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THE ROLES OF LUCK, SKILL, AND ENVIRONMENT IN THE GENERATIVE PROCESS OF BILLIONAIRE ENTREPRENEURS: AN AGENT-BASED SIMULATION APPROACH

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ABSTRACT

Almost all outcome variables in entrepreneurship show right-skewed long-tail distributions, rather than bell-shaped normal distributions that are commonly assumed in entrepreneurship research. However, it is still unclear how the long-tail distributions are generated in the entrepreneurial process. Hence, this study aims to explain the generative process of the distributions and the extreme outcomes on the right tails of the distributions by reproducing the empirical reality using agent-based modelling and simulation (ABMS). We also discerns the roles of luck, skill, and environment in the entrepreneurial process by the simulation approach. The simulation results show that the long-tail distributions and extreme outcomes are reproduced by the mechanisms of preferential attachment and multiplicative effect, even without any individual or environmental variations. This results support the essential role of luck to generate the stylized fact of entrepreneurship.

INTRODUCTION

Entrepreneurship is a process, but our understanding of and approaches to the entrepreneurial process are still limited (Bakker & Shepherd, 2015; Martinez et al., 2011; McMullen & Dimov, 2013; Zahra & Wright, 2011). Recently, it was reported that almost all outcomes as well as input variables in entrepreneurship fit right-skewed long-tail distributions rather than bell-shaped normal distributions (Crawford et al., 2015). Further, these distributions change into more skewed ones in the entrepreneurial process (Shim, 2016). Consequently, we have a small number of billionaire entrepreneurs who become richer over time, while the rest majority remains modest entrepreneurs. This phenomenon can be regarded as a stylized fact of entrepreneurship, since this phenomenon is commonly observed in diverse datasets regarding the entrepreneurial process. Despite this phenomenon is ubiquitous in entrepreneurship, we have just started the discussion on the generative process of the stylized fact. Building on the discussion, this study seeks the answers to these questions: “What mechanisms generate the skewed distributions?”, “What are the roles of luck, skill and environment in the generative process of the extreme outcomes?”

To answer these questions, this study employs agent-based modeling and simulation (ABMS). Using ABMS, this study discerns the roles of luck, skill and environment, as well as their interactive mechanism in entrepreneurship. By elaborating the micro-level mechanism that provides the macro-level stylized fact of entrepreneurship, this study contributes to entrepreneurship research in several ways. First, this study shows that the preferential attachment of resources occurred during the entrepreneurial process may have an essential role to generate the long-tail distributions and billionaire entrepreneurs. Second, this study suggests that the entrepreneurial process can be effectively modeled as a multiplicative process, where ventures’ outcomes are determined by the multiplication of the values from the ventures’ early-stage conditions and path dependency during the process. In the multiplicative mechanism, the added value of an entrepreneurial activity is not determined only by the activity value but also multiplicatively affected by the venture's current value. This multiplicative mechanism and the path dependency seems to beget the stylized fact of entrepreneurship. Namely, the added value of a venture activity will vary according to the venture's previous value, and they tend to repeat similar activities whether the values are positive or negative. Finally, this study presents an agent-based model that simulates the path-dependent multiplicative process of entrepreneurship. This model can be utilized as a baseline model to build more elaborate simulation models in entrepreneurship.

THEORETICAL BACKGROUND

A fair number of distributions found in natural and social phenomena follow long-tail distributions, and we have several mathematical models to describe the long-tail distributions (Clauset et al., 2009). As representative models to describe the distributions, we may consider power-law (PL) and log-normal (LN) distribution models. For most empirical distributions, only an upper part of the distribution follows a specific long-tail model. Thus, it is necessary to estimate a target model's xmin (minimum x) where the model's behavior starts, and ntail denotes how many data points fit the model. If a fitted model's ntail is relatively small, it means that the model describes only a small part of the empirical distribution (Clauset et al., 2009). In addition, the Kolmogorov-Smirnov (KS) statistic is the maximum distance between empirical data and a theoretical model in the cumulative distribution function. This statistic measures the goodness-of-fits between an empirical data and the theoretical models.

In entrepreneurship field, Crawford et al. (2015) show that almost all input and outcome variables fit right-skewed long-tail distributions rather than bell-shaped normal distributions. They refer to these as PL distributions. However, all long-tail distributions are not necessarily PL distributions. We may have alternative long-tail distributions such as LN distributions. Further, Shim (2016) presented the temporal transformation of long-tail distributions from LN to PL in the entrepreneurial process. Through a simulation, he found that the distributional change may emerge through a multiplicative effect of each venture's numerous activities in the entrepreneurial process. This finding suggests that the entrepreneurship is essentially a multiplicative process, where the effects of venturing activities are multiplied rather than added. In this conception, their outcomes can be doubled, halved, or even nullified by their recent activities or random events during the process.

