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Exploring the contingencies of private-collective innovation: An agent-based model

Michael A. Zaggl
Technische Universität München
TUM School of Management
michael.zaggl@tum.de

Christina Raasch
Technische Universität München
TUM School of Management
c.raasch@tum.de

Abstract

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We explore the environmental conditions in which private-collective innovation is likely to emerge and thrive. Our agent-based simulation makes it possible to study multiple contingencies, their interactions and outcomes in a systematic way. We find that the private-collective model of innovation delivers greater innovation performance, and is more likely to be sustainable, if the environment is characterized by low rivalry among agents, high imitability of designs, and extraneous benefits to reputation. Interestingly, the detectability of design plagiarism is negatively associated with system performance and with the emergence and stability of cooperation due to extensive punishment activities. The paper contributes to our understanding of the emergence of private-collective innovation from self-regarding individual behavior and of the system-level performance outcomes, as compared to the canonical private-investment model of innovation.

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The private-collective model has been advanced as a new model specifying the incentives that give rise to innovation in an economy: It involves the free revealing of design information created at private expense, in exchange for a mix of private and collectively provided benefits. We explore the environmental conditions in which private-collective innovation is likely to emerge and thrive. Our agent-based simulation makes it possible to study multiple contingencies, their interactions and outcomes in a systematic way. We find that the private-collective model of innovation delivers greater innovation performance, and is more likely to be sustainable, if the environment is characterized by low rivalry among agents, high imitability of designs, and extraneous benefits to reputation. Interestingly, the detectability of design plagiarism is negatively associated with system performance and with the emergence and stability of cooperation due to extensive punishment activities. The paper contributes to our understanding of the emergence of private-collective innovation from self-regarding individual behavior and of the system-level performance outcomes, as compared to the canonical private-investment model of innovation.

Keywords: private-collective innovation; free revealing; innovation performance; social norms; agent-based modeling

1 Introduction

In the private-collective model of innovation, actors freely reveal proprietary, innovation-related information created at private expense (von Hippel and von Krogh 2003). Viewed from the theoretical vantage of the classic private investment innovation paradigm (Demsetz, 1967; Arrow, 1984) whereby agents innovate and then protect their innovative designs[1] from uncompensated spillovers to gain a monopoly position and maximize profit, such behavior appears irrational. Thus, its proliferation in many domains, ranging from open source software and user innovation communities (von Hippel 2005, 2010; Henkel 2006; Bayus 2013; de Jong et al. 2014) to medicine (Strandburg 2009; DeMonaco et al. 2014) and haute cuisine (Fauchart and von Hippel 2008), initially puzzled researchers. Over the last decade, however, we have gradually built a solid understanding of why rational agents choose to reveal valuable design information to others without recompense. Sharing is rewarded by the recipients in a different "currency" which can take many different forms, e.g. reputation and status, feedback and assistance, reciprocal information sharing, or employment opportunities (Lerner and Tirole 2002; Lakhani and Wolf 2005; Janzik and Raasch 2011; von Krogh et al. 2012 review some of this literature).

More recently, scholars have shifted their emphasis from studies of the "why" of private-collective innovation to examining the institutional, technological and environmental conditions supporting its functioning. Baldwin and von Hippel (2011) show by analytical modeling that a modular product architecture (cf. Baldwin and Clark 2006) and low communication costs are central for private-collective innovation. Di Stefano et al. (2013) point to the importance of social norms relating to information reuse as well as the limiting condition of competition between agents for free revealing of innovation-related information.

Contributing to this direction of research, our paper proposes to undertake a systematic investigation of the contextual conditions that are conducive to the efficacy of private-collective innovation systems. We investigate the contingencies in which self-regarding, boundedly rational agents choose to depart from the private investment model of innovation, which would dictate the protection of proprietary innovation-related information, and to freely reveal their information to other agents. To explore the environmental conditions in which private-collective innovation is likely to emerge and thrive, we developed an agent-based model that allows us to simulate agents' choices of hiding or revealing information and trace their effects at the system level.

Based on multiple simulation experiments for different environmental parameters, we find that the private-collective model of innovation delivers greater innovation performance, and is more likely to be sustainable, if the environment is characterized by low rivalry among agents, high imitability of designs, and extraneous benefits to reputation (the secondary currency in the system). Interestingly, detectability of design plagiarism is negatively associated with system performance and with the emergence and stability of cooperation due to extensive punishment activities. We trace the origins of these effects by considering the impact of the contextual variables on sharing, reuse, and punishment behavior.

The principal contributions of our paper are as follows: To the best of our knowledge, our paper is the first to systematically explore the environmental conditions for private-collective innovation to emerge and be stable. We uncover which conditions render it likely that agents will opt for the traditional private investment model that is based on stand-alone innovation and subsequent protection (and the absorption of unintended spillovers from others, as available), and which conditions will make them prefer a private-collective approach based on (selective) sharing. The private-collective model is a "promising new mode of organization for innovation that can indeed deliver 'the best of both worlds' to society under many conditions" (von Hippel and von Krogh 2003, p. 213). A better understanding of the

[1] A design is a result of an innovation activity that provides benefits exclusively for its possessor.

contingencies of its viability helps us advance theory building on this new mode of organizing for innovation that supports new design creation and diffusion without limiting access.

Further, our results offer a unifying perspective on extant empirical findings of the existence or non-existence of private-collective innovation in various different domains. They offer a coherent set of explanations why we find this mode of innovating in some domains but not in others, and allow us to make predictions with regard to other domains likely to sustain private-collective innovation. They thus bound the oft-described phenomenon of free revealing in innovation.

The remainder of the paper is structured as follows: In section 2, we lay out the theoretical background to our study. Section 3 describes our agent-based representation of the private investment and private-collective models of innovation. Section 4 presents our simulation results. Section 5 discusses our findings and concludes.

2 Background

2.1 The private-collective innovation model

Historically, there have been two canonical models specifying the incentives that give rise to innovation in an economy: In the private-investment model, "the innovation remains a private good for the innovator who retains the rights to consume it, sell it, or provide access to it to third parties for a fee" (Gächter et al. 2010, p. 894). In the collective action model, by contrast, innovators are incentivized by collective or public subsidies to provision innovation as a public good; historically this model has been dominant in science and basic research (Olson 1965; Partha and David 1994; Hargrave and Van de Ven, 2006).

The private-collective model, as first articulated by von Hippel and von Krogh (2003), occupies the middle ground between these two archetypal models of innovation. By definition, it involves the free revealing of design information created at private expense, in exchange for a mix of private and collectively provided benefits (von Hippel and von Krogh 2003). It pivots on the assumption that innovators can obtain private benefits from freely revealing proprietary innovation-related information.

The canonic literature in economics and strategic management promulgates innovation-related information as a valuable resource and encourages two lines of action: preventing knowledge outflows (leakage), and harvesting knowledge inflows (unintended spillovers from others) (Argote and Ingram 2000; Fey and Birkinshaw 2005). In other words, entities are seen as competing by how much external knowledge they can absorb and how much internal knowledge they can protect (Cohen and Levinthal 1990; Liebeskind 1996). Thus, the private-investment model is associated with the "commonplace … view of spillovers as a problem in need of solution" (Frischmann and Lemley 2007, p. 257).

