A MODEL TO MEASURE PORTFOLIO RISKS IN VENTURE CAPITAL

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Abstract
This study constructs and evaluates a risk model for the venture capital industry in which the CreditRisk$^+$ model is adjusted to calculate loss distributions for venture capital portfolios. A forward entry regression with macroeconomic factors as independent variables is used as the procedure to extract systematic factors for the sector analysis. The coefficient of determination R^2 divides the risk into one idiosyncratic risk factor and several systematic risk factors. Under the assumption that macroeconomic factors are independent, the improvement of the R^2 of each forward entry is considered as the weight of the entered factor. Further, under the assumption that all relevant systematic risk factors are incorporated in the model, the systematic risk is entirely explained. The remaining unexplained sample variance is considered the idiosyncratic risk.
The introduced risk model is empirically tested using a portfolio of venture capital financed companies. The database contains more than 2,000 European venture capital-backed companies over the period 1998–2004. The results are highly significant and show that the model is applicable to modelling portfolio risks for venture capital portfolios.
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1. Introduction

The dynamics of the relatively young venture capital market are not yet well understood, so risk assessment and objective performance measurements are difficult to employ. Convincing and generally accepted portfolio models for venture capital investments do not exist in theory or in practice. Broad implementation of a widely accepted risk model would enhance venture capital investments' transparency.

The aim of this study is to develop a practical portfolio model to measure the risks and diversification capabilities of venture capital portfolios. This paper analyzes which of the most common credit risk models can be adjusted to meet the needs of venture capital portfolios and shows that the CreditRisk$^+$ model best fits the needs to quantify risks. CreditRisk$^+$`s data requirements are lower than those for other risk models, the assumptions and parameters are most applicable to the special features in the venture capital market, and the model is easy to implement. The paper analyzes the required adjustments on a theoretical as well as on a practical level and quantifies the effects of correlation and diversification.

The model can be used to calculate the loss distribution for credits to venture capital backed companies. If the model is used to calculate loss distributions for portfolios of venture capital investments, the results can be only considered as the worst case scenario because they do not take into account earnings. To make reasonable investment decisions, it is necessary to estimate both. Due to the lack of accessibility to a representative database of credits to venture capital backed companies, the model is empirically tested using a portfolio of venture capital financed companies.

Section 2 presents some general aspects of the risk profile of venture capital investments and explains which of the most common credit risk models are most appropriate to be adjusted to quantify venture capital portfolios' risk. Section 3 describes the adjustments of the CreditRisk$^+$ model necessary to meet the needs of venture capital portfolios. How to calculate the input parameters is explained, and the sector model is presented. Section 4 describes the database. Section 5 contains the main results from the empirical analysis. Section 5.1 implements the constructed sector analysis model. The results are highly significant and show the predictability of the model. Section 5.2 evaluates the risk profile of venture capital portfolios. Four different default distributions based on different assumptions are calculated.

2. Towards a Risk Model in Venture Capital

2.1 Risk profile of venture capital

Venture capital funds have a higher risk than other more common investments, like shares or bonds, but this risk is compensated for through higher returns on average. They typically invest in young, innovative companies with high growth prospects but also with a relatively high probability to default. Because of these characteristics are common company valuation methods like the discounted cash flow valuation are not very meaningful.

In addition, unlike other investment types, venture capital-backed entrepreneurs do not have any—or, at best, relatively small—collateral. To compensate, venture capital managers have control rights and rights of determination in the companies in which they invest. The deep involvement of venture capital managers and their manifold contacts is very helpful and increases the probability of successfully breaking into a new market.

Despite the high risks, however, there is no convincing risk model for private equity in theory or in practice. As venture capital's risks can not be sufficiently quantified, investors are not able to optimize their investment decisions. An analysis of the portfolio risks enables a quantification of the correlations among the investments and, hence, an evaluation of their diversification capabilities. Probability distributions of potential losses enable a risk structure analysis and a calculation of maximal losses. Investment and divestment decisions can be optimized as they are made on a more objective basis.

Company-specific risks can be eliminated in a portfolio through diversification. If idiosyncratic risk can be priced, the price the entrepreneur receives decreases with the amount of idiosyncratic risk. As a result, if venture capital funds are able to diversify their portfolios more effectively, they should be willing to support riskier projects.[1]

Jones & Rhodes-Kropf (2003) found that idiosyncratic risk premiums are independent from fund investors' individual diversification capabilities. Venture capital funds can decrease idiosyncratic risks through diversification without decreasing received risk premiums. The resulting additional returns can be used to increase venture capital firms' and venture capital investors' profits, or to reduce demanded risk premiums. Hence, a better diversification facilitates more competitive fund proposals, which increase the ability to issue funds.

Jones & Rhodes-Kropf (2003) also determined that a more diversified venture capital investor can price more competitively because he does not need to be compensated as highly for the idiosyncratic risk. The early, successful funds should be able to continue to win the good deals which would lead to a strong persistence in returns (Kaplan & Schoar, 2003). This also suggests that, over time, there should be pressure for the industry to become more concentrated in spite of the principal agent problem. Early success would allow the funds to get larger as investors update their expectations of the venture capitalist's skill. Investors should be willing to trade off a greater principal-agent problem for a greater certainty that they have found a good venture capitalist and be willing to invest more. Larger funds will be more diversified and will, therefore, be able acquire good projects because they hold less idiosyncratic risk.

The fund management typically shares in funds' profits, which are called carried interests. A better risk-return structure through diversification increases funds' as well as fund managers' profits. Further, fund managers' communication of portfolio risks to their investors increases transparency, reduces asymmetrical information distribution and, hence, increases the venture capital firms' reputation. This makes the venture capital firm more attractive and increases its ability to raise money in a following financing round, as well as to issue a follow-on fund.

The more developed a venture capital industries' portfolio management in a country, the larger the amounts of idiosyncratic risks borne by the market, [2] the more attractive venture capital investments become for investors, and the more investments are made. Overall, countries which want to develop a venture capital industry may find that significant time and wealth is required before its venture capitalists become able to bear large amounts of idiosyncratic risks. Therefore, many governments support investments in venture capital through legislation or subsidized capital because they consider venture capital-backed companies, which are typically highly innovative, as growth factors in their economies.[3]

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[1] Jones/Rhodes-Kropf (2003), p.13, 26-27.

