge that it is especially useful for loss-making firms, which comprise 34% of our sample (cf. Table 2). Furthermore, the prevalence of loss making firms has not decreased since 2001 (cf. Figure 3). Although it was especially important in the years after the burst of the tech bubble, there were still around 30% of loss making firms in our sample from 2004 on. During the recent financial crisis this proportion increased to over 35% again.

Following the compelling logic of rational pricing, the original model intends to rationalize high stock prices during the dot-com bubble. Nevertheless, Schwartz/Moon (2000, 2001) are not able to explain the high stock prices rationally as they would need implausibly high volatility estimates. Building on this approach, Pástor/Veronesi (2006) relate extreme valuations to uncertainty. They argue that market valuations could be justified during the dot-com bubble; however they assume a period of 15 years of abnormal profits, which seems quite high in a competitive environment. Therefore, by focusing on matching valuation estimates to observed market values, one might overlook the clear advantages of the model compared to the multiple benchmark. It is well documented in the literature that, first, valuations are highly influenced by market sentiment (see, for example, Inderst/Mueller 2004 or Bauman/Das 2004) which can, second, lead to misvaluations and bubbles (Baker/Wurgler 2007 or Stambaugh et al. 2012). Therefore, regarding the first aspect, our benchmark for the model's accuracy to market values, the Enterprise-Value-Sales multiple (EV-Sales), should naturally yield smaller deviations as it captures the market sentiment. Nevertheless, we need the market environment to check the feasibility of our implementation and it indeed results in comparable accuracy. Put differently, while the Schwartz-Moon model is purely based on historical accounting data, multiples are generally calibrated to capture the current market mood by explicitly relying on the market values of competitor firms. However, this independence of current market sentiment allows the fundamentals based Schwartz-Moon model to detect periods of severe market mispricing, which is in line with the second aspect mentioned above. Consequently, we hypothesize that market valuations can be unjustified during bubble times and add to the literature which indicates that the financial accounting data can serve as an anchor for rational pricing during these times as in Bhattacharya et al. (2010). This is especially true for technology growth firms whose valuations are highly subjective and therefore strongly affected by investor sentiment as documented in Baker/Wurgler (2006). Finter et al. (2012) argue that sentiment plays an important role especially for stocks that are hard to value and demonstrate a sentiment peak during the dot-com bubble. The key results by Keiber et al. (2002) also indicate significant overvaluation during that time. Consequently, we provide additional evidence that a trading strategy based on our model implementation of Schwartz-Moon has economic and statistically significant investment value, both before and after transaction costs. Risk adjusted abnormal returns before transaction costs are as high as 1.5% per month.

The remainder of this paper is structured as follows. In section 2 we provide an overview of the related literature and discuss the properties of technology growth firms in the context of firm valuation. Section 3 discusses the Schwartz-Moon model and introduces the benchmark valuation procedure. Section 4 describes the sample and model implementation. In section 5 we empirically investigate the model's performance and section 6 presents the robustness checks. Finally, section 7 concludes.

2. Related literature: Firm growth and valuation

In this section we briefly discuss the relevant valuation literature with a focus on technology growth companies. To start with, we discuss the "nifty fifty". They were the high-flying growth stocks of the 1960s and early seventies. These companies, including General Electric, IBM, Texas Instruments and Xerox were the growth firms of their time. Due to their notably high valuations, those firms were later compared to new economy stocks enjoying tremendous high valuations in the late 1990s as stated in Baker/Wurgler (2006). Still, while the "nifty fifty" were strongly growing companies, their valuation was based on the ability to generate rapid and sustained earnings growth and persistently increase their dividends. In addition, those firms were already well established large cap entities, thereby confirming Gibrat's rule and the theoretical models of Simon/Bonini (1958) and Lucas Jr. (1967) that assume growth to be independent from firm size. Consequently, growing firms could easily be valued using standard valuation methods such as the Discounted Cash Flow model with analyst forecast data or the Price-Earnings-Ratio with a sufficient peer group.

The tremendous rise in high technology stock prices during the end of the 1990s and its subsequent fall throughout the early years in the new century, known as the dot-com bubble, let the economics of technology firms gain significant attention again. Practitioners and researchers began to realize that internet stocks are a chaotic mishmash defying any rules of valuation.[6] Starting to question the relation between financial ratios and equity value of stocks, as documented by Core et al. (2003), Trueman et al. (2000) analyze new measures of technology firm value drivers such as customer's internet usage. In a more general approach, Zingales (2000) describes the appearance of a new type of firm based on new technology. He finds three factors to disturb existing firm theories: Reduced value generation by physical assets, increased competition and the importance of human assets. But why would new technology have influence on firm valuation approaches?

McGrath (1997) relates investments in high technology firms with real options logic. In her framework, the value of the technology option is the cost to develop the technology. Completing the development of the technology will create an asset which is the underlying right of the firm to extract rents from the technology. This gives three insights.

First, growing technology firms might exhibit losses as they face costs of development, but no yet marketable products. In this context, Demers/Lev (2001) argue that high technology firms require significant up-front capital to establish their technological architecture. In line with this argument, Bartov et al. (2002) find that since the 1990s, innovative high technology firms are expected to grow rapidly, while they are still not profitable. In this study we will present a sample of 29,477 US technology firm quarter observations with median annual sales of 142$m and a significant share (34%) of negative earnings observations. Consequently, we conclude that recent studies on valuation model accuracy requiring positive earnings firms do not include a significant share of high technology companies.

Second, from a stock market perspective, high technology growth firms have specific characteristics. Their stocks are exposed to severe volatility as documented in Ofek/Richardson (2003), which makes it difficult to determine the underlying value. At the same time, there is a strong influence of investor sentiment on the value of technology firms found in Baker/Wurgler (2006) or Inderst/Mueller (2004). Hence, relative valuation methods, i.e., multiples, for high technology firms are heavily influenced by the current mood of the market. Compared to fundamentally based valuation models as DCF, the multiples should not be able to make any statements about overall market over- or undervaluation. Consequently, valuation methods based on financial statement information should therefore have the potential to serve as rationale benchmark during volatile and speculative market periods. This is especially important as prices reflect fundamentals in the long run as presented in Coakley/Fuertes (2006).

Third, the risk of the new technology failing can result in bankruptcy. Thus, the risk of default plays a more central role in valuation of high technology firms. Vassalou/Xing (2004) and Kapadia (2011) report default risk to be a relevant factor for explaining equity returns.[7] While this is the case for all firms, it is particularly important for high technology growth firms, which generally experience higher risk of default compared to mature value firms. The Schwartz-Moon model explicitly takes the risk of defaulting into account. Valuation multiples on the other hand consider default risk only implicitly if markets price this risk correctly and if there are no systematic differences in this risk among the firms of the peer group. Beside the general fact that bankruptcy is costly and negatively affects small and large investors, information on default risk is especially important for under-diversified investors. Cumming/MacIntosh (2003) and Cumming (2008) document tremendous default risks with failure rates of 30% for portfolios that are specialized in young entrepreneurial firms. These results show that valuation models - especially with regard to small companies - should incorporate default risk explicitly. Since this is the case in the Schwartz-Moon framework, this model is preferable to standard approaches, which are typically working on a going concern basis.

In sum, we see that standard valuation procedures are less applicable for high technology firms, which are especially influenced by market mood and exposed to default risk. The firms in our sample are likely comparable to young and growing venture backed firms. In this context, Hand (2005) and Armstrong et al. (2006) find that traditional accounting measures such as balance sheet and income statement are able to explain variation in market values for venture capital backed growing technology firms. Taking these specifics into account, the Schwartz-Moon model might offer a way to determine a fundamentally justified value of high technology growth firms. In the following we present the original model.

3. Valuation models

3.1. Fundamental pricing: The Schwartz-Moon model

The Schwartz-Moon model (2000, 2001) is most easily explained in the context of traditional valuation models, such as the familiar Discounted Cash Flow model, where the cash flow to equity (FTE) is discounted at an appropriate risk adjusted cost of equity. For all these models, one of the most challenging tasks is the derivation of future payoffs. While there are several ways to tackle this problem, the most sensible method is to forecast future balance sheets and income statements and derive the necessary payoff-figures as in Lundholm/O'Keefe (2001). Following this logic, one needs forecasts for the basic financial statement items as shown in the next two figures.

-----------------Please insert Figure 1 approximately here-----------------

-----------------Please insert Figure 2 approximately here-----------------

Since analysts' forecasts for high technology firms are often not available, the commonly applied forecasting technique is the percentage of sales method. Here, one explicitly focuses on revenues forecasts and the other value relevant parameters are tied to these forecasts based on a historical ratio analysis. The revenues forecasts are influenced by many parameters, such as industry dynamics or actions from competitors. Consequently, after some finite forecast horizon, it is reasonably assumed that initially high growth rates of revenues will converge to average industry levels. Finally, the company will achieve a mature, steady-state status and revenues grow with the industry rate. The convergence to industry levels is theoretically well established as in Denrell (2004) and commonly applied in empirical studies concerned with company valuation such as Krafft et al. (2005).

The Schwartz-Moon model is exactly based on these thoughts, since it models the value driving input parameters given by the income statement and the balance sheet with stochastic processes. Below, we present the model as introduced by Schwartz/Moon (2001).

Following the percentage of sales method, revenue dynamics (R) are given by the stochastic differential equation:

$$\frac{dR(t)}{R(t)} = [\mu(t) - \lambda_R \cdot \sigma(t)]dt + \sigma(t) \cdot dz_R(t) \tag{1}$$

where the drift term $\mu(t)$ represents the expected growth rate in revenues and $\sigma(t)$ is the growth rates' volatility. Unanticipated changes in growth rates are modeled by the random variable z_R, following a Wiener process. The risk adjustment term λ_R accounts for the uncertainty and allows for discounting at the risk free rate later. With time t, the initial growth rates converge to their long term growth rate $\bar{\mu}$ following a simple Ornstein-Uhlenbeck process.

$$d\mu(t) = \left[\kappa_\mu(\bar{\mu} - \mu(t)) - \lambda_\mu \cdot \eta(t)\right]dt + \eta(t) \cdot dz_\mu(t) \tag{2}$$

where κ_μ denotes the speed of convergence and $\eta(t)$ is the volatility of the sales growth rate. Different from Schwartz/Moon (2001), we do not make the simplifying assumption that the true and the risk adjusted revenues growth processes are the same, which is why we introduce the risk adjustment term λ_μ. Unanticipated changes in revenues $\sigma(t)$ converge with κ_σ to their long-term average $\bar{\sigma}$, while the volatility of expected growth $\eta(t)$ converges to zero.

$$d\sigma(t) = \kappa_\sigma \cdot \left[\bar{\sigma} - \sigma(t)\right]dt \tag{3}$$

$$d\eta(t) = -\kappa_\eta \cdot \eta(t)dt \tag{4}$$

Summing up, the two main parameters of the revenue process (growth rate $\mu(t)$ and the growth rates' volatility $\sigma(t)$) exhibit the desirably property of long term convergence justified by a competitive market environment.

