Kredit und Kapital, 39. Jahrgang, Heft 2, Seiten 183–210
Abhandlungen

Venture Capital Cycles: Empirical Evidence from the USA

By Roland Füss, Freiburg im Breisgau,
and Andrea Alexandra Nowak, Zurich*

I. Introduction

Dynamic economies require high levels of innovative activity that contribute to the technical progress, and lead to increasing economic growth, such as start-ups and product innovations. In this context, venture capital companies play a central role in supplying new firms with badly needed equity capital. Venture capitalists also assist firms with their portfolios by providing them with strategic and organisational advice, and also in terms of human resources, facilitating their position to support the well directed development of these high-growth companies. As such, they reduce the problem of equity capital deficit, especially in Germany, and create new jobs promoting the growth of employment. In addition, using Neuer Markt or NASDAQ as an example, the listing at the stock exchange has offered venture capitalists an important exit channel, which in turn boosts the formation of venture capital companies. The collapse of these markets, which exhibit a decisive possibility of disinvestment for young technology ventures, causes a collapse of the venture capital industry across industrialized countries.

In contrast to the huge national relevance of venture capitalists, it will be of particular interest to analyze whether a reinforced funding of venture capital follows the recovery of the equity markets. The existence of significant cyclical patterns in the American venture capital market is investigated by using spectral analysis. The main focus, however, is to detect the length of single cycles. This empirical study is based upon the assumption that the venture capital industry in the US could accumulate

* The authors would like to thank an anonymous referee for most helpful comments and suggestions on an earlier draft of this paper. The views expressed are those of the authors and do not necessarily represent the views of the Swiss National Bank.

its experience over several decades. Hence, in recent years, mechanisms have been established, which characterize this venture capital market such as stepwise financing or active monitoring.

In the relevant literature, there is no doubt that the US venture capital industry is influenced by cyclical developments. For example, Jeng and Wells (1998) show that private equity and venture capital markets exhibit fluctuations over time. In addition, the Bygrave and Timmons study (1992) describes and compares the different cycles that characterize the process of venture capital finance and, according to Schoar (2002) "cycles (are) no news to the venture capital industry". All of these statements are based on pure descriptive statistics of annual investments, and correspond to the assumption of cyclical patterns in the US market. In this context, the authors analyze the basic criteria that discriminate between Anglo-Saxon, particularly USA, and Continental Europe, particularly Germany, as it relates to venture capital financing. In these studies, the US venture capital market, in keeping with its Anglo-Saxon tradition, is exemplary in its comparative institutional advantage concerning the shift in financial markets. This is true not just for the US, but according to Belke et al. (2003) for Anglo-Saxon countries in general, which feature financial markets based on stock markets and more developed capital markets. Jeng and Wells (1998) and Belke et al. (2003) assume that the main reason for the success of venture capital funding is a completely developed venture capital market with cyclical developments.

In relation to the economic interpretation of venture capital cycles, Sahlman (1990) argues that such cycles are inevitable but not necessarily bad, if players anticipate and respond to them accordingly. In order to elaborate the importance of cycles in a venture capital market, first note that, in contrast to the pure descriptive identification of a cyclic course, the actual analysis of cycles is related to the length of venture capital financing, which is often neglected in the relevant literature. One exception is provided by Gehrig and Stenbacka (2004) who attribute the cyclical properties of venture capital investments to the behaviour of the financier during project selection. They argue that uncoordinated behaviour in the screening phase generates cycles between high and low screening activities. These screening cycles emerge endogenously from the necessity to screen for best projects. To identify cycles empirically, the authors examine different sectors like biotechnology or telecommunication in the US venture industry. Specifically, the existence of steady cycles can be detected in the sectors of biotechnology, financial services and consumer products. Altogether, the authors identify cycles measuring between two and four quarters, as well as cycles of more than ten years.

In this article, the investment selection is regarded as one part of the investment process. By considering the whole process, we assume a complete, developed venture capital industry, which runs through the entire investment process, including all phases of investment.

The content of this article is organized as follows: The next section describes the concept of venture capital financing. Section III presents a general definition of venture capital cycles and discusses the different stages of a total venture cycle. Section IV then outlines the methodology on ARIMA modeling and spectral analysis. Subsequently, Section V describes the data, offers a short overview of descriptive statistics, and presents the empirical results of the estimation procedures. The final section provides concluding comments.

II. Venture Capital Investments

The concept of venture capital investment is more than that of placing venture capital for disposal. For a successful foundation of a company, two main barriers must be surmounted: (1) the lack of equity capital, and (2) the lack of entrepreneurial experience (Strobel (2002)). Both elements constitute a systematic conjunction, which can be described as follows: "The Venture Capital industry is a major source of funding for the entrepreneurial community. The industry focuses on a early stage, pre-IPO funding opportunities. Typically, a fund is raised, that will be invested in a number of reasonably high risk opportunities. The VC also helps the business develop its management team, and takes seats on the board of the company (NVCA (2004))." A typical situation of venture capital financing, where venture capitalists acquire capital from external investors and invest the pooled funds in innovative high-growth companies, is shown in *Figure 1*.

Venture capital financiers invest in privately held companies, which are capital seekers and investment management companies, entrepreneurs, respectively, by providing them with long-term liable equity, without the receipt of any securities, as is normally required for a bank loan (Weber (2002)). Thus, the provision of equity capital plays the pivotal role because it implies neither a claim of redemption, nor a payment of a fixed interest rate. Hence, no deprivation of liquidity occurs by loan re-

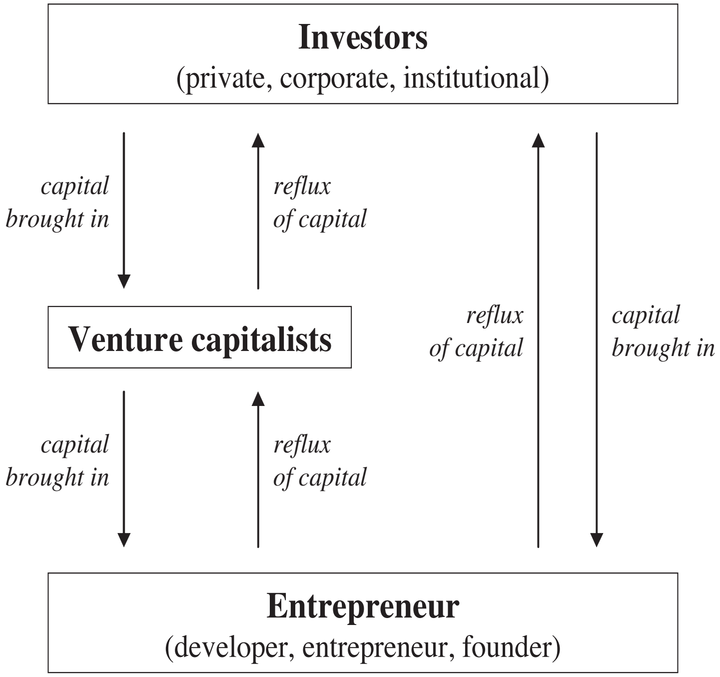


Figure 1: Venture Capital Financing (see Weber 2002)

demptions and interest payable. Since the average maturity of a venture capital fund is restricted to ten years, venture capital funds must complete capital expenditure in investment management companies, within a few years (Sahlman (1990)). Generally, disinvestment takes place after three to seven years, whereas the amounts of holding average between 20 and 35 %. Profits cannot be realized until disinvestments are initiated, as in favour occurs by issuing shares. As mentioned above, the assistance of start-ups in a managerial capacity constitutes an essential characteristic of venture capital financing. In return, for assuming risk, financiers demand guarantees of underwriting and claims cooperation. Hence, the venture capitalist plays an active role during the period of entrepreneurial support, and enters a temporary strategic partnership with the capital acquirer. Concurrently, it is important to support the management in the early stages of development, while the company is expanded. Venture capitalists also have the advantage that they can offer funding, consulting, and control from one source alone in comparison to other financiers (Casamatta (2003)). The allocation of venture capital is not restricted to start-up financing, but also encompasses all stages of corporate financing.

