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The success of art galleries: a dynamic model with competition and information effects

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Abstract An intrinsic characteristic of cultural goods is the unpredictability of their economic success. Arts goods in particular share characteristics with credence, inspection, and experience goods. Accordingly, art collectors rely on the experience and the reputation of art galleries when investing in artwork. Some qualitative sociological studies have found that only a few very successful galleries represent the bulk of the most visible and most successful artists (e.g., Crane in The transformation of the avant-garde: the New York art world, 1940–1985. The University of Chicago Press, Chicago, 1989; Currid in The Warhol economy: How fashion, art and music drive New York City. Princeton University Press, Princeton, 2007). This paper investigates the success of art galleries in a dynamic model, which elaborates different statistical processes that allow us to analyze the development of different types of success distributions in the market for art galleries. Instead of applying standard economic analysis only, we employ methods from statistical physics to construct a model of gallery investment and competition. Our model entails information, competition, and innovation effects. Subsequently, art market data are used to test which version of the model fits best. We find that the lognormal distribution provides the best fit and conclude that the data generating process is compatible with the version of the model, which entails an inhomogeneous geometric Brownian motion. Hence, the success of art galleries depends strongly on information and innovation effects, but is hardly affected by competition effects. We argue that the superstar effect in the case of art galleries can be understood as an

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appropriation of *search and entrance costs,* which emerge whenever consumption requires special knowledge and social inclusion.

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1 Introduction

From an economic perspective, the art market (in a "nutshell") displays the pivotal problems of markets with high quality uncertainty and considerable innovation intensity. New artists entering the market are unknown, and the products they manufacture require a lot of explanation and evaluation. On the other side of the market, collectors and investors know neither the artist nor her or his work. It is the task of galleries to close the gap between artists and collectors/investors. Entering the market of galleries is also a highly risky enterprise since it entails specific investments, particularly in knowledge of arts, i.e., human capital. This specific human capital does not command high returns outside galleries (and museums). Moreover, with established galleries already in the market, it is difficult to establish a new gallery as a newcomer. This structure of the market seems to be well suited for an investigation of its evolutionary dynamics. First of all, the market is clearly defined and separated from other markets as, e.g., the secondary market for known art work. Moreover, "success" in this market is easily observed by the ranking of new artists, introduced by the respective gallery. Although galleries are certainly not in the main interest of economics, we believe they may serve as a model market for intermediaries in markets with high quality uncertainty and innovation. That is why we consider it well suited for an application of our methodology, which can presumably be transferred to similar markets.

To understand art markets in greater detail, it is to be recognized that an intrinsic characteristic of cultural goods is the unpredictability of their economic success. Arts goods share characteristics with credence, inspection, and experience goods. These characteristics create problems for uninformed customers because of the uncertainty about quality that goes hand in hand with artworks. Additionally, it is obvious that art is taste-driven and thus needs an intense, subjective evaluation. A buyer therefore has to overcome this information problem that is inherent in the characteristics of works of art. Some of the studies that examine the evaluation of cultural goods are discussed by Frey (1997), Ginsburgh (2003) as well as Hutter and Throsby (2008). Reputational approaches in this context are provided by Schönfeld and Reinstaller (2007) and Canals-Cerdá (2012).

Uncertain subjective quality evaluations trigger the emergence of institutions in a market economy intended to reduce this uncertainty. Referring to this fact, a whole industry of experts has evolved, which helps to overcome quality uncertainty by actively evaluating and distributing information on works of art (Becker 1982;

Caves 2000; Currid 2007). Particularly, gallery owners like Monika Sprüth have become very important because they decide which artists they will show, which works they will present, and how much they will invest in the development of the artist and the style she or he represents.

In a world centered on stardom and hits, we assume that the glamorous business of arts should not only have superstars on the side of artists, but also winners on the side of galleries. Some qualitative sociological studies have found that only a few very successful galleries represent the bulk of the most visible and most successful artists (e.g., Crane 1989; Currid 2007). Nevertheless, despite the fact that the superstar effects are analyzed in mass markets (e.g., Franck and Nüesch 2007), deep-pocket markets like the market for art galleries are still hardly ever explored. Heretofore, researchers have paid more attention to the economics of museums. For instance, Camarero et al. (2011) provide empirical evidence on innovations in museums and their impact on museums' economic, market, and social performance, whereas Frey and Meier (2006) reflect upon the functioning of museums in general and particularly address the evolution of "superstar museums." Moreover, Frey (1998) investigates the impact of superstar status of museums on museum policy and its consequences for human resource management.

In this context, Rosen's (1981) and Adler's (1985) theories of superstars have been applied to various markets. Ehrmann et al. (2009), for instance, analyze *superstar effects* in the market for quality restaurants, Walls (2010) analyzes weekly DVD sales revenues in North America, Pitt (2010) emphasizes a new understanding of the music industry from a performing rights organization, Filimon et al. (2011) explore stardom and popularity of musical artists in Spain concerning their purchase of CDs, and Nelson and Glotfelty (2012) examine the relationship between movie star power and box office revenues.

In this paper, we examine the success of galleries in the German art market. For instance, when Monika Sprüth opened her first gallery in Cologne in February 1983, she was advocating the talents of the emerging artists *Jenny Holzer, Barbara Kruger, Cindy Sherman,* and *Rosemarie Trockel*. Sprüth countered an art market dominated by male artists with a gallery focused on female artists. Her efforts brought these female artists to international prominence. By doing so, she also helped previously underappreciated female artists with an entirely new style to establish a reputation. Monika Sprüth made very uncertain, but highly innovative long-term investments in some artists with new styles. Her gallery (now *Sprüth & Magers*) subsequently became highly successful.

The main objective of our paper was to analyze quantitatively whether superstar effects exist in this particular market and if so, to find an adequate approximation of the underlying mechanism for the evolution of art galleries. The paper contributes in three ways to the growing literature on superstar effects. First, we take up ideas from statistical physics to model processes that allow us to analyze the development of different types of distributions of success in the market for art galleries. Second, we apply new methods of empirical testing to determine which distribution best fits our data. Our data reveal lognormal distribution (as the consequence of a geometric Brownian motion) constituting the underlying stochastic process. Third, we offer an economic meaning for this process. In doing so, we hypothesize that the art marketing process is not inherently rudderless, and we propose a reversed version of Baumol's (1986) assumption and suggest that the imperfection of the available information on prices and transactions *does* matter (in the sense that better information about the behavior of the market could help to make decisions more effectively).

The rest of our paper is organized as follows: First, we describe the deep-pocket market of art galleries. Then, we outline a theoretical model with different versions for the development process of this market. By combining the characteristics of the market for art galleries with well-known stochastic processes, the paper offers several theoretical probability density functions that would result from the underlying processes. Thereafter, we empirically test which distribution best fits the data. The last section concludes.