Turning to the second item on the income statement, cost dynamics *C(t)* are modeled based on two components. The first component is variable cost dynamics $\gamma(t)$, which is proportional to the firm's revenues. The second component is fixed costs *F*.

$$C(t) = \gamma(t) \cdot R(t) + F \tag{5}$$

Again, cost dynamics are assumed to converge to their industry levels according to the following mean-reverting process:

$$d\gamma(t) = \left[\kappa_\gamma(\bar{\gamma} - \gamma(t)) - \lambda_\gamma \cdot \varphi(t)\right]dt + \varphi(t) \cdot dz_\gamma(t) \tag{6}$$

where κ_γ denotes the speed of convergence at which variable costs $\gamma(t)$ converge to their long term average $\bar{\gamma}$. Here we also adjust for the uncertainty by adding the risk adjustment term λ_γ. Unanticipated changes in variable costs are modeled by $\varphi(t)$, converting deterministically with κ_φ against long term variable cost volatility $\bar{\varphi}$.

$$d\varphi(t) = \kappa_\varphi \cdot \left[\bar{\varphi} - \varphi(t)\right]dt \tag{7}$$

As Schwartz/Moon (2001) suggest, it is reasonable to assume the three speed of adjustment coefficients to be the same, leaving us with one single κ. Dividing *log(2)* by κ yields the half-life of the processes, which can easily be interpreted.[8] While revenues and costs are modeled independently from the balance sheet, the development of property, plant and equipment *PPE(t)* depends on the development of capital expenditures *CE(t)* and depreciation *D(t)*. The former value is assumed to be a fraction *cr* of revenues while depreciation is assumed to be a fraction *dp* of the accumulated property, plant and equipment. Consequently, both financial statements are linked consistently to each other by:

$$dPPE(t) = \left[-D(t) + CE(t)\right]dt \tag{8}$$

Finally, taxes and the dynamics of loss carry forwards are considered by Schwartz/Moon (2001). Since firms can offset initially negative earnings with future positive earnings for tax purposes, we calculate loss carry forward dynamics as:

$$dL(t) = \begin{cases} -\left[Y(t) + Tax(t)\right]dt, & if \quad L(t) > \left[Y(t) + Tax(t)\right]dt \\ -\max\left[L(t)dt, 0\right], & else \end{cases} \tag{9}$$

Controlling for tax payments *Tax(t)* and loss carry forwards *L(t)*, the after tax income $Y(t)$ in the Schwartz-Moon model is given by:

$$Y(t) = R(t) - C(t) - D(t) - Tax(t) \tag{10}$$

Assuming that no dividends are paid and positive cash-flows are reinvested, earning the risk-free rate of interest *r*, the amount of cash available to the firm *X* evolves according to:

$$dX(t) = \left[r \cdot X(t) + Y(t) + D(t) - CE(t)\right]dt \tag{11}$$

Firms fail when their available cash falls below a certain threshold X^* and the enterprise value is set to the liquidation value of *PPE* plus the (negative) cash. Otherwise, the model implied fundamental value at time *t* is calculated by discounting the expected value of the firm at time *T* under the risk neutral probability measure Π with the risk free rate *r*, as the three stochastic processes are corrected for uncertainty by the risk premiums λ_R, λ_μ and λ_γ. The firm's enterprise value consists of two components. The cash amount outstanding and, second, the residual company value, which is calculated as EBITDA = *R(T)-C(T)* times a multiple *M*.

$$\widehat{EV(0)} = E^{\Pi}\{X(T) + M \cdot [R(T) - C(T)]\} \cdot e^{-r \cdot T} \tag{12}$$

The assumptions of no dividend pay-out, no explicit modeling of tax-shields due to the deductibility of interest payments and the solution of the terminal value problem via an exit multiple deserve discussion. While it seems restrictive at first glance, the model is basically employed in a Modigliani/Miller (1958) framework, since it assumes that it does not matter whether equity-owners or the firm holds cash. Furthermore, within the branch of literature concerned with capital structure choice, such as Miller (1977) and Ross (1985), one can argue that advantages and disadvantages of debt financing balance, so it might be a simplifying but justifiable assumption, that the financing decision is not considered explicitly in the Schwartz-Moon model. However, we admit that this might be a simplifying assumption given that an extensive literature focuses on the valuation impact of debt induced tax shields (Husmann et al. 2002, 2006, Ballwieser 2011, Drukarczyk/Schüler 2007 and Kruschwitz/Löffler 2005).

Concerning the terminal value problem, it should be noted, that the finite forecast horizon is chosen to be 25 years as in Schwartz/Moon (2001). Consequently, the calculated terminal value plays only a minor role as shown in the robustness section.

3.2. Introducing a benchmark: Enterprise-Value-Sales-Multiple

The Schwartz-Moon model implementation is based on the principles of historical, fundamental valuation. Therefore, the natural counterpart would be based on a DCF model. As argued earlier, we want to abstract from analyst forecasts and, additionally, the technology firms in our sample often lack analyst coverage. Hence, these input parameters for the DCF model in the large and therefore anonymous dataset are not an option. Alternatively, we turn to relative financial ratios referred to as multiples to provide a sanity check for the magnitude of deviations from market values for our Schwartz-Moon model test.

Multiples are widely used in practice by consultants, analysts and investment bankers as shown for example by Bhojraj/Lee (2002). Among other traditional valuation methods, such as traditional DCF models, they generally produce the smallest deviations from market values as shown by Liu et al. (2002) and Bhojraj/Lee (2002). Thus, we choose to compare the Schwartz-Moon model against this very accurate valuation method. As noted beforehand, there are many multiples available (Price-Earnings, Price-Book, Price-Sales etc.) and they can be implemented in many different ways (simple peer-group comparison vs. sophisticated regression approach). Consequently, we have to choose among these many possibilities. Given the fact that our study is concerned with technology growth firms, many of them have negative earnings or even negative EBITDA. Hence, standard multiples such as Price-Earnings or Enterprise-Value-EBITDA are not applicable. At the same time, we look for a comparable measure which comes close to the idea of the Schwartz-Moon model with the major driving force being sales from its stochastic processes. Since six of the seven critical parameters we identify below depend on sales, our choice is naturally guided to the Enterprise-Value-Sales Multiple. Thus, it provides a reference point to assess the magnitude of deviations.

The Enterprise-Value-Sales method evaluated in this paper follows Alford (1992), where a firm *i*'s value is estimated by the product of firm *i*'s sales at τ and the median of the *j* peer group's (*PG*) EV-Sales multiples.

$$\widehat{EV(t)}_i = Sales(\tau)_i \cdot median_{j \in PG_i} \left\{ \frac{EV(t)_j}{Sales(\tau)_j} \right\} \tag{13}$$

where enterprise value (*EV*) is the market value of equity plus the book value of debt. Note that $\widehat{EV}$ is the estimated value whereas *EV* simply denotes observable information. A key component in relative pricing is the identification of comparable companies. Alford (1992) examines the effects of comparable company selection on relative valuation accuracy and finds that comparable companies selected on industry classification and additional measures such as profitability yield the lowest deviations from observed market values. Therefore, we perform EV-Sales Multiple valuations based on four digit SIC code industry classifications. Within the industry we group firms by their return on net operating assets (RNOA) to account for profitability effects (cf. appendix 1). That is, we choose those six firms that are closest to firm *i*'s RNOA within the preceding year. If fewer than six companies are available in this SIC code classification, we relax this requirement to companies with the same three and two digit SIC code. The peer group median then is calculated to obtain the multiple. The product of the multiple and the firm's sales yields the estimated enterprise value.

4. Data and methodology

4.1. Data collection

To construct our sample of high technology firms, we merge the CRSP database for market data with Compustat North America quarterly and yearly accounting data. In order to calculate industry specific long-term parameter values, we use the complete data set starting 1970 (cf. Appendix 1).[9] However, our main sample considers all firms that fall under the Bhojraj/Lee (2002) high technology industry SIC code definition beginning in 1992 until 2009.[10] That is biotechnology (SIC codes 2833-2836 and 8731-8734), computer (3570-3577 and 7371-7379), electronics (3600-3674) and telecommunication (4810-4841). We add SIC code 7370 (Computer Programming, Data Process) in order to keep firms such as Google or Lycos in our sample. We exclude all firm observations with negative sales, variable costs, capital expenditure and negative enterprise values. This leaves us with 2,262 individual firms covering 29,477 quarters in total as can be found in Table 1 in the appendix.

4.2. Model implementation

The most challenging issue in applying the Schwartz-Moon model is parameter estimation as noted in Schwartz/Moon (2000). Unlike an investment banker who has detailed information about the firm's development, recent m&a activity and strategy decisions, we are valuing a rather anonymous sample of around 30,000 firm quarters. Therefore, our analysis is primarily based on short term historical accounting information, which is the common information set left for these firms.

The Schwartz-Moon model includes 22 different input parameters. While most parameters are estimated on a firm level basis, the long term parameters are determined on industry levels (i.e., three digit SIC codes). Krafft et al. (2005) for example demonstrate a convergence of growth firms' costumer bases to industry averages after a few years. From the perspective of importance, the 22 parameters can be divided into critical and uncritical parameters. The uncritical parameters primarily include initial values for balance sheet items where the estimation is straightforward. The critical parameters with a larger impact on the simulation results come from the revenue and the cost processes because these two processes are the main drivers for a firm's EBIT. More precisely, the seven critical parameters are estimated from quarterly financial statements' sales and costs information and the industry comparison, thereby significantly reducing the complexity of the model. The estimation of the seven critical parameters is presented in the next two paragraphs and their impact is shown in the sensitivity analysis in section 5.

4.2.1. Implementing revenue dynamics

Recall that key input parameters for the firm's revenues are given in equations (1) to (4). Thus, we take the initial sales $R(0)$ as quarterly sales from quarterly accounting statements provided by Compustat for each firm. Initial sales volatility $\sigma(0)$ is calculated using the standard deviation of sales change over the preceding seven quarters and converges to the long term quarterly volatility $\bar{\sigma} = 0.05$ consistent with Schwartz/Moon (2001). Further, they argue that initial expected sales growth $\mu(0)$ should be derived using past income statements and projections of future growth.

Many private shareholders or institutional investors targeting small capitalized growth firms will find it difficult to obtain analyst forecasts. In addition, requiring the availability of I/B/E/S forecasts in particular excludes small firms as noted by Liu et al. (2002). However, to value this type of firm is exactly our aim. Therefore, we do not require any analyst coverage and derive $\mu(0)$ as average sales growth over the prior seven quarterly income statements. While this is notably a weak proxy for future revenues growth, it is information commonly available for all technology firms and therefore easy to apply. Additionally, Trueman et al. (2001) show historical revenues growth to have incremental predictive power over analysts' forecasts for internet firms. Long term sales growth $\bar{\mu}$ is set equal to 0.75% percent per quarter, which corresponds to an assumed long term average annual inflation rate of three percent. Initial volatility of expected growth rates in revenues $\eta(0)$ is estimated firm specifically by the standard deviation of the residuals from an AR(1)-regression on the growth rates, which is similar to the approach of Pástor/Veronesi (2003) to estimate the volatility of profitability.

Different from Schwartz/Moon (2001) who set the speed of adjustment coefficients κ exogenously to 0.1, we allow for mean reverting processes with industry specific (two digit SIC) kappas. The reason is that after an initially individual development, firm processes converge to industry levels as in Krafft et al. (2005). The idea of declining competitive advantages has long been established in the economics literature (Mueller 1977, Mansfield 1985). Dechow et al. (1999) demonstrate its relevance for company valuation. Eventually, Waring (1996) shows that competitive advantages are industry-specific. This is why we rely on economic theory for the concept of competitive advantage periods for our implementation and estimate the convergence to long run values industry-specifically. Schwartz/Moon (2001) argue that the kappa of the revenues growth rate process has the highest impact. Thus, we calculate the adjustment coefficient κ with the help of revenue dynamics by solving the following equation:

$$\sum_{i=t-5}^{t-8} \frac{saleq_i - saleq_{i-1}}{saleq_{i-1}} = \left(\sum_{i=t-1}^{t-4} \frac{saleq_i - saleq_{i-1}}{saleq_{i-1}} \right) \cdot e^{-4 \cdot \hat{\kappa}} \tag{14}$$

As justified above, the estimated firm specific kappas then are pooled to medians for the same two digit SIC codes. We choose two digit over three digit SIC levels to decrease the large variation in this critical parameter. Still, this estimator generates outliers and yields us a range of estimated kappas corresponding to half-lives from one to 70 quarters. In order to avoid the influence of extreme estimates of the kappas corresponding to unreasonable high half-lives, we winsorize these variables at the 1% and 99% percentiles. As the kappas directly influence expected future revenues and costs, the speed of adjustment parameters are crucial for the three stochastic processes.