The private-collective model departs from this central tenet by positing that innovators can appropriate collectively provided benefits by disclosing their design information and making it available for reuse and recombination. Such gains may involve the adoption, feedback and improvement by others (Lakhani and von Hippel), the awarding of reputation and status as an innovator and a contributor to a community, the creation of a signal of competence that enhances job prospects, or the expectation of reciprocal knowledge sharing (von Krogh et al. 2012). The important common denominator across these different types of benefit is that they accrue selectively to those only, who freely reveal their design information. Thus, according to von Hippel and von Krogh (2003, p. 216), the seeming puzzle of the private provision of public goods can be resolved by recognizing that "contributions … are not pure public goods – they have significant private elements even after the contribution has been freely revealed."

While the *provisioning* of innovation-related knowledge is at the core of the private-collective model, it also has important implications for knowledge *reuse*. Once disclosed, design information can be reused and recombined freely in a cumulative innovation process (Murray and O'Mahony 2007). Thus, the private-collective innovation model represents a mode of organizing for innovation that can support new design creation and diffusion without restricting access.

Recent studies also point out, however, that knowledge reuse in private collective innovation systems is not entirely without limitations. Fauchart and von Hippel (2008) identify social norms that define appropriate knowledge reuse. According to di Stefano et al. (2013), the expectation of conformance to these norms critically affects innovators' willingness to freely reveal their knowledge in the first place. Failure to adhere to norms regulating acceptable reuse may entail community-administered *punishment*, involving, e.g., ostracizing deviants and inflicting reputational or financial damage (Oliar and Sprigman 2008; Franke et al. 2014). Fauchart and von Hippel (2008) show how norms-based systems of IP protection can stabilize private-collective innovation systems.

2.2 Conditions known to support private-collective innovation

Private-collective innovation has been observed in many different domains. A number of historical studies have documented its central role in the development of several technologies associated with the industrial revolution, e.g. blast furnaces for iron-making and Bessemer steel (Allen 1983; Nuvolari 2004). The Homebrew computer club (Meyer 2003) and the flat panel display industry (Spencer 2003) have likewise been studied as examples of private-collective innovation. The list of contemporary examples is even longer, including, e.g., software programming (Stuermer et al. 2009), haute cuisine (Fauchart and von Hippel 2008, di Stefano et al. 2013), healthcare products and techniques (DeMonaco et al. 2014), sports equipment designs (Franke and Shah 2006; Hienerth 2006), and other kinds of consumer products (Janzik et al. 2011; de Jong et al. 2014). It is important to note that some of these examples are based on knowledge sharing dyads, with multiple overlapping dyads forming an innovation system (e.g. Fauchart and von Hippel 2008), whereas others are based on one-to-many knowledge sharing, possibly via an online platform (e.g. Gulley and Lakhani 2009).

In terms of the conditions required to sustain private-collective innovation, *rivalry* between the actors involved has been the most-studied aspect. Several studies point out that rivalry in design use bounds actors' willingness to freely reveal design information (Franke and Shah 2003; Baldwin and Clark 2006; Raasch et al. 2008; di Stefano et al, 2013). When designs (not their instantiations) are rivalrous in the sense that they confer a competitive advantage that melts away as others begin to use the same design, innovators' willingness to share will be dampened, ceteris paribus, by this expected loss (Schrader 1991; Reagans and McEvily 2003). Franke and Shah (2003) trace this effect by comparing the extent of sharing across multiple sports communities with varying degrees of competitiveness among athletes. In the domains of haute cuisine and cocktail mixing, the fact that restaurants and cocktail bars only compete locally favors knowledge exchange among chefs: "a Parisian chef will often be unaffected by copying elsewhere" (Raustiala and Sprigman 2012, p. 82). Osterloh and Rota (2007) hypothesize that knowledge sharing and "collection invention" (Allen 1983) will be most readily seen in the pre-commercial phase, when the expected losses from sharing are not as high.

Next to the effect of rivalry, which increases the opportunity cost of knowledge sharing, the literature has identified selective benefits to sharing (cf. section 2.1) as a countervailing factor. Environments that promise significant extraneous benefits to contributors of design knowledge, are thus more likely to see private-collective innovation. As explained, these benefits often arise because pay-offs in a related market (e.g. the labor market for programmers of open source software, Lerner and Tirole 2002, or the downstream market for doctors, Strandburg 2009) are related to reputation in the private-collective innovation system. We call this factor *market-reputation coupling*.

Additional contextual conditions identified by the literature as being conducive to private-collective innovation are: modularity of product architecture (Baldwin and Clark 2006), low-cost communication among contributors (Baldwin and von Hippel 2011), and the availability of a cost-effective distributed production technology (Gambardella et al. 2014).

While these scattered findings are doubtlessly crucial, they still provide an incomplete understanding of the conditions that support the emergence and stability of private-collective innovation systems. In particular, more systematic analysis of the economic conditions that affect the costs and benefits of free revealing seems called for. Such analysis would materially increase our ability to predict in what environments private-collective innovation, the combination of the two traditional paradigmatic models of innovation, will thrive.

2.3 Proposition of additional potentially relevant contextual contingency factors

Based on the extant literature (von Hippel and von Krogh 2003; di Stefano et al. 2013; Franke et al. 2014), it seems likely that contextual factors that shape the costs and benefits of knowledge sharing, knowledge reuse, and enforcement of reuse-related norms can critically affect the functioning of private-collective innovation. We will argue that, based on existing theory, at least three additional parameters can be expected to be influential but their net effect is hard to predict based on extant theory.

First, we would expect *design imitability* to affect the functioning of private-collective innovation. When proprietary designs are easy to copy, e.g. because they are self-revealing in use (Strandburg 2009), this reduces the opportunity cost of sharing (what we may call the "they would get it anyway effect") and thus should encourage actors to share knowledge and thereby earn reputation and other benefits. However, imitability, by enabling design plagiarism (unauthorized reuse), also reduces the need for building a good reputation to earn knowledge spillovers within the community. In other words, it makes the private-investment logic of avoiding knowledge leakage and harvesting spillovers from others, relatively more attractive. Why engage in knowledge sharing and private-collective innovation when you can achieve the same outcome without contributing? In view of these two potentially opposite effects of design imitability, it is not clear whether high-imitability or low-imitability environments are more conducive to private-collection innovation.

Second, we expect the detectability of unauthorized reuse to likewise affect the emergence and viability of private-collective innovation systems; but again the direction of this effect is not entirely clear. On one hand, we could expect that detectability of design misappropriation should stabilize the system by decreasing the expected payoff of misbehavior (Gintis 2008; Zaggl 2014). On the other hand, detection of misappropriation may cause community members to punish the offender, a costly activity that uses resources otherwise spent productively.

The effect of these environmental conditions may be hard to predict, ex ante, as agents sharing and reusing knowledge in private-collective innovation systems adjust their behavior not only to the environmental conditions but also to the changes in behavior these conditions produce in other agents. E.g., di Stefano et al. (2013) emphasize that conditions affecting the expected conformance of knowledge recipients to reuse-related norms will affect the willingness of their peers to share their knowledge in the first place. Further, we expect that contingency factors influencing these different aspects may interact, being either countervailing or mutually reinforcing. E.g., we might expect high imitability to have a different effect in environments also characterized by high detectability than in less transparent environments. Similarly, the effect of imitability might depend on the extent of rivalry and of market-reputation coupling.

These considerations suggest an agent-based model as a suitable tool to simulate the system-level effects of these interacting parameters and decisions in a systematic way and thereby build new theory on the contingency factors affecting the viability of private-collective innovation.