2 Methodological approach

In this paper, we combine economic analysis with methods from "econophysics" (see, for instance, the textbook of Sinha et al. 2011). Because such a procedure is rather uncommon, some explanatory remarks seem necessary. Our main research question—as stated above—is a dynamic one: What kind of dynamic economic process takes effect such that a small, inconsequential firm (here an art gallery) becomes dominant in a field? From a purely economic point of view, three main effects are to be expected: "information" provided by the respective gallery for actual as well as potential art buyers, "specific investments" in the artists a particular gallery represents, and "competition" from other galleries that are also active in the particular (two-sided) market. Specific investments are tools to gain comparative advantage in the market, whereas competition among firms tends to destroy all comparative advantages a particular firm may gain. In short, a Schumpeter (1934, 1942) process of "creative destruction" is to be expected economically. In economics, the method to check the Schumpeter hypothesis is to construct an economic model and to solve it by comparative static or comparative dynamic methods. An econometric analysis with an estimation equation based on the results of the comparative static or comparative static results would then follow suit.[1]

However, the disadvantage of this conventional approach is that it says almost nothing about the dynamic process that governs the empirical results, i.e., the process is a "black box." As is well known, economic processes over time are not deterministic and, hence, one cannot be sure that the results of the process are due to economic variables or pure chance. Instead of applying standard economic analysis only, we employ methods from statistical physics (also called "econophysics") to construct a model of investment and competition for two-sided markets, based on the case of galleries. In contrast to economics, in econophysics, dynamic processes can be specified by a number of rather well-known stochastic processes. Most

[1] A Schumpeterian perspective is also taken by Etro and Pagani (2012) who analyze the determinants of the prices of paintings.

interestingly, these stochastic processes lead to different distributions of the variable under investigation (here the success of art galleries). The empirical distribution of the success variable can be tested as to which theoretical distribution fits best the empirical one. If the result is coherent, it is possible to draw a conclusion on the dynamic process that generated the distribution. In such a way, the stochastic process can be identified. Having identified the dynamic process, the economic mechanism of interaction between galleries' investments and competition can be determined.

The method applied in this paper is as follows: First, the ranking of galleries with respect to their success of promoting artists is formalized. Second, several specified dynamic approaches from statistical physics are employed to model the development of success of art galleries over time. These specified dynamic processes possess well-defined distributions for the success variable of the paper. Third, it is tested which of these distributions fits best the empirical distribution of the success variable.

3 The market for art galleries

Worldwide, there are about 18,000 art galleries, 22,000 museums or art collections, 1,500 auction houses, and 500 fairs, quite recently spanning a market of a double-digit billion dollar volume (Artprize 2011).[2] We use the German art market as a *pars pro toto* for the global art industry. According to BMWi (2009a, b), with an annual turnover of nearly €2 billion in 2008, this art market is one of the smallest branches of the creative industry.[3] This volume is more or less equally distributed among artists (39 %), exhibitions (31 %), and the art trade (e.g., auctioneers, galleries; 30 %). The dominant galleries and art dealers generate a significant percentage of their turnover abroad. Most of the approximately 1,900 German galleries are single-person firms or at least very small enterprises. At most 40–50 galleries compete successfully in the international art market.

Artists who intend to sell their works attempt to do so by using art galleries as middlemen. Galleries are the intermediaries between artists and both art investors and art collectors. The ever-growing demand for the information services of intermediaries should have a positive impact on the likelihood of success for "qualified" art dealers. But do the economics of the gallery sector support the long-term success of individual actors?

Concerning market entry, no specific qualification such as a degree in arts, art history, or in economics is necessary to open a gallery. Other relevant barriers to entering the art market appear to be predominantly absent. Neither economies of scale nor extraordinary capital requirements can be detected from the outset. Switching costs appear to be relatively low and in terms of the concept of Porter's "five forces," only moderate threats—apart from the threat of entry—affect the

[2] In the course of the worldwide economic crisis of 2008, the art market collapsed, but it has been gradually recovering since 2009.

[3] This means 1.5 % of the creative industry and 0.04 % of the overall economy. Aside from any economic figures, the importance of the art market in terms of reputation building (e.g., for cities) should be emphasized.

market. Galleries choose and promote particular artists who represent the "supplier side" in this model framework. The corresponding bargaining power of the individual artist only rises with growing reputation and success in the art market, but initially it is very low.

In contrast, the bargaining power of the "buyer side" (e.g., private collectors) has recently tended to grow (Artprize 2011). However, successful galleries serve a specific wealthy clientele whose purchases of works of art are supposedly price inelastic.

In addition, "rivalry" among galleries is not such an issue as it obviously is in other economic sectors. Keeping in close contact with other galleries as well as with collectors, artists, and museums is essential for successfully communicating the galleries' visions and realizing their strategic ambitions. Because credence, inspection, and experience are central characteristics of art-dealing, art galleries play a key role in determining the development of a whole industry.

Although barriers to entry do not exist to any great extent, the most surprising empirical fact is perhaps the control of this large sector by only a hundred persons. This emphasizes the relevance of a reputation building process in the market for artworks.

Investing in the most recent contemporary art is a very risky endeavor. At the point of a first investment in an artist, it is almost impossible to predict the likelihood of success. One of the reasons is that this kind of art needs to be subjected to the test of time, i.e., people will have to determine whether an artwork has intrinsic aesthetic value or not.[4] So it could well be that the value creation of an artwork is a process in which the work creates its own success, based on an information cascade (Bikhchandani et al. 1992; Watts 2002; Chamley 2004, p. 58) triggered somewhere in the world of arts. A gallery that was successful in the past may have the advantage of having gained an expert reputation in the selection of future trends compared to less successful galleries. The success of such a gallery suggests expertise in predicting future trends, which will lead to creating those trends. Taking the selection of a successful gallery as a signal for a future trend, investors and collectors will invest in the works and artists represented by that gallery which, as a consequence, will become even more successful. In this way, a successful gallery could create self-fulfilling prophecies about future trends through its own selections.

The economic question therefore remains: How can a gallery that was successful in the past gain an ever-increasing reputational advantage as an expert in the selection of future trends compared to less successful galleries?

4 Model

As the most crucial empirical aspect of the arts market, the dominance of a few galleries (ranked by their success in promoting previously unknown artists) in the market is taken for granted. Since art galleries are in the middle between unknown

[4] In a sense, this kind of value creation resembles the pricing processes in the stock market or the selection of a new restaurant whose quality is unknown up to that point (Becker 1991; Karni and Levin 1994; Banerjee 1992).

artists and ignorant potential art buyers, this is a version of a two-sided market. (For a definition and the conceptual background of the latter, see, e.g., Rochet and Tirole 2003, 2004, 2006; Rysman 2009). Rather than analyzing pricing of gallery services and art works, the objective is here to model "success" of art galleries in the above sense. As in most markets—whether one-sided or two-sided—competition, innovation, and information are among the usually expected success factors. However, it is not at all clear how the dynamics of success are to be determined in a market that is prone to high level of quality uncertainty. Instead of employing a purely (more or less static) economic model, it seems more adequate here to use economic ideas of competition, innovation, and information and combine them with known dynamic processes of statistical physics.[5] In such a way, it seems possible to integrate economic knowledge of markets and their underlying evolutionary dynamics.

