Universität Bielefeld

Faculty of Business Administration and Economics

Working Papers in Economics and Management

No. 10-2019
November 2019

R&D Location Strategies

L. Colombo H. Dawid P. Harting

Bielefeld University
P.O. Box 10 01 31
33501 Bielefeld − Germany

ISSN 2196−2723

www.wiwi.uni−bielefeld.de

R&D Location Strategies[*]

Luca Colombo[†] Herbert Dawid[‡] Philipp Harting[§]

November 2019

Abstract

We examine the profitability of different R&D location strategies of firms in a dynamic industry model. Firms engage in imitative and innovative activities in order to improve their products' quality, which determines their competitiveness. When choosing the set of locations in which to operate firms face a fundamental trade-off: co-locating with competitors' generates opportunities to improve product quality through imitation, but at the same time it increases the risk of losing one's competitive edge through outgoing spillovers. Being unable to fully predict competitors' moves, in making location choices firms rely on heuristics based on the expected present values associated with alternative location patterns. In a positive perspective, our model replicates key stylized facts highlighted in the pertinent empirical literature. On normative ground, we identify industry scenarios in which a firm should enter (not enter) a location even if the expected present value of doing so is negative (positive). Our key contribution is to provide a taxonomy of suitable firm location strategies depending on firm type and industry characteristics in a dynamic environment with endogenous cluster formation.

Keywords: Location Strategy, Knowledge Spillovers, Industry Dynamics, Innovation, Imitation

[*]This project has received funding from the European Union Horizon 2020 research and innovation programme under the grant agreement No. 822781 (GROWINPRO) and the Marie Sklodowska-Curie grant agreement No 721846 (ExSIDE). We also gratefully acknowledge the Center for Parallel Computing at the University of Paderborn for providing us with computational resources on the OCULUS high-performance computing cluster.

[†]Department of Economics and Finance, Università Cattolica del Sacro Cuore, e-mail: lucava.colombo@unicatt.it.

[‡]Department of Business Administration and Economics and Center for Mathematical Economics, Bielefeld University, PO Box 100131, 33501 Bielefeld, Germany, email: hdawid@wiwi.uni-bielefeld.de.

[§]Department of Business Administration and Economics, Bielefeld University, Germany, email: pharting@wiwi.uni-bielefeld.de.

1 Introduction

Choosing locations for their R&D and production activities is one of the key choices firms have to make. A large stream of literature, relying on empirical evidence from a variety of industries, highlights that the choice about entering or exiting a specific location heavily depends on firm and location characteristics (see e.g. Alcacer and Chung (2007); Alcacer and Zhao (2012); Livanis and Lamin (2016)). In particular, in knowledge intensive industries, where firms' competitive advantage strongly depends on their ability to create and acquire knowledge (e.g. Cassiman and Veugelers (2006); Chesbrough (2003)), the consideration of induced knowledge flows is an important determinant of location choices (e.g. Alcacer and Chung (2007); Grillitsch and Nilsson (2017)). Furthermore, also the number of locations chosen by firms appears to depend systematically on firm characteristics, like innovative and imitative capabilities (see Leiponen and Helfat (2011)). Notwithstanding this empirical evidence, a systematic analysis of the impact of firm type and industry characteristics on optimal location strategies has not yet been fully developed in a theoretical perspective.

Whereas location choices are often seen as strategic long term decisions, their dynamic aspect is gaining importance in particular for high tech industries characterized by strong dependence on human capital and relatively low physical investments. Katz and Wagner (2014) point out that "*..a remarkable shift is occurring in the spatial geography of innovation*"[p. 1], with innovation districts emerging in many urban areas distinct from the established cluster regions like Silicon Valley. A typical pattern for the establishment of such innovation districts is that highly innovative companies move facilities to a certain district incentivizing other firms to move there as well.[1] In light of this volatility of locational pattern firms have to be aware of potential future changes in the location of key clusters in their industry when estimating the implications of different location choices for their competitiveness. Hence, determining the location choice which yields the highest expected future profit stream is a very challenging task.

