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Inter-event time interval analysis of organizational-level activity: Venture capital market case

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HIGHLIGHTS

- Organizational level behavior shows a similar heavy-tail property in inter-event time distribution as individual level actions.
- Investing and fund-raising activities are both of weaker burstiness and stronger memory effect.
- More active firms exhibit stronger burst and memory effect in the investing and fund-raising behavior.

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ABSTRACT

Examining the venture capital market as a representative case, we made the first empirical study about timing and rhythm in organizational behavior. We analyze inter-event time intervals and find that the fat-tailed property of organizational behavior is similar that found in individual behavior, but that its lower scaling exponent indicates it is more heterogeneous than individual behavior. We quantify the observable burst and memory effect in organizational behavior. The burst effect occurs when organizations make frequent business deals during a short time period. This is a potential factor affecting economic cycles and market turbulence. The memory effect occurs when future organizational behavior correlates with past behavior, which potentially allows the prediction of future behavior. We find fewer bursts and a stronger memory effect in organizational behavior than in individual behavior. This difference may be related to resource constraint, business routine, and market competition. These findings shed light on the changeable features of organizational behavior and economic system. We drew a necessity to extend study on human dynamics to organization dynamics by exploring real organizational data in a wide range and proposing a mechanism to better modeling organizational behaviors. Understanding the temporal characteristics of organizational behavior is essential to understanding economic complexities.

1. Introduction

We can understand the economic world as a complex adaptive system with a number of interacting agents, including investor groups, firms, government agencies, banks and financial institutions, factories, and so on. The behavior of these organizations shapes economic patterns, politics, and society. Their dynamics strongly affect economic crises, financial system stability, industry transformations, and patterns of social welfare [1–6]. Understanding the nature and origin of

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organization behavior is essential in the development of effective industrial practices, and it has been the topic of study for researchers in economics, management, political science, and sociology.

The investigation of temporal patterns in human activities, in particular the inter-event time characteristics of human behavior, has been widely studied by researchers in statistical physics and complex system theory in recent decades [7–10]. The literature on the inter-event time distribution of human behavior is vast and has been reviewed in detail [11–13]. Dynamic patterns including heavy-tail distributions, burstiness, and memory characterize human behavior. These features are found in such individual human interactions as e-mail and letter communications, face-to-face contacts, online social media contacts, mobile phone calls and text messages, massive multiplayer online games, and financial transactions [14–23]. These patterns were also found in non-interactive human behaviors, e.g., searching and editing online, using a library, and human mobility [24–29].

All of these observations are based on an analysis of individual human behavior. Organizational decisions are made by groups of individuals, and there are thus similarities between organizational behavior and individual behavior, but organizational decisions are also influenced by other factors, including organizational structure, business routines, conditions of competition, and resource constraints. We thus need to know whether the heavy-tails, burstiness, and memory dynamics observed in individual human behavior are also present in organizational behavior, how they are the same and how they differ. Our next step is to examine the temporal patterns of organizational behavior. Compared to the data on individual human behavior made widely available through the expanding Internet, data on organizational behavior is difficult to obtain. Perhaps this explains why inter-event time studies of organizational behavior are rare.

We here carry out an empirical analysis of the venture capital (VC) market to uncover the rules governing the dynamics of organizational behavior. Venture capital provides start-up funds to the small business, enabling them to grow. The goal of venture capital investors is to identify future market leaders while they are in their early stages and to thus maximize their eventual return on their initial investment. Venture capital firms are intermediaries that link financial markets and product markets to promote industry innovation, but venture capital firms can also display herd behavior that causes overheated investment and asset bubbles.

We here analyze dynamic patterns in the behavior of the venture capital firms. Section 2 describes the dataset and its statistical properties. Section 3 analyzes the inter-event time probability density of venture capital firms. Section 4 presents a study of the burst and memory effects in venture capital firms, in particular, the similarities and differences between organizational behavior and individual behavior. Section 5 presents conclusions and final remarks.