To analyze the success of galleries in a two-sided market, its success has to be defined quantitatively. Let X_i be the number of points a gallery $i(i = 1, \ldots, N)$ gains by representing artists who have recently become highly esteemed. For instance, take the top-ten ranking of artists and allocate a certain number of points to each of the places in the ranking, with the largest number of points to be allocated to the highest-ranked artist and so on in descending order:

$$X_1 > X_2 > \cdots > X_N. \tag{1}$$

Obviously, i is the rank of gallery X_i. According to Stanley et al. (1995), the ranking can be formalized as follows:

$$\frac{i}{N} = 1 - F(X_i) \tag{2}$$

or equivalently:

$$\ln i = \ln[1 - F(X_i)] + \ln N, \tag{3}$$

with $F(X_i)$ as the cumulative distribution function of X_i.

The question is what kind of distribution the observations X_i of the gallery success performance measure will follow.

First of all, there is competition among galleries for success with the artists they represent. It is well known that competition has an equalizing effect on the relative success of competitors. This actually is one of the main effects of competition. Therefore, the relative success of galleries will have a tendency to the mean success, μ (this is called a "mean-reverting" stochastic process; see, e.g., Kloeden and Platen 1992):

$$\mathrm{d}X_i(t) \propto \theta \cdot (\mu - \lambda \cdot X_i(t)) \tag{4}$$

with $\mathrm{d}X_i(t)$ the change of $X_i(t)$ over time t; μ mean value of success $X_i(t)$ with $\mu > 0$; θ parameter for the speed of reversion to the mean, $\theta > 0$, and λ parameter with which the state of $X_i(t)$ enters the mean-reverting process, $0 \leq \lambda \leq 1$.

[5] For a representative sample of research in this field, see the papers in the Journal of Dynamics and Control 32(1), 2008: 1–320: "Applications of statistical physics in economics and finance."

In (4), θ is a parameter that measures the speed with which deviations from the mean return to it again. This speed of convergence may be interpreted as the degree of competition intensity on the respective market. Put differently, $1/\theta$ could be defined as a measure of market failure. With this interpretation, μ would be the long-term equilibrium success value for galleries in a competitive market.

The parameter λ measures the influence of the state variable X_i in the mean-reverting process. Since it is assumed to be in the range between zero and unity, even large states of X_i may have a small influence on the mean-reverting process. Economically, this may mean that highly successful galleries support the mean-reverting effect of the competition between galleries to only a minor extent. A reason for this may be that the galleries undertook long-term investments in some artists (with new styles) that later became highly successful and that this investment is unique, or at least well-nigh impossible to imitate. A good example of both a very successful and a very innovative gallery is the above-mentioned gallery, *Sprüth & Magers*. Advocating female artists with a new style, Monika Sprüth gave birth to several star artists of international reputation.

In a sense, λ may be interpreted as a measure of the degree of innovation in arts[6], which was triggered by high-risk investments in some artists. The innovation is the greater, the smaller λ is.

A first model for the success of galleries (or even success in two-sided markets with high quality uncertainty), particularly for the achievements of galleries, can be formalized as follows. Let the dynamics of X_i be described by the following stochastic differential equation:

$$\mathrm{d}X_i(t) = \theta \cdot (\mu - X_i(t))\mathrm{d}t + \sigma \cdot X_i(t)\mathrm{d}W(t) \tag{5}$$

with σ variance of $X_i(t)$, $\sigma > 0$, and $\mathrm{d}W(t)$: a standard Wiener process with zero mean and standard deviation $(\mathrm{d}t)^{1/2}$.

In (5)—the dynamic process constitutes an *inhomogeneous geometric Brownian motion* (Bhattarchaya 1978; Zhao 2009)—the innovation effect λ is set to unity.[7] In this case, there is a mean-reversion effect of competition, which depends on the parameter θ; in (5), this effect is independent of the innovation effect that is assumed to be a normally distributed random variable. Moreover, as already indicated above, θ depicts the speed with which the variable X_i converges to its mean, μ. A high θ signals economically a very quick convergence and vice versa. For art galleries (and presumably various other intermediary platforms in two-sided markets), it is to suspect that θ may not be very high. The reason is that there are specific investments required and there are economies of scale and scope: An established gallery may use its expertise and connections to find and promote new artists easier and at lower costs than potential competitors. Hence, even if there is

[6] Here, innovation only means that, e.g., some new style is chosen, which is substantially *different* from the prevailing style.

[7] This dynamic process for X_i is an adaptation of the model of Wyart and Bouchaud (2003, p. 248), which is analyzed more rigorously in Bouchaud and Mézard (2000). See also Bouchaud (2001, pp. 107, 110) for the dynamics of the distribution of wealth. However, the economic interpretation of the process is quite different from their interpretation. See Appendix 3 for a further explication of the derivation of (5) from Wyart and Bouchaud (2003).

competition between galleries, the speed of mean reversion of their success might be rather slow.

As shown by Wyart and Bouchaud (2003), referring to Bouchaud and Mézard (2000), the stationary distribution for this process is $p(x) \sim x^{-1-(1+\theta/\sigma_0^2)}$ (with $p(x)$ as the probability density of X_i), which has a power-law tail. Hence, if (5) was the correct model for art galleries, one should find a *power-law distribution* as the best fit for the distribution of X_i.[8]

However, besides the competition effect measured by θ and the innovation effect measured by λ, there might be an additional effect associated with art galleries. This group of effects is formed by the information cascades mentioned above. Suppose that art investors consider X_i as a signal for the success of gallery i in predicting the value of an artist it represents. To have an influence on the investors' behavior, X_i must contain information that overrules the personal information investors may already have (Chamley 2004). Because the intrinsic value of artworks is a matter of aesthetic taste, and because aesthetic taste is at the market level, a collective rather than a personal matter, only success of a gallery above the mean success level contains information that is more valuable than the investors' privately held information (i.e., their personal aesthetic taste). Hence, for being a signal that contains information on the ability of a gallery to predict the collective aesthetic value of artworks, $X_i > \mu$ is required. Therefore, it might be the case that

$$\mathrm{d}X_i(t) \propto \frac{X_i(t)}{\mu}. \tag{6}$$

Relation (6) implies that "success breeds success." This may be interpreted as the consequence of a very high ambiguity with respect to the aesthetic value of most contemporaneous artworks. In a sense, processes of the "success breeds success" kind create the value of the works they represent. In the theory of networks, this effect is attributed to "preferential attachment:" because some nodes in a network are better linked than others, they attract even more new links.[9] In this paper, the final reason for success is the—perhaps accidental—information cascade triggered by the initial success, which is taken as a signal of expertise in forecasting profitable art developments. In that respect, our model elaborates on the basic idea of evolutionary (game) theory that actions which are more "fit" (under the current distribution of actions) tend over time to displace less fit actions (Friedman 1991). Correspondingly, galleries are assumed to behave as if they were maximizing profits over time, i.e., the more "fit" galleries will on average have acquired more profit than the less fit.