3 Agent-based model

A private-collective innovation system involves multiple interacting, yet autonomous entities or strategic units, which can be either individuals or firms (agents). Strategic interdependencies between their individual payoffs cause their behavior to co-evolve, with multiple feedback loops producing complexity and endogeneity. This impedes the use of empirical field data. While, in principle, laboratory data could be employed, this would narrow down the scope of the investigation considerably. Hence, a complex systems approach (cf. Anderson 1999), specifically an agent-based simulation, is best suited to our purpose. Agent-based modeling enables sophisticated thought experiments that involve a high degree of complexity (e.g., Gilbert and Troitzsch 2005). While the adoption of agent-based modeling in management research has been slower than in associated social science disciplines (Davis et al. 2007), many scholars emphasize its strength in theory development in management and organizational research and call for its broader adoption (Davis et al. 2007; Harrison et al. 2007).

In section 3.1, we explain the static structure of our agent-based model. It consists of innovative designs, agents, environmental parameters, and some auxiliary parameters. Section 3.2 moves on to describe its dynamic processes.

3.1 Static structure

3.1.1 Innovative designs

Designs are represented by a numerical vector. The sum of the vector's elements represents its economic value. Each design has associated with it the point in time when it was created and the time when it will lose its value because of obsolescence.

Each design is owned by the agent that developed it. Still, other agents may also know the design, either because the owner shared it with them or because the design has become public knowledge (cf. 3.1.3, *imitability*).[2] All agents who know or possess a design can produce instantiations of it. Each agent can know an unlimited number of designs, but own no more than three.

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[2] For the sake of clarity, we italicize variable names.

3.1.2 Agents

Agents are self-regarding, boundedly rational units that make strategic decisions to maximize their payoff, that is, the economic value of their designs. The model is agnostic as to whether agents obtain this value by using their designs themselves or by selling their designs or instantiations thereof on a market.

Agents are described by behavioral patterns, which may differ across agents as well as in time and indicate their propensity to engage in the following behaviors:

First, agents need to choose between reusing some other agent's design of which they have gained knowledge and staying with their own design. We call this their *openness*. High openness indicates that the agent is likely to adopt some other agent's design.

Second, agents need to decide on the magnitude of the innovative step they want to perform on a given design. They can change one element (which they can pick freely) of the design vector at a time. We fix the magnitude of the change based on their own design (*innovation step*) at 0.25, and let them choose their innovative step based on others' designs on the interval [-0.5, 0.5], i.e. relative to innovation step. If their attempted innovation succeeds, the value they pick for the innovative step is added to the vector element, thus increasing the value of their design. Thus, making a large innovative step appears advantageous. However, if their attempt to innovate fails, the same value is deducted, thus reducing the value of their design. Innovation success or failure is determined randomly, thus representing the principle of trial and error in innovation.

Importantly, agents decide to either keep their innovation secret (following the private-investment model of innovation) or to share it with another agent who requests to know it (following the private-collective model). As explained in the theory section, sharing will increase their reputation in the agent network, which is represented by a number on the interval [0,1]. For all agents, reputation is initialized with a value of 0.5.

Third, when agents decide to share, they may either share indiscriminately with any agents who requests to know their design, or they may prefer to share selectively, discriminating among requestors based on the requestors' reputation. This decision is implemented in our model as *selectivity of sharing,* a number on the interval [0,1], where 0.3, means that an agent will share his design with a requestor only if the requestor's reputation exceeds 0.3. A value of 0 indicates indiscriminate sharing, and a value of 1 indicates that the agent will never share his design with others. (This part of the model is adopted from Nowak and Sigmund 1998a,b).

Fourth, agents search the network for unauthorized copies of their own designs. If they find another agent using a design that is very similar to one of their own designs, they may or may not punish that agent, the likelihood being their *propensity to punish*. This involves a *punishment cost* to the punisher, and produces a negative *impact* on the punished agent. Both of these costs are implemented as a loss of reputation, following empirical findings as well as modeling canon (e.g., Fehr and Fischbacher 2004; Fehr and Gächter 2002; Gintis 2008).

Each individual agent has a certain propensity to engage in the four behaviors just described: reusing the designs of others, innovating, sharing and punishing. These propensities are subject to learning; i.e. the agent adjusts his behavior to maximize his payoff based on the "experience" he gains through interactions with other agents. Reputation is the "currency" in which compliance is rewarded in the private-collective innovation system. It is accumulated by design sharing, capitalized by reciprocal sharing, and destroyed by design plagiarism (either detecting and punishing it or being detected and punished).

3.1.3 Environmental variables

As explained in the theory section, prior research suggests that rivalry and market-reputation coupling affect the functioning of private-collective innovation systems. In addition, we have argued that *imitability* and *detectability* are also likely to do so. In our model, these contextual characteristics are included as exogenous variables, that is, their values are determined by the experimental design. They vary between, but not within simulation runs.

The variable *rivalry* is introduced as the economic value of a design *d* depends on the number of agents n_d that copy this design (in original or modified form) as follows: It is equal to $score_d /(1 + r * n_d)$. By this formula, if design use is non-rivalrous (*rivalry = 0*), the value an agent can expect to obtain from his design is not affected by others also using his design. If *rivalry* = 1, the agent will obtain the *n*th part of the value of his design.

Market-reputation coupling, as explained in section 2, indicates that the economic value of a design increases with its owner *o*'s reputation *s*. The tighter the coupling, the larger the value *m*. In detail the market-reputation coupling *m* affects the value of a design *d* as $m * s_o * score_d + (1-m)\ score_d$. (This weighting is applied after *rivalry* was factored in, as previously explained.)

Imitability reflects the ease of copying a design without knowledge transfer from its inventor. It is instantiated as a parameter on the interval [0,1] that represents the time, as a share of design lifetime, that is required for reverse reengineering. A value of .25, for instance, means that all designs are public knowledge, and open to copying, during the last 25 time steps of a 100-step lifetime. In industries where reengineering is very easy, such as fashion, imitability would be close to 1.

Detectability reflects the share of agents among whom the focal agent will spot plagiarized copies of his designs – his range of "visibility". A value of 1 implies that the agent can spot plagiarized copies in all of her peers' designs and determine whether they are similar to one of her own designs. Setting detectability to 0 makes punishment impossible.

3.1.4 Auxiliary parameters

Some additional auxiliary parameters are necessary. They are fixed, subject to robustness checks, and not varied as part of the experimental design. We set design lifetime to 100 time steps and the number of agents to 30. Punishment cost is fixed to 0.01 and punishment impact to 0.06. Sharing impact, i.e. the reputational gain (loss) from (not) sharing, is set to 0.04. Table 1 provides an overview of the model's variables.

Table 1: Overview of model variables

Parameter	Description	Dynamics
Openness	Choice of design template (own design or design shared by other agent)	Learning
Innovation step using others' designs	Degree of change if another agent's design serves as template	Learning
Selectivity of sharing	Reputation required in the requestor of design information	Learning
Propensity to punish	Probability to punish if misuse is observed	Learning
Reputation	Public value representing agent's reputation	Endogenous
Rivalry		Exogenous
Imitability		Exogenous
Market-reputation coupling		Exogenous
Detectability		Exogenous

Punishment impact	Negative reputational impact of punishment on the punished	Exogenous
Punishment cost	Cost of punishment to the punisher	Exogenous
Sharing impact	Reputation gain (loss) in case of (not) sharing	Exogenous

3.2 Model process

The model process is iterative. It proceeds until the predefined number of iterations has been reached. One iteration, or one time step, of the model is defined by the following sequence:

First, two agents are chosen randomly from the population in the roles of donor (she) and donee (he). The donor shares one of her designs with the donee if his reputation is greater or equal than the donor's threshold (cf. section 3.1.2, selectivity of sharing). If she decides to share, she randomly chooses one of her designs, the donee gets knowledge of that design. The donor gets reputation of the variable *sharing impact* (0.04) each time, the donee uses the design for innovation.