4.2.2. Implementing cost dynamics

Recall that the input parameters for the cost dynamics are given in equations (5) to (7). Schwartz/Moon (2001) propose to calculate costs using a regression of costs on revenues, where the intercept represents constant fixed costs and the slope is the initial variable costs. On a large scale application, this leads to cases in which the intercept becomes negative. Those firms would exhibit negative fixed costs, an extremely steep slope and unreasonably high variable costs. Therefore, we deviate from this approach, calculating the variable costs $\gamma(0)$ as the average over the preceding eight quarters of variable costs plus fixed costs divided by revenues. In doing so, we ensure costs to be within reasonable levels. Including fixed costs into this approach assumes that fixed costs grow linearly with firm growth. This might be a weak assumption but seems to be more reasonable than assuming independence from growth. The firm's long term cost ratio $\bar{\gamma}$ is calculated based on the long term industry median. For each one digit SIC industry, we calculate a growing window median costs ratio beginning in 1970 and up to 2009. Valuing firm *i* at time *t*, we use firm *i*'s industry's long term median cost ratio until time *t*-1 as the expected long term costs. As costs directly determine a firm's profit, both the initial and the long term cost parameters are crucial and strongly affect the results. The initial volatility of costs φ_0 is obtained by running firm specific AR(1) regressions on the cost ratios and calculating the standard deviation of the residuals. Long term volatility of variable costs $\bar{\varphi}$ is determined as a growing window industry median cost ratio on a three digit SIC code level starting 1970. Finally, we assign the industry specific medians of the estimated standard deviations to the individual firms. This is consistent with assuming similar developments within industries.

In the following, we present the uncritical parameters, which do not affect estimated firm value results largely.

4.2.3. Implementing balance sheet and the remaining income statement items

Recall that the input parameters for the balance sheet and the remaining income statement items, such as depreciation, are given in equation (8), (9) and (11). Initial property, plant and equipment *PPE(0)* is calculated as Compustat items for net property plant and equipment plus other assets. Due to acquisition activity and other expansion related investments, capital expenditures and depreciation ratios are extremely noisy for growing firms. The use of a constant investment and depreciation rate based on historical accounting information might therefore lead to biased results. To overcome biases of expansion related one time effects, we model firm *i*'s constant rates of investment *cr* and depreciation *dp* as the long term industry median. For firm *i*'s cash and cash equivalents *X* at time *t*, we calculate the sum of Compustat items for cash, total receivable minus accounts payable, other current assets and treasury stock.

4.2.4. Implementing environmental and risk parameters

In line with Schwartz/Moon (2000, 2001) and given the long term interest rate from the Federal Reserve, we use for simplicity the risk free rate of 5.5% p.a. which translates to 1.35% per quarter. However, as shown by an intensive sensitivity analysis in the robustness section, it does not drive the results. Corporate tax rates are 35% as in Keiber et al. (2002). The risk premium for each of the stochastic processes λ_i (i= R, μ, γ) is calculated as:

$$\rho_{r_M,i} \cdot \sigma_{r_M} = \frac{Cov(r_M,i)}{\sigma_i} \tag{15}$$

where r_M is the return of the Nasdaq Composite Index over the preceding seven quarters and σ_{r_m} is the Nasdaq Composite Index standard deviation. Thereby, as mentioned earlier, we can use one risk free rate for discounting for all firms. Adjusting the processes for risk and discounting at the risk free rate also stems from economic theory (see, e.g. Harrison/Kreps 1979).

4.2.5. Implementing simulation parameters

For each valuation, we use 10,000 simulations with steps of one quarter and up to 25 years. At the end of the simulation horizon, the enterprise value is given by the time *t*=100 cash value plus the residual value EBITDA multiplied by 10 in line with Schwartz/Moon (2001). We additionally verified this multiple over the whole CRSP-Compustat North America merged database from year 1980 to 2010 and found that its median value is 9.12 based on 170,393 observations. A firm fails at any given time *t*=*s*, where $s \in [1;100]$, within the simulation horizon when the available cash falls below zero. The liquidation value then is given as:

$$\widehat{EV}_{SM_s}^{liq} = \begin{cases} PPE_s + X_s, & if\ -X_s < PPE_s \\ 0, & else \end{cases} \tag{16}$$

where PPE_S is the amount of property, plant and equipment at default plus the negative cash X_S available. The Schwartz-Moon model estimated enterprise value is calculated by averaging all 10,000 simulated enterprise values and discounting the average value to time *t*=0.

4.3. Summary statistics

Table 2 reports summary statistics for our sample.

-----------------Please insert Table 2 approximately here-----------------

Panel A, Table 2, shows the industry distribution primarily based on the SIC code classification by Bhojraj/Lee (2002). The largest group is computer firms, accounting for 40% of our sample. Other major industries are electronics (31%), biotechnology (18%) and telecommunications (11%). Panel B, Table 2, reports financial statement information. For convenience, we report flow items from the income statement as annualized values calculated as the sum over four quarters. On average, firms report annual revenues of \$1.8 billion. A median revenue figure of \$142 million shows the existence of extreme upscale outliers and the small firm structure of our sample. Median cash and cash equivalents holdings is \$72 million, while we also find some firms with negative cash holdings. This is the case for firms where the accounts payable exceeds the sum of cash, treasury stock and receivables, but this only occurs in 1% of the observations. Median total assets are \$170 million. The large asset variation, with the smallest firm reporting total assets of less than \$1 million and the largest firm with assets above \$280 billion, shows significant heterogeneity within the sample. Median leverage, calculated as interest bearing debt scaled by total assets, is 7%. As expected, we find debt financing to be only a minor security choice for technology growth firms. Within 34% of all observations, the underlying firm reported negative earnings and therefore profitability oriented multiples, such as Price-Earnings, cannot be considered. Median annual earnings are 4 \$m, while we also face extreme upside and downside outliers. Even taking EBIT into account as a profitability measure, 28% of all firm quarter observations report negative profits. Panel C, Table 2, reports summary statistics for the seven critical parameters used within the Schwartz-Moon approach. On average, firms exhibit mean annual sales growth rates of 29% over the preceding 7 quarters, while we also face several annual growth rates of more than 1,000% percent. The mean initial cost ratio, calculated as total costs scaled by sales, is 91%, while maximum values are up to 150%. This indicates the growth firm's potential to reduce costs over time to increase profitability in the long run. The long term cost ratio is calculated using a growing window approach based on three digit SIC industry classifications to capture industry specific characteristics. While being on comparable median levels to initial costs, this approach assures less volatile long term cost structures indicated by the significantly reduced inter quartile range. The long term annual revenues growth is exogenously set to a 3% inflation rate. The initial volatility of revenues growth rate has a median of 5%, while the corresponding measure for the initial volatility of variable cost ratio is 8%. The latter also has a higher variability pictured by an inter-quartile range of twice the growth rate's initial volatility. Finally, the speed of convergence has a median of 17% corresponding to a half-life for the stochastic processes of 4.1 quarters. Panel D, Table 2, reports market values. Market capitalization is considered four months following the date the underlying financial statement refers to. This way we verify that financial statement information was available to market participants by the time we analyze market values.[11] Overall, the median enterprise value in our sample is $321 million calculated as the sum of market capitalization provided by CRSP plus long term debt and debt in current liabilities.

-----------------Please insert Figure 3 approximately here-----------------

To address the concern that the Schwartz-Moon model's special ability to value loss making firms could have decreased in importance since the dot-com bubble, Figure 3 illustrates the proportion of loss making firms over the whole sample period. We can clearly see that this proportion remains fairly stable around 30% over time. While it naturally peaked during the dot-com bubble with more than 50%, it was still above 30% for the boom years thereafter. Hence we conclude that the application of the model is not restricted to the dot-com bubble but it can be used in a broader context.

5. Main empirical results

5.1. Feasibility and deviations from market values

Valuation accuracy is generally based on logarithmic deviations or percentage deviations. For comparison, we report both deviation measures in Table 3 to shed light on our research question regarding overall valuation accuracy. Absolute log deviations are defined as the ratio of the estimated value to the market value, $abs \log deviation = abs(\ln(\widehat{EV}/EV))$. The absolute percentage deviation is the absolute difference between actual and model predicted price, scaled by the actual price, $abs \text{ rel } deviation = abs((\widehat{EV} - EV)/EV)$. Panel A, Table 3, reports absolute log deviations for the 29,477 firm quarter observations. Column one reports the accuracy with respect to market values of the Enterprise-Value-Sales multiple controlling for industry and return on assets as in Alford (1992). Over the whole time period, the relative valuation approach yields median deviations of 59%, which is in line with Liu et al. (2002) findings in their tables 1 and 2. The mean of 75% shows the existence of upscale outliers from a fundamental valuation perspective. The fraction of companies which exhibit deviations larger than one is 27%. Column two reports results for the Schwartz-Moon model. In terms of absolute log deviations, this approach yields slightly higher deviations with a median of 63%. The difference is significant on a 1% level due to the large sample size. The interquartile (IQ) range, as the primary measure of dispersion, shows a slightly looser fit than for the Enterprise-Value-Sales Multiple and the fraction of deviations larger than one is slightly higher as well.

Panel B, Table 3, reports results for absolute percentage deviations. In line with the absolute log deviations results, the EV-Sales-Multiple yields a small but still significantly higher accuracy than the fundamental Schwartz-Moon model (2 median percentage points). In this case, however, the Schwartz-Moon model represents the tighter fit considering the IQ-range. Mean and standard deviation are influenced by outliers and therefore are rather high.

-----------------Please insert Table 3 approximately here-----------------

In sum, we conclude that - on average over the time period from 1992 to 2009 - the Schwartz-Moon model is nearly as accurate as the EV-Sales-Multiple with respect to deviations from observed market values.

Looking closer at the accuracy to observed market values, Table 4 reports median absolute log valuation deviations for several industries and different firm sizes. Panel A, Table 4, reports results for different industries aggregated into two digit SIC codes.

-----------------Please insert Table 4 approximately here-----------------

Although we find only a slight overall performance difference for the Schwartz-Moon model and the Enterprise-Value-Sales-Multiple, these two approaches differ considerably among industries. Looking at the absolute log deviations on two digit SIC levels, we see that Schwartz-Moon results in lower median deviations for chemicals firms under SIC code 28 and computer companies (SIC codes 35, 73). On the other hand, the multiple valuation approach yields predicted valuations clearly closer to observed market values for telecommunication firms (SIC code 48) and biological research companies (SIC code 87). However, these two industries represent together less than 16% of the total sample, where biological research firms contribute only 5%. Looking in more detail at the telecommunication firms reveals that the telecommunication firms in our sample are four times larger than the average firm measured by sales and, together with the biological research companies, have the smallest volatilities in growth. As result, standard valuation approaches as the multiples consequently show smaller deviations from market values. Interestingly, in supplementary analyses we also find that the Schwartz-Moon model indicates the most substantial overvaluation over the whole period for telecommunication firms. This is consistent with anecdotal evidence that telecommunication firms were notably overvalued around the dot-com bubble (e.g. Endlich 2004). Without them the Schwartz-Moon model would perform on average more accurate than the EV-Sales-Multiple with an overall median log deviation of 0.56 compared to 0.59. Panel B, Table 4, reports deviations for different firm sizes. As a measure of firm size we use total assets. As expected, both valuation approaches yield the largest deviations for those 25% of observations where firms reported total assets below 50 $m. Still, the Schwartz-Moon model produces smaller deviations. By contrast, the relative valuation approach produces value estimates considerably closer to observed market values the larger the underlying firms become, resulting in clear “outperformance” for the last quartile.