Combining the competition, innovation, and information effects in (4) and (6) as well as taking into account accidental further effects, the process that describes the evolution of the success variable X_i over time may be given by the following stochastic differential equation:

[8] See also *Power-Law Distribution* in Appendix 1.

[9] This aspect of networks is a big topic in the physics literature on the statistical mechanics of network development; see, for instance, Krapivsky and Redner (2001); Berger et al. (2004).

$$\mathrm{d}X_i(t) = \theta \cdot (\mu - \lambda \cdot X_i(t)) \cdot \left(\frac{X_i(t)}{\mu}\right)\mathrm{d}t + \sigma \cdot X_i(t)\mathrm{d}W(t) \tag{7}$$

which can be written as:

$$\mathrm{d}X_i(t) = \theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right) \cdot X_i(t)\mathrm{d}t + \sigma \cdot X_i(t)\mathrm{d}W(t) \tag{8}$$

with σ variance of $X_i(t)$, $\sigma > 0$, and $\mathrm{d}W(t)$ a standard Wiener process with zero mean and standard deviation $(\mathrm{d}t)^{1/2}$.

The evolution Eq. in (6) can be interpreted as follows:

(a) For $\lambda = 0$, a *geometric Brownian motion* with $\mu = \theta$ results (e.g., Dixit and Pindyck 1994, p. 71; Metcalf and Hassett 1995):

$$\mathrm{d}X_i(t) = \theta \cdot X_i(t)\mathrm{d}t + \sigma \cdot X_i(t)\mathrm{d}W(t). \tag{9}$$

In this stochastic process, there is no force that drives the success of galleries back to the long-term mean. In economic terms, this means that there is no effective competition effect. Put differently, there might even be strong competition, e.g., measured by sizeable market entry and exit, but the level of innovation of some leading galleries may be of such importance that their success advantage cannot be competed away.

(b) For $0 < \lambda \le 1$, a *mean-reverting geometric Ornstein–Uhlenbeck process* emerges from (6) (Dixit and Pindyck 1994, p. 161; Metcalf and Hassett 1995). In this version of the model, competition might be effective to a certain extent. As a consequence, all three kinds of effects are effective: information, competition, and innovation.

(c) The expected percentage change of the success variable X_i is for $\lambda = 0$ given by θ and for $0 < \lambda \le 1$ by $\theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right)$. Moreover, the expected absolute change is defined by $\theta \cdot X_i(t)$ for $\lambda = 0$ and by

$$\theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right) \cdot X_i(t) = \theta \cdot X_i(t) - \left(\frac{\theta\lambda}{\mu}\right) \cdot (X_i(t))^2 \tag{10}$$

for $0 < \lambda \le 1$.[10]

First, the stochastic process without the competition effect, the *geometric Brownian motion* ($\lambda = 0$) in (7) is examined.[11] The probability density of the geometric Brownian motion at a fixed time is formulated by Reed and Jorgensen (2004):

$$f(X_i(t)) = \left(\frac{1}{\left(X_i(t)\sigma\sqrt{2\pi \cdot t}\right)}\right) \cdot \exp\left[\left(\frac{-\left(\frac{\ln X(t)}{X_o} - \left(\theta - \frac{1}{2\sigma^2}\right) \cdot t\right)^2}{2\sigma^2 t}\right)\right] \tag{11}$$

[10] See also for this interpretation Epstein et al. (1998, p. 158).

[11] For a solution of the stochastic differential Eq. (7), see also Appendix 2.

Hence, the probability density function originates a lognormal distribution with a mean θ.[12] This result is important for the empirical investigation below: If the success of galleries is best described by a lognormal distribution, the underlying stochastic process may be a geometric Brownian motion. In the interpretation of the stochastic process adopted here, it implies that galleries are extremely innovative ($\lambda = 0$); competition among galleries under these circumstances only has the effect of driving up or down the average success of galleries to θ instead of μ (θ may or may not be larger than μ). With respect to intermediary platforms in general, the value which is to be expected in this case for θ is not clear. If competition among platform intermediaries induces a business creation effect (i.e., increasing the number or value of completed deals between buyers and sellers), which is larger than the business stealing effect (i.e., reducing the number or value of deals completed by the single platforms), the success variable will increase over the former mean value and vice versa. Hence, it is the interaction of these two effects, which is decisive. This corresponds to the theory of evolutionary economics: what survives in a dynamic selection process is likely to be determined in some complicated and nonlinear way by the distributions of actual populations present at a point in time and by their history (Dosi and Nelson 1994; Tordjman 1998), i.e., the results are path-dependent.

Second, the result of the stochastic process with a competition effect ($0 < \lambda \leq 1$), the *mean-reverting geometric Ornstein–Uhlenbeck process* in (6), is analyzed.[13]

(a) A non-trivial solution exists if and only if $2\theta > \sigma^2$ and it is a Gamma density[14]:

$$f(X_i) = \frac{\left[\left[\frac{2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2}\right]^{\left((2(\mu+\lambda))/\sigma^2\right)-1}\right]}{\Gamma\left(\left(\frac{2\theta}{\sigma^2}\right)-1\right)X_i^{(2\theta/\sigma^2)-2}} \cdot \exp\left[\left(\frac{-2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2}\right)\cdot X_i\right] \tag{12}$$

(b) For $\sigma \to 0$, a Dirac Delta distribution results whose mass is concentrated in μ/λ.

(c) For $\theta > \sigma^2$, the Gamma density function has a maximum at $X_i = \frac{\mu\left(\theta-\sigma^2\right)}{(\theta\lambda)}$, and for $\sigma^2 \in (\theta, 2\theta)$, the maximum is 0.

As a consequence, for $2\theta > \sigma^2$, a *Gamma distribution* of the success measure of galleries is to be expected empirically. Based on the economic reasoning in this paper, this result would be in accordance with a geometric Ornstein–Uhlenbeck model for gallery success, which implies that galleries could be considerably more innovative. Moreover, the more the parameter λ approaches unity, the lower the level of innovation would be.

In the following empirical analysis, we will test which distribution function for $F(X_i)$ in Eq. (3) above will fit best.