The development of a company from its foundation to a well-developed corporation is characterized by a process of different development phases and growth stages, which cannot be distinguished exactly from each other. Financing with venture capital not only occurs subject to the developmental status of the company, but also from the amount of funds needed by the company for its growth process financing. There exists no worldwide uniform definition of venture capital, but rather different countries choose their particular definitions depending on the financing stage in which a company acquires capital. Thereby we have to distinguish between the terms 'private equity' and 'venture capital'. In general, the term 'private equity' covers the following stages: (1) seed-, (2) start-up-, (3) expansion-, (4) bridge-, (5) turnaround-, (6) replacement capital-, (7) MBO-, (8) MBI-, and (9) LBO-financing. In contrast, the term 'venture capital' usually covers only the first three stages of financing and explicitly excludes the latter phases. Investments in the seed and start-up stages, so-called early-stage financing, are especially necessary for economic development and structural change because the allocation of capital in this stage is prerequisite for new companies in establishing their business. This form of financing is naturally associated with the highest risk portfolio undertaken by companies.

The prime reasoning behind gradual capital allocation is the reduction of agency conflicts between the company and the venture capitalist, such as moral hazard and adverse selection. On one hand, the venture capitalist takes control of the financing project and has the ability to terminate any unsuccessful project in time. Furthermore, they are able, due to their experience, to differentiate between good and bad companies. On the other hand, financing in stages can boost the motivation of the company to work on profit, such as in the case of providing funds in total at the beginning of the investment. In addition, to reduce asymmetric information, venture capitalists intensively enforce the professionalism of start-ups, thus making it possible for a young professional company to be founded. This applies particularly to a company with technology at its base. Most studies show that, with respect to equal funding, younger and smaller companies apply for more patents than already established companies (Acs and Audretsch (1991), Cohen and Klepper (1992)).

The national importance of start-ups and small companies is indisputable. It is accepted that young technology ventures affect economic

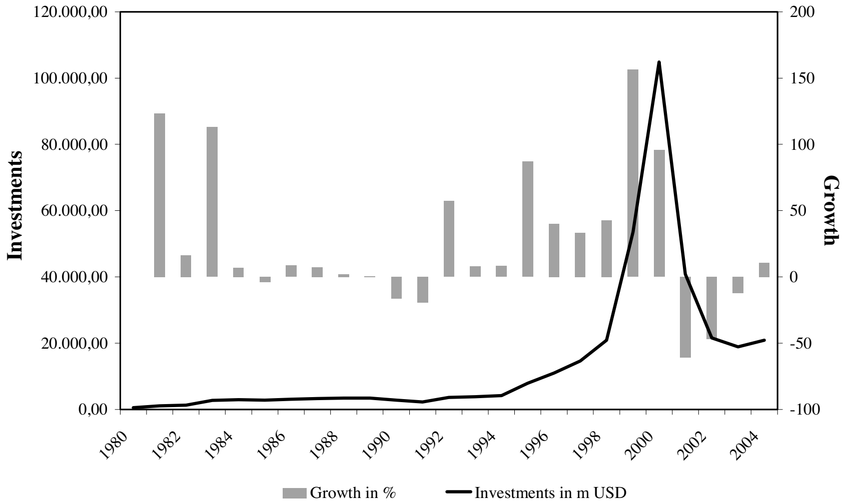


Figure 2: Venture Capital Investments in the US from 1980 to 2004

structural change, due to their high innovative ability and flexibility. This in turn results in the creation of employment opportunities and the flourishing of new sectors. The accelerated and cyclical performance of the US venture capital industry reflects the movement and the importance of this industry. It has shown that, in the last two decades, the US market has benefited by supporting young innovative companies with the provision of fresh capital. The volume of venture capital markets did not increase permanently, but rather, is characterized by a recurring cyclical development that includes phases of expansion and recession over time. In the 1940's, the cooling-down of venture capital market preceded a boom in the 1960's that was again replaced by a downtrend in the 1970's. Following this, in the late 1970's, the trough from the first cycle was reached. In contrast, in the beginning of the 1980's, the second cycle started with an upward trend as displayed in *figure 2*.

In 1980, investment in venture capital amounted to approximately USD 500 million and increased to approximately USD 4 billion in 1989. During the earlier years, the annual amount invested almost doubled, until 1984, when it began to slow, and ended in the first peak of this upward trend in 1989. In the beginning of the 1990's, this cycle was displaced by the temporary last cycle. In the first half of this decade, the venture capitalists realized average growth rates, while in the second half, a steadily increasing trend provided above-average growth rates up to the 2000 peak with approximately USD 105 billion. However, already in 2001, these booms were knocked over to consolidation.

Concerning the actual development, venture capitalists invested around USD 5.5 billion in the fourth quarter of 2003, which exhibited a distinct increase compared to the first quarter of the same year at USD 4.2 billion. With the exception of the second quarter of 2004 (USD 5.9 billion), the results of 2004 are in the average band of the last ten quarters, as the amounts constantly ranged between USD 4.2 billion and USD 5.4 billion.

In light of the previous results, we may conclude that the US venture capital market is driven by cyclical developments, where phases of above-average growth rates alternate with periods of slow growth, and sometimes pass into phases of contraction. Due to the existence of general conditions in the USA that still favour the venture capital industry (e.g. IPO's, solid structures etc.) and its growth, it is assumed that an upward movement can again be expected. Accumulatively, these findings indicate an upcoming fourth cycle of the US venture capital industry.

III. Venture Capital Cycles

The existing results are closely linked to questions surrounding the relevance of identifying venture cycles for the entire venture capital industry. In answer to this question, it is also important to know whether, and how, the relationship between a fully developed venture capital market and venture capital cycles can be determined.

In response to these questions, it is best perhaps to begin with a general definition of 'cycles' in a macroeconomic framework. In this context, attention is directed to economic theory, where small differences in the national social product can be interpreted as cyclical fluctuations of an existing potential within an economy (Metz (2002)). Therefore, cycles exist if a sequence of growth rates with consistent regularities or certain patterns can be recognized. Consequently, they represent the subject of explanation, in the theory of business cycles. According to this, fluctuations in terms of cycles may not be attributed to random effects, but rather, they are characterized by continuous patterns of development and cyclical regularities. In this respect, it is important to correlate the identification of cycles as signalling the recurring stabilization of the economic situation.

When referring to venture capital financing, throughout the whole investment process, we assume that a fully developed venture capital industry passes through a complete investment process in all its phases. Venture capital financing represents a typical time-limited minority stake, executed in iterative stages. Accordingly, Gompers and Lerner (1999) refer to venture capital as "a cycle that starts the raising of venture fund; proceeds through the investing in, monitoring of, and adding value to firms; continues as the venture capitalist exits successful deals and returns capital to their investors; and renews itself with the venture capitalist raising additional funds. To understand the venture capitalist industry, one must understand the whole venture cycle." This process consists of the following six stages:

1. At the *fundraising* stage, venture capital companies raise capital primarily from institutional investors, pension funds and insurance companies.