2. Data description

We use the activity records of the Chinese venture capital market from 1998 to 2017 that provide venture capital investment data and venture fund-raising data. The first quantifies the venture capital investment in early-stage companies in exchange for equity or ownership. Each record provides the name of the venture capital firm and the date when the investment is made. The dataset includes 1561 venture capitalists and 17253 investment activities. The fund-raising data provides the source and amount of venture capital funds from wealthy individuals, pension funds, insurance companies, family offices, foundations, and other pools of cash. Each fund-raising record provides the name of the venture capitalist who sells the fund and the date that the fund is open to potential investors. This dataset includes 794 venture capital firms and 3197 fund-raising activities. We acquired all of this data from the China Venture database (https://www.chinaventure.com.cn/), which contains over 90% of all venture capital investing and fund-raising events

Fig. 1 shows the distribution of investment and fund-raising activities. Most venture capital firms make fewer than ten investments and carry out fewer than ten fund-raising events during each observation period, but a few extremely active firms make and carry out many more of both. The event number distribution of both datasets deviates from a normal distribution and fits a power-law decay. We find the approximate power-law scaling exponent to be -2.09 and -2.65 respectively for investing and fund-raising. The exponents are estimated by using power law fitting method proposed by Newman et al. [30]. All the power-law exponents reported in this paper are obtained by such a method.

This result agrees with previous studies on human dynamics and firm scale distribution, indicating that there is no way to average the activities of all venture capital firms [31,32]. Thus our result also indicates that traditional approaches that use an average value and variance do not reflect the heterogeneity of venture capital market.

3. Inter-event time interval distribution

In our dataset we denote each investment and fund-raising activity an "event" and build an event sequence $E(t_i)$ for each firm. We define the inter-event time τ_i to be the time interval between two consecutive events made by a same venture capital firm

$$\tau_i = t_i - t_{i-1}, \tag{1}$$

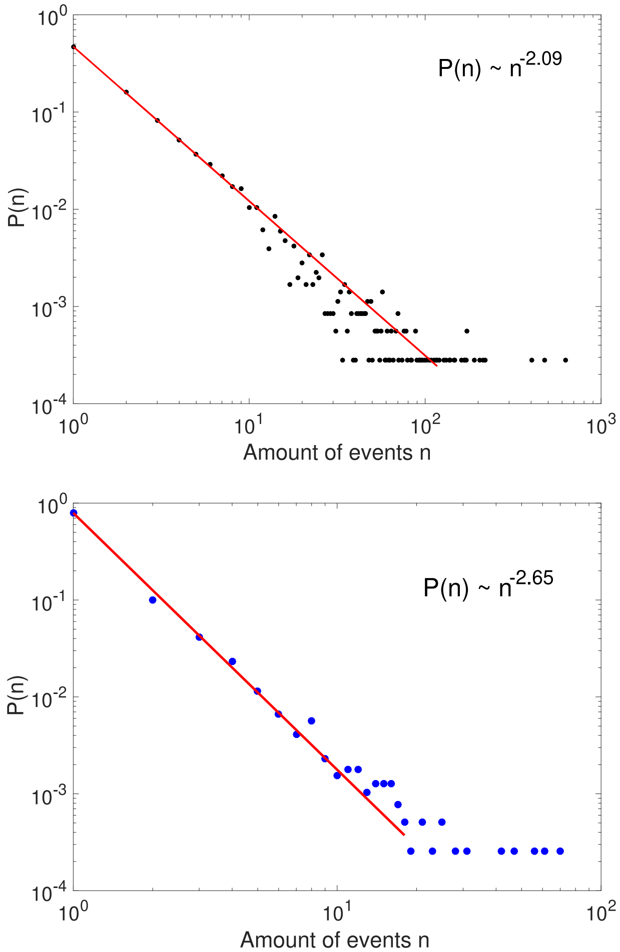

Fig. 1. The probability density function of event number of (top) investing dataset and (bottom) fund-raising dataset on log–log axes. The horizontal axis denotes the event number of each single venture capital firm, and the longitudinal axis denote the probability density of event number. Red line shows the fitted power-law distribution with exponents obtained through power law fitting model by Newman et al.