Various random multiplicative models have explained the long-tail phenomena, such as firm size, city size, and web graph (e.g., Richiardi, 2004). However, the purely random multiplicative models only provide LN distributions rather than PL distributions. This is a slightly different result comparing with the empirical findings in entrepreneurship. In the adjacent research fields, it has been shown that modified random multiplicative models can explain the emergence of PL distributions (Levy & Solomon, 1996; Manrubia & Zanette, 1999; Nirei & Souma, 2002, 2007). This literature implies that a modified multiplicative model may explain the emergence of PL distribution in entrepreneurship. Using agent-based simulation model, this study implements a random-walk model to test the multiplicative mechanism in entrepreneurship. Numerous random-walk models have been suggested to show the role of chance events in management and organization fields (Denrell et al., 2015).

METHOD

This study established an agent-based model (ABM). The purpose of this model is to explain the micro mechanism that generates the long-tail distributions in entrepreneurship. This ABM has two types of agents (i.e. Entrepreneur and Investor) and two types of object (i.e. Opportunity and Resource). The amount of Resource was modeled as state variables of Entrepreneurs and Investors.

Initially, multiple Entrepreneurs, Investors, and Opportunities are randomly located in the simulation space. The Entrepreneurs' efforts to grow their ventures were modeled as their movements within the simulation space. All Entrepreneurs randomly move to one of eight nearby locations in the hope of finding Investors or Opportunities. Each movement can end up in an empty space or at the location of an Investor or an Opportunity. If an Investor is found, 30% probability of a successful investment was assumed, and the amount of the investment is up to the venture's present resource. If an Opportunity is found, the Opportunity can be exploited if the venture can make the required investment. In that case, the return value from the Opportunity is determined by the multiplication of the investment (assumed as a random value which is 1.0~1.5). The Entrepreneurs continue to search for Investors and Opportunities in the simulation space.

At the outset the 1,000 Entrepreneurs are randomly located in a simulation space with 10,000 locations (100 x 100). Across this space are also located 300 Investors and 300 Opportunities. At this time, each Entrepreneur is assumed to have one Resource, and each Investor is assumed to have three Resources to invest. Also, each Opportunity is assumed to require a certain amount of investment between 0 and 10. This ABM has three submodels that have different configurations. The main submodel tests the roles of Investor (preferential attachment mechanism) and Opportunity (multiplicative effect mechanism) simultaneously, while the other submodels test the effect of Investor or Opportunity separately. For each of the three submodels, 100 simulations were performed using a commonly used ABMS program, NetLogo 6.0. The outcome distributions over the simulations were analyzed at 100, 200, 300, 400, and 500 iteration time steps (ticks).

RESULTS

In order to check whether the simulation outcomes fit the PL distribution, each outcome distribution's goodness-of-fit for the PL model was measured by the Kolmogorov-Smirnov (KS) statistic and the proportion of points that fit the PL model were estimated by counting the number of data points that fit the PL model (ntail). Table 1 shows the goodness-of-fits (KS) for PL model and the proportion of fitted data points (ntail/n) for all simulation results. Table 1 shows that all three submodels have satisfactory goodness-of-fits (KS) for PL model (0.035-0.071) and the proportion of fitted data points (ntail) is increasing over the process. Overall, these simulation results are highly congruent with the stylized fact of entrepreneurship.

Table 1. Goodness-of-fits (KS) for PL distributions and the proportion of fitted data points (n_{tail}/n).

Submodels	100 ticks	200 ticks	300 ticks	400 ticks	500 ticks
Goodness-of-fits (KS)					
Opportunity & Investor	0.055	0.046	0.040	0.036	0.035
Opportunity-only	0.071	0.059	0.050	0.044	0.042
Investor-only	0.061	0.060	0.062	0.059	0.060
Fitted data points (n_{tail}/n)					
Opportunity & Investor	18.5%	24.3%	27.5%	36.4%	44.2%
Opportunity-only	12.2%	19.0%	23.3%	30.7%	31.8%
Investor-only	18.5%	22.3%	22.8%	23.5%	21.7%