2. During the course of the *deal generation,* the venture capital company gathers information about potential investment management companies.

3. Within the *screening* phase, potential investment management companies are compared with the criteria of the venture capital investors in a multi-level process. At the end of this stage, the financiers decide whether or not to enter into negotiations with the relevant venture.

4. In the *approval and structuring* stage, the two parties bargain the investment conditions and the applied financing instruments.

5. Subsequently, the beginning of monitoring and consulting the management, mark the phase of *post investment activities*.

6. At the end of the process, disinvestment signalizes the *exit* and, therefore the realization of profits, which can be gained in different ways. The venture capital provider can realize profits by: (1) an *initial public offering (IPO),* (2) a *trade sale* of the whole company, (3) a *secondary sale* of the shares held by the venture capitalist to another venture capital company or financier, (4) *buyback* of shares by the investment management company, (5) *reorganization* of the investment management company, and, (6) *write-off* in the case of total loss as well.

In accordance with the theory, the above described investment process spans between two and seven years (see Gompers and Lerner (1999)). As a whole, the course of the process is important because the venture capital company's profit depends solely on successful disinvestment of the investment management company, which normally pays no dividend to the capital provider. According to numerous investigations, the disinvestment of investment management companies by IPO's constitute the most attractive channel of exit (Jeng and Wells (1998), Gompers (1998)). Jeng and Wells (1998) even show that IPO's are the chief cause for these cyclical fluctuations in the venture capital industry. Black and Gilson (1998) also argue that without highly developed and efficient IPO markets for dynamic companies, the venture capital industry would stagnate. Hence, such markets are considered key elements in the performance of a venture capital market. Consequently, the maturity of a venture capital market depends on the two following fundamental features: the efficiency of IPO markets and the iterative sequence of the investment process in all phases of the cycle.

In the next section, time series properties of US venture capital investments are examined to show whether or not the venture capital market exhibits statistically significant processes of cycles. In doing so, the main focus refers to the econometric method of spectral analysis, which represents an appropriate approach in identifying the single lengths of cycles. At the beginning of the empirical analysis, we assume that the venture capital sector in the USA could accumulate experience over several decades. In comparison to typical German venture capital companies, which are still emerging and inexperienced in their business, the scope of American knowledge is greater. In the USA, certain mechanisms have been established over the years, that characterize the venture capital sector, such as gradual financing or active monitoring, and consolidate their structures.

IV. Methodology

Typically, time series analysis describes a permanent duality of two approaches. A time series in the so-called *time domain* can be interpreted as a sequence of data where the modeling of the underlying stochastic process takes centre stage. An equivalent representation exists in terms of the *frequency domain* where the substantial properties of a process present an interaction of deterministic and stochastic oscillations, with different frequencies. The corresponding approach to model stochastic processes in the frequency domain is referred to as *spectral analysis*.

Under the assumption that the data for analysis contains cycles of a fixed length, spectral techniques can be most useful. Accordingly, these techniques may be used to identify and 'extract' the approximate length of dominant cycles in data, which has non-periodic cycles. In spectral analysis, the main focus changes from an amplitude-time domain, to an amplitude-frequency domain, in order to determine the importance of cycles of different frequencies, in accounting for the behaviour of a variable Y (Hamilton (1994)). Therefore, the spectral approach extends the traditional decomposition of a time series into trend, cycle, seasonal, and erratic movement, and bases it on a rigorous foundation. In doing so, a stationary time series is decomposed into many uncorrelated components, each associated with a period or frequency.

1. Time Domain

Essentially, the ARIMA model is an approach to economic forecasting based on time series data. It requires the series used in the estimation process to be stationary. Any failure to observe this condition will lead to spurious regression. Hence, before estimating the ARIMA model, it is necessary to test for stationarity using the Dickey-Fuller unit root test. Subsequently, the three-stage approach of model identification, parameter estimation and model checking of Box-Jenkins (1976) is applied.

The tests for unit roots are also known as Dickey-Fuller (DF) (Dickey and Fuller (1979)) and Augmented Dickey-Fuller tests (ADF) (Dickey and Fuller (1981), Said and Dickey (1984)). If a time series exhibits a unit root, it will be integrated of order one, I(1). Furthermore, as discussed by Engle and Granger (1987), a series is said to be integrated of order d, I(d), if the d times differenced series has a stationary invertible ARMA representation.

$$\Delta \mathrm{Y_t} = \mu + \beta \mathrm{t} + \gamma^* \mathrm{Y_{t-1}} + \sum_{\mathrm{i=1}}^{\mathrm{p-1}} \phi_{\mathrm{i}} \Delta \mathrm{Y_{t-i}} + \varepsilon_{\mathrm{t}}, \tag{1}$$

where $\gamma^* = (\gamma - 1)$ and $\varepsilon_t \sim \mathrm{iid}(0, \sigma^2)$.

If $\gamma^* = 0$, i.e. γ is equal to one, then the Y series is said to have a unit root and is non-stationary, and the ΔY_t series will be stationary, I(1). The parameters μ and β test for the presence of drift and trend components, respectively.

An ARIMA model is a univariate model that seeks to depict a single variable as an Autoregressive Integrated Moving Average process. Herein, a time series is called an autoregressive process of order p, AR(p), since the actual value of Y, at time point t, is determined by p past values Y_{t-i}, i = 1,..., p. If the generating process for a random variable Y_t follows a MA(q) process, Y_t is a weighted average of shocks ε_{t-q} and ε_t is a white noise series. A parsimonious parameterization results in the definition of ARIMA(p,d,q) models, where d describes the order of integration respectively, which is the required degree of differencing for stationarity. If Y_t is an ARIMA(p,d,q,) process, then the series evolves according to the following specification:

$$\alpha(B)[1-B)^d Y_t - \mu] = \beta(B)\varepsilon_t, \tag{2}$$

where μ is the mean of the differenced series of interest (often zero), B is the backshift operator and ε_t is a white noise error term.[1]

2. *Frequency Domain*

In spectral analysis, the initial focus is on the amplitude-frequency domain. Basically, spectral analysis commences with the assumption that any series $\{Y_t\}$, can be transformed into a set of sine and cosine waves (Hamilton (1994)).[2] This decomposition is carried out with the Fourier (harmonic) analysis[3], in which the time series is transformed in a sum of cosine- and sine-functions. The overlapping of this originated Fourier series again results in an empirical time series. According to this, any series, $\{Y_t\}$, can be specified as a weighted sum of periodical functions $\cos(\omega)$ and $\sin(\omega)$:

$$Y_t = \mu + \sum_0^{\pi} \alpha(\omega)\cos(\omega_t)d\omega + \sum_0^{\pi} \alpha(\omega)\sin(\omega_t)d\omega, \tag{3}$$

---

[1] For detailed discussion of ARIMA modeling, see *Box* and *Jenkins* (1976), *Lütkepohl* (1993), and *Hamilton* (1994).

[2] For the characterization of harmonic waves, general trigonometric functions are used.