-----------------Please insert Figure 4 approximately here-----------------

For a complete picture, Figure 4, Panels A and B show the median absolute deviations over time on a quarterly basis spanning 1992 to 2009 for the two valuation approaches. They report the absolute log and relative deviations and show the large volatility of model accuracy over the whole time period. During the first half of the 1990s, the absolute deviations generated by the Schwartz-Moon model (red curve) are highest while the multiple (blue curve) yields quite small deviations. Thereafter, the absolute deviations evolve approximately synchronously and increase for both valuation methods with a peak in 2000 around the speculative bubble. This rise is probably based on the extreme high valuations as reported in Ofek/Richardson (2003). With the burst of the bubble the deviations decrease again. Noteworthy the Schwartz-Moon model results in higher accuracy during this time, which might be caused by its explicit consideration of default risk. Generally, the Schwartz-Moon model's absolute deviations display "spikes" which we will discuss below. In sum, the accuracy perspective with respect to market values above can be regarded as feasibility check, which is passed by our model implementation.

5.2. Detecting over- and undervaluation: The trading strategy

Turning to our key research question, we examine whether the Schwartz-Moon model can differentiate and detect periods of market over- and undervaluation. Therefore, we loosely distinguish between four market periods in the sample time span from 1992 to 2009: From the beginning of the time span in 1992 to around 1998 as the period before the dot-com bubble. This is followed by the time of the dot-com speculation bubble, its burst by the end of 2001 and the recovery until around 2007. Finally, the time from mid-2007 until 2009 covers the recent financial crisis.

-----------------Please insert Figure 5 approximately here-----------------

Figure 5, Panels A and B, report the non-absolute median log and relative deviations in order to detect market mispricing from a fundamental perspective. Positive (negative) deviations thereby result from higher (lower) predicted than observed values, hence representing market undervaluation (overvaluation). As argued earlier, the multiple approach is driven by market sentiment and therefore cannot distinguish between the four periods. Hence, the multiple's deviations remain fairly stable around zero as in Liu et al. (2002). On the other hand, the non-absolute deviations from Schwartz-Moon indicate an undervaluation of the growing technology market in the first period, which is declining until around 1998. Parallel to skyrocketing market values of technology firms, Panel A and B of Figure 5 reveal the decreasing deviations from the fundamental model's perspective in the second period. Therefore, the Schwartz-Moon model correctly pictures the general overvaluation of the technology sector during that time. Interestingly, this period of fundamental overvaluation also covers the third period and lasts until 2007 due to depressed growth prospects. By entering the last period at the beginning of the financial crisis in 2007, the picture changes again. The Schwartz-Moon model now indicates an undervaluation of the technology sector. The reason might be a market-overreaction from a fundamental perspective, resulting in the undervaluation of firms during the peak of the financial crisis 2007/08. Around the beginning of 2009 - simultaneously to a 6-year low of the Nasdaq Composite Index - the Schwartz-Moon deviations result in a clear "spike". From the accuracy perspective above, the spike results in lower accuracy of the Schwartz-Moon model, whereas a method like the EV-Sales-Multiple, which captures the market mood, produces higher accuracy. However, the multiple does not have the ability to indicate over- or undervaluation. Being close to the market value is not necessarily a desired characteristic of a model when trying to identify misvalued stocks. Therefore, these “spikes” indicate severe technology market’s deviations from fundamental values.

In order to examine the model’s ability to detect misvaluation further, we perform a trading strategy based on calendar time regressions. Calculating abnormal returns for the three-factor model by Fama/French (1993) with an additional momentum factor following Carhart (1997) enables us to explore the investment value of the Schwartz-Moon model. Therefore, we form long and short portfolios for the undervalued and overvalued stocks identified by the model. Every quarter stocks enter the portfolio for a predefined time span of one, two or three years, taking into account the time until publication of the financial reports as done before. Thereby, we consider two specifications. The first approach is to form the portfolios on a "fixed" over- or undervaluation of more than 50%, while the second considers relative quintiles, where the stocks are sorted into quintiles every quarter according to the misvaluation predicted by the Schwartz-Moon model. The stocks in the most overvalued (undervalued) quintile are then sold short (invested in). The calendar time regressions are calculated on a monthly basis with equally weighted stock returns.[12] Additionally, we take total round-trip transaction costs for buying and selling into account as in Keim/Madhaven (1998). Their study provides an estimation procedure for the costs incurred by institutions in trading exchange-listed stocks depending on their market capitalization. Similar to Liu/Strong (2008), we limit the half-way transaction costs at 2% to eliminate unreasonable estimates. They further argue that transaction costs have declined over time such that transaction costs used in this paper can be interpreted as an upper bound. Hence, this ensures that the abnormal returns after transactions costs represent the lower bound of the risk adjusted profit, which could have been realized by an institutional investor. This conservative perspective ensures that, by finding abnormal returns after costs, it would be profitable for investors to follow the investment strategy.

-----------------Please insert Table 5 approximately here-----------------

The results are presented in Table 5. Note that for the short portfolios trading profits are also represented by positive alphas. We can clearly see that buying stocks, which are identified as undervalued by the Schwartz-Moon model, produce significant monthly abnormal returns before transaction costs in Panel A, Table 5. With around 1.2% for the one year to 0.9% for the three year holding period, these risk-adjusted returns are both economically and statistically significant for the “fixed” and the relative quintile approach. Forming long-short portfolios would increase the abnormal returns before transaction costs up to more than 1.5% for the short holding period. Interestingly, the short portfolios themselves do not produce significant abnormal returns. Although still positive, they are not significantly different from zero. This implies that growth stocks, which seem overvalued from a fundamental perspective, can nevertheless justify their high valuation when meeting the high expectations as in Pástor/Veronesi (2003). Eventually, Panel B, Table 5, demonstrates that the abnormal returns also hold after accounting for transaction costs, as the portfolios are only adjusted once per quarter. Overall, the magnitude of abnormal returns is consistent with the annual abnormal returns of 13.2% found by Abarbanell/Bushee (1997), who implement a trading strategy based on fundamental analysis.

Finally, to assess whether the Schwartz-Moon model provides reasonable default probabilities, we extend the market mispricing results by analyzing the generated bankruptcy figures over time.

-----------------Please insert Table 6 approximately here-----------------

Recall that one of the advantages of the Schwartz-Moon model compared to the sales-multiple approach is that it produces estimates for the probability of default for a 25-year period. Table 6 reports summary statistics on the model implied default rates. The median default rate for our sample is 29% while for less than 2% of the observations there were no defaults during the 10,000 simulations. These are reasonable levels as, e.g. Cumming/MacIntosh (2003) report failure rates up to 30% for venture capital investors' portfolios mainly consisting of technology firms.

-----------------Please insert Figure 6 approximately here-----------------

Figure 6 shows the evolvement of the median predicted number of defaults over time. There is a clear upward trend from the mid 1990s until 2000 reflecting the increased business activity. During the burst of the dot-com bubble in 2000, the Schwartz-Moon model predicts median default rates of up to 40%. This high level remains until the beginning of 2009 with another peak in 2008, whereafter it drops to levels around 25% again. Compared to the market credit spread of Baa rated corporate bonds to US treasury bills, the Schwartz-Moon model seems to be reacting to fundamental credit risk changes before the market does. This can also be seen at the dot-com bubble around 2000. Interestingly, the model predicted default probabilities remain high from 2003 on whereas the market implied credit risk is declining until 2007. In sum, we conclude that the Schwartz-Moon model shows the ability to illustrate market over- and undervaluation, while we suggest that the credit risk aspects of Schwartz-Moon would be worthwhile to explore in future research.

6. Robustness checks

Given that the Schwartz-Moon model needs multiple input parameter estimates, of which we identified seven as critical, this section provides robustness tests. Table 7 summarizes the results for the sensitivity analysis for the seven critical parameters and, additionally, for the interest rate and the terminal value multiple. By varying the input parameters for a range of +/-10%, we see that the median absolute deviations remain fairly stable except for the long term cost ratio. Looking more closely at the default rates, the driving parameters are identified as initial and long term cost ratios as well as, to a smaller extent, the speed of convergence. The high impact of the long term cost ratio is reasonable because a 10% change in an average long term cost ratio of 0.9 is rather high, resulting, e.g. in a decupling of the long term profit margin from 0.01 to 0.1. Varying the terminal value multiple from 10 to 9 and 11 only has a small impact as the multiple is applied only after a time horizon of 25 years. Moreover, looking at the detailed planning period and the terminal value separately reveals that the terminal value contributes only around 30% to the company value. Thus, we conclude that the chosen terminal value multiple of 10 seems reasonable for the reasons mentioned in section 4, but does not influence our results unduly.

Generally, in contrast to the absolute deviations, the estimates for the probability of default react more sensitive to a change in input parameters because the threshold for the cash level stays exogenously at zero. Overall, the results are robust despite the notable number of parameters.

Table 7 also illustrates that varying the constant risk free rate does not alter the results. However, we re-estimated the firm values for time specific interest rates derived from 10-year US treasuries.[13] For every quarter in the sample period 1992-2009 we take the corresponding yield for the 25 year simulation. Using these yields at the start of each quarter as input leads to risk free rates between 2% and 8%. As result we find that the Schwartz-Moon model performs even better when using time-specific interest rates. In unreported (but available upon request) tables we show median log deviations of 0.60 compared to 0.63 reported in Table 3 and on average around 0.20% higher abnormal returns compared to Table 5. However, we focus on the original model and consider the reported results therefore as conservative.

-----------------Please insert Table 7 approximately here-----------------

Additionally, we recalculate the results based on the Global Industry Classification Standard (GICS) instead of the SIC classification with the definition of high technology firms provided by Kile/Phillips (2009). They argue that GICS provide higher accuracy to identify high technology firms than SIC codes and hence should be preferred. However, our results (unreported, but available upon request) remain qualitatively the same.

Finally, as argued above, our results are interpreted in two ways. The first view is a market mispricing perspective and focuses on the time dimension, meaning that the model price is correct and the market might be wrong. The second perspective averages the results over the complete time span from 1992 until 2009 and compares model predicted values to real market values. Here, deviations of model predicted values from market values are regarded as inaccuracy, meaning that the market values can be - on average - used as a correct benchmark and thus incorporate the notion of market efficiency. With the second view in mind, we predict, that - on average - the Schwartz-Moon model prices should be positively correlated with observed market values. To test this prediction, Table 8 reports regression results, where the observed market value is regressed on the predicted value to determine the model's explanatory power. We should expect a positive and significant coefficient, however it does not have to be close to one as Schwartz-Moon estimates the firm's fundamental value independently from market sentiment. The regression results fulfill these expectations with the estimated coefficients being positive and significant.[14]

-----------------Please insert Table 8 approximately here-----------------

7. Discussion and conclusion

The valuation of innovative growth firms is a challenging task as these firms often deviate from basic assumptions such as exchange listing, positive earnings, sufficient size or analyst coverage mandatory to most common valuation procedures. To value this type of firm Schwartz/Moon (2000, 2001) develop a valuation methodology in which firm value arises under the development of primarily three stochastic processes for revenues, growth and costs. Although this model has several theoretical advantages over common valuation approaches, its performance had yet to be tested on a large sample of firms. Based on economic theory, this paper implements the Schwartz-Moon model relying on externally available historical accounting information and benchmarks this implementation against a common multiple valuation approach on around 30,000 technology firm quarter observations for the period of 1992 to 2009. The implementation we suggest is both sensible and robust and therefore broadly applicable. Given the 22 input parameters of the Schwartz-Moon model, it is clear that there are multiple ways to implement the model. Changing the estimation of the input parameters naturally changes the results. However, we think our implementation based on economic theory is reasonable and intuitive. Further, it only relies on seven critical parameters estimated from the financial statements, thereby reducing the model's complexity. Moreover, in the robustness section we show that varying the input parameters at a range of ten percent does not change the results qualitatively. Hence, this paper is a plausible first step to extent this line of research.