This paper aims at developing a theory of firms' strategic R&D location choices by relying on a dynamic industry model incorporating heterogeneous firms and a number of different industry environments. Throughout the paper we consider all innovative and imitative activities of firms as R&D and focus on (expected) knowledge flows as a crucial factor behind firms' location choices. A key feature of our approach is that we analyze optimal location choice strategies in a dynamic context, where location

[1] Prominent examples in this respect are the moves of Twitter to the Mid-Market neighborhood in San Francisco or of Google to Bakery Square in Pittsburgh, leading to the emergence of innovation districts at these locations.

patterns of competitors endogenously change over time. In general, firms are not able to perfectly predict future developments in location patterns, but our analysis shows that their strategies should nevertheless account in a systematic way for expected future changes in the location pattern of the industry. In particular, in light of this dynamic aspect we explore how optimal location strategies, determining the target number and selection of R&D locations, differ between imitation- vs. innovation-oriented firms and depend on the relative share of innovation vs. imitation oriented competitors.

Overall, the contribution of this paper is twofold. First, in a positive perspective, we develop a properly micro-founded theoretical framework to investigate heterogeneous firms' location choices in different industry environments. The key property of this framework is that it is fully consistent with the stylized facts identified in the literature. Second and more important, in a normative perspective, we show that there exist scenarios in which firms should systematically deviate from choosing the action yielding the highest expected future profits under the current location pattern. In particular, we characterize the optimal deviation as a function of the attributes of the firm and of its industry environment.

In our analysis, we rely on an agent-based industry simulation model with firms competing in a quality-augmented Cournot oligopoly.[2] Each firm's product quality depends on its innovation capabilities and on its technical knowledge (that is assumed to be distributed across locations), so that firms benefit from knowledge complementarities when choosing multiple locations. A firm can improve its product quality through innovation, imitation, or the usage of the knowledge publicly available in a location where it is active. Firms characterized by different abilities to innovate or imitate choose whether to enter, exit, or switch across locations, based on strategy rules incorporating the trade-off between the expected gains from imitating competitors and the potential losses resulting from being imitated.

We assume that firms are able to predict the probabilities of innovation and imitation of all firms in the industry, as well as the profit implications of such events for a given distribution of firms across locations. However, they face strategic uncertainty about the future location choices of their competitors and are not able to fully predict them. To deal with this uncertainty, firms are assumed to apply a relatively simple heuristic decision rule when considering a possible change of location.[3] More

[2] We use a simulation model since the complexity of the dynamics emerging from the interplay of the location decisions of heterogeneous firms precludes an analytical treatment. The potential of agent-based models for the analysis of industry dynamics and strategic firm behavior has been demonstrated for example in Li et al. (2019); Landini et al. (2017) or Dawid and Reimann (2011). This literature, however, so far has not treated firms' location choice, which is an innovative feature of our analysis.

[3] The merit of using relatively simple decision heuristics for making good decisions in complex

specifically, we focus on a family of decision rules based on the (normalized) difference between the expected value of the discounted future profit streams with and without a potential location change, keeping the locations of all competitors constant. Each rule is characterized by a single threshold parameter determining how large this difference has to be for location entries, exits, and switchings. If this strategy parameter is set equal to zero, then the rule coincides with the net present value (NPV) one where expected future profit streams are proxied by the value determined under the assumption that location choices of competitors stay constant.

As a first step, we show – using an empirically based parametrization of the model – that the location patterns emerging in our framework are fully consistent with the available empirical evidence on different aspects of firms' location choices. In particular, our model jointly reproduces a number of stylized facts identified in the pertinent literature.[4] (i) Consistently with Alcacer and Chung (2007), we find that technologically advanced firms entering an industry tend to avoid locations with industrial activity to distance themselves from competitors. Conversely, technological laggards tend to favor locations with high industrial activity in order to maximize inwards spillovers. (ii) Imitation oriented firms tend to choose a higher number of locations than firms introducing 'new to the market' innovations, as shown in Leiponen and Helfat (2011). (iii) The effect of the number of competitors in a location on the propensity of technologically leading firms to leave that location is positive and larger than the effect on laggards (see Livanis and Lamin (2016)).