[3] The Fourier analysis is the mathematical technique to decompose a given time series in frequency components, which solely may applied to non-deterministic processes (*Schlittgen* and *Streitberg* (1994)).

where μ is the mean of the series and ω denotes a particular frequency, which represents the number of cycles per unit of time by measuring all cycle lengths at interval zero to 2π. This relates to the trigonometric functions of sine and cosine, which pass through a full wave within this interval (2π). The inverse of the frequency ω, indicates the period P by describing the complete length of a cycle, and hence may be represented by $2\pi/\omega$.[4] The amplitudes display the intensity of particular frequencies in a time series. The relationship between the frequency ω, and the length of a period j, is given by the expression $\omega_j = 2\pi j/T$. Thus, high frequency dynamics (large ω_j) are synonymous with short cycle processes, while low frequency dynamics (small ω_j) may be likened to long cycle processes. Accordingly, it is the specification of the period length, and the number of observations, that leads to the calculation of a cycle's length. Hence, it considers the period of a cyclical function, instead of its frequency. The intensity at which certain frequencies are included in the time series can be graphically demonstrated by the sample spectrum $s(\omega)$, which is displayed in a periodogram $I(\omega)$. The spectral decomposition of a single time series yields the spectral density function or autospectrum over the frequency interval $(0,\pi)$. In addition, it also measures the relative importance of each of the frequency bands, in terms of its contribution to the overall variance of the time series. This function can be termed the 'variance spectrum' since spectral analysis is essentially an analysis of the variance of a time series, in terms of frequency. The spectrum does not contain additional information to the autocovariance function, and mathematically, the spectrum is determined by the Fourier cosine transformation of the autocovariance function (i. e. the series is filtered). Both represent information about the variance of a time series, but from completely different viewpoints. The autocorrelation function combines information in the time domain, whereas the spectrum considers information in the frequency domain. Therefore, the illustration of time series must be transformed into the frequency domain. In doing so, an appropriate estimator of the spectrum has to be found. To estimate the unknown spectrum $s(\omega)$ of a series, it is practical to discuss the periodogram as an estimator. In turn the periodogram $I(\omega)$ is a function of the frequency, which measures, for every frequency ω, the intensity of harmonic waves in the original data.[5] Since the calculation of all the fre-

[4] For example, a frequency of 0.1 cycles exhibits a period of ten months.

[5] Therefore, to estimate the sample spectrum, the area under the periodogram in a given small frequency range approximates the proportion of the variance of the series in that frequency range.

quencies of empirical data is very time consuming, only selected frequency points are estimated. Thus, it is sufficient that we consider the periodogram for the frequencies between 0 and 0.5. The spectral peaks indicate peaks, in the variance of the series in the given frequency ranges, which may be indicative of a cyclical pattern in the series. In general, we cannot observe frequencies greater than 0.5 cycles per time interval, or periods less than twice the interval of the observations.[6] This highest observable value is known as the Nyquist frequency (Leiner 1998). High frequency dynamics are akin to short cycle processes, while low frequency dynamics may be likened to long cycle processes.

The problem with estimating the spectrum, in this seemingly obvious way, is that the estimator is not consistent. This means that the variance of the estimator does not decrease as the sample size increases.[7] Consequently, the raw periodogram is only a rough estimation of the spectrum, and any conclusion of the periodicity via periodogram must be regarded suspiciously (Broersen 2002). In relevant literature, various methods have been developed as an adequate estimator for the spectrum. On one hand, parametric approaches exist based on the estimation of ARIMA-processes. On the other hand, the spectrum can be estimated by using nonparametric methods and Kernel estimators, respectively.[8] The estimation of the parameters of the spectrum, so-called 'autoregressive spectral estimation', implies the acknowledgement of the ARIMA model order, and will be used in the following analysis of the venture capital investments. The basic idea behind this is that, before using the spectral analysis, the time series needs to be transformed in such a way that the spectrum of the transformed data becomes as smooth as possible. According to this procedure, it is possible to estimate a spectrum $s(\omega)$, to each frequency ω, when the order of the model is specified and the corresponding parameters estimated. The estimator possesses the property to attain the true value with increasing observations, and is therefore, qualified for spectrum analysis. "The accuracy of the parametric spectrum is typically better than the best of all possible periodogram estimates (Broersen (2002), p. 211)."

[6] ω can take a maximum value of 0.5 since for a discrete series a smaller period than of two time units does not exist (*Stier* (2001), p. 179).

[7] In addition, effects like aliasing, leakage and harmonics must receive attention in interpreting the periodogram (*Schlittgen* and *Streitberg* (1994)).

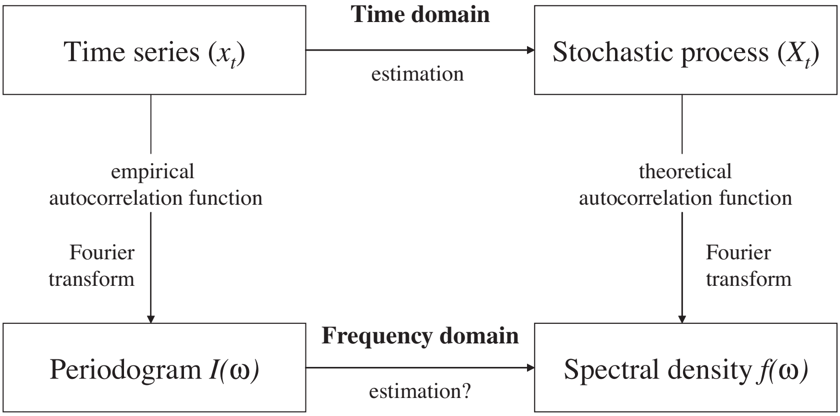
[8] In contrast to the nonparametric methods, the parametric statistical procedures represent tests, which postulate specific distribution functions for the valuations. Their level of scales allow for the calculation of distribution parameters, like expected value and variance.

All nonparametric methods are essentially based on the smoothening of the periodogram using a moving average, in order to receive a stable estimator for the spectrum.[9] The relevant literature distinguishes between direct and indirect spectral estimators. The former approach smooths the periodogram by appropriate spectral windows implying the existence of direct spectral windows. For this purpose, the spectral density is weighted by moving averages over selective discrete ordinates of the periodogram. So, the direct spectral estimator is the weighted sum over the periodogram, and the sequence of the weights is called the *discrete periodogram window*. The spectral density has to be multiplied with different techniques of windowing (for example Daniell-windowing), which vary according to their amplitude in the periodogram window. This approach produces spectral windows of the spectral estimator, where the periodogram looks through the real spectrum.

Compared to the direct spectral estimator, with direct smoothing, in the frequency domain, the indirect spectral estimation makes use of the relationship between the periodogram and the autocorrelation function. The basic idea is to enhance the estimation characteristics of the periodogram by an appropriate modification of the autocovariances. This change is consistent with a multiplication of the autocovariances being observed in a time series by a sequence of weighting coefficients (lag windows). Thus, in comparison to the periodogram, not all autocovariances are included in the estimation (Schlittgen and Streitberg (1994), p. 79). Depending on the choice of lag windows, unstable autocovariances with high lags will be faded out, and estimators of low variance are generated.[10] Herein, the closeness to the time domain is explicitly reflected, because the introduction of a weighting sequence for the autocovariances leads to a continuous version of direct spectral estimators (Schlittgen and Streitberg (1994)). According to this, multiplication in the time domain corresponds to a convolution in the frequency domain of the periodogram. *Figure 3* briefly composes the several coherencies mentioned above.

9 For a detailed introduction to these methods, see *Schlittgen* and *Streitberg* (1994).

10 This method also features several techniques of windowing, which differ by their weighting function, for example the Bartlett- and the Tukey-window.