where the unit of inter-event time is a day. If two events occur on the same day, we classify them as one event. We thus obtain a sequence of inter-event time interval

$$S(\tau_i) = \tau_1, \tau_2, \ldots, \tau_{n-1}, \tag{2}$$

where the number of events $n \geq 2$. From this sequence we compute the probability density function of inter-event time intervals, i.e., the inter-event time interval distribution $P(\tau)$. In traditional behavior analysis, event occurrence is assumed to be a Poisson process in which the probability that n events occur within a bounded interval follows the distribution

$$P(n) = \frac{\lambda^n e^{-\lambda}}{n!}, \tag{3}$$

where λ is the average number of events per interval, which here is equal to the variance of the distribution. In a random and homogeneous Poisson process, the inter-event times are exponentially distributed [33]

$$P(\tau) = \frac{1}{\langle\tau\rangle} e^{-\tau/\langle\tau\rangle}, \tag{4}$$

where $\sigma = \langle\tau\rangle$. In many empirical processes in nature and society, inter-event time distributions have heavy tails that range over several magnitudes. Here the fluctuations characterized by the variance σ are much larger than the average $\langle\tau\rangle$, indicating that $P(\tau)$ for real data is not an exponential distribution.

Fig. 2 shows the inter-event time distribution of one venture capital firm for consecutive investments and fund raising activities. The inter-event time distribution of both activities exhibits heavy-tail behavior, which is closer to a power-law distribution than an exponential distribution. The Kolmogorov–Smirnov distances [30] between the fitted portion of these

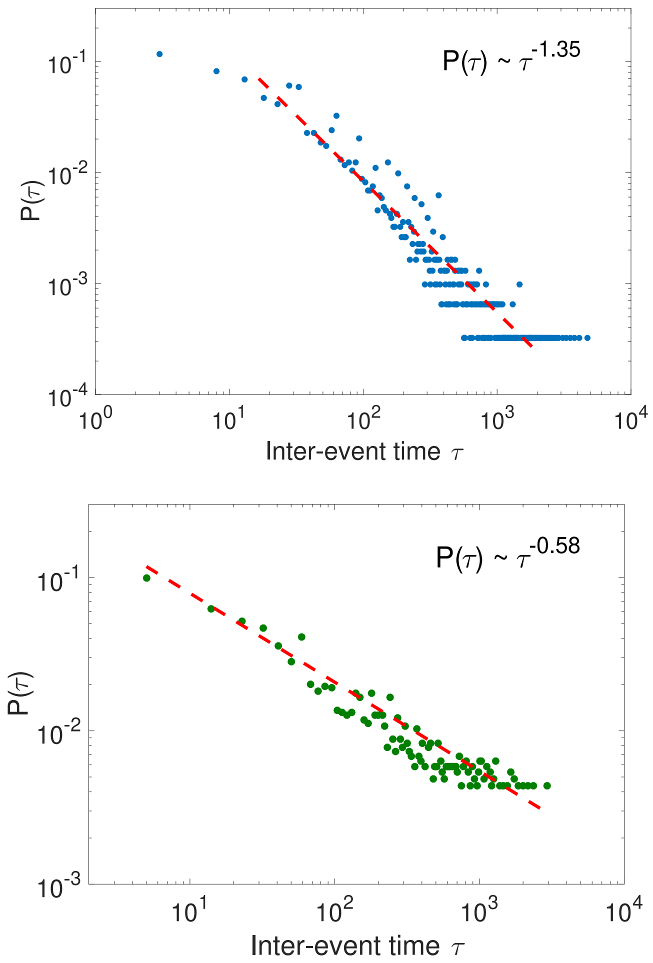

Fig. 2. The distribution of the inter-event time intervals for the venture capital firm (top) investing and (bottom) fund raising activities on log–log axes. Red dash line represents the fitted power-law function with exponent −1.35 and −0.58 respectively.

two datasets and the fit are smaller than 0.05, indicating they both obey a power-law distribution. Thus

$$P(\tau) = \tau^{-\alpha}. \tag{5}$$

For investment events, we obtain a scaling exponent $\alpha = 1.35$, the approximate exponent of the first universality class that includes WWW browsing, e-mail usage, and book checking activities proposed by Barasin [34]. For fund-raising events the exponent is $\alpha = 0.58$, a value seldom found in individual human data. In the Karsai et al. review of the empirical study of human dynamics, the α value of most human activities is >0.8 [11].

Although this indicates that most venture capital firms make investments or sell funds within a short period of time, we still see long waiting times, consistent with the most individual human inter-event time distributions. We find that the longest waiting time is ≈17 years for investing and 15 years for fund-raising. Although the average time interval here is approximately six months for investing and twelve months for fund-raising, it fails to reflect the heterogeneity of organizational behavior.