Our results are as follows. Primarily, we find that the Schwartz-Moon model performs overall nearly as accurate as the Enterprise-Value-Sales Multiple concerning market values in our implementation. On industry levels, however, there are differences with chemicals and computer firms having significantly lower deviations for the Schwartz-Moon model. Additionally, it is closer to observed market values for smaller firms measured by total assets and can be employed for non-listed firms. Thus, while for "standard" firms with positive earnings and publicly listed equity common valuation methods as the multiples might exhibit higher accuracy, the Schwartz-Moon model can be considered as method to value firms that deviate from these "standards" and also allows privately owned firms to be valued. Overall, this accuracy perspective with respect to market values can be considered as an overall feasibility check, which our model implementation passes. Second and most importantly, the Schwartz-Moon model shows the ability to indicate severe mispricing by the market as it both pictures the overvaluation during the dot-com bubble and the undervaluation during the 2008 financial crisis due to the overreaction by the markets. We support this finding by forming a highly profitable trading strategy on buying undervalued and selling overvalued stocks. Given the theoretical advantages, the empirical results and its fundamental perspective, we conclude that the Schwartz-Moon model for once can be seen as supplement that can help to provide fundamental value estimates as anchor during times of overoptimistic or overpessimistic technology market sentiment.

After testing the original model in this paper, future research could investigate several possible extensions. First, as technology growth firms also mature, dividends can play a role.[15] Therefore dividends could be included as fraction of earnings or a complete dividend policy could be defined. One first approach for approximately 80 observations can be found in Dubreuille et al. (2011), however having established how the original Schwartz-Moon model performs on more than 29,000 observations seems to be a necessary and logical first step. Second, future research might also look at taxes in more detail and consider tax shields as they affect firm values (see, e.g. Husmann et al. 2002, 2006, Ballwieser 2011, Drukarczyk/Schüler 2007 and Kruschwitz/Löffler 2005). Finally, the Schwartz-Moon model also represents well the increased frequency of defaults around the dot-com bubble. Consequently, its performance as a credit risk model should be explored in future research.

Endnotes

[1] Wall Street Journal (05/17/12): Facebook Prices IPO at Record Value.

[2] Reuters (11/04/11): Groupon's IPO biggest by U.S. Web company since Google. Wall Street Journal (01/17/12): Zynga Chief Talks IPO, Lessons Learned. Wall Street Journal (06/11/11): Pandora Raises IPO's Size.

[3] There are five more recent working papers on the Schwartz-Moon model which demonstrate the interest in the model. Dubreuille et al. (2011) and Baek et al. (2009) look at the valuations of IT firms, however, they use small samples of 76 and 6 observations, respectively. Moreover, they only cover one single year, i.e. 2003 and 2009, respectively. Ehrhardt/Merlaud (2004) and Baek et al. (2004) have even smaller samples with 3 and 1 firms only. Baule/Tallau (2009) have a different focus as they investigate the use of the Schwartz-Moon model in the context of option markets. They also have a very small sample of 3 firms and cover only the years 2003 to 2006. Consequently, none of these studies offers a test of the original model on a large cross section of firms and over a longer time period.

[4] In fact, taking a closer look at recent valuation model accuracy studies such as Liu et al. (2002) or Bhojraj/Lee (2002), most of them exclude all firms that do not fulfill criteria such as positive earnings, analyst coverage, share price larger than $3 and minimum sales of $100 million.

[5] Requiring basic analyst data as 1-year-, 2-year-ahead sales and gross margin forecasts for our sample firms would reduce our sample by over 60%.

[6] Wall Street Journal (12/27/99): Analyst Discovers the Order in Internet Stocks Valuation.

[7] For a controversial debate on the effect of default risk on firm value we refer to Homburg et al. (2004, 2005), Kruschwitz et al. (2005) and Rapp (2006).

[8] Assuming exponential decay, the half-life can be derived by solving the following equation for t_h: $e^{-\kappa t_h} = \frac{1}{2}$.

[9] These parameters are the long term variable costs, the long term volatility of variable costs, the capital expenditure rate and the depreciation rate.

[10] We start with the first quarter 1992 since we need eight quarters of accounting information from 1990; since then data availability is reasonably complete for all required items. Moreover, it sufficiently covers the inception of the industry as well as the peak and burst of the dot com bubble as described in Bhattacharya et al. (2010).

[11] Additionally, we considered market capitalization two and three-months following the date the financial statements refers to as well as mean values over six months following this date. Our results are not influenced by this decision.

[12] We allow stocks to enter the portfolio even if they are already invested in. Restricting the multiple inclusion reduces the reported abnormal returns only slightly.

[13] We thank an anonymous referee for this suggestion.

[14] We also re-estimated all specifications employing linear feasible general least squares estimators and results (unreported, but available up on request) are qualitatively the same.

[15] We thank an anonymous referee for this suggestion.

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Appendix 1

Variable Definitions

No.	Label		Description	Measurement (abbreviations are Compustat mnemonics)
	critical parameters			
1	μ_0	=	initial growth rate of revenues	$=\frac{1}{7}\sum_{t=0}^{-6}\ln(\text{saleq}_t/\text{saleq}_{t-1})$
2	η_0	=	initial volatility of the sales growth rate	$=\sqrt{\frac{1}{n-1}\sum_{j=0}^{t}(\widehat{\varepsilon_{t-j}}-\bar{\varepsilon})^2}$, where $\widehat{\varepsilon_j}$ are the estimated residuals of the AR(1) process: $\mu_t=\alpha+\beta\mu_{t-1}+\varepsilon_t$
3	φ_0	=	initial volatility of variable costs	$=\sqrt{\frac{1}{n-1}\sum_{j=0}^{t}(\widehat{\varepsilon_{t-j}}-\bar{\varepsilon})^2}$, where $\widehat{\varepsilon_j}$ are the estimated residuals of an AR(1) process on the cost rate c=(cogsq+xsgaq)/saleq: $c_t=\alpha+\beta c_{t-1}+\varepsilon_t$
4	γ_0	=	initial variable cost	$=\frac{1}{8}\sum_{t=0}^{-7}\frac{cogsq_t+xsgaq_t}{saleq_t}$
5	$\bar{\mu}$	=	long term sales growth rate	= 0.0075
6	$\bar{\gamma}$	=	industry median long term variable cost	$=median_{sic3}\sum_{t=1970}^{T}\frac{cogs_t+xsga_t}{sale_t},\ for\ T=1992,\dots,2009$
7	κ	=	speed of adjustment	$=median_{sic2}\left(-\frac{1}{4}\ln\left(\sum_{t-5}^{t-8}\frac{saleq_t-saleq_{t-1}}{saleq_{t-1}}/\sum_{t-1}^{t-4}\frac{saleq_t-saleq_{t-1}}{saleq_{t-1}}\right)\right)$
	uncritical parameters			
8	R	=	revenues	= saleq
9	X	=	cash and cash equivalents	= cheq + rectq + acoq + tstkq – apq
10	L	=	loss carry forward	= tlcf
11	P	=	property, plant and equipment	= ppent + aoq
12	σ_0	=	initial sales volatility	$=\sqrt{\frac{1}{7}\sum_{t=0}^{-7}\left(\frac{saleq_t-saleq_{t-1}}{saleq_{t-1}}-\mu_0\right)^2}$
13	$\bar{\sigma}$	=	long term volatility	= 0.05
14	$\bar{\varphi}$	=	industry median long term volatility of variable costs	$=median_{sic3}\left(std_{t=1970}^{T}\left(\frac{cogs_t+xsga_t}{sale_t}\right)\right),for\ T=1992,\dots,2009$
15	F	=	fix costs	= 0
16	cr	=	industry median capital expenditure rate	$=median_{sic3}{}_{t=1970}^{T}\left(\frac{capx_t}{sale_t}\right),\ for\ T=1992,\dots,2009$
17	dp	=	industry median depreciation rate	$=median_{sic3}{}_{t=1970}^{T}\left(\frac{dp_t}{ppent_t+ao_t}\right),\ for\ T=1992,\dots,2009$

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(Variable Definitions continued)

No.	Label	Description	Measurement
18	τ	= tax rate	= 0.35
19	r_f	= risk free rate	$= \sqrt[4]{(1+0.055)} - 1 = 0.0135$
20	λ_R	= risk premium sales	$= \rho_{r_M,sales} \cdot \sigma_{r_M} = \frac{Cov(r_M,sales)}{\sigma_{sales}}$
21	λ_μ	= risk premium sales growth	$= \rho_{r_M,\mu} \cdot \sigma_{r_M} = \frac{Cov(r_M,\mu)}{\sigma_\mu}$
22	λ_γ	= risk premium variable costs	$= \rho_{r_M,\gamma} \cdot \sigma_{r_M} = \frac{Cov(r_M,\gamma)}{\sigma_\gamma}$
	M	= terminal value multiple	= 10
	EV_t	= company (entity) value	$= price \cdot shrout + dlttq + dlcq$
	$RNOA_t$	= return on net operating assets	$= \frac{\sum_{t=1}^{-4} EBITQ_t}{ppentq+actq-lctq}$

Data Sources

COMPUSTAT

Quarterly data (q)			Annual data (a)		
item number	mne-monic	description	item number	mne-monic	description
#1	xsgaq	Selling, General, and Administrative Expenses	#8	ppent	PP&E (Net) – Total
#2	saleq	Sales (Net)	#12	sale	Sales (Net)
#5	dpq	Depreciation and Amortization	#14	dp	Depreciation and Amortization
#21	oibdpq	Operating Income Before Depreciation (EBITDA)	#41	cogs	Cost of Goods Sold
#30	cogsq	Cost of Goods Sold	#52	tlcf	Tax Loss Carry Forward
#36	cheq	Cash and Equivalents	#69	ao	Assets – Other
#37	rectq	Receivables - Total	#128	capx	Capital Expenditures
#39	acoq	Current Assets - Other	#189	xsga	Selling, General, and Administrative Expenses
#40	actq	Current Assets - Total			
#42	ppentq	PP&E (Net) - Total			
#43	aoq	Assets - Other			
#44	atq	Assets - Total			
#45	dlcq	Debt in Current Liabilities			
#46	apq	Accounts Payable			
#49	lctq	Current Liabilities - Total			
#51	dlttq	Long-Term Debt - Total			
#54	ltq	Liabilities - Total			
#58	req	Retained Earnings - Quarterly			
#59	ceqq	Common Equity - Total			
#69	niq	Net Income (Loss)			
#98	tstkq	Treasury Stock - Dollar Amount - Total			

CRSP

Monthly data		
n.a.	price	stock price (adjusted for stock splits etc.)
n.a.	shrout	shares outstanding (adjusted for stock splits etc.)