Source: Schlittgen and Streitberg (1994, p. 353)

Figure 3: Specification of Time Series in Frequency and Time Domain

V. Empirical Investigation of US Venture Capital Cycles

The central stage of the empirical investigation takes the application of spectral analysis, as described in the preceding section. First, we consider the time series of the total investment in the time domain where we focus on the modeling of the underlying stochastic process. In the equivalent representation of frequency domain, the interaction of deterministic and stochastic waves of various frequencies, is the essential characteristic of the process. Unlike the analysis in the time domain, based on the interpretation of the autocorrelation function, the spectral analysis rests upon the spectrum. In the time domain, the presentation is limited to the analysis of the process modeling, as basis of the successive spectral analysis.

1. Data and Descriptive Statistics

The quarterly data of the US venture capital industry is taken from NVCA (2004) for the period 1995Q1 to 2004Q4. Due to the use of quarterly data, T = 40, observations in the estimation period are available. *Figure 4* presents the venture capital investments in different levels. The time series does not follow a common trend as shown in the top-left

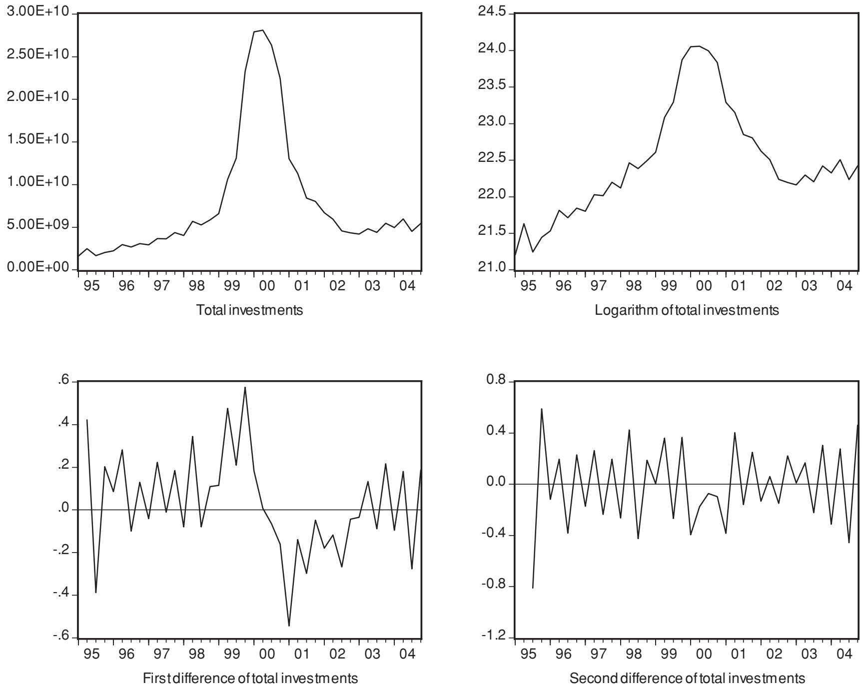


Figure 4: Logarithm and Differences of Venture Capital Investments

hand corner of the diagram. First, a weak trend can be detected from 1995 to mid 1999, followed by a jump in the level up to the second quarter of 2000. Subsequently, the values drop rapidly in the end of 2000, and the investments result in a phase of stagnation.

In addition to the graphical inspection, the descriptive statistics in *table 1* show the empirical moments of the distribution in different levels. On average, US venture capitalists investigate USD 7.88 billion in the period under consideration. The maximum amount of USD 28.1 billion was reached in the second quarter of 2000, whereas at the beginning of the observation period the minimum amount invested was USD 1.6 billion.

The average growth rate of US venture capital investments amount to 3.10 % per quarter. While the original data, according to Jarque-Bera test, does not follow a normal distribution, with skewness of zero and

Table 1

Descriptive Statistics

	mean	median	max	min	std.dev.	skewness	kurtosis	J.B.-statistic
level (USD bn)	7.88	5.12	28.10	1.63	7.38	1.7866	4.9592	27.68***
log level	22.48	22.36	24.06	21.21	0.76	0.6221	2.7976	2.6483
Δlog	0.0310	–0.0114	0.5756	–0.5438	0.2353	0.0156	3.0421	0.9978

Based on quarterly total investments from 1995Q1 to 2004Q4, T = 40 observations;
*** for significance at 1% level (rejection of the normal distribution); J.B. = Jarque-Bera test

kurtosis of three, the log values of the first differences are normally distributed. Furthermore, we obtain a substantially high standard deviation of 23.53% in the quarterly growth rates, which can also be recognized from the graph, down and to the left in *figure 4,* influenced by the sharp decline after 2000.

The empirical moments of a distribution only exhibit explanatory power, if the time series is weakly stationary. Hence, the first step in the estimation of an ARIMA model is to assess the stationarity of a time series. When the natural logarithms of the original data exhibit non-stationarity, successive differencing is carried out until the correlogram of the differenced series dies out. The required degree of differencing to ensure stationarity, is reported in the last plot of *figure 4*. In order to achieve weak stationarity, the natural logarithms of the series have to be second-differenced.

After the time series becomes stationary, the model is identified by considering the autocorrelation and partial autocorrelation function. Thus, it appears that an ARIMA(2,2,2) model can be chosen which provides the best estimation, according to the Akaike information criterion (Akaike (1973)).[11] The estimation results of the twice-differenced logarithmic investment series X_t are as followed:

[11] In addition, the estimated process satisfied the properties of stationarity and invertibility. For the residuals, the null hypothesis of white noise cannot be rejected so that there is no structural information left.

(4) $$\hat{X}_t = -0.0055 - 0.4116\hat{X}_{t-1} + 0.5865\hat{X}_{t-2} - 0.9069\hat{\varepsilon}_{t-2}$$

(0.0068)	(0.1472)	(0.1454)	(0.0986)
[–0.8044]	[–2.7967]	[4.0327]	[–9.2024]

$R^2_{adj.} = 0.6656$, AIC = –0.7158, SIC = –0.5398,
LogL = 16.8840, Q(4) = 0.219, Q(12) = 0.218

Both the regression coefficients, and the regression as a whole, are highly significant at the 1% significance level.[12] The adjusted coefficient of determination (adjusted R^2) explains about 66.56% of the variance of the transformed time series. Thus the logarithmic investment values of venture capital industry can be described by an ARIMA(2,2,2) model.

If a series exhibits a seasonal component, an early consequent seasonal adjustment provides indication of cyclical structures in that time series. A closer specification of these cyclical structures requires the analysis in the frequency domain by applying spectral analysis.

2. Identification of Investment Cycles

The results of ARIMA modeling, and the values of the partial autocorrelation function of the twice-differenced series, deliver primary evidence of cycle length between two and three quarters. To apply the methodology of time series in the frequency domain, the spectra are estimated by using an autoregressive spectral estimator, which in turn requires the modeling of ARIMA processes.

The Census X-12-ARIMA method may be applied to estimate the spectra for seasonal effects via an autoregressive spectral estimator (Findley et al. (1998)). This method seems adequate because the periodic cycles may be hidden by outliers in the years 2000 and 2001, and therefore could be located in periods before and after the cycle actually occurs. The detection of seasonal effects, as well as the low false alarm rate, also attaches great importance to this analysis.[13] This means that the indicated peaks are definitely significant, and not simply the result of distor-

12 The standard errors and t-statistics are reported in parentheses and brackets, respectively. The ARIMA model is selected by minimizing the Akaike information criterion (AIC), or Schwarz criterion (SIC) values. Q(4) and Q(12) are respectively the Ljung-Box statistics at lag 4 and 12 of the residuals.