[2] See Jones/Rhodes-Kropf (2003), p.26-27.

[3] In Europe, this development is backed by government programs like tax-driven vehicles, subsidisation, and financial institutions which act like market players.

2.2 Analysis of risk models

The following section illustrates which of the common credit risk models is most appropriate for application to venture capital portfolios. The models are analyzed in terms of how their assumptions and data requirements fit the characteristics of venture capital in order to quantify venture capital portfolios' risks as realistically as possible. The standard approaches which are analyzed are CreditMetrics^{TM}, CreditRisk^{+}, CreditPortfolioView, and PortfolioManager^{TM}.[4] These models can be classified into asset value models and models based on default rates.[5]

The asset value models are developed from the 1974 Merton model, which regards credits as a put option on the company value. The most important models are CreditMetrics[6] and PortfolioManager.[7] An important aspect of these models is that they need continuous pricing and long time series of the investments to calculate migration matrices. Because the venture capital market is both young and illiquid, neither continuous pricing nor long track records are available. Finally, asset value models are not appropriate vehicles with which to model venture capital portfolios' risks.

Default rate-based models calculate credit defaults directly. Unlike asset value models, default rates are assumed to be exogenous and are derived from historical data. Correlations among default rates are incorporated by jointly shared systematic factors. The most important models are CreditPortfolioView[8] and CreditRisk^{+}[9] CreditPortfolioView estimates default rates through a regression model with macroeconomic factors as independent variables. The disadvantage of this approach is that migration matrices need to be calculated. Because the available data for venture capital funds is insufficient to calculate migration matrices, the model cannot be applied to determine risks for venture capital portfolios.

In comparison to other risk models, CreditRisk^{+} considers only events of default, not rating-grade changes. The general approach is designed to calculate a one-year default distribution, and correlations are incorporated indirectly, so a complex direct estimation is not required. The primary advantage of this model is its relatively low data requirements and the absence of the requirement to estimate migration matrices. Only default probability, default rate's standard deviation, sector classification, exposure, and recovery rates are needed to analyze the portfolio risks. The risk assessment takes place in a closed analytical form without complex simulations. The model is appropriate for illiquid portfolios, which are typical in the venture capital industry. In summary, the CreditRisk^{+} model has the capability to be adjusted for venture capital portfolios and is, therefore, chosen to be adjusted to analyze the risk profile of venture capital portfolios.

2.3 CreditRisk^{+}

In CreditRisk^{+} each obligor has one of two possible states at the end of the period: default or non-default. Default correlations are incorporated by K risk factors x. Conditional on x, it is assumed that defaults of individual obligors are independently distributed Bernoulli random variables. The conditional default probability $p_A(x)$ is a

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[4] As these models are widely described in literature, and as the focus of this paper is the modification and implementation of a portfolio model for venture capital, a comprehensive description of the models which do not fit the requirements is not undertaken. To get more general information about the models, see references like Caouett/Altman/Narayanan (1998), Ong, (2000), Crouhy/Galai/Mark (2000), Jarrow/Turnbull (2000), and Gordy (1998).

[5] See Wahrenburg/Niethen (2000), p. 237ff.

[6] See J.P. Morgan (1997).

[7] See Moody's Corporation (2005).

[8] See Wilson (1997c, d) and Wilson (1998).

[9] See Credit Suisse Financial Products (1997).

function of the realization of risk factors x, the vector of factor loadings w_{Ak} $(k=1,...,K)$, and the rating class $\zeta(A)$ of obligor A:[10]

$$p_A(x) = \overline{p}_{\zeta(A)}\left(\sum_{k=1}^{K} w_{Ak} x_k\right) \quad (1)$$

$\overline{p}_\zeta$ is the unconditional default probability for a rated ζ obligor. The risk factors are positive and have a mean of 1. The weights w_{Ak} quantify how sensitive obligor A is to each risk factor. The factor loadings for each obligor total 1 to guarantee that $E[p_A(x)] = \overline{p}_{\zeta(A)}$.

CreditRisk+ introduces three different approaches to model sector analysis.[11] It models default risk, not by calculating the default distribution directly, but by using the probability-generating function (pgf) to calculate the defaults.

3. A Risk Model for Venture Capital

3.1 Input parameters

The tool with which to estimate portfolio risks with CreditRisk+ in practice is a publicly provided VBA™ program from Credit Suisse Financial Products.[12] The program requires the following input parameters for each creditor in order to calculate portfolio risk: net-exposure, expected default rate, default-rate volatility, and the segmentation of the creditor's total risk in company-specific and systematic risk factors. Because CreditRisk+ calculates default rates for a single period, the incorporated parameters are determined for yearly observation periods, which equal the calendar year.

The expected default rate is calculated as the long-term average default rate $\overline{P}_k$ for all K sectors: $\overline{P}_k = \frac{1}{N}\sum_{A=1}^{N} I_{A,k} \quad with \quad I_A = \begin{cases} 1, & default \\ 0, & else \end{cases}$ (2)

A default is defined if all or part of the company is sold at loss or if the whole investment is a total loss with no sales revenues (total write-off). A loss occurs if the sales price is lower than the corresponding investment amount. If a company has more than one exit during the period for which the default rate distribution is calculated, the single results are added up. The final sum decides if it is a default or not.

The default probability equals the expectation of I, and the variance can be calculated as $Var(I_A) = E\left[(I_A - E(I_A))^2\right] = p_A(1-p_A) \quad with \quad p_A = P(I_A = 1)$ (3)

Because of the relatively short history of our database, the calculation of the default rate volatility is based on a seven-year period, which is not an adequate time frame with which to calculate the default rate volatility. If the default rates are very small, they can be used as a proxy for the volatility: $Var(I_A) = p_A$. Therefore, this model uses default rates as an estimator for default rate volatility.[13]

[10] In CreditRisk+ – Technical Document are the conditional probabilities given by $p_i(x) = \overline{p}_{\zeta(i)}(\sum_{k=1}^{K} w_{ik}(x_k/\mu_k))$ and the risk factor x_k has mean μ_k and variance σ^2. Here, the constants $1/\mu_k$ are incorporated into the normalized x_k. without any loss of generality. See Credit Suisse Financial Products (1997).