12 See also the definition of the *lognormal distribution* in Appendix 3.

13 For a solution of the stochastic differential Eq. (6), see also Appendix 2.

14 See also the definition of the *Gamma distribution* in Appendix 1.

5 Empirical analysis

In an annual procedure undertaken since 1970, the world's most in-demand artists have been issued (and honored) in ranking lists under the title of *Kunstkompass*. This success and reputation barometer excludes any monetary measure,[15] but considers the number of (single and group) exhibitions in internationally prestigious museums and reviews in famous art magazines. Analyzing the top 100 entities of the *Kunstkompass*-rankings for the years 2001, 2004, and 2008, we corroborate Crane's discovery from 1989 that only a few galleries represent almost all of the most visible and most successful artists.[16] We cover an investigation period of 7 years. This restriction is not expected to affect considerably the results in comparison with examining other years. It may also be added that the conjoined study of gallery success and its change over time is not intended in this paper but is an issue for ongoing research. As indicated above, we consider three particular years (2001, 2004, and 2008), assess the galleries' ranking according to the success of artists they promote, and analyze empirically the distribution of the galleries' rankings.

To start with, in Fig. 1, the accumulated scoring points per gallery, which we interpret as a measure of the galleries' success/reputation, are plotted against their rank.[17]

This depiction suggests a distribution, which seems to be similar to a power law. Referring to the geometric Brownian motion in (9), another probability distribution intrinsically related to the power law is the lognormal distribution, e.g., only a small deviation in a multiplicative process[18] decides whether it yields a power law or a lognormal distribution (Champernowne 1953; Gibrat 1930, 1931; Kesten 1973; Simon 1955 and Steindl 1965). Displaying the gallery data in log–log plots (see Fig. 2), we observe that each year forms what is nearly a straight line, which is a necessary, but not sufficient, condition for the existence of a power-law distribution. In particular, Mitzenmacher (2004) emphasizes that this property is also valid for lognormally distributed data, at least approximately, if the variance is large enough.

The previous considerations concerning the *inhomogeneous geometric Brownian motion*, the *geometric Brownian motion* and the *geometric Ornstein–Uhlenbeck process*, lead us to the following hypothesis:

[15] To check the relationship between a gallery's reputation according to the *Kunstkompass* score value (X) of the year 2004 and the average price per piece of art promoted by the respective gallery, a correlation test was performed. To do this, the (gallery wise) sum (Y) of the average price per artwork for every single artist promoted was calculated with the assumption that all artists are approximately equally productive. The outcome of the correlation test of X and Y shows a strong relation, but not a perfect one (Kendall's Tau 0.441; Spearman's Rho 0.633—both at 0.01 level). Although there is a number of ways to model gallery success, we suppose that it seems reasonable to focus on an evaluation based on this type of measurement.

[16] The *Kunstkompass* ranking was deliberately chosen as a metric for gallery success. Despite the fact that it contains 100 galleries only, a more complete list of galleries would distend the tail of the distribution without changing significantly the results or interpretations of our analysis.

[17] For each gallery, we added up the achieved score points of every promoted artist among the top 100 ranks.

[18] Multiplicative processes are commonly used to describe the growth of organisms or networks.

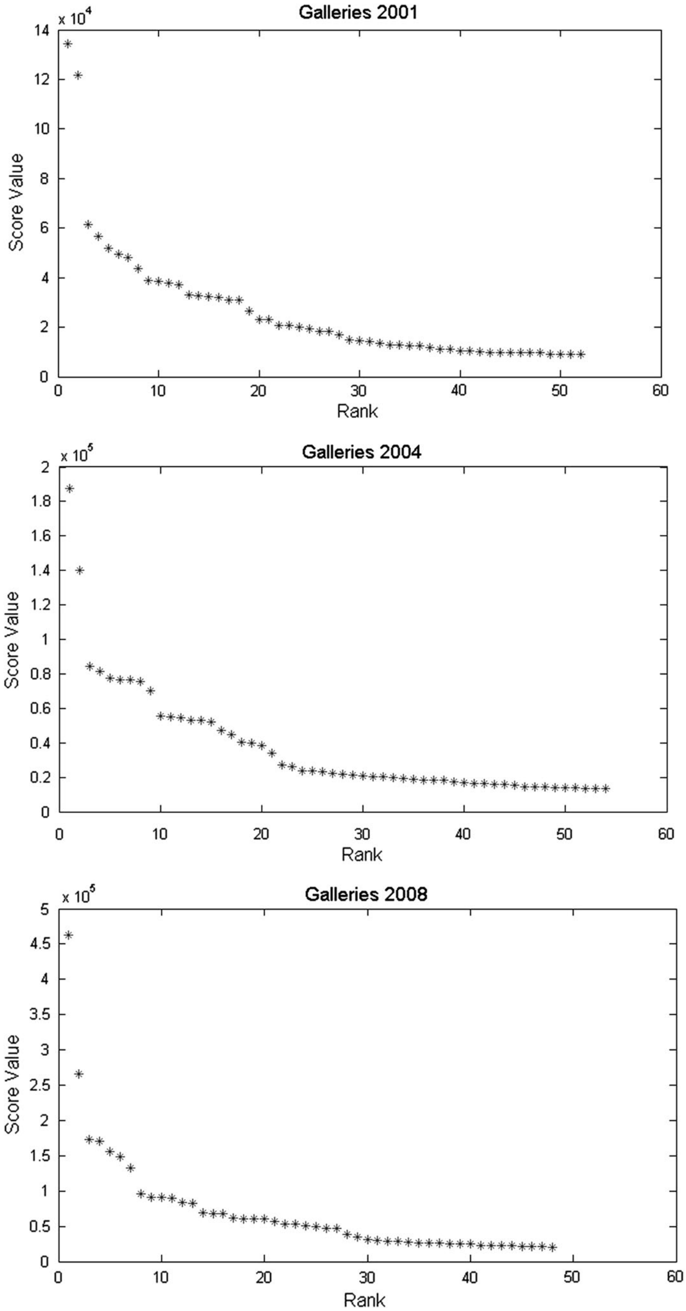

Fig. 1 Rank–score plots for the success of galleries 2001, 2004, and 2008

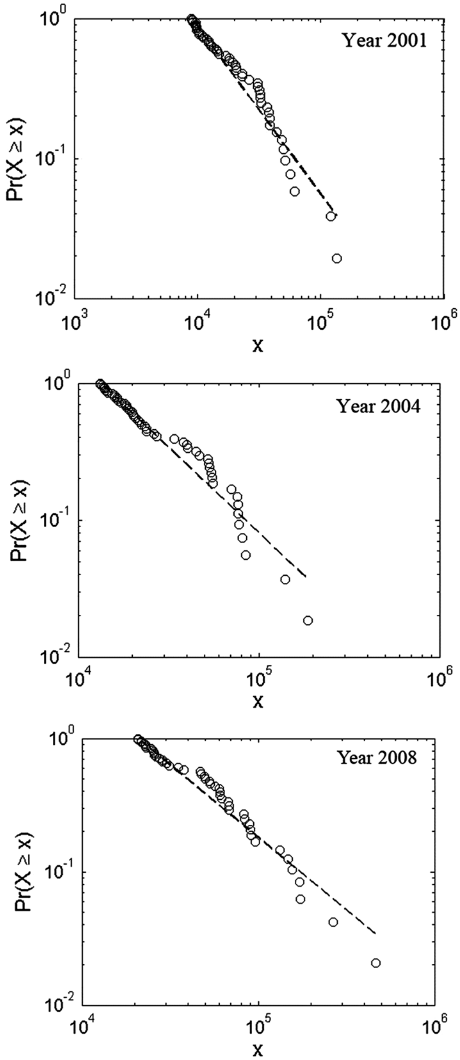

Fig. 2 Log–log plots for the success of galleries 2001, 2004, and 2008

Success of art galleries follows a power law, a lognormal distribution, or a Gamma distribution.