Next, one randomly selected agent gets the chance to innovate. She decides, based on her *openness*, whether to modify one of her own designs or one of the designs that she has obtained from other agents (via free revealing or because it has become publicly known). She picks the best design from either sets and tries to improve on it. As explained, the magnitude of her change is fixed if she builds on her own prior design, and variable if she builds on someone else's (cf. *innovation step using others' designs*). The agent becomes the possessor of the modified design, and the design assumes the current simulation time as its time of origination. If the agent's number of designs exceeds the limit of 3, her least valuable design is removed from her portfolio.

As the final part of the sequence, one agent gets the chance to identify plagiarists and punish them.[3] Her decision to search for pirated designs is determined by her *propensity to punish*, and her search radius is limited by *detectability*. All pirated designs she finds are deleted.

3.3 Learning

Agents have the ability to learn. A learning algorithm implements their optimization aspirations under the variable conditions given by a dynamically changing system of interacting agents. Evolutionary algorithms are frequently used for computational modeling. The concept of evolutionary learning is inspired by the theory of natural selection (Holland 1975).

We model a continuous-type selection mechanism as follows: In every 50th time step, the agent with the lowest aggregate design value retains this portfolio, but assumes a cross-over of the behavioral patterns of the two agents with the most valuable design portfolios (e.g. their strategies in terms of adopting the designs of others, innovating, sharing and punishing).[4] The crossover includes a random share of the strategies of the most successful agent and the remainder from the next best agent.[5] Further, the replacement is subject to mutation, with each element of the strategy vector modified by a value chosen from a uniform distribution on the interval [-0.05, +0.05].

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[3] For comparison, she rounds the single elements of the design vectors. If they are identical after rounding, punishment applies if her own design has anteriority.

[4] The algorithm can be seen as a process of cultural learning and as such does not require replacing all the attributes of the agent.

[5] The strategies of both agents are ordered on a vector and cut at a random position. The first part of one vector is combined with the second part of the other vector.

As a robustness check, we also implemented and tested other variants of evolutionary learning. They did not produce qualitatively different results.[6]

3.4 Outcome measures/Dependent variables

To assess the outcomes of the model at the macro level, we consider *innovation performance*. *Innovation performance* captures the technological advancement achieved by the agents and its diffusion within the system. It is calculated as the sum of the economic values of all the designs that have not yet expired.

In addition to *innovation performance*, we measure social activity. For that purpose, we use the average reputation as a proxy and call that dependent measure *average reputation*. It captures the effort invested by the agents in the future benevolence of others. It predicates the prevalence of knowledge sharing and thus the thriving of the private-collective innovation system. Regarding average reputation, we observe two equilibria: the cooperative equilibrium and an uncooperative equilibrium. In the cooperative equilibrium *average reputation* is close to its maximum of 1. In that state the system is thriving. In contrast, almost no voluntary exchange happens in the uncooperative state, which is characterized with an *average reputation* of (almost) 0. States in-between the two extremes are unstable.

For measuring agents' behavior we define measures by counting several activities for each simulation run. 1) Sharing is the frequency of all sharing activities. 2) *Authorized reuses* counts all innovation activities in which the innovation is based on a design template from an earlier sharing activity. 3) *Instances of plagiarism* is the number of innovations based on a publicly known design template that has not been shared with the innovating agent. 4) *In-house creations* represent the number of all innovations based on designs possessed by the innovating agent. 5) *Punishment* is the frequency of how often the opportunity to punish has been taken.

3.5 Experimental design

We design a simulation experiment with the following settings: *rivalry* = {0; 0.5; 1}, *market-reputation coupling* = {0.000; 0.125; 0.250}, *imitability* = {0.05; 0.10; 0.15; … ; 0.75}, and *detectability* {0.1; 0.3; 1.0}. Thus, our experimental design comprises 432 combinations of settings. For each setting, we conduct 10 simulation repetitions (thus, 4,320 runs in total). This choice of 10 repetitions per setting, a relatively small number, is conservative; it prevents weak effects from becoming statistically significant. We terminate the simulation after 400,000 time steps. This very long simulated time period makes it likely that the most likely equilibrium will eventually prevail.

The behavioral characteristics agents are initialized randomly. All agents start with a reputation of 0.5 and possess one design with a value of zero.

4 Simulation results

The results of the simulation model are presented in four steps: First, we describe some general characteristics of the model (section 4.1). Second, the activities of the agents are analyzed (section 4.2 and section 4.3). In section 4.4, we examine innovation performance. Finally, we consider the equilibria (section 4.5).

[6] For instance, another evolutionary algorithm that we implemented affects the entire population discretely. Again, the two best-performing agents replace the single worst-performing agent. Further, this mechanism does not stop here, but moves on to replace the second agent from the bottom by the third- and fourth-best performing agents, and so on until all agents have either been involved in a cross-over or replaced. In this algorithm, updating also resets the design portfolios and reputations of all agents to the initialization state.

4.1 Descriptive results

We observe four basic types of outcomes in most of the simulation experiments. The plots in Figure 1 exemplify these four types. The black line shows *innovation performance*, which tends to increase over time. This is as expected since agents continually invest in improving the quality of their designs. The brown line represents *average reputation*; its trajectory distinguishes the four cases shown in Figure 1. It is either high (close to 1, indicating a cooperative equilibrium, cf. top right plot) or low (close to 0, indicating a non-cooperative equilibrium, cf. bottom right plot) and stable, or it can switch between the two states (upper left and bottom left).

In all simulation runs, the system moves to either the cooperative or the uncooperative equilibrium (*average reputation* of approx. 1 or 0) almost immediately after the beginning of the simulation run. Some simulation runs exhibit subsequent changes between the two social equilibria: In the top-left run (Figure 1), the system thrives initially and then collapses. Conversely, the bottom-left run languishes in the uncooperative equilibrium for a while in which there is no voluntary exchange of designs among agents, but then undergoes rapid emergence of cooperation. These equilibrium switches are due solely to agents successively and interdependently optimizing their strategies. We call these changes *collapse* and *emergence*, respectively. Note that they typically happen within a very short time period.

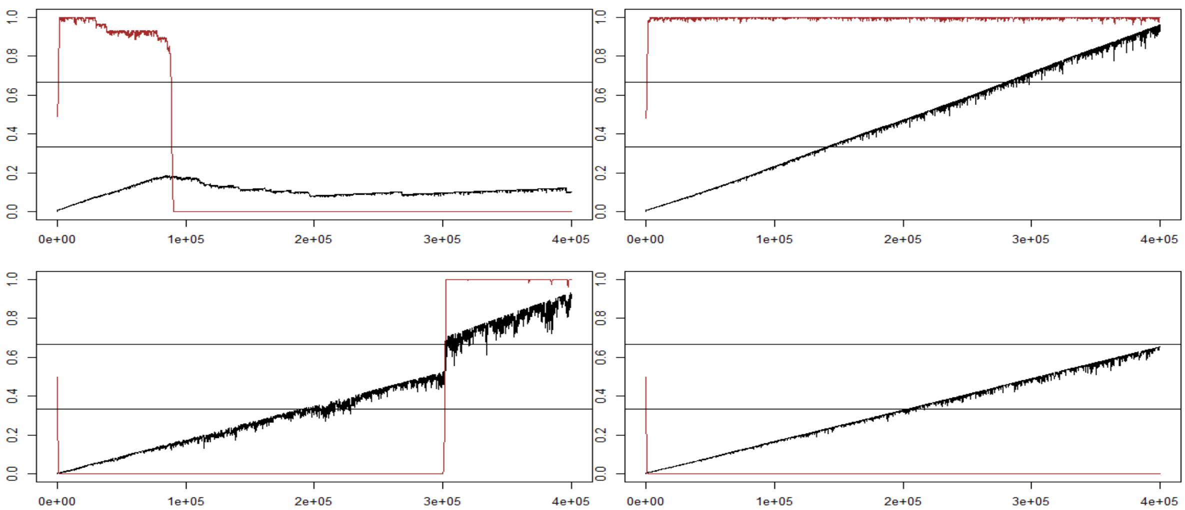

Figure 1: Longitudinal view of 4 simulation runs. Black: innovation performance, brown: average reputation.