Having established the ability of our framework to endogenously generate location patterns that are consistent with the stylized facts, we take a normative approach and use our model to characterize the type of strategy that is the most profitable for different types of firms in different industry environments. We find that for a firm with a higher ability to imitate than to innovate, which we refer to as an 'imitator', it is optimal to apply a standard NPV rule – i.e. to enter (exit) a location if and only if the estimated discounted future profits under the current location pattern of competitors

environments has been discussed e.g. in Gigerenzer and Gaissmaier (2011). In particular they argue that heuristics with few free parameters are in many uncertain environments characterized by 'ecological rationality' in the sense that they are better adjusted to generate good decisions than more sophisticated rules with a higher number of free parameters reacting more sensibly to the observed data. See Joo et al. (2019) and Cui et al. (2018) for recent contributions analyzing the performance of heuristics in different managerial decision problems. The potential of agent-based models as a tool to replicate aggregate level empirical patterns from individual decision making based on heuristics has been highlighted e.g. in Smith and Rand (2018).

[4]The reproduction of the stylized facts is carried out for a benchmark setting in which all firms in the industry use the instance of our class of strategy rules that coincides with the net-present-value rule.

are higher if the firm adds (drops) that location – when the firm is operating in an industry populated mainly by innovative firms (those with higher ability to innovate than imitate).[5] However, more surprisingly, there are a number of cases in which following the standard NPV rule is not optimal. In particular, if the majority of competitors are also imitators, then it is optimal for an imitator to enter (exit) a location as long as the change of the estimated value of discounted future profits, based on the current locations of all competitors, exceeds a *strictly negative* (*positive*) threshold. Intuitively, it can be profitable for an imitator to enter a location with negative NPV in such an industry environment because the fact that the location is relatively attractive for that imitator implies that it is also attractive for other imitators and with high probability additional imitators will enter the location in the future. Since these additional entries enlarge the options for imitation in the location, the NPV under the current location pattern systematically underestimates the value of that location for an innovator. The optimal location strategy of the firm should then account for that bias.

The key properties of the optimal location strategy of an 'innovator' – i.e. a firm more able to innovate than to imitate – are quite different than those of an imitator. When such a firm operates in an industry where most competitors are imitators, it is optimal to enter (exit) a location whenever the associated change in the value of the estimated discounted future profits computed taking as given competitors' current locations exceeds a *strictly positive* (*negative*) threshold. A similar intuition to that developed above also explains this result. By entering a location the innovator makes it more attractive for the imitators in the industry and therefore imitators will enter that region in the future with higher probability. This reduces the value of the location for the innovator, which is concerned about outwards spillovers. In an industry in which also the majority of competitors are innovators, entering a location will not result in a systematic change of the location patterns of the competitors and no systematic bias arises from considering the NPV under the current location pattern. Accordingly, we find that it is optimal for an innovator in such and industry environment to enter (exit) a location as long as the change in estimated discounted future profits is non-negative (non-positive).

[5] Optimality here has to be interpreted within the considered class of decision rules. Restricting attention to this class captures the bounded rationality of decision makers facing a complex dynamic environment, at the same time allowing us to gain insights about important qualitative properties of the location rules that are most profitable. In light of the rich structure of our industry environment, characterizing a Markov-Perfect-Equilibrium of a dynamic game assuming all Markovian strategies for each firm as the strategy space is not feasible.

The rest of the paper is organized as follows. Section 3 illustrates the structure, dynamics, and parametrization of our model. Section 4 focuses on the validation of the model, showing that its insights are fully consistent with the key stylized facts identified by the pertinent literature on firms' location choices. Finally, Section 5 uses the model to investigate firms' optimal location strategies, showing that it is often optimal for firms to depart from the usage of standard NPV rules in taking their decisions. Section 5 concludes and two appendices contain the technical details of the model and robustness checks on our numerical analysis, respectively.