To exclude other similar, potentially competing distributions, a one-sample Kolmogorov–Smirnov test (KS test) is applied; the result is that the assumption of an exponential, a Poisson, as well as of a normal distribution is not statistically significant for each of the years 2001, 2004, and 2008 (at a significance level of 0.05). Then, a KS test is applied again to the data in order to test for a lognormal distribution. For the years 2008 and 2001, our hypothesis of logarithmic normality turns out to be statistically significant, but not for 2004. Eliminating the four galleries with the lowest accumulated score values from the 2004 data, a significant

Table 1 Fitted parameters according to the *lognormal* distribution for gallery success

Year	2001	95 % Conf. interval	2004	95 % Conf. interval	2008	95 % Conf. interval
μ	9.9179	[9.7243, 10.1115]	10.2788	[10.0920, 10.4655]	10.8408	[10.6232, 11.0584]
σ	0.6952	[0.5826, 0.8622]	0.6842	[0.5751, 0.8446]	0.7494	[0.6238, 0.9386]

Scaling parameters of the lognormal distribution

μ mean, σ standard deviation

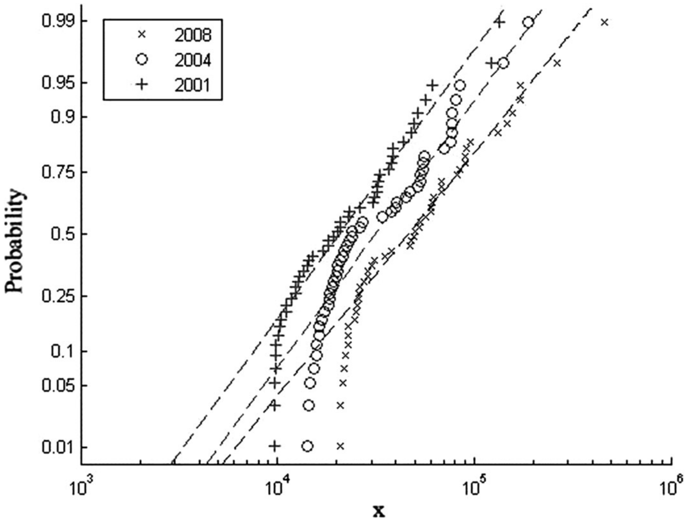

Fig. 3 Probability plot for *lognormal* distribution of the success of galleries 2001, 2004, and 2008[++]. [++]The ordinate axis' scale depicts the success probability based on a lognormal distribution; the axis of abscissae has a log scale

test result for this year (significance level 0.05) is found, too.[19] The fitted parameters are shown in Table 1. Figure 3 displays a probability plot comparing this distribution (dashed line) with the actual distribution in the gallery data.

To test the power-law hypothesis more rigorously, we employ the recent algorithm developed by Clauset et al. (2009) for analyzing power-law distributed data: First, we fit the datasets to power-law configurations. Particularly, we obtain the following maximum-likelihood estimates of the scaling exponent α shown in Table 2.[20] After this, the KS statistics for each of the datasets from 2001, 2004, and 2008 are computed.

For the further analysis, again following Clauset et al. (2009), 1,000 synthetic power-law datasets (with $n = 300$ observations each) are constructed for each of the three datasets from 2001, 2004, and 2008, respectively, selecting the scaling parameter α (see Table 2) and the minimum threshold value equal to those of the

[19] This way the dataset of the year 2004 is reduced from 54 to 50 entities.

[20] See also *Power-Law Distribution* in Appendix 1.

Table 2 Fitted parameters according to the *power-law* distribution for gallery success

Year	2001	95 % Conf. interval	2004	95 % Conf. interval	2008	95 % Conf. interval
α	2.1965	[1.5451, 2.7021]	2.2465	[1.6005, 2.8141]	2.0869	[1.4922, 2.6773]

α: scaling parameter of the power-law distribution

Table 3 Fitted parameters according to the *Gamma* distribution for gallery success

Year	2001	95 % Conf. interval	2004	95 % Conf. interval	2008	95 % Conf. interval
α	1.9785	[1.3849, 2.8265]	2.0566	[1.4479, 2.9211]	1.6760	[1.1610, 2.4196]
β	1.3482e+04	[8.9857e+03, 2.0227e+04]	1.8400e+04	[1.2369e+04, 2.7372e+04]	4.2255e+04	[2.7562e+04, 6.6780e+04]

α, β: scaling parameters of the Gamma distribution

distribution that best fits the observed data. After running the same fitting procedure from above for the synthetic power-law datasets, we compute their corresponding KS statistics. Eventually, the p value is defined as the ratio of the synthetic KS statistics, which exceed the KS statistic of the empirical data. We get a clear result for all three datasets indicating that the power-law hypothesis has to be ruled out. It is worth noting that this result is obtained with the relatively lenient rule $p \leq 0.05$.

Finally, the data are fitted with the maximum-likelihood method according to the assumption of a Gamma distribution; the parameters are presented in Table 3. A chi-square goodness-of-fit test at the 0.05-significance level is carried out with the result that the assumption of a Gamma distribution can be ruled out for each of the datasets of 2001, 2004, and 2008.

Put briefly, our observations are consistent with the hypothesis that the data are drawn from a lognormal distribution. In Fig. 4, the estimated (lognormal) complementary cumulative distribution functions (CCDFs) for the years 2001, 2004, and 2008 are contrasted with the respective empirical CCDF.

Concerning distributions connatural to power laws, the CCDF is linearly related to size:

$$\log P(x > x_o) \approx c - \alpha \log(x_0), \tag{13}$$

where c is a constant and α the scaling parameter.[21]

This means (12) becomes an exact approximation as $x_o \to \infty$ and therefore indicates Fig. 4 to be a convenient depiction to assess the fit of data to power-law-related distributions (Dinardo and Winfree 2010). We choose this display to highlight the fit of our data to the lognormal distribution for all 3 years examined (globally and particularly in its tail).

[21] See above and also *Power-Law Distribution* in Appendix 1.