13 Herein, the advantage of the periodogram appears whose estimators indeed have similar powers of resolution, as the autoregressive spectral estimator, but a significantly higher alarm false rate.

tions of the adjusted time series. In this context, it is important to visually discriminate significant spectral peaks from their insignificant counterparts. According to Soukup and Findley (2003), from this analysis there arise the following four basic problems:

The selection of

– an appropriate spectral estimator,

– an applicable output series for the spectral estimation,

– significant frequencies according to the spectral peaks, and

– significant spectral peaks.

The graphical presentation of the spectral plot in *figure 5* shows, on the left hand side, the spectrum of the differenced adjusted time series. The graph, on the right hand side, illustrates the series of irregular components modified by the outliers. The vertical solid line illustrates the seasonal frequencies, and the two dashed lines describe the frequencies of the generated process related to the quarters. It is assumed that the logarithmic series was adjusted adequately because none of these vertical lines breaks through the time series in a significant peak (Findley et al. (1998)). For the X-12-ARIMA method, a period, specifically a cycle takes one year, i.e. according to the relevant frequencies, for quarterly data the significant spectral peaks are 1/4 and 1/2.[14]

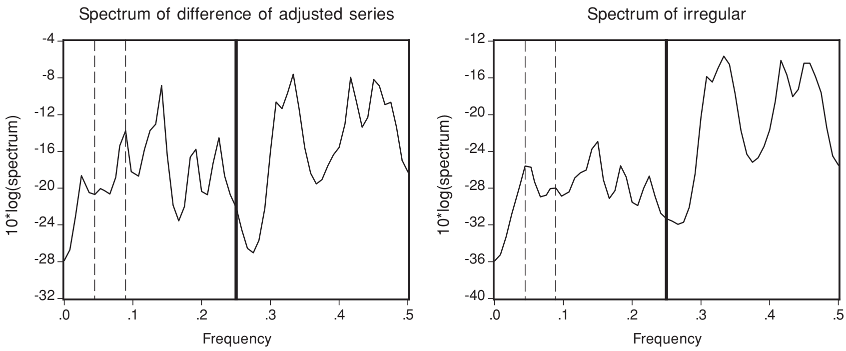


Figure 5: Spectral Density Functions

14 By indicating the frequency the number of cycles taking place per time unit is determined, e.g. a frequency of 0.5 represents a period of two quarters.

The autoregressive model is chosen as estimator for the spectrum, which in units of decibel can be described as:

$$(5) \qquad 10\log_{10}\left(\frac{\sigma_m^2}{2\pi\left|1-\sum_{j=1}^{m} c_j e^{2j\lambda\pi}\right|^2}\right), \quad 0 \leq \lambda \leq 0.5$$

Figure 5 shows that the spectral mass is dispersed over the whole frequency domain and exhibits periodical spectral peaks. The wavelike development constitutes a basic indication for an ARIMA, instead of a white noise process, where all frequencies would provide the same contribution to the process variance. For the spectrum of a seasonally influenced series, it was expected that there existed peaks at certain frequencies, in this case, at the seasonal frequencies of ω = 0.25 and ω = 0.50. However in *figure 5,* distinct peaks are detected at frequencies of 0.13, 0.337, as well as 0.479, where the spectral mass is explicitly concentrated. The frequency of 0.337 is recorded during a period of 2.97 quarters, which is significant in spite of adjustment of the hot issue phase, produces no meaningful results. This frequency involves a particularly distinct outlier component and is therefore disregarded. Moreover, it is not the season frequency of 0.25 that dominates the series, but the frequency of 0.479 close to 0.5 that is significant. According to this 0.479 cycles per quarter pass, which correspond to a period of 2.09 quarters, these quarters can be identified independently of the hot issue phase. The frequency of 0.13 cycles per quarter shows that cyclical structures in the time series also exist. This, on one hand can be attributed to the season figure (ω = 0.479), or on the other hand to the separate periodicity of the time series itself (ω = 0.13). Thus, the series of venture capital investments exhibits two significant cycles at 99% confidence level; one over 7.69 quarters, and the other over 2.09 quarters. The latter corresponds to both the cycle length of the autocorrelation function within the time domain, and the cycle length identified by Gehrig and Stenbacka (2004) within the stage of project selection. Since the screening activity is part of the entire investment process, this low frequency reflects the short-term fluctuations very well. The result of 7.69 quarters is associated with the theory of a full investment process, which should take between two and seven years. Without consideration of the hot issue interactions, an increase in quarters is of high probability. Overall, there is enough evidence to suggest that the US venture capital market constitutes a fully developed market. More interestingly, occurrence of stable cycles, computed with aggregate data shows that on average each single venture capitalist invests in the same period.

To affirm the evidence of cyclical nature in this market, we extend the approach to a disaggregated level by zooming on the different sectors of this industry.

3. Investment Cycles by Industry

On the aggregate level, we identified two significant cycles which dominate the time series. When we examine venture capital investments for different sectors, we obtain a contradictory picture. While one low and one high cycle dominates the time series for some industries, stable cycles occurred more often in other industries. The disaggregated analysis covers 16 different sectors such as biotechnology, electronics, computers, financial services and telecommunication (see table 2 of the appendix). As opposed to the total investments time series, these data include all stages of venture financing (see p. 193). If we look at the original time series it is clear that all the series exhibit regular cyclical movements. We note that in almost all sectors aggregate investments follow a similar pattern, with the exception of electronics, healthcare, semiconductor and telecommunications. In addition, some sectors such as biotechnology (35.71 q/p), business (35.71 q/p), consumer (17.24 q/p), media (20.41 q/p) and networking (19.23 q/p) feature significantly long cycles. In these industries, multiple cycles are observed as well, with the spectral mass being concentrated in both low and high frequencies. The frequency of 0.337 detected in the time series for total investments was not meaningful because of the hot issue phase, a feature observed in all sectors. In the IT and medical sectors, there are stable cycles of between 2 and 8 quarters, while in the other sectors such as software, telecommunications and industrial, cycles of between 2 and 6 quarters could be observed.

Overall, we see that almost all industries exhibit short cycles around high frequencies, which are highly significant in statistical terms. If we examine the long cycles, i.e. low frequencies, we note differences. While nearly all sectors have insignificant cycles around the hot issue phase, some feature very long cycles of between 17 and 35 quarters per period, while others have cycles of between 5 and 8 quarters per period.

VI. Summary and Conclusions

The national importance of start-ups and small companies is indisputable. It is unquestionable that due to their high innovative ability and flexibility, young technology ventures affect the economic structural change. This results in the creation of new jobs and the opening up of new sectors. In this context, venture capital companies play a central role by providing new firms with necessary funds. However, the concept of venture capital investment is more than that of just placing venture capital for disposal. At the same time, the venture capitalist helps businesses develop their management team, and enters into a temporary strategic partnership with the capital acquirer, through taking seats on the board of the company. Venture capital financing represents a typical time-limited minority stake that is executed in iterative stages. Such a venture capital cycle starts with the raising of venture funds, proceeds with the investing in, monitoring of a company, while adding to its value. At the end of the process, disinvestments signalize the exit, and the realized profits return to their investors.

The innovative thrust of this empirical investigation was not only the identification of significant cyclical patterns in the US venture capital market, but also, the detection of single cycle length. The latter is often neglected in literature of this kind. With descriptive statistics, we suppose a complete developed venture capital industry, that runs through the entire investment process, including all investment phases. The course of the process as a whole is important because the profit of the venture capital company depends solely on successful disinvestment of the investment management company, which normally pays no dividend to the capital provider.