Note also that inter-agent cumulative innovation outperforms intra-agent cumulative innovation. The plots show that the uncooperative equilibrium restricts the *innovation performance* of the system. E.g., the two runs on the left indicate that a change in *average reputation* (brown line) affects *innovation performance* (black line). Still, some level of *innovation performance* can be achieved without social exchange: Agents can create designs without the help of others, just by variation and selection of their own design portfolio or by relying on reverse engineering of the publicly known designs.

4.2 Agent behavior

In this section, we focus on the activities of the agents and examine the influence of the exogenous variables. To simplify the analysis, *detectability* is not taken into consideration for now, but will be analyzed separately in the next section. Table 2 lists the observed behavior of the agents, specifically the mean of the 10 replications for each setting of *authorized reuses* (innovations based on shared designs), *instances of plagiarism* (innovations based on public innovation templates that have not been shared), *in-house innovations* (innovations based on the focal agent's own designs), *sharing* (the instances of free revealing), and *punishment* (instances of punishment of unauthorized reuse).

The table shows that imitability has a very strong effect. *Market-reputation coupling* and *rivalry* also have an effect unless *imitability* is zero.

Table 2: Agents' activities dependent on the environmental conditions (detectability = 1)

Detectability = 1			*Authorized reuses*	*Instances of plagiarism*	*In-house innovations*	*Sharing*	*Punishment*
Imitability = 0.00	*Rivalry*	0.0	206,222	0	189,929	382,428	1,558
		0.5	201,304	0	194,857	382,570	1,388
		1.0	208,643	0	187,488	382,366	1,666
	Market-reputation coupling	0.000	207,243	0	188,886	382,222	1,561
		0.125	207,969	0	188,163	382,418	1,619
		0.250	200,957	0	195,225	382,724	1,431
Imitability = 0.25	*Rivalry*	0.0	83,460	210,487	106,053	335,116	7,855
		0.5	72,082	187,671	140,247	338,190	7,139
		1.0	72,549	189,219	138,232	335,114	6,726
	Market-reputation coupling	0.000	72,011	214,655	113,335	291,426	9,261
		0.125	77,947	187,352	134,701	355,090	5,942
		0.250	78,133	185,370	136,497	361,904	6,517
Imitability = 0.50	*Rivalry*	0.0	55,234	273,316	71,451	258,853	11,207
		0.5	50,741	238,465	110,794	284,667	8,279
		1.0	45,890	245,688	108,422	254,678	8,047
	Market-reputation coupling	0.000	39,146	284,108	76,746	182,380	13,111
		0.125	56,803	238,511	104,686	307,735	7,738
		0.250	55,916	234,848	109,235	308,083	6,685
Imitability = 0.75	*Rivalry*	0.0	15,828	315,442	68,730	120,754	11,494
		0.5	23,441	307,206	69,352	176,485	6,654
		1.0	17,121	304,736	78,143	137,195	7,309
	Market-reputation coupling	0.000	8,182	354,577	37,241	54,994	11,566
		0.125	24,658	292,526	82,816	189,046	7,129
		0.250	23,550	280,281	96,169	190,394	6,762

The frequency of *authorized reuses* is negatively influenced by *imitability*. Since the two variables can be seen as substitutes in enabling the reuse of others' designs, it seems intuitive that *imitability* reduces *authorized reuses*. *Market-reputation coupling* has a large positive effect on the number of *authorized reuses*. However, this effect is moderated by *imitability* and only applies under a high *imitability*. The effect of *rivalry* on *authorized reuses* is not clear.

In the same way, instances of *plagiarism* increase with *imitability*. *Imitability* enables *unauthorized copying*. The relationship is non-linear (see Figure 2). By increasing *imitability* from 0.00 to 0.05 the frequency of *plagiarism* jumps from 0 to 143,897. *Market-reputation coupling* reduces the instances of *plagiarism*. The effect of *rivalry* is again weak or non-existent.

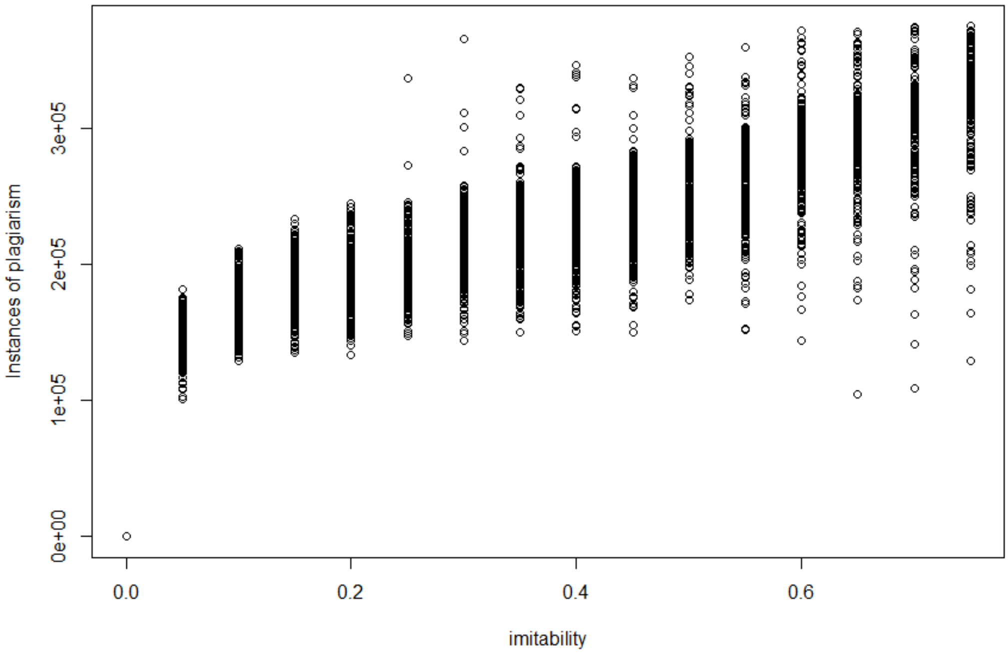

Figure 2: Instances of plagiarism in dependence on imitability

The frequency of *in-house innovations* increases with *market-reputation coupling* and *rivalry* and decreases when *imitability* is high. The positive relation to *market-reputation coupling* shows that agents are reluctant to copy from others and thus switch to *in-house innovation* when the total value of their reputation increases. This effect becomes stronger when *imitability* increases. Similarly, when *rivalry* is high, the agents tend to increase their focus on in-house innovation.

Instances of *sharing* (free revealing) increase with *market-reputation coupling*. Close coupling between reputation and market success incentivizes agents to share their designs with others. For higher values of *imitability*, *rivalry* seems to have a non-linear effect. *Sharing* decrease in environments with high *imitability*, because *imitability* is a natural substitute.