4. Burst and memory effect

4.1. Burst effect

The temporal activity patterns of social and natural systems, e.g., human correspondence and earthquakes, exhibit burst behavior in which many events rapidly occur within a short period of time followed by a long period of time in which there are few or no events. There have been many studies investigating burst patterns in human behavior [35–39].

We here examine whether venture capital investing and fund-raising exhibit burst effects. The power-law-like distribution of inter-event times for consecutive organizational activities indicates burst effects in organizational behavior dynamics. Fig. 2 shows that most organizational activities occur in fewer than 100 days.

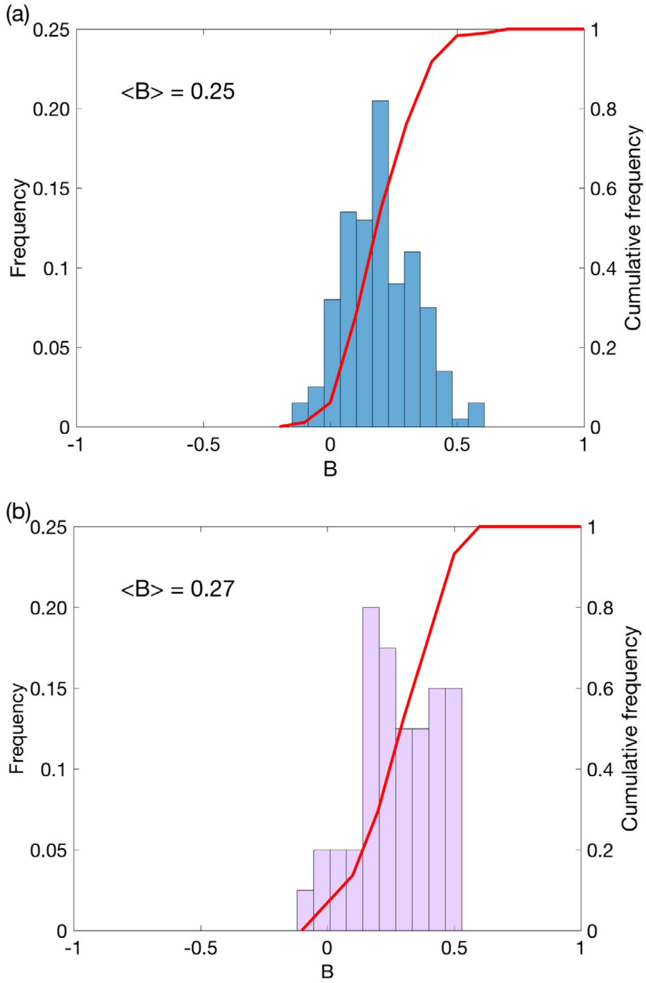

Fig. 3. Histogram of burstiness calculated for (a) investing activities and (b) fund-raising activities. Bars show density and red line represents the cumulative density of parameter B.

We apply the measurement parameter B proposed by Goh and Barabási to quantify the burst level in venture capital firm behavior [36]. Here the burst level of a venture capital firm is defined

$$B = \frac{\sigma - \langle\tau\rangle}{\sigma + \langle\tau\rangle}, \tag{6}$$

where σ and $\langle\tau\rangle$ are the standard deviation and mean value of the series of inter-event time intervals, respectively. The magnitude and the sign of B are related to the burst level of an inter-event time interval sequence. The highest burst level signal is denoted $B = 1$ and a neutral sequence is denoted $B = 0$. When $B = -1$ the corresponding sequence is a completely regular (periodic) sequence. When B is positive, the standard deviation σ is greater than the mean value $\langle\tau\rangle$, i.e., the series has a higher burst level when B is close to unity. In contrast, when B is close to -1 the series becomes more regular.

We calculate the parameter B for the investing and fund-raising data of each venture capital firm. Fig. 3(a) and (b) show the frequency distribution of B for investing and fund-raising, respectively. The average B value is 0.25 for investing and 0.27 for fund-raising. The red curve is the cumulative distribution of B, and we conclude that B is positive in $\approx$ 90% of venture capital firm investing and fund-raising, indicating that both activities exhibit burst behavior. Note that when investing 50% of venture capital firms exhibit $B < 0.2$, indicating a relatively weak burst effect. When fund-raising $\approx$ 70% of venture capital firms exhibit $B > 0.2$, indicating a strong burst effect.