[11] The sector models are described in section 3.2 "Sector Analysis".

[12] See: http://www.csfb.com/institutional/research/credit_risk.shtml.

[13] See Credit Suisse Financial Products (1997), p. 44.

Net-exposure $E_{A,t}^{net}$ is the possible amount of loss in the case of a default. It is calculated as the exposure $E_{A,t}$ reduced at the average recovery rate $\overline{RR_k}$ of sector k:[14]

$$E_{A,t}^{net} = (1-\overline{RR_k})E_{A,t} \tag{4}$$

The exposure for venture capital is defined in this paper as the invested amount in company A at time t. The total investment amount is considered because, due to very low or missing securities, the total sum is at risk in the case of a default. The exposure is re-determined in each period and equals the exposure of the previous period $E_{A,t-1}$, plus follow-on investments $F_{A,,t}$, minus discharges $D_{A,t}$ of proportionate investment amounts from partial sales, full exits or total write-downs:

$$E_{A,t} = E_{A,t-1} + F_{A,t} - D_{A,t}\,. \tag{5}$$

If it is a full exit or total write-down, $D_{A,t}$ equals $E_{A,t-1}+F_{A,t}$. The discharged investment amount $D_{A,t}$ is the sum of sales $S_{A,t}$ plus write-offs or less write-ups. In the case of a write-off, it is a default; otherwise, it is not.

The recovery rate is the share of the exposure which the investor obtains in the case of a default. It is calculated as the average over the entire period for each rating class ζ, and is in the interval [0; 1). The recovery rate of company A equals the ratio of sales revenue to the corresponding investment amount:

$$\text{If } I_A = 1 \text{ then } RR_A = \frac{S_A}{D_A} \tag{6}$$

with S_A *= sales revenue,* E_A *= exposure,* D_A *= discharge.*

3.2 Sector analysis

A sector model for venture capital investments is presented in this section. A concretion is necessary, as CreditRisk$^+$ does not provide a convincing model with which to identify appropriate sector classifications.

A rating model is necessary to adjust CreditRisk$^+$ to venture capital-financed companies. The rating determines a company's unconditional default probability for one period. Company-specific data, which is not usually available for venture capital-backed companies, is needed to make a rating. Further, the explanatory power of the balance sheet is low because of the inherent characteristics of venture capital-financed companies.[15] Therefore, typical credit sector rating models, like scoring, discriminant analysis, logistic regression or artificial neural networks, are not used in this framework.

The transfer of publicly available rating grades from external rating agencies onto venture capital-backed companies is not recommended because the companies which are used to evaluate the rating model are not comparable to the venture capital-financed companies to be rated. The available rating grades typically refer to large or medium-sized companies with publicly available information, not to venture capital-backed companies.

The simple rating approach uses the average default probability of all portfolio companies as an estimator for the unconditional default probability. This paper extends this approach by using company-specific variables to classify companies in risk classes. The risk class determines the rating of the company. The unconditional ex-

[14] The term (1-RR) is also called *loss given default* (LGD).

[15] Venture capital-backed companies are typically very young, unprofitable companies which operate in innovative markets with high, but uncertain, growth prospects.

pected default rate of a company equals the average default probability of its risk class.

In this approach, the company's industrial sector is used as rating variable.[16] It is assumed that companies which are in the same industrial sector are influenced by similar risk factors and, therefore, have similar unconditional default probabilities. Regression results of previous studies have shown that industrial sector-specific default probabilities can be successfully estimated by macroeconomic variables.[17] It is also possible that the macroeconomic environment influences companies' default rates.

CreditRisk$^+$ introduces three different approaches to model sector analysis, and this section adjusts all three approaches to venture capital investments. The first approach assumes that all companies are assigned to a single sector so, besides the rating classification, this sector analysis does not require classification into several sectors. A default correlation of 1 is assumed among the obligors; changes in default rates of all obligors are parallel and have the same direction.

The second sector analysis classifies each company to one sector, so the sector classification equals the rating of the company, and the number of sectors equals the number of rating classifications. Segmentation into industrial sectors assumes uncorrelated sector default rates because all companies of one sector are explained by one factor, i.e., its sector.

The third approach assigns each company to different sectors, following the assumption that a number of independent systematic factors and one idiosyncratic factor influence the company's fortunes. Numerous studies analyzed the predictability of macroeconomic factors on the default rate.[18] Highly significant regression results, as well as extremely well established coefficients of determination, show that macroeconomic factors have a high explanatory power to project default rates. Therefore, this approach uses macroeconomic variables as risk factors which represent the systematic influence on the sector-specific default rate. Sector default rates are estimated by regression of macroeconomic factors as independent variables.

Multivariate regressions assume metric-scaled dependent variables. As default rates $P_{\zeta,t}$ are in the interval of [0;1], the following transformation of the default probability is used to create a dependent variable $Z_{\zeta,t}$ which is metric-scaled and in the interval [-∞;+∞]:

$$P_{\zeta,t} = 1/(1+exp(Z_{\zeta,t}) \qquad (7)$$

transformation leads to

$$Z_{\zeta,t} = ln(1/P_{\zeta,t} - 1) \qquad (8)$$

with $P_{\zeta,t}$ = default probability for companies with rating ζ in time t

$Z_{\zeta,t}$ = transformed default probability for companies with rating ζ in time t

[16] Other possible variables are stage or country. Stage can be used as an indicator for the company size and company age. Jones/Rhodes-Kropf (2003) found a significant correlation between stage and idiosyncratic risk in the venture capital industry. Ong (2000, p.145) identified a correlation between company size and idiosyncratic risk for credit financed companies. To our knowledge, no study in the venture capital industry examined the factors which influence the correlation between default probabilities and stage. Because no explanatory variables are known, the stage is not used as a classification variable in this paper. A classification into sector-stage-samples or sector-country-samples is not applicable because the number of each sample is too small due to the limited number of observations in the database. As all companies are located in the European Union, it can be assumed that the resulting error of a missing sector-country-sample classification is relatively low.