The number of *punishments* decreases with *market-reputation coupling* and *rivalry*. The former effect can be explained by the loss of reputation that accrues to the punisher. Thus, when *market-reputation coupling* is strong, this increases the opportunity cost of punishing. The latter effect, the mitigating effect of *rivalry* on the frequency of *punishment*, arises because reusing others' designs has a lower payoff when rivalry is high, which in turn reduces the number of imitations, and thus punishment. It should be noted that the *propensity to punish*, i.e. the probability that an agent punishes when observing misuse, increases when *rivalry* is high. When *imitability* increases, *punishment* also increases in frequency. The opportunities for misuse proliferate, and thus *punishment* also becomes more frequent.

4.3 Agent behavior and the impact of *detectability*

In this separate analysis we focus on the variable *detectability*. We list the influences of *rivalry* and *market-reputation coupling* with *imitability* in the same way as in section 4.2 but for the setting of *detectability* = 0.3 instead of 1.0. We focus mainly on the differences to resulting from the change in *detectability* (table 6, in the appendix makes it easier to compare both settings by showing the differences between table 3 and table 2).

Table 3: Agents' activities dependent on the environmental conditions (detectability = 0.3)

Detectability = 0.3			*Authorized reuses*	*Instances of plagiarism*	*In-house innovations*	*Sharing*	*Punishment*
Imitability = 0.00	*Rivalry*	0.0	217,142	0	179,123	383,324	734
		0.5	209,934	0	186,329	383,103	698
		1.0	201,690	0	194,597	383,164	619
	Market-reputation coupling	0.000	218,211	0	177,894	381,652	2,320
		0.125	230,303	0	165,771	381,928	3,354
		0.250	223,066	0	172,969	382,183	4,880
Imitability = 0.25	*Rivalry*	0.0	99,561	220,874	79,565	359,600	5,002
		0.5	81,657	191,333	127,010	361,798	3,140
		1.0	79,887	188,641	131,472	360,792	3,155
	Market-reputation coupling	0.000	73,817	240,083	86,100	290,639	20,756
		0.125	77,195	225,687	97,118	316,634	16,747
		0.250	91,850	212,550	95,600	359,224	5,501
Imitability = 0.50	*Rivalry*	0.0	67,047	273,747	59,206	298,050	5,344
		0.5	59,302	240,123	100,575	318,087	3,535
		1.0	56,599	242,415	100,986	303,162	3,361
	Market-reputation coupling	0.000	48,823	289,741	61,436	228,288	26,005
		0.125	55,951	267,610	76,439	279,686	13,505
		0.250	65,440	255,711	78,850	318,139	4,764
Imitability = 0.75	*Rivalry*	0.0	31,447	332,928	35,625	202,517	4,196
		0.5	27,387	319,641	52,972	194,566	2,624
		1.0	29,927	324,022	46,051	208,345	2,858
	Market-reputation coupling	0.000	20,020	345,244	34,737	130,208	21,653
		0.125	28,236	326,166	45,598	191,980	15,938
		0.250	30,663	324,621	44,716	208,602	9,944

We observe an increase in the frequency of *authorized reuses* by reducing *detectability* to 0.3 for most of the settings of *rivalry*, *market-reputation coupling* and *imitability*. Since agents can misuse voluntarily shared designs in the same way as they can misuse not authorized designs, this is a natural result. The frequency of *instances of plagiarism* increases for the settings of *rivalry*, *market-reputation coupling* and *imitability* because of the same reasoning. At the same time *in-house innovations* shrink in their number. The frequency of *sharing* underlies an interaction: For small settings of *imitability*, the reduction of *detectability* results in an increase of the *sharing* frequency by fixing *rivalry*, but a decrease by fixing *market-reputation coupling*. Also for *punishment* an interaction effect can be observed: For *imitability* = 0. An increase in *market-reputation coupling* has a positive influence on the number of *punishment* activities. For higher values of *imitability*, it has a negative influence on the number of *punishment* activities. The overall amount of punishment activities increases by reducing the *detectability* to 0.3.

4.4 Innovation performance

Next, we examine the influence of the environmental conditions on innovation performance of the system. For that purpose, we calculate a linear regression model, which can be used in this case because we found that relationships between the dependent and independent variables are roughly linear.

Table 4: Regression analysis of environmental variables predicting innovation performance

	Estimate	beta	Std. Error	t-value	
(Intercept)	136640.8		1040.2	131.356	***
Rivalry	-12915.3	-0.075	894.8	-14.434	***
Market-reputation coupling	17378.8	0.025	3579.0	4.856	***
Imitability	285037.6	0.934	1584.8	179.856	***
Detectability	-12661.9	-0.069	946.7	-13.375	***

*** $p < .001$. $n = 4{,}320$

The environmental variables account for $R^2 = 0.884$ (adjusted $R^2 = 0.884$) of the variance. All environmental variables have a significant influence on innovation performance. As predicted by theory (cf. section 2), high *rivalry* is associated with lower innovation performance. *Market-reputation coupling* positively influences *innovation performance*. This is reasonable but by no means trivial. *Market-reputation coupling* ties market success directly to reputation. This creates an additional incentive for agents to share their designs, which in turn accelerates innovation progress. However, at the same time, *market-reputation coupling* also restricts the reuse of the designs of others. To avoid punishment, which is more harmful under high *market-reputation coupling*, agents are more reluctant to build on the designs of others.

Imitability has the strongest, and notably positive effect on innovation performance. *Detectability* tends to reduce innovation performance. This effect is somewhat surprising; *detectability* could be expected to positively impact performance. After all, higher *detectability* implies that the re-use of IP can be monitored more comprehensively, which should render the norms-based IP system more efficacious (cf. section 2.3). However, *detectability* also results in a reluctance to build on the designs of others as it increases the likelihood of being punished. This dampening effect on cumulative innovation counteracts *innovation performance*.

4.5 Equilibrium selection

We measure the influence of the environmental variables on the equilibrium the system has moved into by the end of the simulation time, i.e. whether they have arrived at a cooperative or uncooperative state. For that purpose, we calculate a logistic regression, which predicts the case of a selection of the cooperative equilibrium.

Table 5: Logistic regression of environmental variables predicting cooperative equilibrium

	Estimate	Std. Error	Wald Z	p
(Intercept)	-7.802	0.372	20.96	.000
Rivalry	0.554	0.185	3.00	.003
Market-reputation coupling	12.533	0.930	13.48	.000
Imitability	-7.813	0.491	-15.91	.000
Detectability	-4.008	0.236	-16.98	.000
Cragg & Uhler's R^2		.509		

$n = 4{,}320$.

The regression shows that all environmental variables have a statistically significant impact on the emergence of cooperation. *Rivalry* has a small but positive effect, i.e. it does not reduce the probability for cooperation to emerge, as could be expected based on extant theory. While it does have a negative effect on *innovation performance* (cf. section 4.4), a negative impact on the nature of system equilibrium is not observed.

The effect of *market-reputation coupling* is large and also positive. While it has only a weak positive impact on *innovation performance*, it renders the emergence of cooperation more likely. *Imitability* reduces the probability of a cooperative equilibrium, as does *detectability* – an unexpected finding.

5 Discussion and conclusion

5.1 Summary

The literature on the economics and strategy of innovation identifies two canonical models specifying the incentives that give rise to innovation in an economy: the private-investment model and the collective action model. The private-collective model occupies the middle ground between these two archetypal models of innovation. By definition, it involves the free revealing of design information created at private expense, in exchange for a mix of private and collectively provided benefits (von Hippel and von Krogh 2003). It rests on the assumption that innovators can obtain private benefits from freely revealing proprietary innovation-related information. Extensive empirical research has documented the prevalence of this model in many B2B and B2C industries.