2 Related Literature

Our paper is related to several streams of research. First, we build on the large amount of empirical work examining the role of local knowledge spillovers for firm location and the emergence of agglomerations.[6] Whereas early work (e.g. Ellison and Glaeser (1997)) has highlighted that the existence of local knowledge flows between firms is a driver for the emergence of firm agglomerations,[7] more recent studies point towards the relevance of the trade-off between inwards and outwards spillovers in determining how attractive local proximity to competitors is for a firm. For instance, Giarratana and Mariani (2014) find, based on a rich dataset of European inventions, that in locations with high levels of absorptive capacity firms tend to reduce their use of external knowledge sources fearing to be imitated. Relatedly, Grillitsch and Nilsson (2017) employ Swedish firm level data to show that knowledge intensive firms benefit less from local knowledge spillovers than firms with comparably low in-house knowledge and that their location in a knowledge intensive region might actually have a negative impact on their growth.

Starting with Shaver and Flyer (2000) seminal contribution, a number of empirical studies have shown that firms' location decisions are affected by the trade-off between (expected) inwards and outwards spillovers. This stream of literature finds that different types of firms evaluate this trade-off differently and therefore systematically differ in their location choices. Alcacer and Chung (2007) consider the location decisions of firms entering the United States through greenfield investments and show that a higher industrial activity in a region – measured by the number of patents – reduces the probability that technical leaders in their industry, in terms of R&D intensity, locate in that region. For technical laggards, exactly the opposite effect arises. Whereas Alcacer

[6]Clearly there are also other important aspects relevant for location choice that have been extensively discussed in the literature, like the availability of high-skilled workers (e.g. Almazan et al. (2007)), or institutional conditions (e.g. Lee and Mansfield (1996); De Beule and Duanmu (2012)).

[7]Such knowledge flows might run through several channels, in particular face-to-face communication between employees or labor mobility, see e.g. Grillitsch and Nilsson (2017).

and Chung (2007) focus on firms' selection of the location to enter, Livanis and Lamin (2016) consider the effect of inward and outward spillovers on the decision to leave a location. In particular, they study which factors underline firms' decisions to close their R&D facilities in a region. Consistently with the hypothesis that the balance of (perceived) knowledge inflows and outflows for a firm drives location decisions, they find that technologically leading firms are more likely to close their R&D facilities as the presence of other domestic labs increases, whereas laggards are less likely to do so. Again, these findings suggest that leaders design their location strategies in a way to avoid outwards spillovers.[8] Furthermore, Livanis and Lamin (2016) also show that laggards are less likely to leave a location in which technological leaders, rather than other laggards, are present.

The observation that the trade-off between (expected) inwards and outwards spillovers affects location choices has been confirmed in the context of multi-national enterprises (MNE). Using Italian data, Mariotti et al. (2010) find that MNE are reluctant to agglomerate with domestic firms due to their perception that knowledge inflows from such firms are on average lower than the leakages towards them. However, MNE are willing to co-locate with other MNE since they expect a positive balance of inwards and outwards spillovers in this case. Belderbos et al. (2017) show that also within the group of MNE location strategies differ systematically. Focusing on the sign of the impact of the strength of 'local' science in a country on a firm's probability of locating in that country, they find that it depends on how strongly a MNE's R&D activities are science oriented.

Leiponen and Helfat (2011) focus on the *number* of R&D locations as an important property of firms' location strategies and show that also in this respect expected inwards and outwards spillovers play an important role. In particular, they show that the type of R&D activities of a firm – imitative versus new-to-the-market – determines whether innovation output is positively correlated with multi-location R&D. For 'imitative' innovations, where knowledge sourcing from external sources is crucial, they find a positive correlation between the number of R&D locations and output, whereas no such correlation is found for 'new-to-the-market' innovations.

Our paper contributes to this rich empirical literature along several dimensions. First, we provide an integrated theoretical framework for analysis that considers both

[8]Several alternative approaches for avoiding outwards spillovers have been identified in the literature, like strengthening internal linkages (Alcacer and Zhao (2012); Belderbos and Somers (2015)), or increasing the technological distance to co-located firms (Wang and Zhao (2018)). In our model, we abstract from such alternative approaches and focus on exit from a location as the main instrument to avoid outwards spillovers.

entry and exit (as well as location switching) decisions as crucial parts of a firm's location strategy. Second, we show that the empirically observed differences in location choices of technological leaders and laggards are consistent with both types of firms using an identical strategy rule based on a net present vale criterion applied under naive expectations about the future changes in the location patters of competitors. Third, we show that the optimal strategy rules differ between leaders and laggards and that firms should adjust their strategy rules depending on the innovativeness of their competitors in the industry. Hence, our analysis provides a theoretical underpinning for the observed empirical patterns and also provides new managerial implications relative to the pertinent literature.