These results indicate that fund-raising events are clustered within short time intervals, and that investing is more uniformly distributed over time. This difference may be because investment requires a higher resource level than fund raising, and this constrains the investment frequency into short time periods. The average B value for activities in venture capital firms is approximately the same as that for such individual human activities such as email usage, library patronage,

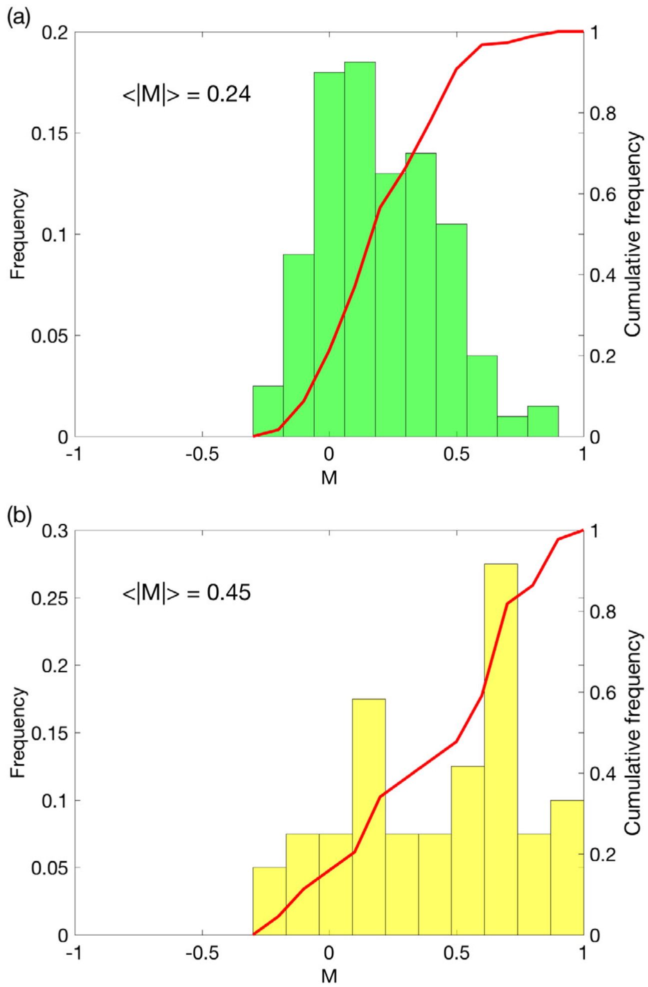

Fig. 4. Histogram of memory effect parameter M calculated for (a) investing activities and (b) fund-raising activities. Bars show density and the red line represents cumulative density.

call center recording, and making phone calls, with B ranging from 0.2 to 0.3 [40]. In addition, the burst effect in venture capital investing and fund-raising is much weaker than the burst effect in such individual online interactions as participating in virtual worlds and editing Wikipedia—both of which have an average B value much higher than 0.5 [22].

We also calculate the Pearson correlation coefficient between the burst effect level and event level in both venture capital datasets. This coefficient C is defined

$$C = \frac{Cov(X, Y)}{\sigma_X \sigma_Y}, \tag{7}$$

where $Cov(X, Y)$ is the covariance, X the series of burst levels B_i for venture capital firm i, and Y the series of event number N_i. We find that the correlation coefficient C in investing and fund-raising are 0.27 and 0.38, respectively, indicating that the greater the number of transactions, the stronger the burst effect.

4.2. Memory effect

We here investigate whether there is a memory effect in venture capital firm behavior. To measure memory we calculate the short term memory coefficient M, defined [36,41]

$$M = \frac{1}{n_\tau - 1} \sum_{i=1}^{n_\tau - 1} \frac{(\tau_i - m_1)(\tau_{i+1} - m_2)}{\sigma_1 \sigma_2}, \tag{8}$$