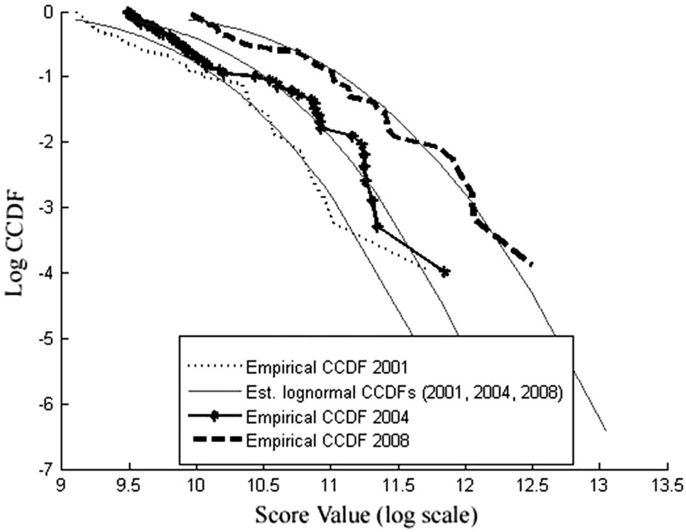

Fig. 4 Log–log plot of complementary cumulative distribution functions of the success of galleries 2001, 2004, and 2008

6 Conclusions

In this paper, the evolutionary dynamics of economic processes that are driven by competition, innovation, and information are formalized by combining economic knowledge with dynamical methods of physics. The information aspect is of special interest here since the dynamic success of galleries (and other platform intermediaries) is investigated whose main task is to reduce quality uncertainty and to promote deals between suppliers and demanders. The emphasis of the paper is put on identifying and separating competition, innovation, and information effects. Furthermore, it is shown how the most likely dynamic process (among the potential processes) can be identified empirically. Galleries as platform intermediaries in the two-sided market of contemporary art are a good example in this respect.

Galleries are central to the promulgation of new works of art to investors and collectors, because they operate at the customer's interface of the cultural value chain. In a certain sense, the artistic decisions and financial investments of gallery owners promote the reputation of both works and artists. Hence, galleries deem to be good examples for intermediary platforms in two-sided markets. The method applied as well as the results gained may be extendable to other intermediary platforms in two-sided markets with a high level of quality uncertainty and innovation.

The success of galleries is expected to depend crucially on three determinants: an information effect, an innovation effect, and a competition effect. Employing the above-mentioned methods, it is demonstrated theoretically that these determinants may support different empirical characteristics of the measurable success of art galleries.

Empirically, we find the success of galleries to be best described by a lognormal distribution, which means that the underlying stochastic process is most likely a geometric Brownian motion. In the interpretation of this stochastic process given here, this implies that galleries are very innovative. Moreover, it seems that the (loosely defined) degree of innovation of a few leading galleries is supported over time by information cascades in such a way that their success advantage cannot be eroded by competition. This means that there is no force that drives the success of galleries back to the long-term mean. Even if there was strong competition, e.g., measured by sizeable market entry and exit, the degree of innovation of some leading galleries may have been of great importance. In fact, very successful galleries start building up a reputation by being very innovative in the first place.[22] As the case of the acclaimed gallery owner Monika Sprüth has illustrated, she has helped to establish a reputation for previously underappreciated female artists with a new style. Her efforts brought those female artists to international prominence and success for her new gallery too.

This initial innovation can become a starting point for information cascades: reputable galleries are followed by experts, collectors, and museums (Crossland and Smith 2002). Prominent galleries can even have an impact on artists, persuading them to reshape their creative style toward works that may have higher commercial potential (Currid 2007). In a certain sense, experts in other fields that are prone to high levels of quality uncertainty may be considered as intermediary platforms, even if there is no institutionalized connection between the intermediary and the suppliers and demanders on these markets. Having established a high reputation for quality sensitivity, experts for technical systems as well as restaurant or travel guides may gain a market position that is not contestable. In a similar way, financial intermediaries as, e.g., banks with specific knowledge about firms and their investment projects, may also gain uncontestable positions with respect to firms and investors. More generally, two-sided markets with high quality uncertainty or information deficits on the one hand and high levels of specific investments of the respective intermediary on the other hand seem to function in a similar way as art galleries with respect to artists and collectors or investors.

Investments in works of art cannot be separated from their social context, i.e., the exclusive art world in a wider sense. By choosing the most notable and respected art galleries, customers minimize the search costs of gaining endorsement by discussion partners in that world (Adler 1985). Robinson's (1961, p. 398) remark that "…fashion serves as a means of demonstrating command over current, as opposed to former, output," seems to be directly applicable to the arts, too. As art investors and collectors cannot be equally well informed about each and every gallery, they will choose a limited number of preferred galleries whose exhibited works are innovative according to the public discourse, which means that they are "demonstrating command over current" (Robinson 1961, p. 398). Following Adler (1985), star galleries absorb part of consumers' savings in search costs—including the "entrance fees" to exclusive art circles—by demanding high prices and receiving public reputation for their products.

[22] We cannot exclude the problem that by examining the survivors, we are really only looking at those gallery "strategies" that were ex post successful (see Brown et al. 1992). However, we do not consider this a considerable effect because of the absent barriers to entry that characterize the industry.

Thus, the superstar effect in the case of galleries can be understood as an appropriation of *search and entrance costs,* which emerge whenever consumption requires special knowledge and social inclusion.

In a continuous process, a few star galleries develop and seem to be able to establish an uncontestable market position. This result is in line with the findings of Salganik et al. (2006) and Salganik and Watts (2008) that social influence contributes very strongly to the inequality of outcomes in cultural markets. Contrary to the finding by de Vany and Walls (1999) that past success does not predict future success in the movie industry,[23] forecasts of expected gallery success are not completely meaningless: the underlying stochastic processes of success may help to improve our understanding of the evolution of superstar effects in the art markets. As it seems, film studios do not feature such a strong mediating role in the vertically integrated market for movies as galleries do in the two-sided art market. Besides, a multitude of moviegoers is opposed to a relatively small number of art dealers and experts. Consequently, this scaling effect could be accountable for unleashing different dynamics in these two markets. Moreover, it is neither supposed nor claimed here that the identified/hypothesized process is fixed and that it will never change, but it seems to provide a useful (first) approximation.

In addition to these results, we find that also economic peculiarities may be main drivers of the evolution of success (not only) in cultural markets when quality uncertainty is high for the final customers and when on the side of the intermediary platform specific investments are required to build up a sustainable reputation with both artists as well as art collectors and investors. Having established such a reputation, competition among intermediary platforms plays hardly any role. It seems very likely that this result could be generalized for other two-sided markets with high quality uncertainty.

With a growing number of two-sided markets with platform intermediaries, the methods applied in this context may be suitable to differentiate between competition, innovation, and information effects in these markets. The detailed adoption of the approach considered here to other industry-specific platforms and the examination of differences concerning transferability, limitations, and empirical evidence is a topic of further research.