By developing a dynamic model of location choice that incorporates emerging knowledge spillovers as well as strategic interaction in a multi-firm setting, we substantially extend the theoretical literature in this domain. Theoretical approaches to analyze firms' location choices in the presence of knowledge spillovers are surprisingly sparse. Gersbach and Schmutzler (1999) analyze a static multi-stage duopoly model in which the choice of R&D and production locations of both firms induces external and internal spillovers that influence production costs. Considering a similar multi-stage framework Gersbach and Schmutzler (2011) study the interplay of firms' decision about foreign direct investment and R&D offshoring. Belderbos et al. (2008) analyze the role of spillovers for the R&D location decision of multi-national firms in a static model with strategic interaction. Consistently with much of the empirical evidence reviewed above they show that technology leaders invest more in domestic R&D, thereby reducing outgoing spillovers, the larger is the parameter governing the strength of external spillovers between firms. Lagging firms, in contrast, increase the share of foreign R&D as technology sourcing becomes more effective.

Due to the static nature of these studies they cannot distinguish between firms' entering and exiting decisions and also cannot take into account potential path dependencies emerging from location decisions. In particular, technological leadership and relative competitiveness might change over time. Furthermore, the duopoly structure of these models does not allow to study the implications of the co-existence of a firm cluster with isolated competitors. Colombo and Dawid (2014) address these issues by considering a dynamic oligopoly model where all firms initially choose their location and then continuously compete on a joint market. Production costs change over time and are determined by own R&D effort, and in case of co-location with other firms, by incoming local spillovers. It is shown that initial advantages with respect to the knowledge stock as well as superior R&D technology of a firm reduce the incentives of that firm to join competitors in a cluster. Differently from the model considered in this paper, in Colombo and Dawid (2014) firms are restricted to a single location and also cannot relocate after they have made their choice at the beginning of the game. Instead, in this paper, firms have the possibility to react to dynamic changes in the industry structure and in their relative competitiveness by entering a new location, exiting an existing one, or relocating their R&D activities between two locations. This allows for a much richer analysis of firms' location strategies.

3 The Model

We consider an industry populated by a set $\mathcal{N}_t$ of firms that compete on a common market. Firms engage in R&D activities, which can be conducted in several locations, in order to improve their product quality. At each time $t = 1, 2, ...$ firms interact in the market in the framework of a quality augmented Cournot oligopoly (see e.g. Symeonidis (2003)). R&D consists of innovative and imitative activities by firms that are located in the same region and differ in their ability to innovate and imitate. Each location is characterized by a level of academic activity, influencing the innovation probabilities of firms in that location, and by specific location costs (capturing e.g. rental and labor costs).[9] Firms routinely reconsider their location choices, comparing the expected future profit flows associated to entering, exiting, or switching locations with those in the status quo. Each location strategy (exit, entry, switching) of a firm is determined by an (exogenously given) threshold parameter, such that the action is taken only if the expected net present value of the considered move exceeds that threshold. Additionally, the industry dynamics exhibits market entry and exit.

3.1 Product Quality, Innovation, Imitation

Denote with $\mathcal{L}_{i,t} \subseteq \mathcal{L}$ the set of R&D locations of firm i, where $\mathcal{L}$ is the set of available locations. Each location $l \in \mathcal{L}$ is characterized by the costs ϑ_l^{loc} of operating in that location. The set of all firms located in region l at period t is denoted with $\mathcal{F}_{l,t}$.