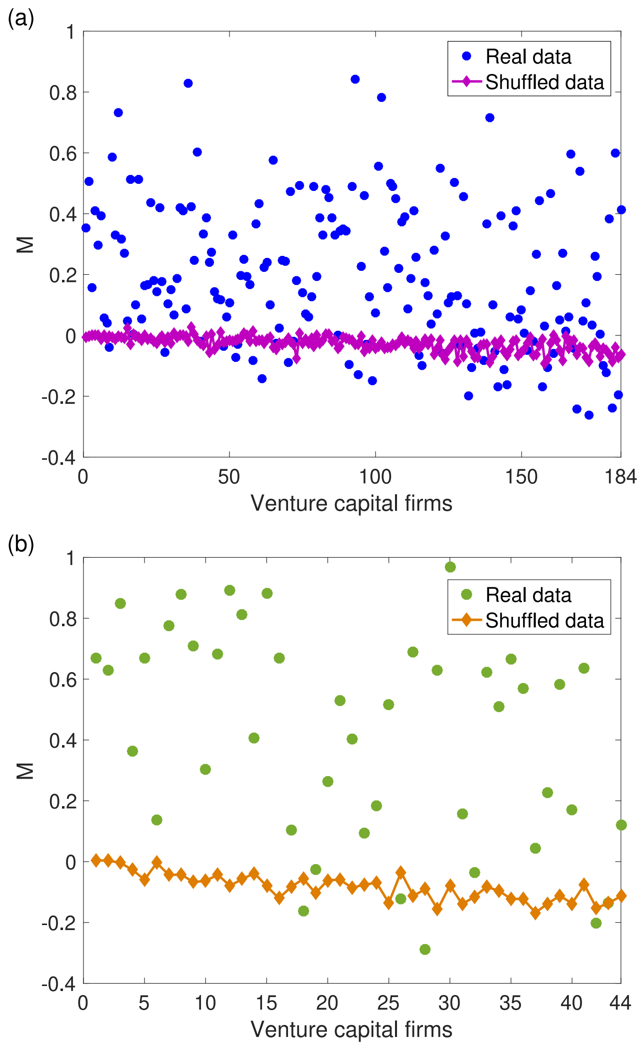

Fig. 5. M value of each venture capital firm for real event sequence and corresponding random shuffled sequence. (a) for investing dataset and (b) for fund-raising dataset.

where n_τ is the number of time intervals measured from the event sequence, and m_1 (m_2) and σ_1 (σ_2) are the average and the standard deviation of inter-event time interval sequences,

$$S_1(\tau_i) = \tau_1, \tau_2, \ldots, \tau_{n-2}, \tag{9}$$

and

$$S_2(\tau_{i+1}) = \tau_1, \tau_2, \ldots, \tau_{n-2}. \tag{10}$$

The memory value M ranges from -1 to 1. When $M > 0.2$ there is a significant positive correlation between series S_1 and S_2, where a short (long) inter-event time is followed by another short (long) inter-event time. When $M < -0.2$ there is a negative correlation between series S_1 and S_2 and a short (long) inter-event time is followed by a long (short) inter-event time. There is no significant memory effect for the M values in the closed interval between -0.2 and 0.2.

Fig. 4 plots the distribution of M for both investing and fund-raising. We find a high skewness, that $\approx$ 45% of the investing activities have an absolute value higher than 0.2, and that the average M is 0.24. In fund-raising we also find that $\approx$ 70% of the venture capital firms exhibit $M > 0.2$ and that the average value is 0.45.

Previous studies of individual human behavior found a very low or negligible short-term memory, with M values between -0.15 and 0.15 [42,43]. Empirically we find that $M > 0.2$ for most venture capital investing and fund-raising events, indicating that firm behavior exhibits a stronger short-term memory than individual human behavior.

To determine whether the high short-term memory effect exhibits a power-law distribution, we compare the frequency of M for a real event series with a random shuffled series. We shuffle the data of the inter-event series but preserve its