In this paper, we explored the environmental conditions in which private-collective innovation is likely to emerge and thrive. Extant theory suggests that rivalry among agents and market-reputation coupling both affect the viability of private-collective innovation. We proposed that design imitability and the detectability of plagiarism also have an effect; in both cases, the direction of the net effect is unclear, ex ante, as there are countervailing forces at work. Our agent-based simulation of a private-collective innovation system makes it possible to study these contingencies and their outcomes in a systematic way.

Some of our key findings are as follows: First, while rivalry among agents does reduce the amount of sharing and the performance of the innovation system, as anticipated by the literature, it does not reduce the likelihood of private-collective innovation to emerge. We even find a small positive effect. Second, in environments where reputation in the system is coupled to success in a related (e.g. downstream) market, as is the case in open source software or in haute cuisine, for instance (Lerner and Tirole 2002; Fauchart and von Hippel 2008), there is less design plagiarism and more intentional free revealing of designs. This is true even though punishment is more costly to the agents in such markets, which could endanger system stability. System performance is higher in environments characterized by market-reputation coupling. Third, imitability has a strong effect on behavior and outcomes. Interestingly, while increasing innovation performance at the system level, imitability makes it less likely that a private-collective innovation system will emerge and be stable. Finally and unexpectedly, the detectability of design plagiarism has a negative effect both on innovation performance and on the emergence and stability of private-collective innovation. This suggests that some level of ignorance about imitation by others improves outcomes by keeping agents from converging to an inferior high-punishment equilibrium.

5.2 Contributions and implications for research

Our paper contributes to our understanding of the emergence of private-collective innovation from self-regarding individual behavior and of the system-level performance outcomes, as compared to the canonical private-investment model of innovation. We uncover which conditions render it likely that agents will opt for the traditional private investment model that is based on stand-alone innovation and subsequent protection (and the absorption of unintended spillovers from others, as available), and which conditions will make them prefer a private-collective approach based on (selective) sharing. Our paper is the first to systematically explore multiple conditions for private-collective innovation to be functional and effective. Our agent-based simulation model makes it possible to study contingencies and their outcomes in a quantitative, causal way. Our results highlight that, self-regarding behavior notwithstanding, private-collective innovation systems can emerge across a considerable range of environmental conditions. Still, it becomes clear that some environments are less benign than others.

Further, our results offer a unifying perspective on extant empirical findings of the existence or non-existence of private-collective innovation in various different domains. They offer a coherent set of explanations why we find this mode of innovating in some domains but not in others, and allow us to make predictions with regard to other domains likely to sustain private-collective innovation. They thus bound the oft-described phenomenon of free revealing in innovation and inform the large and growing literature on open and user innovation by identifying supporting and limiting factors.

Incidentally, while this was not the focus of this paper, our results also lend support to the hypothesis of the so-called piracy paradox (Raustiala and Sprigman 2006), which argues that imitability increases innovation performance by generating demand for new designs – even when the older ones would actually still be usable. The best-known instantiation of the piracy paradox is the fashion industry. Our model shows that imitability is a driver of innovation performance, but also counteracts the stability of norms-based systems of free revealing. These are two necessary conditions for supporting the hypothesis of the piracy paradox.

Our approach accounts for path dependencies and multiple equilibria in emerging social systems. In our model, path dependencies can engender considerable variation in outcomes even when environmental conditions are being held constant. Thus, systems may be stuck in the private-investment model even when that model is inferior. It would be valuable for future research to assess the potential of uncooperative systems to become functional private-collective innovation systems, contingent on environmental conditions. Further, our model can be adapted to fit conditions in specific domains and to study their functioning.

5.3 Implications for practice

Regarding the governance of private-collective innovation systems, our findings suggest that those in a position to influence such systems (e.g. research managers or the managers of firm-sponsored open innovation communities) should closely monitor changes in agents' behavior. Specifically, we observed in our simulations that a decline in agents' reputation (i.e., trading reputational damage for the misappropriation of others' ideas) is a strong indicator for the imminent system failure. Timely counteraction is crucial to prevent the tipping of a functional system into an uncooperative equilibrium where agents do not exchange information and cumulative innovation performance suffers. Focus should be on measures similar to the construct of *average reputation* in our model, which are good predictors of collapse and are also easy to implement. In many communities using web-based communication systems, the requisite information already exists.

Our findings also indicate some caution with regard to the oft-espoused view that full detectability is best for disciplining individual's self-regarding behavior and thereby enabling superior social outcomes. High levels of detectability can damage performance and increase the likelihood that cooperation will not emerge, or at least not be stable.

6 References

Allen, R. C. (1983) Collective Invention. *Journal of Economic Behavior and Organization*, 4(1):1–24.

Argote, L.; Ingram, P. (2000) Knowledge Transfer: A Basis for Competitive Advantage in Firms. *Organizational Behavior and Human Decision Processes*, 82(1):150–169.

Arrow, K. J. (1984) Collected Papers of Kenneth J. Arrow, Volume 4: The Economics of Information. Belknap Press, Cambridge, MA.

Baldwin, C. Y.; Clark, K. B. (2006) The Architecture of Participation: Does Code Architecture Mitigate Free Riding in the Open Source Development Model?. *Management Science,* 52(7):1116–1127.

Baldwin, C.; von Hippel, E. (2011) Modeling a paradigm shift: From producer innovation to user and open collaborative innovation. *Organization Science*, 22(6):1399–1417.

Bayus, B. L. (2013) Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community. *Management Science*, 59(1):226–244.

Cohen, W. M.; Levinthal, D. A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1):128–152.

Dahlander, L.; Magnusson, M. G. (2005) Relationships between open source software companies and communities: Observations from nordic firms. *Research Policy*, 34(4): 481–493.

Davis, J. P.; Eisenhardt, K. M.; Bingham, C. B. (2007) Developing Theory through Simulation Methods. *Academy of Management Review*, 32(2): 480–499.

Demsetz, H. (1967) Toward a Theory of Property Rights. *The American Economic Review*, 57(2):347–359.

de Jong, J. P.; von Hippel, E. A.; Gault, F.; Kuusisto, J. H.; Raasch, C. (2014) The Diffusion of Consumer-Developed Innovations: Patterns in Finland, working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2426498

Fauchart, E.; von Hippel, E. (2008) Norms-based intellectual property systems: The case of French chefs. *Organization Science*, 19(2):187–201.

Fehr, E.; Fischbacher, U. (2003) The nature of human altruism. *Nature*, 425(6960):785–791.

Fehr, E.; Fischbacher, U. (2004) Third-Party Punishment and Social Norms, *Evolution and Human Behavior*, 25(2):63–87.

Fehr, E.; Fischbacher, U.; Gächter, S. (2002) Strong reciprocity, human cooperation, and the enforcement of social norms. *Human Nature*, 13(1):1–25.

Fehr, E.; Gächter, S. (2002): Altruistic Punishment in Humans. *Nature*, 415(6868):137–140.

Franke, N.; Shah, S. (2003) How Communities Support Innovative Activities: An Exploration of Assistance and Sharing among End-Users. *Research Policy*, 32(1):157–178.

Frischmann, B. M.; Lemley, M. A. (2007) Spillovers. *Columbia Law Review*, 107(1):257–301.

Gächter, S.; von Krogh, G.; Haefliger, S. (2010) Initiating private-collective innovation: The fragility of knowledge sharing. *Research Policy*, 39(7):893–906.

Gambardella, A.; Raasch, C.; von Hippel, E. (2014) The User Innovation Paradigm: Impacts on Markets and Welfare. Bocconi University - Department of Management and Technology.