Table 1: Sample selection procedure

	Description	Time Period	Observations (Firm Quarters)	No. of firms (Compustat identifier: GVKEY)
1	Firm-quarter observations on the intersection of COMPUSTAT and CRSP	1961Q1-2009Q4	940,513	22,904
2	drop observations with changing fiscal years or duplicates in terms of NPERMNO (unique identifier from the CRSP database) and date or GVKEY (unique identifier from the COMPUSTAT database) and date	1961Q1-2009Q4	-13,726 =926,787	22,904
3	drop observations with missing market data from CRSP	1961Q4-2009Q4	-20,100 =906,687	22,894
4	drop observations that are not within the extended Bhojraj/Lee (2002) SIC code definition	1961Q4-2009Q4	-751,686 =155,001	5,276
5	drop observations, where relevant items* are negative	1971Q1-2009Q4	- 63,223 =91,778	3,779
6	keep data within time span	1992Q1-2009Q4	-19,410 =72,368	3,363
7	drop observations with missing data for the Schwartz-Moon input parameter	1992Q1-2009Q4	-42,891 =29,477	2,262

This table shows the sample selection procedure. We use the quarterly CRSP/Compustat merged database in order to obtain our sample. Thus, all accounting items are from the quarterly Compustat database, with few exceptions such as loss carry forwards which are only available on a yearly basis. These yearly data items are obtained from the Compustat Annual data files. All market data, i.e., prices and shares outstanding, were obtained from the monthly CRSP database. Market data from CRSP is used four month after the fiscal year quarter for each company to ensure, that market prices incorporate the last available accounting information. We use the high technology industry SIC code definition of Bhojraj and Lee (2002) in this study. That is biotechnology SIC codes (2833-2836 and 8731-8734), computer SIC Codes (3570-3577 and 7371-7379), electronics (3600-3674) and telecommunication (4810-4841) extended in this paper by SIC code 7370. The considered time span ranges from Q1 1992 to Q4 2009.

* These items -stated as Compustat mnemonics- are: acoq aoq apq capxy cheq cogsq tlcf dlcq dlttq dpq ppentq rectq saleq tstkq xsgaq.

Table 2: Summary statistics

Panel A: Industry Distribution	**Biotechnology**		**Computers**		**Electronics**		**Telecom**	**Total**
# obs.	5,282		11,813		9,217		3,165	29,477
%	18%		40%		31%		11%	100%
Panel B: Financial statement information	**Mean**	**Median**	**q25%**	**q75%**	**IQ-Range**	**Min**	**Max**	**% negative obs.**
Revenues	1,822.15	141.98	46.10	566.37	520.27	0.05	125,760.56	0%
Cash and Cash Equivalents	792.87	71.76	18.36	278.37	260.00	-2,202.75	120,248.00	1%
Total Assets	2,696.26	169.74	49.91	831.83	781.92	0.68	284,528.00	0%
Leverage	17%	7%	0%	25%	25%	0%	2764%	0%
Earnings	133.46	3.83	-3.46	32.86	36.32	-56,329.70	19,337.00	34%
EBIT	261.08	8.28	-0.71	62.49	63.20	-5,378.40	23,910.00	28%
Panel C: Key ratios	**Mean**	**Median**	**q25%**	**q75%**	**IQ-Range**	**Min**	**Max**	
Annual Sales Growth	29%	19%	9%	36%	27%	0%	1373%	-
Initial Variable Cost Ratio	91%	88%	79%	96%	17%	62%	150%	-
Long Term Variable Cost Ratio	91%	91%	88%	95%	6%	85%	98%	-
Long Term Annual Revenue Growth	3%	3%	3%	3%	0%	3%	3%	-
Initial Volatility of Revenues Growth Rate	7%	5%	3%	9%	6%	1%	22%	-
Initial Volatility of Variable Cost Ratio	17%	8%	4%	17%	13%	2%	93%	-
Speed of Convergence	0.17	0.16	0.14	0.19	0.06	0.08	0.31	-
Panel D: Market values	**Mean**	**Median**	**q25%**	**q75%**	**IQ-Range**	**Min**	**Max**	
Market Capitalization	3,991.63	267.82	67.79	1,147.09	1,079.31	0.26	505,037.44	-
Enterprise Value	4,606.48	320.69	80.89	1,445.86	1,364.97	0.28	505,037.44	-

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(Table 2 continued)

This table reports summary statistics for a sample of 29,477 technology firm quarter observations. Panel A reports the sample's industry distribution according to Bhojraj/Lee (2002) with SIC codes in parentheses: biotechnology (2833-2836 and 8731-8734), computers (3570-3577 and 7370-7379), electronics (3600-3674) and telecommunications (4810-4841). Note that we add SIC code 7370 to their sample definition. Panel B reports financial statement information. All financial statement items are on a quarterly basis (q) unless stated otherwise as annual items (a) in appendix 1. Note that quarterly flow figures are aggregated to meaningful yearly figures. Thus, each observation contains the sum of the last four quarter values. COMPUSTAT item mnemonics are given in parenthesis. All values are given in million $ except of percentages denoted as %. Revenues are given by sales (saleq) and are annualized. Cash and cash equivalents is calculated as the sum of cash (cheq), receivables total (rectq), current assets other (acoq) and treasury stocks (tstkq) minus accounts payable (apq). Total assets is the balance sheet total (atq). Leverage is calculated as interest bearing debt, which is the sum of debt in current liabilities (dlcq) and long term debt (dlttq), divided by total assets (atq). Earnings are defined as net income/loss (niq) and EBIT is operating income (oibdpq) after depreciation (dpq). Panel C reports key ratios. Annual sales growth is the annualized growth rate of the current quarter. The initial variable cost ratio is measured by the mean of the ratio of costs of goods sold (cogsq) plus selling, general, and administrative expenses (xsgaq) divided by sales (saleq). Long term variable cost ratio is calculated using a growing window approach based on three digit SIC code industry classification beginning in 1970 and until the most recent quarter. The long term annual growth rate of revenues is set to 3%. The initial volatility of revenue growth rates is determined from the standard deviation of the residuals from an AR(1) regression of the growth rates. Analogously, the initial volatility of the variable cost ratio is determined from the AR(1) regression residuals of the cost ratios. The speed of convergence parameters result from the convergence of the previous eight quarterly sales data points as presented in appendix 1. Panel D reports market data. Market capitalization is calculated from CRSP as price times shares outstanding. Enterprise value is the sum of market capitalization, long term debt (dlttq) and debt in current liabilities (dlcq).

Table 3: Deviations from market values

	Deviations		
Panel A	**Absolute log deviations**		
	EV-Sales	Schwartz-Moon	delta
Median	0.59	0.63	-0.04***
IQ-Range	0.78	0.81	
90%-10%	1.48	1.53	
95%-5%	1.92	1.96	
Mean	0.75	0.78	
Standard deviation	0.64	0.67	
>100%	0.27	0.29	
Panel B	**Absolute percentage deviations**		
Median	0.54	0.56	-0.02***
IQ-Range	0.66	0.57	
90%-10%	2.31	1.75	
95%-5%	3.94	3.06	
Mean	1.16	1.40	
Standard deviation	4.74	27.78	
>100%	0.23	0.18	
N	29,477	29,477	

This table reports the distribution of deviations from observed market values for various prediction measures. Panel A reports absolute log deviations, defined as the absolute logarithm of the ratio of the estimated value to the market value. Panel B reports absolute percentage deviations. Absolute percentage deviation is the absolute difference between actual and model predicted price, scaled by the actual price. The table values represent the median, the inter-quartile range (IQ-Range), 90th-percentile minus 10th-percentile (90%-10%), the 95th-percentile minus 5th-percentile (95%-15%), the mean, standard deviation and the percentage of deviations larger than 100% (>100%). The delta column represents the difference which is tested for significance with the Wilcoxon sign rank test. One/ two/ three asterisks represent significance at the 10%/ 5% / 1% level.

Table 4: Deviations by industry classification and firm size

		Median absolute log deviations			
Panel A: by 2 digit SIC codes					
	Industry	EV-Sales	Schwartz-Moon	delta	# obs.
28	chemicals	0.62	0.52	0.11***	3,799
35	computer (hardware)	0.65	0.53	0.11***	3,272
36	electronics	0.56	0.57	-0.01*	9,217
48	telecommunication	0.47	1.00	-0.53***	3,165
73	computer (software)	0.61	0.59	0.02***	8,541
87	biological research	0.70	1.49	-0.80***	1,483
Total		0.59	0.63	-0.04***	29,477
Panel B: by firm size classification					
0 - 25%		0.72	0.70	0.03**	7,370
26% - 50%		0.62	0.61	0.01*	7,369
51% -75 %		0.54	0.56	-0.02*	7,369
76% - 100%		0.50	0.64	-0.15***	7,369
Total		0.59	0.63	-0.04***	29,477

This table reports the distribution of median log deviations, defined as the absolute logarithm of the ratio of the estimated value to the market value for firms. Panel A reports absolute log deviations for firms according to their two digit SIC code. Panel B reports absolute log deviations by firm size quartile. Firm size is measured by total assets (Compustat item: atq). The delta column represents the difference which is tested for significance with the Wilcoxon sign rank test. One/ two/ three asterisks represent significance at the 10%/ 5% / 1% level.

Table 5: Trading Strategy

Panel A: Abnormal Returns before Transaction Costs

			12 months	24 months	36 months
fixed	long	monthly abn. Ret	1.19%	1.05%	0.92%
		t-statistic	(2.34)***	(2.05)**	(1.82)*
	short	monthly abn. Ret	0.46%	0.40%	0.42%
		t-statistic	(0.79)	(0.70)	(0.76)
quintiles	long	monthly abn. Ret	1.16%	1.07%	0.92%
		t-statistic	(2.27)**	(2.12)**	(1.83)*
	short	monthly abn. Ret	0.36%	0.39%	0.42%
		t-statistic	(0.60)	(0.68)	(0.74)

Panel B: Abnormal Returns after Transaction Costs

			12 months	24 months	36 months
fixed	long	monthly abn. Ret	1.03%	0.98%	0.88%
		t-statistic	(2.04)**	(1.92)*	(1.74)*
	short	monthly abn. Ret	0.34%	0.34%	0.39%
		t-statistic	(0.59)	(0.61)	(0.70)
quintiles	long	monthly abn. Ret	0.99%	1.00%	0.88%
		t-statistic	(1.94)*	(1.99)**	(1.75)*
	short	monthly abn. Ret	0.24%	0.34%	0.39%
		t-statistic	(0.41)	(0.59)	(0.68)

This table presents the results for a long (short) trading strategy for undervalued (overvalued) stocks identified by the Schwartz-Moon model. Every quarter stocks enter the portfolio for a predefined time span of 1, 2 and 3 years due to the Schwartz-Moon model. The "fixed" column represents a trading strategy based on an over- or undervaluation of more than 50%. For the "quintiles" column the stocks are sorted into quintiles every quarter according to the misvaluation predicted by the Schwartz-Moon model. The most undervalued (overvalued) quintile is then invested in (sold short). The portfolios assume a 1$ investment in every stock and stocks can enter the portfolio multiple times. For these portfolios Panel A shows the intercept in basis points from a regression of the monthly portfolio excess return on the four factors of Carhart (1997) for the period 1992 to 2009 (*N*=216). Further, it shows the t-statistics of these intercepts and the t-statistic of the difference of the portfolio returns. The "short" portfolios assume short positions, thus trading profits are represented by positive alphas. Panel B displays the abnormal returns after transaction costs by using the results of Keim/Madhaven (1998). We use heteroskedasticity-robust standard errors. One/ two/ three asterisks represent significance at the 10%/ 5% / 1% level.

Table 6: Model implied default probability

Default rates

	Schwartz-Moon
Median	29%
Mean	35%
Standard deviation	29%
Zero default obs.	492
All default obs.	256

This table reports summary statistics of model implied default rates for 29,477 firm quarter observations for the Schwartz-Moon model. Median, mean, and standard deviation values are obtained by the ratio between defaulted simulation paths and 10,000, the total number of simulations per firm quarter. Zero/All default obs. reports observations in which the respective model predicted no/complete failure in all simulation paths.