[17] See Knapp/Hamerle (1999) and Wilson (1997 c).

[18] See Hamerle/Liebig/Rösch (2002).

The regression model is:

$$Z_{\zeta,t} = \beta_{\zeta,0} + \sum_{\zeta=1}^{Z} \beta_{\zeta,k} x_{k,t} + \varepsilon_{\zeta,t} \tag{9}$$

with $\beta_{\zeta,0}$ = absolute term for companies with rating ζ

$\beta_{\zeta,k}$ = regression coefficient of risk factor *k* for companies with rating ζ

$x_{k,t}$ = risk factor *k* in time *t*

$\varepsilon_{\zeta,t}$ = interfering variable for companies with rating ζ in time *t*

A forward entry regression is used as the procedure to extract systematic factors. At each step after step 0, the entry statistic is computed for each eligible value for entry in the model. If no effect has a value on the entry statistic which exceeds the specified critical value for model entry, then stepping is terminated; otherwise, the effect with the largest value on the entry statistic is entered into the model. The variable with the largest increase of R^2 is used as the entry statistic. An increase of 5 percentage points of the R^2 is used as the specified critical value for model entry. Stepping is also terminated if the maximum number of steps is reached. Wilson (1997c) analyzed a multi-factor model to explain logit-transformed default rates and showed that three macroeconomic factors explain more than 90% of the variation of the default rate. Therefore, stepping of the forward entry regression is terminated if three variables are entered in the regression.

The coefficient of determination R^2 is used to divide the risk into one idiosyncratic risk factor and several systematic risk factors. The coefficient of determination R^2 is the proportion of a sample variance of the dependent variable that is explained by independent variables when a linear regression is done. Assuming that macroeconomic factors are independent, the improvement of the R^2 of each forward entry can be interpreted as the proportion of the entered factor to explain the sector default rate. The increase of each entered factor *k* is used in this approach as the weight w_{Ak} of a ζ rated company *A*. The sum of all weights of the systematic factors equals R^2.

It is assumed that all relevant systematic risk factors are incorporated in the model, and the systematic risk is entirely explained under this assumption. The remaining not-explained sample variance, $1-R^2$, is considered as the idiosyncratic risk of the rating class.[19] The sum of the weights of the idiosyncratic risk factor and the systematic risk factors is 1; the sector default rate is, therefore, unbiased.[20]

Single-sector default rates are not independent of one another. Correlations are incorporated in this approach as the forward entry regression for each sector uses the same macroeconomic factors as independent variables' population, from which the regression selects a maximum of three variables.[21]

The regression results from Knapp & Hamerle (1999) are used to choose macroeconomic factors.[22] This study performed regression analyses for different sectors to select among several macroeconomic factors those with the highest significance. It can be shown that the sector default rates can be explained very well by few, mostly for all sectors identical macroeconomic factors.[23] Because Knapp & Hamerle (1999) analyzed a very large set of macroeconomic variables and because the regression re-

[19] The idiosyncratic risk of each company is assigned an additional sector in CreditRisk$^+$ which is called the sector 0.

[20] The expected sector default rate of the model equals the actual default rate.

[21] Another possibility would be to abandon the independent assumption between the sectors by integrating correlation effects into the model. Bürgisser/Kurth/Wagner/Wolf (1999, p.2ff.) described such a method, which is neither easy nor feasible to implement.

[22] Dr. Knapp kindly provided us the variables.

[23] See Knapp/Hamerle (1999, p.140).

sults of this study are highly significant, it is assumed that all relevant factors are included in this approach. The included variables are: Producer Price Index (PPI), Gross Domestic Product (GDP), Value of Retail Sales (Ret_Sal), 3 Month Euribor Interest Rate (Euribor), Industrial Production (Ind_Prod), Dow Jones Euro Stoxx 50 (Stoxx), Euro-Dollar-Exchange-Rate (EUR_USD), Oil Price (Oil), and Unemployment Rate (UnEmR). Except for Unemployment Rate (UnEmR), Euro-Dollar-Exchange-Rate (EUR_USD), Oil Price (Oil) and 3-Month Euribor Interest (Euribor), all are index-based variables in our sample and show relative changes. The non-index-based variables have to be transformed into growth rates as follows:

$$x_{k,t} = \frac{F_{k,t}}{F_{k,t-1}} - 1 \tag{10}$$

with $x_{k,t}$ = growth rate of macroeconomic variable *k* in time *t*

$F_{k,t}$ = stationary value of macroeconomic variable *k* in time *t*

One assumption in regression analysis is that residuals are uncorrelated. This assumption is often violated in time series because time-dependent variables are often highly correlated. Because this approach transforms the time series in growth rates, this source of error can be reduced.

Knapp (2002) determined that all macroeconomic variables affect the default rate with a lag of one to two years. Thus, the necessary variables are known *ex-ante* and do not need to be estimated separately, which avoids an additional source of error. The lagged impact is also empirically and theoretically supported by other authors.[24] In this approach, time lags of t=0,-1,-2 of all macroeconomic factors are separately incorporated to consider the impact of the sector-specific time lag.[25]

4. Data Sample

We are grateful to have had access to the database of a private equity fund investor who invests in venture capital funds in several European countries. The database includes information about the funds' portfolio companies, like investment and divestment amounts, write-offs, and sales revenues. Other information known about each fund includes sector, stage and geographical region.

Our last data update is from the end of April, 2005. Because there is a time gap between reports' closing date and delivery, only data collected before December 31, 2004, is considered. In addition, those funds that do not have the typical fund structure—like mezzanine funds, and atypical buyout funds—are eliminated, as are all funds that have not yet had a drawdown. The final sample of nearly 200 funds were invested in more than 2,000 companies. The average net-exposure is EUR 2,339,715 and the median is EUR 1,283,041.