While spectral analysis is most useful under the assumption that the data for analysis contains cycles of a fixed length, it is also useful to identify and 'extract' the approximate length of dominant cycles in data which has non-periodic cycles. The time series of venture capital investments delivers the first evidence of cycle length between two and three quarters by modeling the underlying stochastic process using the ARIMA technique. By way of contrast, our research showed that both the ARIMA estimation, and the spectral analysis, can capture short-term fluctuations between two and three quarters corresponding to the cycle length identified by Gehrig and Stenbacka (2004) during the stage of project selection. The second located cycle of 7.69 quarters is associated with the theory of a full investment process, involving between two and seven years. Overall, there is sufficient evidence to suggest that the US venture capital market constitutes a fully developed market that exhibits cyclical properties. Thus, we expect that in the future, actual consolidation will again follow an increasing trend.

References

Acs, F., and D. B. *Audretsch* (1991), "R&D, Firm Size and Innovative Activity", in Z. J. Acs and D. B. Audretsch, Innovation and Technological Change, New York, 39–59. – *Akaike,* H. (1973), "Information Theory and an Extension of the Maximum Likelihood Principle", in: B. N. Petrov and F. Csaki (eds.), Second International Symposium on Information Theory, Akademiai Kiado, Budapest, 267–281. – *Belke,* A., R. *Fehn,* and N. *Foster* (2003), "Does Venture Capital Investment Spur Employment Growth?", CESifo Discussion Paper, No. 930. – *Black,* B. S., and R. J. *Gilson* (1998), "Venture Capital and the Structure of Capital Markets: Bank versus Stock Markets", Journal of Financial Economics, **47,** 243–77. – *Box,* G., and G. *Jenkins* (1976), Time Series Analysis, Forecasting and Control, San Francisco. – *Broersen,* P. M. (2002), "Automatic Spectral Analysis with Time Series Models", Transactions on Instrumentation & Measurement, **51,** 211–17. – *Bygrave,* W. D. and J. A. *Timmons* (1992), Venture Capital at the Cross-roads, Boston. – *Cohen,* W. M., and S. *Klepper* (1992), "The Anatomy of R&D Intensity Distributions", American Economic Review, **82,** 773–99. – *Dickey,* D. A. and W. A. *Fuller* (1979), "Distribution of the Estimators for Autoregressive Time Series with a Unit Root", Journal of the American Statistical Association, **74,** 427–31. – *Dickey,* D. A. and W. A. *Fuller* (1981), "Likelihood Ratio Tests for Autoregressive Time Series with a Unit Root", Econometrica, **49,** 1057–72. – *Engle,* R. F., and C. W. J. *Granger* (1987), "Co-Integration and Error Correction: Representation, Estimation and Testing", Econometrica, **55,** 251–276. – *Findley,* D. F., B. C. *Monsell,* W. R. *Bell,* and M. C. *Otto* (1998), "New Capabilities and Methods of X-12 ARIMA Seasonal-Adjustment Program", Journal of Business & Economic Statistic, 16, 127–151. – *Gehrig,* T. and R. *Stenbacka* (2004), "Venture Cycles: Theory and Evidence", in V. Kanniainen, C. and C. Keuschnigg (eds.): Venture Capital, Entrepreneurship, and Public Policy, MIT-Press, 151–177. – *Gompers,* P. A. (1998), "Venture Capital Growing Pains: Should the Market Diet?", Journal of Banking and Finance, **22,** 1089–1104. – *Gompers,* P. A. and J. *Lerner* (1999), The Venture Capital Cycle, Cambridge. – *Jeng,* L. A. and P. C. *Wells* (1998), "The Determinants of Venture Capital Funding: Evidence Across Countries", Working Paper, Harvard Business School. – *Hamilton,* J. D. (1994), Time Series Analysis, New Jersey. – *Leiner,* B. (1998), Grundlagen der Zeitreihenanalyse, München. – *Lütkepohl,* H. (1993), Introduction to Multiple Time Series Analysis, 2^{nd} ed., Berlin et al. – *Metz,* R. (2002), "Trend, Zyklus und Zufall, Bestimmungsgründe und Verlaufsformen langfristiger Wachstumsschwankungen", Vierteljahresschrift für Sozial- und Wirtschaftsgeschichte, Stuttgart. – *National Venture Capital Association* (NVCA) (2004), Money Tree Survey, Investments by Industry 1995–Q4 2004. – *Said,* S. E., and D. A. *Dickey* (1984), "Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order", Biometrika, **71,** 599–607. – *Schlittgen,* R., and B. *Streitberg* (1994), Zeitreihenanalyse, München. – *Schoar,* A. (2002), "New Ventures and Venture Capital: Dealing with the current Environment", Presentation to the MIT Enterprise. – *Soukup,* R. J. and D. V. *Findley* (2003), "On the Spectrum Diagnostic used X12 ARIMA to indicate the Presence of Trading Day Effects after Modeling or Adjustments", Proceedings of the American Statistical Association, Business and Economic Statistic Section, 144–49. – *Stier,* W. (2001), Methoden der Zeitreihenanalyse, Berlin. – *Weber,* C. (2002), Diversifikation versus Spezialisierung-Vorteilhaftigkeit von Portfoliostrategien bei Venture Capital Investments, München.

Appendix

See page 207 and 208.

Table 2: **Results by Industries**

Model / Sectors	Biotechnology ARIMA(0,2,2)	Business ARIMA(2,2,2)	Computer ARIMA(0,1,4)	Consumer ARIMA(3,1,2)	Electronic ARIMA(0,1,1)	Financial ARIMA(2,1,3)	Healthcare ARIMA(1,2,1)	Industrial ARIMA(2,1,0)
μ	–0.0004 (0.0088)	–0.0145 (0.0091)	–0.0037 (0.0250)	–0.0215 (0.0853)	0.0139*** (0.0043)	0.0445 (0.1052)	–0.0053* (0.0030)	0.0004 (0.0429)
α_1	–	–1.2715*** (0.1685)	–	–0.6245*** (0.2070)	–	0.4436*** (0.1574)	–0.4462*** (0.1197)	–0.2948* (0.1573)
α_2	–	–0.3894** (0.1658)	–	–	–	–	–	–0.4094** (0.1608)
α_3	–	–	–	0.4015** (0.1819)	–	–	–	–
β_1	–1.2213*** (0.1070)	–	–	0.5923** (0.2359)	–0.9975*** (0.0392)	–0.9964*** (0.0292)	–0.9973*** (0.0958)	–
β_2	0.3048*** (0.1619)	–0.8966*** (0.0912)	–	–0.4041* (0.2067)	–	–	–	–
β_3	–	–	–	–	–	0.6009*** (0.0254)	–	–
β_4	–	–	–0.8537*** (0.0947)	–	–	–	–	–
adj. R^2	0.6731	0.6428	0.1552	0.2095	0.4252	0.4457	0.7720	0.1515
AIC	0.9611	2.1022	1.1088	1.6632	1.6252	1.8647	0.8684	1.2947
SIC	1.0904	2.2782	1.1941	1.8831	1.7105	2.0389	0.9990	1.4253
LogL	–15.2505	–33.8397	–19.62203	–24.9369	–29.6905	–30.4976	–13.0646	–20.9510
Q(4)	0.207	0.271	0.117	–	0.459	0.277	0.093	0.555
Q(12)	0.234	0.085*	0.467	0.592	0.660	0.675	0.371	0.849
Low frequency (Quarter)	0.028*** (35.71)	0.028*** (35.71)	0.142*** (7.04)	0.580* (1.72)	0.194*** (5.15)	0.150*** (6.67)	0.187*** (5.35)	0.174*** (5.75)
High frequency (Quarter)	0.416*** (2.40)	0.430*** (2.33)	0.490*** (2.04)	0.410*** (2.44)	0.466*** (2.15)	0.390*** (2.56)	0.490*** (2.04)	0.352*** (2.84)