Gilbert, N.; Troitzsch, K. G. (2005) Simulation for the Social Scientist. Open University Press, Maidenhead, UK, 2nd edition.

Gintis, H. (2008) Punishment and Cooperation, *Science*, 319(5868):1345–1346.

Hargrave, T. J.; Ven, A. H. V. D. (2006) A Collective Action Model of Institutional Innovation. *Academy of Management Review*, 31(4):864–888.

Harrison, J. R.; Lin, Z.; Carroll, G. R.; Carley, K. M. (2007) Simulation Modeling in Organizational and Management Research. *Academy of Management Review*, 32(4):1229–1245.

Henkel, J. (2006) Selective Revealing in Open Innovation Processes: The Case of Embedded Linux. *Research Policy*, 35(7):953–969.

Holland, J. H. (1975) Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. The MIT Press, Cambridge, MA.

Janzik, L.; Raasch, C. (2011) Online Communities in Mature Markets: Why Join, Why Innovate, Shy Share?. *International Journal of Innovation Management*, 15(4):797–836.

Lakhani, K. R.; von Hippel, E. (2003) How Open Source Software Works: Free User to User Assistance. *Research Policy*, 32(6):923–943.

Lakhani, K. R.; Wolf, R. G. (2005) Why Hackers do What They do: Understanding Motivation and Effort in Free/Open Source Software Projects, in: Feller, J.; Fitzgerald, B.; Hissam, S.; Lakhani, K. R. (Eds.): *Perspectives on Free and Open Source Software*, The MIT Press, Cambridge, MA, pp. 3–21.

Lerner, J.; Tirole, J. (2002) Some Simple Economics of Open Source. *The Journal of Industrial Economics*, 50(2):197–234.

Liebeskind, J. P. (1996) Knowledge, Strategy, and the Theory of the Firm. *Strategic Management Journal*, 17(2):93–107.

Meyer, P. B. (2003) Episodes of Collective Invention. U.S. Bureau of Labor Statistics, Working paper WP-368.

Nowak, M. A.; Sigmund, K. (1998a) The dynamics of indirect reciprocity. *Journal of Theoretical Biology*, 194(4):561–574.

Nowak, M. A.; Sigmund, K. (1998b) Evolution of indirect reciprocity by image scoring. *Nature*, 393(6685):573–577.

Nowak, M. A.; Sigmund, K. (2005) Evolution of indirect reciprocity. *Nature*, 437(7063):1291–1298.

Murray, F.; O'Mahony, S. (2007) Exploring the Foundations of Cumulative Innovation: Implications for Organization Science. *Organization Science*, 18(6):1006–1021.

Nuvolari, A. (2004) Collective Invention during the British Industrial Revolution: The Case of the Cornish Pumping Engine. *Cambridge Journal of Economics*, 28(3):347–363.

Oliar, D.; Sprigman, C. (2008) There’s no free laugh (anymore): The emergence of intellectual property norms and the transformation of stand-up comedy. *Virginia Law Review*, 94(8):1787–1867.

Olson, M. (1965) The Logic of Collective Action: Public Goods and the Theory of Groups. Harvard University Press, Cambridge, MA.

Partha, D.; David, P. A. (1994) Toward a New Economics of Science. *Research Policy*, 23(5):487–521.

Penrose, E. T. (1951) The Economics of the International Patent System. Johns Hopkins University Press, Baltimore.

Raustiala, K.; Sprigman, C. (2006) The piracy paradox: Innovation and intellectual property in fashion design. *Virginia Law Review*, 92(8):1687–1777.

Raustiala, K.; Sprigman, C. (2012) The Knockoff Economy: How Imitation Sparks Innovation. Oxford University Press, Oxford, UK.

Reagans, R.; McEvily, B. (2003) Network Structure and Knowledge Transfer: The Effects of Cohesion and Range. *Administrative Science Quarterly*, 48(2):240–267.

Di Stefano, G.; King, A.; Verona, G. (2013) Kitchen confidential? Norms for the use of transferred knowledge in gourmet cuisine. *Strategic Management Journal*.

Schrader, S. (1991) Informal Technology Transfer between Firms: Cooperation through Information Trading. *Research Policy*, 20(2):153–170.

Spencer, J. W. (2003) Firms’ Knowledge-Sharing Strategies in the Global Innovation System: Empirical Evidence from the Flat Panel Display industry. *Strategic Management Journal*, 24(3):217–233.

Strandburg, K. J. (2009) User innovator community norms: At the boundary between academic and industry research. *Fordham Law Review*, 77(5):2237–2274.

Stuermer, M.; Spaeth, S.; von Krogh, G. (2009) Extending Private-Collective Innovation: A Case Study. *R&D Management*, 39(2):170–191.
Trivers, R. L. (1971) The evolution of reciprocal altruism. *The Quarterly Review of Biology*, 46(1):35–57.
von Hippel, E. (2010) Comment on 'Is open innovation a field of study or a communication barrier to theory development?'. *Technovation*, 30(11–12):555.
von Hippel, E. (2005) Democratizing Innovation. The MIT Press, Cambridge, MA.
von Hippel, E. A.; von Krogh, G. (2003) Open source software and the "Private-Collective" innovation model: Issues for organization science. *Organization Science*, 14(2):209–223.
von Krogh, G.; Haefliger, S.; Spaeth, S.; Wallin, M. W. (2012) Carrots and rainbows: Motivation and social practice in open source software development. *MIS Quarterly*, 36(2):649–676.
Zaggl, M. A. (2014) Eleven mechanisms for the evolution of cooperation. *Journal of Institutional Economics*, 10(2):197–230.

7 Appendix

Table 6: Agents' activities dependent on the environmental conditions: difference between the results from the setting detectability = 0.3 and detectability = 1.0

			Authorized reuses	*Instances of plagiarism*	*In-house innovations*	*Sharing*	*Punishment*
Imitability = 0.00	*Rivalry*	0.0	10,920	0	-10,806	896	-824
		0.5	8,630	0	-8,528	533	-690
		1.0	-6,953	0	7,109	798	-1,047
	Market-reputation coupling	0.000	10,968	0	-10,992	-570	759
		0.125	22,334	0	-22,392	-490	1,735
		0.250	22,109	0	-22,256	-541	3,449
Imitability = 0.25	*Rivalry*	0.0	16,101	10,387	-26,488	24,484	-2,853
		0.5	9,575	3,662	-13,237	23,608	-3,999
		1.0	7,338	-578	-6,760	25,678	-3,571
	Market-reputation coupling	0.000	1,806	25,428	-27,235	-787	11,495
		0.125	-752	38,335	-37,583	-38,456	10,805
		0.250	13,717	27,180	-40,897	-2,680	-1,016
Imitability = 0.50	*Rivalry*	0.0	11,813	431	-12,245	39,197	-5,863
		0.5	8,561	1,658	-10,219	33,420	-4,744
		1.0	10,709	-3,273	-7,436	48,484	-4,686
	Market-reputation coupling	0.000	9,677	5,633	-15,310	45,908	12,894
		0.125	-852	29,099	-28,247	-28,049	5,767
		0.250	9,524	20,863	-30,385	10,056	-1,921
Imitability = 0.75	*Rivalry*	0.0	15,619	17,486	-33,105	81,763	-7,298
		0.5	3,946	12,435	-16,380	18,081	-4,030
		1.0	12,806	19,286	-32,092	71,150	-4,451
	Market-reputation coupling	0.000	11,838	-9,333	-2,504	75,214	10,087
		0.125	3,578	33,640	-37,218	2,934	8,809
		0.250	7,113	44,340	-51,453	18,208	3,182