The basis from which to calculate the one-year default rate distribution is the calendar year. The number of observations per company in the analysis equals the number of calendar years the company is held by a fund. In the end, the analysis contained more than 8,000 observations.

The strength of the sample comes from the fact that all of its funds have to report, which is very different from the databases of a data provider like Venture Economics. Moreover, by using the investor's database, this study had access to all information

[24] Hamerle/Knapp/Ott/Schacht (1998, p.429) empirically analyzed the predictability of risk factors and made a sector-risk sensitivity analysis. Their study discovered that macroeconomic factors have a lagged impact. Bär (2002) theoretically analyzed the necessity for integrating lagged macroeconomic variables by using yearly lags.

[25] The selection in the forward entry regression of the lagged macroeconomic variables follows the coefficient-of-determination selection criteria, which were previously described.

available to the fund investor, unlike the database of Venture Economics, where only anonymous and aggregated data is available. Thus, the bias of the sample is limited to that of atypical investment behaviour of the fund investor with respect to the general market. Generally, we believe that the fund investor's investment behaviour is a good representation of the European private equity industry.[26]

A point of contention might be that the average fund age of the portfolio is about four years and nine months and that most funds are still active. A longer time series would improve the predictability of the developed risk model; however, we are aware that the sample largely captures the period 1998–2004, during which the industry showed a dramatic increase, followed by a considerable consolidation.

With fewer than 100 observations, the number of exits before 1998 is relatively low. Another database from a large European investor is included to increase the number of observations in order to make reasonably meaningful regressions.[27] The second database is comparable with the first database regarding the sector- and regional investment focus, and the databases are combined to calculate the sector default rates for the period 1993–2004. It is possible that the merged database contains some observations twice because the second database is anonymous, and a removal of double observations is not feasible. The resulting bias is relatively low because the overlapping observations are random and should not meaningfully distort the ratio of defaults and non-defaults on average.

As shown in Table 1, the default rates for years with more than 70 observations are between 2% and 14% and show a relatively high fluctuation.[28] The sectors with the highest default rates are Communications and Computer. Thus, the default rates since 2000 are on a higher level than they were previously.

Table 1
Default rate by industrial sector and year

Default rate	93	94	95	96	97	98	99	00	01	02	03	04	Avg.
Biotechnology	**10%**	**0%**	**4%**	**0%**	7%	2%	4%	2%	2%	3%	4%	6%	7%
Communications	**4%**	**3%**	**1%**	3%	5%	4%	4%	5%	9%	13%	11%	14%	8%
Computer	**13%**	**2%**	6%	2%	4%	3%	2%	4%	7%	11%	13%	11%	7%
Consumer	**0%**	8%	11%	3%	6%	6%	3%	3%	4%	8%	6%	6%	5%
Industrial Production	3%	2%	3%	3%	4%	5%	5%	6%	4%	4%	2%	7%	4%

This table presents the default rate by industrial sector for European venture capital-financed companies for the period between 1993 and 2004. The default rates are calculated on the basis of the merged database of two large European venture capital investors. The bold numbers used fewer than 70 companies to calculate the default rate. The last column shows the average which is the average of all observations during the period 1993–2004.

[26] The fund-of-fund investment behavior is compared with the cumulated data for the European venture capital market, as provided by EVCA.

[27] The two databases are merged only to calculate default rates. The other analyses are based only on the initial database.

[28] Default rates' standard deviations are not shown because the number of observations is too low to calculate meaningful standard deviations. The model uses the average sector default rate as an estimator for the standard deviation. See section Input Parameter.

The recovery rates are shown in Table 2. Since 2000, the recovery rates decreased significantly and fluctuated around 14%, possibly because of the booming capital markets in 1998 and 1999. As the capital markets were doing very well in 1998 and 1999, it can be assumed that it was easier to sell bad investments for a better price during this time.

Table 2
Recovery Rates

Year	1998	1999	2000	2001	2002	2003	2004	Average by Number
Recovery Rate	30%	25%	13%	15%	14%	13%	15%	15%

This table shows the recovery rates by years and by industrial sectors.

Multi-collinearity exists if variables are linearly inter-correlated among each other. Such data redundancy can cause overfitting in regression analysis models. The coefficients of correlation are examined to determine multi-collinearity. The largest correlation between two independent variables has a value of |0.74|. The average correlation between the included macroeconomic variables is |0.31|. It can be assumed that the regression results are not distorted by multicollinearity because only values of about |0.9| indicate high correlation.[29]

5. Empirical Evidence

5.1 Sector analysis

This section shows the results of implementing the sector-analysis model described above. Table 3 shows the regression results and the weights. F-tests and t-tests confirm that the regression results are highly significant.[30] The weight of the systematic risk of the single sectors varies between 5.1% and 25.2%. As venture capital-financed companies are typically small, young and growth-oriented, it could be assumed that they have higher idiosyncratic risks in comparison to the large, established companies. [31] As the average R^2 is smaller than for the regression results of larger companies used in previous studies,[32] the results confirm the assumption that venture capital-financed companies have higher idiosyncratic risks in comparison to large, established companies.

The Durbin-Watson test is used to test the regressions for autocorrelation. The Durbin-Watson values (*dw*) are in the range of *dw*=1.5 for the Computer sector and *dw*=3.1 for the Industrial sector.[33] Hence, the values are either in an interval in which no autocorrelation can be suggested or they are in the statistical indeterminacy inter-

[29] See Kennedy (2003), p. 209.
[30] The forward entry regression uses nine independent variables, but in the final sector regression results, only seven variables are selected from the forward entry regression model, deleting the macroeconomic variables EUR_USD and Oil. Therefore, the sector analysis includes only seven systematic risk factors and one idiosyncratic risk factor. The regression results for the Consumer sector includes only two independent variables because the third selected variable does not improve the R^2 in the required increase of 5 percentage points.
[31] See Knapp/Hamerle (1999).
[32] See Wilson (1997 a, b, c, d).
[33] A value close to zero indicates positive autocorrelation; a value close to 4 indicates negative autocorrelation. Values close to 2 indicate non-autocorrelation of the residuals.

val, in which case no conclusions can be made.[34] As the time series is relatively short, a reliable testing of the regression on linearity and heteroscedasticity is not feasible.