Table 7: Sensitivity Analysis

			Median	IQ-Range	Mean	Std Dev	Median	IQ-Range	Mean	Std Dev
		abs log dev	0.63	0.81	0.78	0.67	0.63	0.81	0.78	0.67
0	**baseline**	abs rel dev	0.56	0.57	1.40	27.78	0.56	0.57	1.40	27.78
		prob of def	0.29	0.42	0.35	0.29	0.29	0.42	0.35	0.29
				+10%				**-10%**		
		abs log dev	0.63	0.82	0.78	0.67	0.63	0.82	0.78	0.67
I	initial growth rate of revenues	abs rel dev	0.56	0.58	1.52	34.43	0.56	0.56	1.30	22.59
		prob of def	0.30	0.44	0.35	0.29	0.29	0.43	0.34	0.29
		abs log dev	0.63	0.81	0.78	0.67	0.63	0.81	0.78	0.67
II	volatility of revenues growth rate	abs rel dev	0.56	0.57	1.39	27.56	0.56	0.57	1.41	28.05
		prob of def	0.29	0.44	0.35	0.29	0.30	0.44	0.35	0.29
		abs log dev	0.62	0.82	0.79	0.69	0.63	0.82	0.79	0.66
III	initial variable cost	abs rel dev	0.54	0.53	1.23	25.40	0.57	0.61	1.57	29.13
		prob of def	0.36	0.49	0.40	0.30	0.24	0.40	0.31	0.28
		abs log dev	0.62	0.81	0.78	0.66	0.63	0.82	0.79	0.68
IV	initial volatility of variable cost	abs rel dev	0.55	0.57	1.40	27.07	0.56	0.57	1.40	27.92
		prob of def	0.30	0.44	0.35	0.29	0.29	0.44	0.35	0.29
		abs log dev	0.63	0.82	0.78	0.67	0.62	0.81	0.78	0.67
V	long term revenue growth	abs rel dev	0.56	0.58	1.45	29.13	0.55	0.56	1.35	26.52
		prob of def	0.30	0.44	0.35	0.29	0.29	0.44	0.35	0.29
		abs log dev	1.56	1.15	1.64	0.91	0.81	0.98	0.95	0.75
VI	long term costs	abs rel dev	0.80	0.25	0.91	7.61	0.89	2.21	3.37	56.56
		prob of def	0.74	0.33	0.68	0.24	0.06	0.25	0.17	0.24

(continued on next page)

(Table 7 continued)

VII	speed of convergence	abs log dev	0.63	0.82	0.78	0.66	0.62	0.82	0.79	0.70
		abs rel dev	0.56	0.56	1.03	7.32	0.56	0.59	3.66	191.67
		prob of def	0.27	0.45	0.33	0.29	0.32	0.43	0.37	0.28
VIII	interest rate	abs log dev	0.62	0.81	0.78	0.67	0.63	0.82	0.79	0.67
		abs rel dev	0.55	0.55	1.30	25.05	0.57	0.59	1.52	30.88
		prob of def	0.28	0.44	0.34	0.29	0.31	0.44	0.36	0.29
IX	terminal value multiple	abs log dev	0.63	0.82	0.78	0.67	0.63	0.81	0.78	0.67
		abs rel dev	0.56	0.58	1.45	28.72	0.55	0.56	1.35	26.85
		prob of def	0.29	0.44	0.35	0.29	0.29	0.44	0.35	0.29

This table reports summary statistics for the sensitivity of the absolute log deviation (abs log dev), the absolute relative deviation (abs rel dev) and the probability of default (prob of def) for a +/- 10% change of parameters. The table values represent the median, the inter-quartile range (IQ-Range), the mean and the standard deviation of the three measures. The first row gives the baseline case as means of comparison. In the nine following rows the corresponding input parameter is first increased by 10% to calculate the Schwartz-Moon results. The same procedure is then performed for a 10% decrease. All items such as initial growth rate of revenues are explained in appendix 1.

Table 8: Regression Analysis

Industry/Size		Type	Coefficient	Constant	No. of obs.	Overall R^2 (fixed effects)/ Adj. R^2 (rank regression)	Prob. > F
Panel A							
28	chemicals	Fixed Effects	0.12***	21.66***	3,799	0.18	0.00
		Rank Regression	0.90***	388.93***	3,799	0.83	0.00
35	computer (hardware)	Fixed Effects	0.13***	16.33***	3,272	0.38	0.00
		Rank Regression	0.93***	21.02***	3,272	0.86	0.00
36	electronics	Fixed Effects	0.19***	15.85***	9,217	0.45	0.00
		Rank Regression	0.96***	-1222.46**	9,217	0.84	0.00
48	telecommunica-tion	Fixed Effects	0.10***	39.01***	3,165	0.30	0.00
		Rank Regression	0.77***	6058.77***	3,165	0.74	0.00
73	computer (software)	Fixed Effects	0.08***	16.63***	8,541	0.16	0.00
		Rank Regression	0.92***	1800.03***	8,541	0.80	0.00
87	biological research	Fixed Effects	0.12***	19.67***	1,483	0.17	0.01
		Rank Regression	0.79***	6486.30***	1,483	0.66	0.00
all		Fixed Effects	0.13***	20.02***	29,477	0.32	0.00
		Rank Regression	0.89***	1676.00***	29,477	0.79	0.00
Panel B							
0 - 25%		Fixed Effects	0.04***	6.40***	7,370	0.07	0.00
		Rank Regression	0.40***	2835.11***	7,370	0.15	0.00
26% - 50%		Fixed Effects	0.04***	13.40***	7,369	0.05	0.00
		Rank Regression	0.30***	7712.83***	7,369	0.09	0.00
51 - 75%		Fixed Effects	0.09***	23.14***	7,369	0.12	0.00
		Rank Regression	0.42***	10363.46***	7,369	0.20	0.00
76% - 100%		Fixed Effects	0.14***	39.12***	7,369	0.33	0.00
		Rank Regression	0.54***	11680.79***	7,369	0.34	0.00
all		Fixed Effects	0.13***	20.02***	29,477	0.32	0.00
		Rank Regression	0.89***	1676.00***	29,477	0.79	0.00

This table reports the results of a fixed effects regression and a rank regression of observed firm value on predicted firm value including a constant. We choose the fixed effects specification after rejecting the random effects model based on a Hausman test ($p<0.01$). In addition, the fixed effects model is also preferred to a pooled OLS estimate after performing an F-test on the firm fixed effects, which are significantly different from zero. The fixed effects regressions are performed on a per share basis and take time and firm cluster effects into account as in Petersen (2009). Adjusted R^2 is reported for the rank regression, while the overall R^2 shows model fit in case of the fixed effect estimates. The rank OLS regressions are performed on market values consistent with Iman/Conover (1979). Panel A presents regressions which are performed per two digit SIC industry classification. Panel B shows the results per size quartile, which is measured by total assets. One/ two/ three asterisks represent significance at a 10%/ 5%/ 1% level.

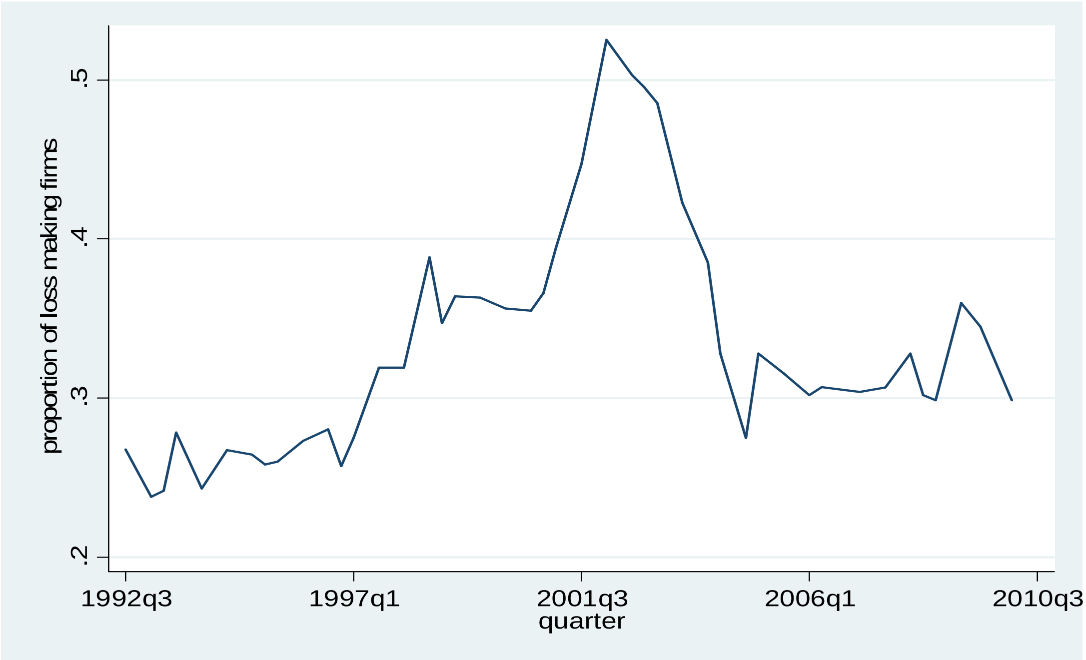
Figure 1: Income statement illustration

Income statement for time span ended at time t	
Revenues	(R)
- Costs	(C)
- Depreciation	(D)
- Tax	(tax)
= Net income	(Y)

Figure 2: Balance sheet illustration

<table>
<tr><td colspan="2">Balance Sheet at time t</td></tr>
<tr><td>Property, Plant & Equipment (PPE)</td><td rowspan="2">Equity</td></tr>
<tr><td rowspan="2">Cash (X)</td></tr>
<tr><td>Debt</td></tr>
<tr><td>Total Assets</td><td>Liabilities and Stockholders' Equity</td></tr>
</table>

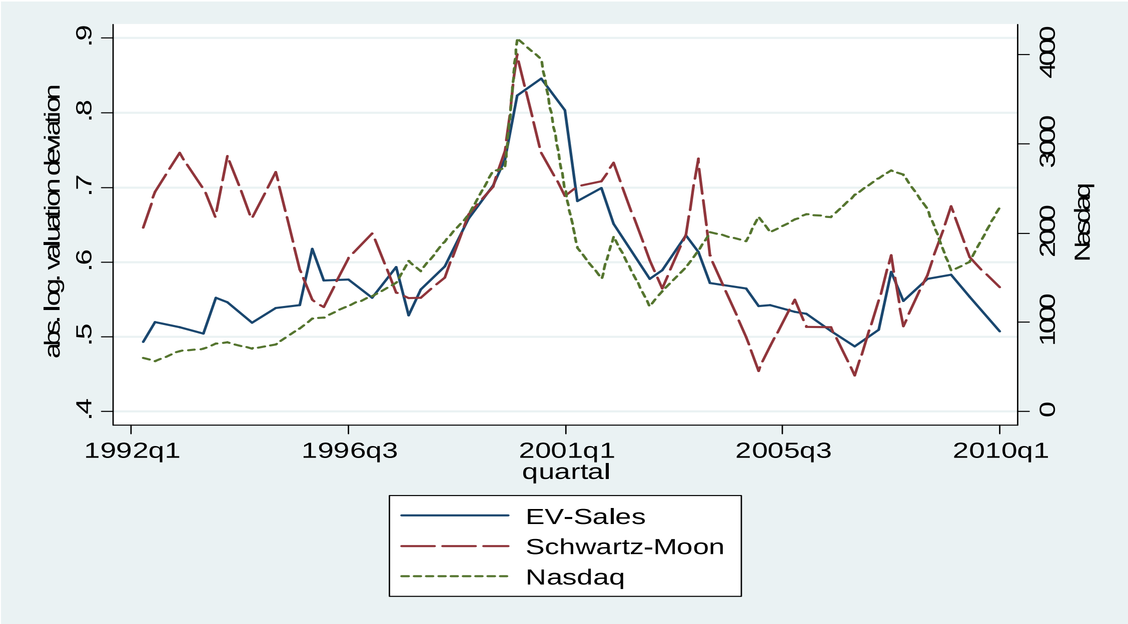
Figure 3: Proportion of loss making firms over time