Continue page 208

Table 2: Continued

Sectors / Model	IT ARIMA(0,1,4)	Media ARIMA(0,2,4)	Medical ARIMA(1,2,1)	Networking ARIMA(2,1,2)	Retailing ARIMA(1,1,4)	Semiconductor ARIMA(1,1,4)	Software ARIMA(1,2,4)	Telecommunic. ARIMA(2,1,4)
μ	0.0151 (0.0804)	–0.0047 (0.0125)	–0.0036** (0.0017)	–0.0599 (0.0723)	0.0167 (0.1193)	0.0653 (0.0666)	–0.0027 (0.0133)	–0.0139 (0.0768)
α_1	–	–	–0.5510*** (0.1419)	–	–0.7881*** (0.0876	–0.6787*** (0.1233)	–0.9951*** (0.0339)	–
α_2	–	–	–	0.8135*** (0.0653)	–	–	–	–0.6418*** (0.0980)
α_3	–	–	–	–	–	–	–	–
β_1	–	–1.2716*** (0.0624)	–0.9969*** (0.0562)	–	0.7062*** (0.1749)	0.6938*** (0.0762)	–	–
β_2	0.6868*** (0.1354)	0.8232*** (0.0426)	–	–0.9224*** (0.0308)	–0.4039*** (0.1868	–	–0.3226* (0.1597)	1.3824*** (0.1837)
β_3	–	–	–	–	–	–	0.3262** (0.1505)	–
β_4	–0.3006** (0.1445)	–0.4630*** (0.0337)	–	–	0.2495*** (0.1343)	0.5729*** (0.0829)	–0.3434** (0.1651)	0.4172** (0.1620)
adj. R^2	0.3912	0.8632	0.7763	0.3660	0.3349	0.1394	0.6394	0.3478
AIC	0.9223	1.1333	0.3476	0.6352	2.6394	0.6054	0.0425	0.4727
SIC	1.0503	1.3057	0.4782	0.7658	2.8549	0.7778	0.2602	0.6468
LogL	–14.9857	–17.5330	–3.4299	–8.7510	–45.1482	–7.5020	4.2136	–4.7447
Q(4)	0.238	0.129	0.881	0.143	–	0.223	–	0.337
Q(12)	0.860	0.578	0.419	0.269	0.525	0.757	0.303	0.641
Low frequency (Quarter)	0.122*** (8.20)	0.049*** (20.41)	0.115*** (8.70)	0.052*** (19.23)	0.163*** (6.13)	0.193*** (5.18)	0.206*** (5.85)	0.211*** (4.74)
High frequency (Quarter)	0.490*** (2.04)	0.416*** (2.40)	0.331*** (3.02)	0.460*** (2.17)	0.334*** (2.99)	0.438*** (2.28)	0.413*** (2.42)	0.427*** (2.34)

Notes: ***, **, * for significance at 99%, 95% and 90% confidence level. The standard errors are reported in parentheses. The ARIMA model is selected by minimizing the Akaike information criterion (AIC), or Schwarz criterion (SIC) values. Q(4) and Q(12) are respectively the Ljung-Box statistics at lag 4 and 12 of the residuals.

Summary

Venture Capital Cycles: Empirical Evidence from the USA

Due to their high innovative ability and flexibility, young technology ventures facilitate structural change in the economy. This results in the creation of new jobs and the opening up of new sectors. In this context, venture capital companies play a central role by providing new firms with the required funds. However, the objective of venture capital investments is more than simply making venture capital available. Venture capitalists also help businesses to develop their management team, and enter into a temporary strategic partnership with the capital acquirer by taking seats on the board of the company. Venture capital financing represents a typical time-limited minority stake that is executed in iterative stages.

The innovative thrust of this study is not only to identify significant cyclical patterns in the US venture capital market but also to ascertain the length of economic cycles, an aspect often neglected in previous studies. By way of contrast, the research shows that both the ARIMA technique and spectral analysis capture short-term fluctuations of between two and three quarters, corresponding to cycle length as identified by Gehrig and Stenbacka (2004) during the stage of project selection. The second cycle of 7.69 quarters located in this study is associated with the theory of the full investment process, which involves a period of between two and seven years. Overall, there is evidence that the US venture capital market constitutes a fully developed market with cyclical properties. Thus, it is expected that the current market consolidation will once again increase in intensity. In addition, venture capital investments are investigated for a range of different industries, with contradictory results. While one low and one high cycle dominates the time series for some sectors, stable cycles occurred more often in other industries. (JEL C22, E32, E44, G24)

Zusammenfassung

Venture-Capital-Investitionen: Eine empirische Untersuchung der zyklischen Entwicklungen am US-amerikanischen Markt für Risikokapital

Unternehmensneugründungen und Innovationen leisten einen wesentlichen Beitrag zum technischen Fortschritt und damit zu einem erhöhten wirtschaftlichen Wachstum einer Volkswirtschaft. Venture-Capital-Gesellschaften spielen in diesem Zusammenhang eine zentrale Rolle, indem sie in privat gehaltene Unternehmen investieren und so langfristig haftendes Eigenkapital zur Verfügung stellen. Der Prozess der Venture-Capital-Finanzierung läuft dabei in sich wiederkehrenden Phasen ab, welcher die Kapital- und Beteiligungsakquisition, die Beteiligungsauswahl und -verhandlung sowie die Investitions- und Desinvestitionsphase umfasst. Der VC-Prozess als Zyklus an sich fordert profitable Exitmöglichkeiten für den VC-Geber, d.h. einen ausgereiften VC-Markt.

Im Vordergrund des Beitrags stehen die empirische Identifikation sowie die Bestimmung der Länge signifikanter zyklischer Verläufe in US-amerikanischen Venture-Capital-Investitionen. Sowohl bei der Schätzung eines ARIMA-Modells im Zeitbereich als auch bei der Anwendung der Spektralanalyse im Frequenzbereich konnten kurzfristige Schwankungen zwischen zwei und drei Quartalen festgestellt werden, die mit der von Gehrig und Stenbacka (2004) identifizierten Zyklenlänge für die Screening-Phase übereinstimmen. Der zweite, mithilfe der Spektralanalyse gewonnene Zyklus, dauert 7,69 Quartale an. Dieses Ergebnis entspricht den theoretischen Erkenntnissen über die Dauer eines vollständigen Investitionsprozesses. Damit konnte nachgewiesen werden, dass es sich beim Venture-Capital-Markt der USA um einen vollständig ausgereiften Markt mit zyklischen Eigenschaften handelt. Anhand dieser Resultate ist zu erwarten, dass im Anschluss an die aktuelle Konsolidierungsphase ein Aufwärtstrend folgen wird. Im Rahmen einer disaggregierten Betrachtung der Venture-Capital-Investitionen für einzelne Branchen konnten die Ergebnisse nur teilweise bestätigt werden.