Table 3
Sector analysis

Industrial Sector	Variable	Lag	Coef-ficient	t-test	Weight	R^2	dw-test	F-test	p-value
Bio-technology	Constant		-1.45	**-18.5**	6.2%	94%	2.28	**30.20**	5.1×10^{-04}
	GDP	1	-12.75	**-7.0**	62.2%				
	Euribor	2	4.82	**4.6**	25.3%				
	Ind_Prod	0	2.23	**2.5**	6.3%				
Communi-cations	Constant		1.08	**4.9**	5.1%	95%	2.75	**49.91**	1.6×10^{-05}
	UnEmR	0	-23.99	**-10.3**	57.9%				
	Stoxx	1	-0.69	**-6.2**	29.8%				
	PPI	2	4.77	**3.4**	7.2%				
Computer	Constant		1.02	2.2	11.4%	89%	1.53	**20.78**	3.9×10^{-04}
	GDP	0	-16.88	**-4.2**	63.5%				
	UnEmR	1	-19.19	**-4.0**	10.1%				
	Ret_Sal	2	-9.82	**-3.2**	15.0%				
Consumer	Constant		-1.09	**-24.6**	21.2%	0.79	1.70	**14.87**	2.0×10^{-03}
	Ret_Sal	2	-10.88	**-5.0**	45.3%				
	Stoxx	0	-0.52	**-3.6**	33.5%				
Industrial Production	Constant		-0.55	-1.5	25.2%	75%	3.11	**7.94**	8.8×10^{-03}
	Euribor	2	-4.64	**-3.2**	40.9%				
	Stoxx	0	0.60	**3.3**	25.0%				
	UnEmR	1	-6.73	**-1.7**	9.0%				

This table shows the results of the stepwise entry regression by industrial sectors. Lag indicates the lag of the selected variable. The weights for the variables equals the improvement of the R^2 of each forward entry. The weight of the constant, which equals the remaining not-explained sample variance, is the weight of the idiosyncratic risk factor. The bold numbers are significant at the 5% level.

Table 4 shows the comparative empirically observed default rates and estimated default rates for each sector. The numbers show clearly the predictability of the model. Default rates diverge on average only about 0.8 percentage points from the empirically observed default rate, with a maximum difference of only 3.1 percentage points. Therefore, on the basis of these outcomes, the developed regression model can be considered to be reliable. However, the capacity of the results remains restricted as the number of observations is relatively low.

[34] The critical value, i.e., the limit of the critical band, depends not only on the number of observations and the number of independent variables but also on the calculated values of the regression coefficient. Thus, the critical band of the typically used tables for this test does not reach a decision if the value is in this band.

Table 4 Actual versus estimated default rates										
Industrial Sector	Biotech-nology		Communi-cations		Computer		Consumer		Industrial Production	
Year	Act.	Est.	Act.	Est.	Act.	Est.	Act.	Est.	Act.	Est.
1993	9.8%	10.4%	3.8%	4.1%	**13.0%**	**14.7%**	---	8.0%	2.6%	2.6%
1994	---	12.9%	3.4%	3.7%	1.8%	2.3%	**7.6%**	**5.6%**	1.9%	2.0%
1995	3.7%	3.3%	1.5%	1.6%	**5.6%**	**8.2%**	10.8%	11.2%	2.8%	2.4%
1996	---	4.4%	3.2%	2.7%	1.8%	1.9%	**2.8%**	**4.2%**	2.8%	2.8%
1997	**6.7%**	**5.6%**	4.7%	4.7%	**3.8%**	**2.3%**	6.1%	7.0%	3.6%	3.7%
1998	2.0%	2.3%	4.2%	3.9%	3.3%	4.0%	**5.5%**	**4.1%**	5.2%	5.0%
1999	3.6%	4.0%	4.1%	5.0%	2.0%	2.3%	3.4%	3.1%	5.0%	5.3%
2000	2.4%	2.5%	5.1%	5.7%	3.8%	3.5%	2.6%	3.0%	5.6%	6.3%
2001	2.0%	1.8%	**9.4%**	**7.2%**	6.6%	7.5%	4.4%	4.6%	3.8%	3.8%
2002	3.5%	4.4%	**12.9%**	**16.0%**	**10.7%**	**8.8%**	7.8%	7.2%	**4.3%**	**3.1%**
2003	4.4%	4.0%	11.1%	9.8%	**13.0%**	**11.3%**	5.5%	6.3%	**1.9%**	**3.2%**
2004	5.6%	5.1%	14.1%	12.6%	**11.1%**	**7.9%**	5.6%	5.1%	**7.1%**	**5.6%**
Maxi-mum Differ-ence	1.1%		3.1%		3.2%		2.0%		1.5%	
Average Absolute Differ-ence	0.4%		0.9%		1.3%		0.7%		0.5%	
This table shows the actual default rates and forecasted default rates by industrial sector. The bold numbers show a difference between actual default rate and forecasted default rate of more than 1 percentage point.										

The numbers show clearly the predictability of the model. Default rates diverge on average only about 0.8 percentage points from the empirically observed default rate, with a maximum difference of only 3.1 percentage points. Therefore, on the basis of these outcomes, the developed regression model can be considered to be reliable. However, the capacity of the results remains restricted as the number of observations is relatively low.

5.2 Venture capital risk

The publicly available CreditRisk$^+$ tool is used to evaluate the default distribution.[35] Graph 1 shows the analyzed models, which are based on different assumptions. The portfolio loss is shown as the ratio of loss to exposure as of December 31, 2004.[36] The risk model is empirically tested using a portfolio of venture capital financed companies. As the model does not take into account that venture capital backed companies' returns are, in theory, unlimited, the results can be considered as the lower bound for loss distributions for loans of venture capital financed companies.