The quality $q_{i,t}$ of the product of firm i can be improved over time through product innovation and imitation. Since the focus of our analysis is on firms' location choice rather than on the determination of innovation and imitation efforts, we abstract from firms' effort choices. In particular, we assume that each period t firm i successfully

[9]Other factors related to production conditions and costs are also likely to be important in determining firms' location choices. However, here we abstract from such factors to concentrate on the role of R&D activities.

innovates with probability

$$\mathbb{P}(\text{prod. innov. by firm } i) = \lambda_{i,t}\Psi_i,$$

where Ψ_i is the innovative ability of firm i and

$$\lambda_{i,t} = |\mathcal{L}_{i,t}|^{\sigma}, \quad \sigma > 0, \tag{1}$$

captures the effect of the current set of firm i's R&D locations on its innovation probability. Firm ability, $\Psi_i > 0$, is assumed to be constant over time. Furthermore, we assume that Ψ_i is sufficiently small such that $\Psi_i|\mathcal{L}|^{\sigma} < 1$ for all firms i. Consistently with the arguments provided e.g. by Leiponen and Helfat (2011) this formulation captures the idea that firms profit from being close to different streams of academic knowledge in different locations, where for reasons of simplicity we assume that the level of academic activity is identical in each location. More precisely, firm i's innovation productivity $\lambda_{i,t}$ increases with its number of locations. The parameter σ determines how strongly innovation productivity is (positively) affected by the diversification of innovation activities across different locations. In particular, for $\sigma = 0$ no positive effect of diversification exists, while the effect becomes stronger the larger σ is. For $\sigma \in (0, 1)$ there is R&D substitutability across regions in the sense that the innovation probability of a firm present in several locations is lower than the sum of the innovation probabilities arising if in each of these locations one 'single-location' firm is performing R&D.

A successful innovation yields a new product quality. In order to account for the uncertainty associated with innovation processes, we assume that the extent of the product improvement is stochastic. The resulting quality is given by

$$\tilde{q}_{i,t} = q_{i,t}(1 + \eta_{i,t}),$$

where $\eta_{i,t}$ is drawn from a uniform distribution on $[0, \bar{\eta}]$. Furthermore, we assume that firm i can imitate any firm $k \in \mathcal{F}_{l,t}$ in any location $l \in \mathcal{L}_{i,t}$ with a fixed probability $\xi_i \geq 0$. To keep our analysis as simple and transparent as possible, we divide the population of firms into two groups that we refer to as 'innovators' and 'imitators'. All innovators share the same innovative and imitative abilities, $\Psi^{in} > 0$ and $\xi^{in} \geq 0$ respectively. For imitators, the corresponding abilities are $\Psi^{im} > 0$ and $\xi^{im} \geq 0$, where we assume that the innovative ability of innovators is strictly larger than that of imitators and that the imitative ability of imitators is strictly larger than that of innovators, i.e. $\Psi^{in} > \Psi^{im}$ and $\xi^{im} > \xi^{in}$.

Upon successful imitation of firm k in region l, firm i is able to achieve the same quality $q_{k,t}$ as that firm. To account for the fact that product innovations become part of the 'standard' product with some delay (see e.g. Klepper (1996)), we assume that all product qualities become available to all firms after ω periods. Combining the different channels of quality improvements, we obtain that

$$q_{i,t+1} = \max[q_{i,t}, \bar{q}_{t+1-\omega}, \hat{q}_{i,t}, \tilde{q}_{i,t}], \tag{2}$$

where $\hat{q}_{i,t} = \max_{j \in \mathcal{I}_{i,t}} q_{j,t}$, and $\mathcal{I}_{i,t} \subseteq \mathcal{N}_t$ denotes the set of firms successfully imitated by firm i in period t. Furthermore, $\bar{q}_t = \max_{j \in \mathcal{N}_t} q_{j,t}$ denotes the best quality on the market in period t.