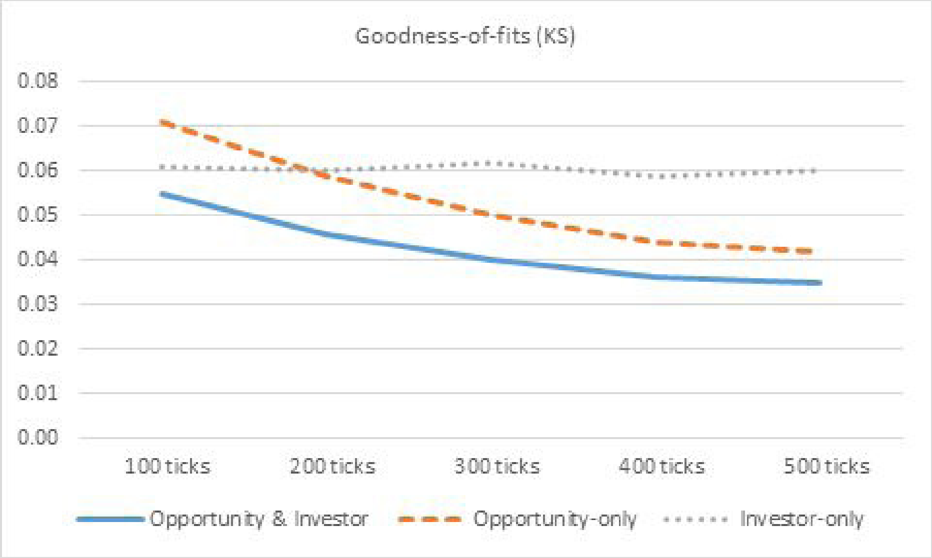
Values are represented by averages of 100 simulations per each submodel.

The n_{tail} denotes how many data points fit to the PL model, thus n_{tail}/n shows the proportion of the fitted number (n=1000).

The KS statistic measures the goodness-of-fit between an empirical distribution and a theoretical model, which is the maximum distance between the empirical data and the theoretical model in the cumulative distribution function.

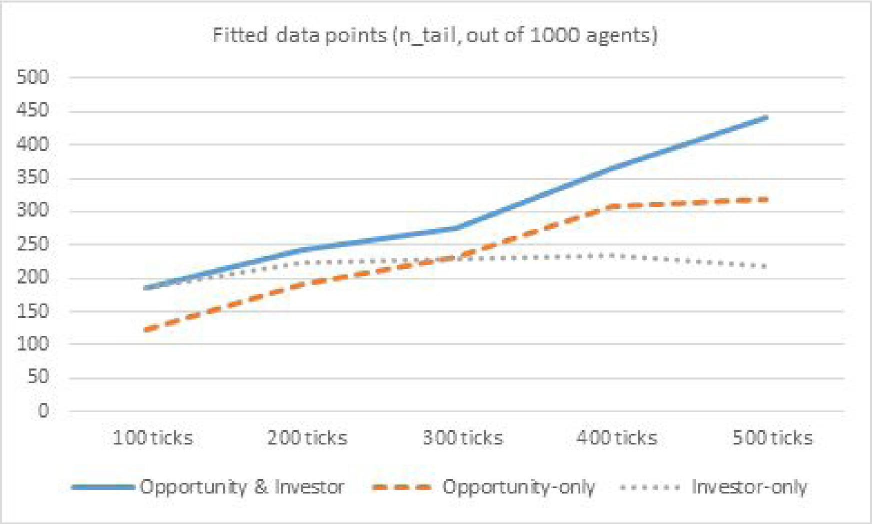
To visualize how quickly each submodel converges towards a PL distribution, Figure 1 and 2 contrast the three submodels and their fitness measures. As Figure 1 shows, the opportunity-only and investor-only models show different effects on the goodness-of-fits (KS) for the PL distributions during the venturing process.

Figure 1. PL distributions' temporal changes of goodness-of-fits (KS) by submodel.



Similarly, Figure 2 shows the different effects of opportunity and investor on the number of fitted data points. The investor-only model plateaus around 20% of 1000 outcomes fitting the PL distribution, while in the opportunity-only model, the proportion of outcomes that fit the PL distribution eventually exceeds 30% but shows a tendency towards a plateau. In comparison, the combined submodel initially follows the investor-only model, with an initial plateau around 20%, but then outperforms both other submodels to exceed 40%, and climbing.

Figure 2. PL distributions' temporal changes of fitted data points (n_{tail}) by submodel.



Overall, the illustrative ABMs successfully reproduce the PL distributions of venture outcomes with a minimal set of concepts and behavioral rules. With additional investigations, the micro-level validity of the behavioral rules may be secured.

Discussion & Implications

Based on a random-multiplicative process, the ABMs reproduced the PL distributions. These simulation results confirm that, without any individual variations, the preferential attachment and multiplicative effect can generate the skewed outcomes in entrepreneurship. In entrepreneurship research, there have been discussions on the role of chance, luck, or randomness in some entrepreneurial processes, such as firm growth process (Coad et al., 2013; Derbyshire and Garnsey, 2014). Building on the discussions, our simulation shows that the randomly determined ventures' early-stage conditions and the multiplicative effect of their path-dependent activities and events during the entrepreneurial process may generate the skewed outcomes in entrepreneurship. This chance explanation can be regarded as a "null finding" but the chance should be regarded as an essential micro-mechanism that provides the outcome distribution in entrepreneurship.

Methodologically, we revised and employed an agent-based random-walk model, which has been used in various management studies (see Denrell et al., 2014). In future studies, entrepreneurship scholars may utilize more refined ABMs with additional empirical datasets to test the aforementioned propositions.

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