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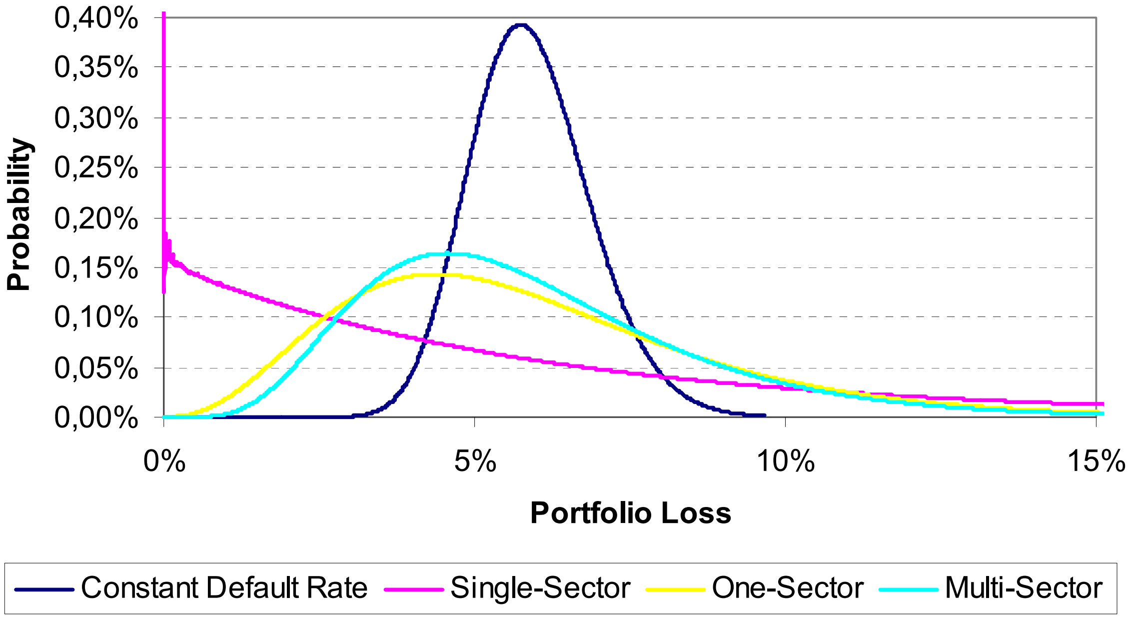
[35] CreditRisk$^+$ is developed from Credit Swiss First Boston (CSFB) and is a Microsoft Visual Basic for Applications (VBATM) tool available for download. See http://www.csfb.com/institutional/research/credit_risk.shtml.

[36] The portfolio losses, as well as further results, are shown at the rate of the exposure to ensure anonymity of our data provider.

Graph 1. Default Distribution
This graph shows the expected default distribution for 2005 by sector models. The loss is shown as a ratio of loss amount to exposure as of December 31. 2004.



The model with constant default rates considers no default rate uncertainties. As shown in Graph 1, the probability for very small and very large portfolio losses is underestimated because correlations among companies are not considered in this approach. This leads to an underestimation of the portfolio risk.

The single-sector model has only one sector. This approach implies that changes in default rates among companies within an industrial sector have the same direction and are parallel, and the assumed high default rate correlations among companies within a sector lead to an overestimation of portfolio risk and portfolio loss. The probability of extreme losses— very high as well as very low losses—is relatively high.

Company correlations are more sophisticated when incorporated in the one-sector model and the multi-sector model. The portfolio risk of these models lies between the non-varying default rate model and the single-sector model. This allows a more realistic portfolio risk estimation. The one-sector model classifies each company in one risk sector, which equals its industrial sector, and the default rate is determined by classification into that industrial sector. This requires the assumption that companies within an industry have a default rate correlation of 1, whereas companies which are not in the same industry have a correlation of zero. Diversification effects between companies of different industries are incorporated, but the effect is overestimated because a correlation of zero is understated. Diversification effects of companies within an industrial sector are not considered because changes in default rates among these companies have the same direction and magnitude. In summary, the effects compensate one another, but it is not clear which effect dominates.

The multi-sector model uses the results of the sector analysis' regression model to weight each factor. It classifies each company into one idiosyncratic risk factor and seven systematic risk factors, following the assumption that a number of independent systematic factors and one idiosyncratic factor influence the company's default rate. Because this model takes company-specific risks into account, the diversification effect is larger in comparison to the one-sector approach. Further, the sources of risk of the idiosyncratic sector are company-specific and, therefore, independent from each other. The resulting default correlation of this idiosyncratic risk factor is zero.[37] In comparison with the first multi-factor model, probability for small and very large portfolio losses is lower because the diversification and correlation effects are more realistically considered.

Table 5 shows the descriptive statistics and the value at risk for 2005 by sector models. The expected loss of all models is identical, whereas the default rate distribution differs.[38] As expected, the 95% value at risk (VaR) confidence level shows that the expected loss for the one- and multi-sector models lies between the model with non-varying default rates and the single-sector model. Backtesting of the introduced venture capital risk model is not feasible because the venture capital industry is a relatively young industry and the time series of this study is relatively short.

Table 5
Value at risk

	Constant Default Rate	Single Sector	One Sector	Multi Sector
Expected Loss	5.91%	5.91%	5.91%	5.91%
Standard Deviation	0.97%	3.34%	3.04%	2.70%
VaR Quartile	Portfolio Loss			
50.0%	5.9%	4.1%	5.4%	5.4%
75.0%	6.5%	8.2%	7.5%	7.3%
90.0%	7.2%	13.7%	9.9%	9.5%
92.5%	7.4%	15.4%	10.6%	10.1%
95.0%	**7.6%**	**17.9%**	**11.6%**	**11.0%**
97.5%	8.0%	22.0%	13.3%	12.5%
99.0%	8.4%	27.5%	15.4%	14.4%

This table shows the descriptive statistics and the value at risk for 2005 by sector models. The data are shown as the ratios of actual value to exposure.

Table 6 shows a comparison of forecasted losses and realized losses for 1999–2003. The results show that the realized losses are below the forecasted 95% confidence level losses and an increasing trend in the ratio of realized loss to expected loss. A potential bias occurs as our data provider began investing in 1997; the database is relatively young and no fund is liquidated. Because fund managers generally hold their investments between five and eight years, the losses are underestimated, especially in the first years. The older the fund gets, the more realistic the estimations.