3.2 Cournot Equilibrium

On the demand side, we consider a representative consumer with utility function

$$U(x,q) = \alpha \sum_{i \in \mathcal{N}} x_i - \frac{1}{2} \sum_{i \in \mathcal{N}} \frac{x_i^2}{q_i^2} - \gamma \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N} \setminus \{i\}} \frac{x_i q_j}{q_i q_j}, \tag{3}$$

where x_i denotes the quantity of the product of firm $i \in \mathcal{N}$ that is consumed, and q_i the quality of that product. The consumer maximizes utility with respect to x_i subject to a given fixed consumption budget $\beta > 0$. By inverting the resulting demand function, we obtain for firm i at time t that

$$p_i(x_t, q_t) = \theta(x_t, q_t) \left(\alpha - \frac{x_{i,t}}{q_{i,t}^2} - \gamma \sum_{j \in \mathcal{N}_t \setminus \{i\}} \frac{x_{j,t}}{q_{i,t} q_{j,t}} \right), \tag{4}$$

where $\theta(x,q)$ is a multiplier ensuring that the consumer's budget constraint is satisfied. We normalize marginal production costs of all firms to zero. Standard calculations yield that the equilibrium profit of firm i can be written as[10]

$$\pi_i(q_t) = \frac{\alpha^2 \theta(x_t^*, q_t)}{(2-\gamma)^2 (2+\gamma(n_t-1))^2} \left((2-\gamma) q_{i,t} + \gamma \sum_{j \in \mathcal{N}_t \setminus \{i\}} (q_{i,t} - q_{j,t}) \right)^2 - \sum_{l \in \mathcal{L}_{i,t}} \vartheta_l^{loc}, \tag{5}$$

where x_t^* is the vector of Cournot equilibrium quantities and $n_t = |\mathcal{N}_t|$ denotes the number of firms in the industry at time t. Hence, the profit of firm i increases with respect to its own product quality, but it diminishes if the quality of a competitor increases. This property of our market framework is crucial to understand the effects on a firm's profit of the innovation and imitation of the firm itself and of those of its competitors.

[10] In Appendix A we provide a derivation of the inverse demand and of the firms' equilibrium quantity decisions.

3.3 Location Decisions

In each period, firm i considers to change the set of locations in which it operates with probability ρ. We assume that firms can at most enter or exit one location at each point in time – e.g. because of the transaction costs involved in changing locations. Hence, at any point in time a firm has three different strategies to change its set of locations: exiting, entering, or switching location (i.e. moving from one of its locations to another). Location decisions are based on a net present value criterion. Net present values are estimated by applying Monte Carlo simulations of possible evolutions of the market environment over a planning horizon of length T, taking into account possible changes of firms' qualities.

For a given profile of firm locations $\tilde{\mathcal{L}} = (\tilde{\mathcal{L}}_i)_{i \in \mathcal{I}}$, firm i estimates the present value of its future profit stream as

$$\pi_{i,t}(\tilde{\mathcal{L}}) = \mathbb{E} \sum_{\tau=1}^{T} \delta^{\tau} \pi_i(\tilde{q}_{t+\tau}), \tag{6}$$

where $\tilde{q}_{j,t} = q_{j,t}$ for all $j \in \mathcal{N}_t$, $\tilde{q}_{j,t+\tau}$ denotes the quality profile in period $t+\tau$ (which from the perspective of period t is a stochastic variable) and $\delta \in (0,1)$ denotes the discount factor. It should be noted that the expectation is taken under the assumption that the firm location profile remains constant between periods t and $t+T$.[11] This simplifying assumption captures the fact that firms operate in a stochastic environment with strategic uncertainty about future changes in their competitors' location decisions. Therefore, the expression calculated according to (6) is in general only a proxy of the actual net present value that would take into account the actual location strategies of all competitors.

Considering first the possibility of entering a location. For each $k \notin \mathcal{L}_{i,t}$, the firm calculates a proxy of the net present value (relative to the current present value) of entering location k. Let $\mathcal{L}_i^{en}(k) = \{k\} \cup \mathcal{L}_{i,t}$ be the set of firm locations after entering

[11] To approximate the expected value on the right hand side of (6), we consider the mean value over a batch of ς Monte-Carlo simulations. To make the simulation runs under the different location choice options better comparable, the random parts of the realization of events is fixed across the considered scenarios for each firm and each decision in a given period. To be more precise, for each event occurring with some probability (that might vary across the scenarios) a single schedule of realizations of a (uniformly distributed in [0,1]) random variable is determined for each run in the batch. This schedule is used in each of the scenarios to determine whether the event occurs by checking whether the value of the random variable is lower than the event probability. This procedure ensures that the systematic effects of probability changes are not dominated by the noise resulting from different realizations of the random variables across scenarios.