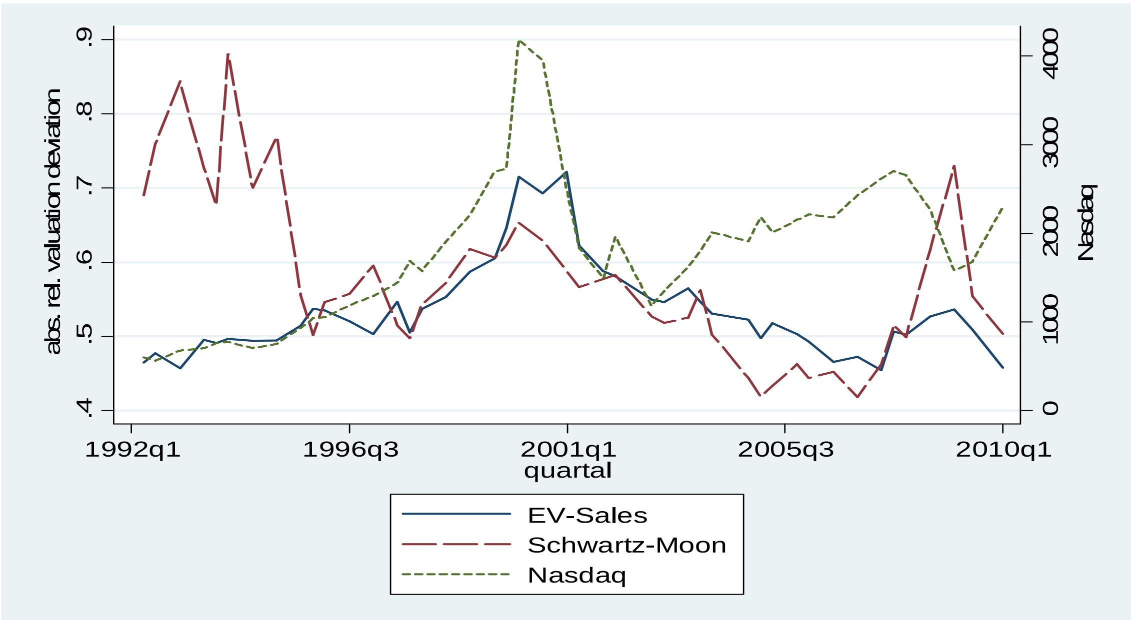
This figure shows the proportion of loss making firms per quarter in our sample for the time period 1992 to 2009. Therefore, for every quarter the firm quarters with negative earnings are divided by the total number of firm quarter observations in that quarter.

Figure 4: Quarterly median absolute deviations

Panel A: Quarterly absolute log deviations



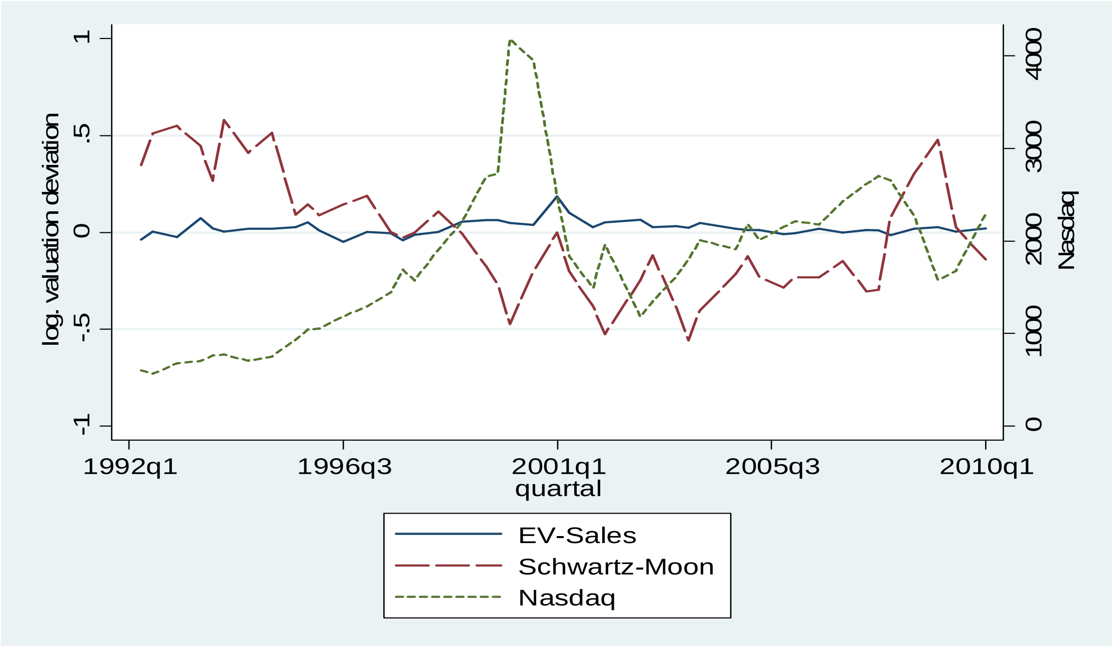
Panel B: Quarterly absolute percentage deviations



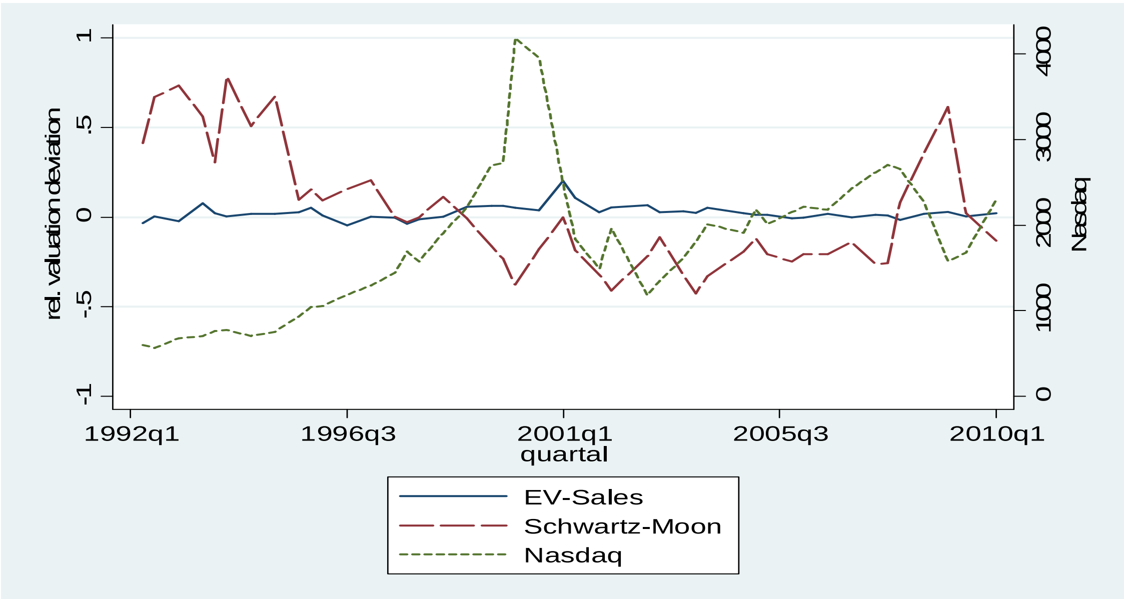
This figure shows quarterly median valuation deviations spanning the time 1992 until 2009. Panel A reports median absolute log deviations defined as the absolute logarithm of the ratio of the estimated value to the market value. Panel B reports median absolute relative deviations which is the absolute difference between actual and model predicted value, scaled by the actual value. The blue, solid line reports deviations for the Enterprise-Value-Sales-Multiple. The red, dashed line reports deviations for the Schwartz-Moon model. The green, dashed-dotted line reports the Nasdaq Composite as benchmark.

Figure 5: Quarterly median non-absolute deviations

Panel A: Quarterly log deviations

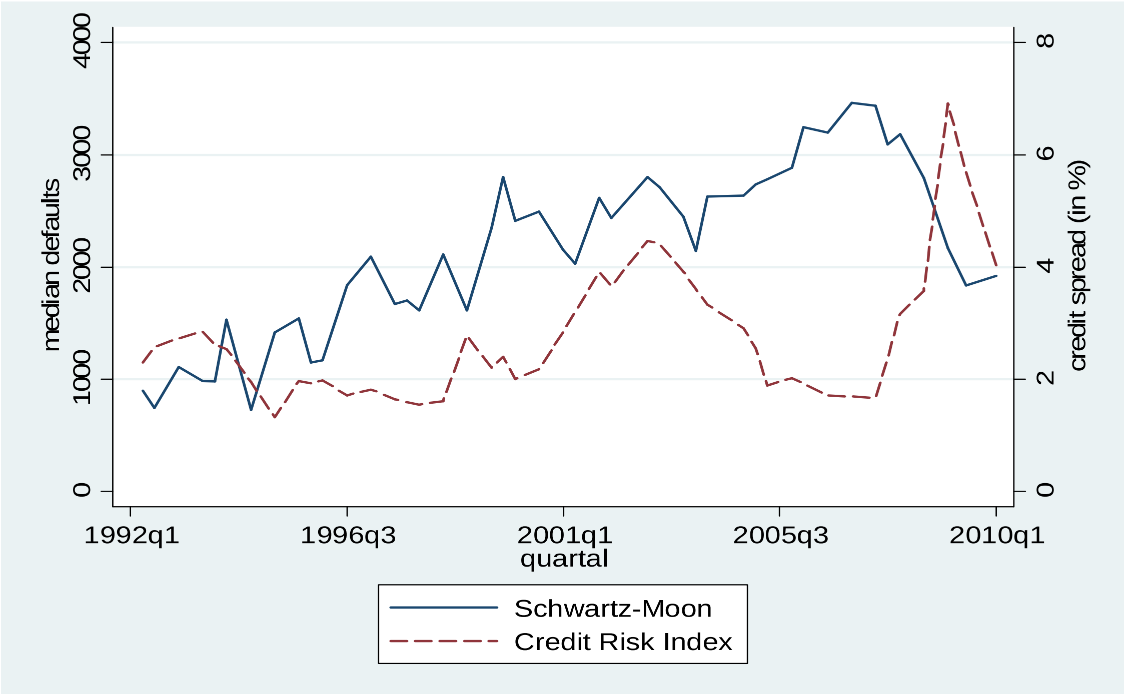


Panel B: Quarterly percentage deviations



This figure shows quarterly median deviations spanning the time 1992 until 2009. Panel A reports median log deviations defined as the logarithm of the ratio of the estimated value to the market value. Panel B reports median relative deviations which is the difference between actual and model predicted value, scaled by the actual value. The blue, solid line reports deviations for the Enterprise-Value-Sales-Multiple. The red, dashed line reports deviations for the Schwartz-Moon model. The green, dashed-dotted line reports the Nasdaq Composite as benchmark.

Figure 6: Median quarterly defaults



This figure shows quarterly median predicted defaults per 10,000 simulation runs spanning the time 1992 until 2009. The blue, solid line reports defaults predicted by the Schwartz-Moon model. The red, dashed line reports the credit spread between Moody's Seasoned Baa Corporate Bond Yield and U.S. 5-year treasury securities in percentage points as benchmark.