Appendix 1: Relevant distributions

Power-law distribution

A quantity x obeys a power law, if it is drawn from a probability distribution

$$p(x) \propto x^{-\alpha} \tag{14}$$

where $\alpha > 0$ is a constant scaling parameter.

[23] De Vany and Walls (1999) argue that when the audience makes a movie a hit, no amount of "star power" or marketing can alter that because movies' revenues are Lévy-distributed, i.e., their variances are not finite. Thus, choosing portfolios of movies seems advisable compared to promoting individual movie projects (whereas art galleries reduce their risks by promoting a "portfolio of artists"). Still, film studios constitute a profoundly uncertain business.

(In practice, only a few empirical phenomena follow a power-law distribution for all values of x, but often the power law can be applied for values above a certain threshold $x_{\min}$.)

Lognormal distribution

A random variable X obeys a lognormal distribution, if its logarithm is normally distributed. The probability density function of a lognormal distribution is described as

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma x}\exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right), \tag{15}$$

where $\mu \in \mathbb{R}$ is the mean and $\sigma \in \mathbb{R}$ the standard deviation ($\sigma > 0$ and $x > 0$).

Gamma distribution

A Gamma distribution is defined by the probability density function

$$f(x) = \left[\frac{\alpha^\beta}{\Gamma(\beta)}\right]x^{\beta-1}\exp(-\alpha x), \tag{16}$$

where $\alpha \in \mathbb{R}$, $\beta \in \mathbb{R}$ ($\alpha > 0$, $\beta > 0$ and $x \geq 0$)

Appendix 2: Relevant processes

Brownian motion

$$\mathrm{d}X_i(t) = \theta \cdot (\mu - \lambda \cdot X_i(t)) \cdot \left(\frac{X_i(t)}{\mu}\right)\mathrm{d}t + \sigma \cdot X_i(t)\mathrm{d}W(t)$$

with σ variance of $X_i(t)$, $\sigma > 0$, and $\mathrm{d}W(t)$ a standard Wiener process with zero mean and standard deviation $(\mathrm{d}t)^{1/2}$.
The explicit solution of (7) reads [see, e.g., Dixit and Pindyck (1994, pp. 71, 81)]:

$$X_i(t) = X_0 \cdot \exp\left[\left(\theta - \frac{\sigma^2}{2}\right) \cdot t + \sigma \cdot W(t)\right]. \tag{17}$$

The expected value of X_i is given by

$$E[X_i(t)] = X_0 \cdot \exp(\theta t) \tag{18}$$

and the variance by

$$\mathrm{var}[X_i(t)] = X_0^2 \cdot \exp(2 \cdot \theta \cdot t) \cdot \left[\exp\left(\sigma^2 \cdot t\right) - 1\right] \tag{19}$$

(see, e.g., Dixit and Pindyck 1994, pp. 71 f.).

Mean-reverting geometric Ornstein–Uhlenbeck process

$$\mathrm{d}X_i(t) \propto \frac{X_i(t)}{\mu}$$

The explicit solution is given by Kloeden and Platen (1992):

$$X_i(t) = \frac{\exp\left[\left(\theta - \frac{\sigma^2}{2}\right)t + \sigma W(t)\right]}{\frac{1}{X_0} + \theta\int_0^t \exp\left[\left(\theta - \frac{\sigma^2}{2}\right)s + \sigma W(t)\right]\mathrm{d}s} \tag{20}$$

To calculate the probability density of X_i, $f(X_i)$, the stochastic process defined by (6) has the following stationary forward Fokker–Planck equation (Pasquali 2001, p. 169; see also Ewald and Yang 2007, p. 8):

$$\frac{\mathrm{d}}{\mathrm{d}X_i}\cdot\left[\theta\left(1 - \frac{\lambda}{\mu}X_i\right)X_i f(X_i)\right] - \frac{1}{2}\cdot\frac{\mathrm{d}^2}{\mathrm{d}X_i^2}\cdot\left[\sigma^2 X_i^2 f(X_i)\right] = 0 \tag{21}$$

As shown by Pasquali (2001, pp. 169 f.) (see also Ewald and Yang 2007, p. 11), this equation has the following solutions for the density function $f(X_i)$:

(a) A non-trivial solution exists if and only if $2\theta > \sigma^2$ and it is a Gamma density:

$$f(X_i) = \frac{\left[\left[\frac{\left(\frac{2\cdot\theta\lambda}{\mu}\right)}{\sigma^2}\right]^{\left((2(\mu+\lambda))/\sigma^2\right)-1}\right]}{\Gamma\left(\frac{2\theta}{\sigma^2} - 1\right)X_i^{(2\theta/\sigma^2)-2}}\cdot\exp\left[\frac{-2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2}X_i\right]$$

In this case, mean and variance are given by

$$E(X_i) = \frac{\mu}{\lambda} - \frac{\mu\sigma^2}{(2\theta\lambda)} = \left(\frac{\mu}{\lambda}\right)\cdot\left(1 - \frac{\sigma^2}{2\theta}\right) \tag{22}$$

and, respectively,

$$\mathrm{var}(X_i) = \frac{\mu^2\sigma^2}{(2\theta\lambda^2)} - \frac{\mu^2\sigma^4}{(4\theta^2\lambda^2)} = \frac{\mu^2\sigma^2}{(2\theta\lambda^2)}\cdot\left(1 - \frac{\sigma^2}{(2\theta)}\right). \tag{23}$$

(b) For $\sigma \to 0$, a Dirac Delta distribution results whose mass is concentrated in μ/λ.

(c) For $\theta > \sigma^2$, the Gamma density function has a maximum at $X_i = \frac{\mu\left(\theta-\sigma^2\right)}{(\theta\lambda)}$ and for $\sigma^2 \in (\theta, 2\theta)$the maximum is 0.

Appendix 3

Equation (5) in the text

$$\mathrm{d}X_i(t) = \theta\cdot(\mu - X_i(t))\mathrm{d}t + \sigma\cdot X_i(t)\mathrm{d}W(t)$$

is derived from the differential equation of Wyart and Bouchaud (2003) (incorporating the variables as defined for this paper):

$$\frac{\mathrm{d}X_i(t)}{\mathrm{d}t} = \theta \cdot \left[\left(\frac{1}{N}\right)\sum_{j=1}^{N} X_j(t) - X_i(t)\right] + \eta_i(t) \cdot X_i(t)$$

with $\eta_i(t)$ as a Gaussian random variable.

Using $\frac{1}{N}\sum_{i=1}^{N} X_i(t) = \mu$ and $\eta_i(t) = \sigma \cdot \xi(t) = \sigma \cdot \mathrm{d}W_t$ with $E\xi(t) = 0$ and $E\xi(t)\xi(t^{'}) = \delta(t - t^{'})$ for all $t, t' \geq 0$ and $\xi(t) = \frac{\mathrm{d}W_t}{\mathrm{d}t} \forall t$ (see Jetschke 1989, pp. 216–218), the differential equation can be written as (5) in the text.

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