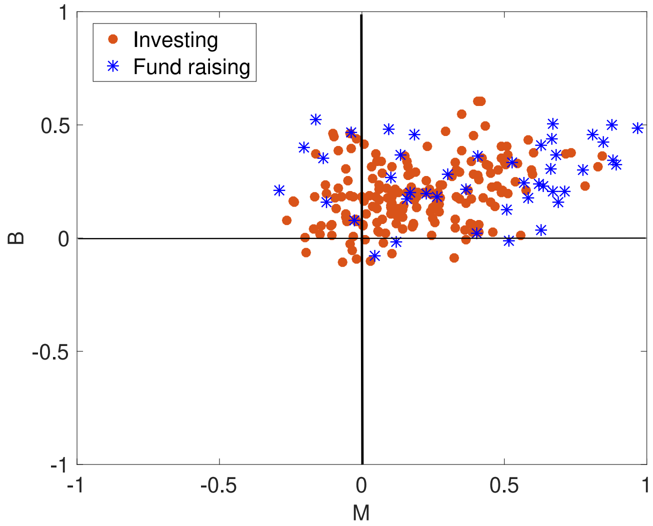

Fig. 6. The memory–burstiness phase diagram for venture capital firms' investing and fund raising activities. The horizontal axis denotes parameter M used to quantify memory effect, and the longitudinal axis denotes parameter B quantifying burst effect. Each point represents a venture capital firm.

distribution. We first extract a series of inter-event time intervals for each venture capital firm and then shuffle the sequence of extracted series to create a shuffled version of the real sequence. This shuffling destroys any temporal correlations in the original event sequence, including the temporal burst event patterns, and assigns a random time to each event over the observation time window. We perform this shuffling 30 times each series and calculate the mean value of memory parameter M.

Fig. 5 shows M for real activities in which the data fluctuate in a broad range and the average M value for the corresponding shuffled data series is close to zero. We find that the memory effect of inter-event time intervals in organizational behavior is not driven by its power-law distribution.

We also calculate the correlation coefficient C between the number of events and the memory effect. We find that for investing $C = 0.17$ and for fund-raising $C = 0.31$. As in burst effects, when there are more events the memory effect is stronger. This may be because when the growth of a venture capital firm reaches a certain scale it adopts its own investing and fund-raising rhythm, which must be strictly followed, and this creates memory effects in which future time intervals are influenced by previous short-term time intervals.

4.3. Memory–burst effect diagram

We study venture capital firm density over the memory–burst diagram to find the behavior patterns of most firms. Fig. 6 shows that the investing and fund-raising patterns of most firms are in the high-M, mid-B region of the (M, B) phase diagram. This differs from previous individual human behavior studies that find low-M and high-B [40,43,44].

This indicates that organizational and individual human behaviors have different temporal patterns. The latter has a higher burst effect and a weaker memory effect. This may be because (i) both investing and fund raising are relatively rational decisions made by a groups of people instead of spontaneous and emotional decisions made by individuals, (ii) organizational activities have a higher resource cost than individual human actions, and this constrains short-term organizational behavior, and (iii) organizations tend to follow specified business strategies and routines and this creates a memory effect.

5. Conclusion and outlook

We have empirically studied the investing and fund raising behavior of venture capital firms in China using an inter-event time interval analysis. Both the investing and fund-raising inter-event time interval distributions have fat-tails and – contradicting the traditional exponential distribution – they follow a power-law distribution. The scaling exponent of investing is 1.35, which is approximately the same as that of individual human behavior, but the scaling exponent of organizational fund-raising is 0.58, which is outside the range of most human behavior.

We find that venture capital firm behavior exhibits burst effects in which many investments are fund-raising events occur within a short time period that is following by a long silent period. This behavior is similar to individual human behavior, but the burst level in organizational behavior is lower than in individual human behavior. This may be because organization activities have a higher resource cost – in capital, human resources, and information – that constrains the burst level, a constraint that much less affects individual human behavior. In venture capital firms the burst effect also correlates with the number of organizational activities. The greater the number of firm activities, the stronger the burst effect levels.

Short term memory effect in an inter-event time sequence indicates that the current waiting time interval is dependent on the previous time interval. When an inter-event time sequence has a positive memory effect, the short (long) time intervals are followed by other short (long) time intervals. Most individual human behavior has a weak, almost negligible short-term memory effect, but the investing and fund raising of organizations have a strong short-term memory effect. This may because organizational actions are strongly affected by defined company routines and strategies that strengthen the short-term memory effect.

This is a first attempt to understand the temporal characteristics of organizational behavior through an analysis of the venture capital market. We conclude that organizational behavior exhibits a wide range of temporal patterns that reflect a variety of mechanisms described in previous studies of human dynamics.

There are many organizational activities in the real-world economy that await future study. The dynamics of organizational behavior are as strong a factor as the dynamics of individual human behavior in understanding the rapid transitions in our fast-changing world.

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