[37] See CreditRisk$^+$ (1997), p.20f.

[38] If a fund invests in a company in the year of the final exit, losses are lowered by approximately the investment amount which is made in the exit year, because this investment is not incorporated into the exposure which is used to calculate the default distribution. The exposure to calculate the default distribution for year *t* refers to the exposure of December 31 at year *t-1*.

Table 6
Expected loss versus realised loss

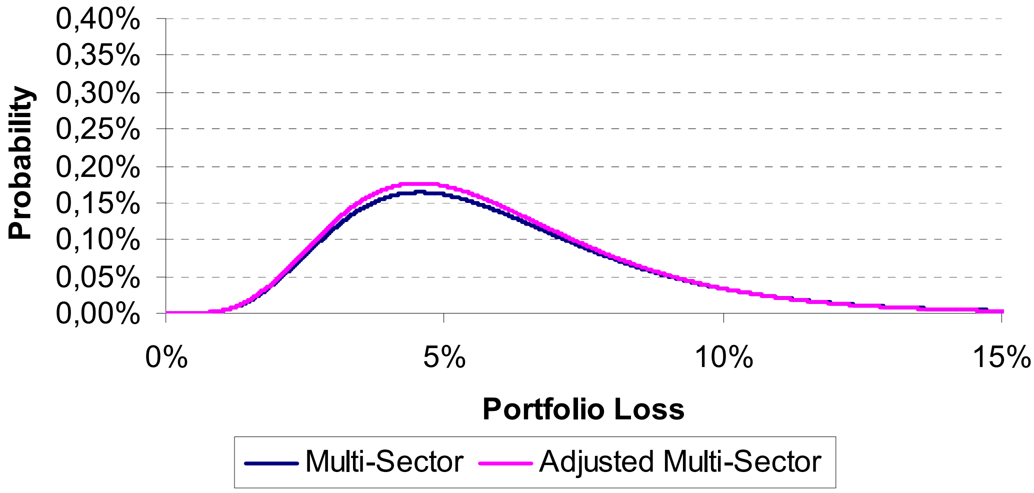
Year (t)	Expected Loss (t) to Exposure (t-1)	Realized Loss (t) to Exposure (t-1)	Realized Loss (t) to Expected Loss (t)	VaR 95% (t) to Exposure (t)	Position of Realized Loss (t) in VaR
1999	6.5%	1.6%	25.2%	13.5%	5%
2000	6.6%	2.8%	42.9%	12.7%	8%
2001	6.6%	3.5%	53.2%	12.4%	14%
2002	6.5%	8.3%	129.3%	12.2%	78%
2003	6.2%	11.4%	182.1%	11.7%	94%
2004	6.0%	8.6%	142.6%	11.3%	84%
2005	5.9%	---	---	11.0%	---

This table shows the expected loss and realized loss as a ratio of portfolio exposure by year. The exposure refers to the closing date of December 31 of the former year because the portfolio loss refers to the composition of the portfolio at this date. In respect to the data provider, the numbers are shown as ratios to the exposure.

Diversification effects can be shown by using marginal risk. The marginal risk capital is obtained in Merton and Perold (1993) by calculating the risk capital required for the portfolio without a new business, and subtracting it from the risk capital required for the full venture capital portfolio. It enables an optimization of venture capital portfolios because it is used to make investment and divestment decisions. To get a picture of the degree of the marginal risk, the total exposure is reduced about 5% on all investments which have the largest ratio of marginal risk to net-exposure.[39] Both default distributions are shown in Graph 2.

Graph 2. Risk-Adjusted vs. Original Default Distribution

This graph shows the expected default distribution for 2005 bydifferent portfolios. In the risk-adjusted portfolio, the total exposure is reduced about 5% on all investments which have the largest ratio of marginal risk to risk exposure. The loss is shown as a ratio of loss amount to corresponding exposure as of December 31, 2004.



[39] The marginal risks are calculated for the 95th percentile.

As shown in Table 7, the decrease of expected loss, standard deviation, and value at risk is greater than the 5% decrease of the net-exposure. Therefore, the marginal risk can be used to optimize venture capital portfolios. However, an exclusive examination of potential losses is unsuitable to optimizing venture capital portfolios because this analysis considers only risks and does not take returns into account. An advanced portfolio management should include both risks and rewards, i.e., potential losses as well as potential returns.

Table 7.
Risk-adjusted portfolio

	Original Portfolio	Adjusted Portfolio	Change of the Absolute Values
Expected Loss	5.91%	5.84%	-6.44%
Standard Deviation	2.70%	2.63%	-7.61%
VaR Quartile	Portfolio Loss		
50.0%	5.4%	5.4%	-6.22%
75.0%	7.3%	7.2%	-6.56%
90.0%	9.5%	9.3%	-6.87%
92.5%	10.1%	9.9%	-6.95%
95.0%	11.0%	10.8%	-7.05%
97.5%	12.5%	12.2%	-7.20%
99.0%	14.4%	14.1%	-7.37%

This table shows the descriptive statistics and the forecasted value at risk for 2005 for the multi-sector model by different portfolios. The original portfolio contains all companies. In the adjusted portfolio, the total exposure is reduced about 5% for all investments which have the largest ratio of marginal risk to net-exposure. The data for the original portfolio and the adjusted portfolio are shown as the ratios of actual value to exposure.

6. Conclusion

Convincing and generally accepted portfolio models for venture capital investments do not exist in theory or in practice. Broad implementation of a widely accepted risk model would enhance venture capital investments' transparency. A better risk assessment allows a more accurate loss estimate of the venture capital fund investments. This makes fund investors' follow-on investment decisions less difficult and enables more reliable liquidity and investment planning. This study constructs and evaluates a risk model for the venture capital industry on the basis of the CreditRisk$^+$ model. The practicability of the model is successfully tested through an empirical analysis with data from one of the largest European venture capital investors. As relatively little effort is required to implement the model, it can be a practical tool in enhancing active portfolio management.

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