k, then the relevant net present value is given by

$$NPV_{i,t}^{en}(k) = \frac{\pi_{i,t}(\mathcal{L}_i^{en}(k)) - \pi_{i,t}(\mathcal{L}_{i,t}) - \vartheta^{en}}{\pi_{i,t}(\mathcal{L}_{i,t})}.$$

The parameter ϑ^{en} captures the costs of entering a location, which is assumed to be homogeneous across locations and firms. Analogously, the firm computes the (relative) net present value of exiting for each location $l \in \mathcal{L}_{i,t}$, denoted by $NPV_{i,t}^{ex}(l)$, and the net present value $NPV_{i,t}^{sw}(l,k)$ of replacing location l by location k, for each pair $l \in \mathcal{L}_{i,t}$ and $k \notin \mathcal{L}_{i,t}$, in its set of locations. Exit and switching costs are denoted by ϑ^{ex} and ϑ^{sw}, respectively.

Among all options to enter, exit, or switch locations, the firm only considers those that satisfy the criterion $NPV_{i,t}^{en}(k) \geq K_i^{en}$, $NPV_{i,t}^{ex}(l) \geq K_i^{ex}$ and $NPV_{i,t}^{sw}(l,k) \geq K_i^{sw}$, respectively. The parameters $K_i^{en}, K_i^{ex}, K_i^{sw}$ determine the location choice strategy (enter, exit, switch) of firm i. We explore the specific role of these strategy parameters in the second part of the paper. As will be shown below, the case of $K_i^{en} = K_i^{ex} = K_i^{sw} = 0$ that would correspond to the standard net-present-value rule is not always optimal. Intuitively, this is due to the fact that a firm's location decision might influence competitors' future location choices, which introduces systematic biases of the NPV proxies calculated under the current location pattern.

In case the threshold value is not met for any of the considered options, the firm does not change its location choice. Conversely, if there are several changes in the set of locations that satisfy the firm's heuristic rule for potential location changes, the option with the highest net present value is selected.

3.4 Industry Dynamics and timeline of the model

The dynamics of the model is not only driven by changes in firms' locations but also by entry in, and exit from, the industry. In each period, a new firm enters the industry with probability $\chi^{en}\zeta^{en}(\bar{\pi}_t)$, where $\bar{\pi}_t = \beta/|\mathcal{N}_t|$ is the average industry profit and $\partial\zeta^{en}/\partial\bar{\pi}_t \geq 0$. The function ζ^{en} is normalized in such a way that $\zeta^{en}(\beta/\hat{n}) = 1$, where $\hat{n}$ is a parameter determining the average number of firms in the industry. Hence, χ^{en} determines the average entry rate in the industry. The new entrant is an innovator or an imitator with equal probability, which determines its imitation probability and innovative ability (ξ_i, Ψ_i). The product quality of the entrant's product is chosen according to the uniform distribution $U[\bar{q}_t, q_t^{max}]$ if the entrant is an innovator, where $\bar{q}_t$ is the average and q_t^{max} the maximal quality on the market at time t. An imitator enters instead with a quality q_t^{min}, which is the minimal quality on the market in t. This distinction is based on the assumption that an innovation oriented firm considers entering a market only if it has already developed relevant innovations for that market, whereas an imitation oriented firm needs to first enter the market before being able to improve its product quality. The location choice of an entrant firm i is determined by choosing the location with maximal value $\pi_{i,t}(\{k\})$ across all locations $k \in \mathcal{L}$.

Concerning market exit, we assume that in each period each firm exits the industry with probability $\chi^{ex}\zeta^{ex}(\pi_i(q_t))$, where $\partial\zeta^{ex}/\partial\pi_i \leq 0$ and ζ^{ex} is a logit function normalized in order to guarantee that $\sum_{i\in\mathcal{N}_t}\zeta(\pi_i(q_t)) = 1$. In what follows, we consider a parameter setting such that $\chi^{ex} = \chi^{en}$. The chosen formulation guarantees in a simple way a stationary fluctuation of the number of firms in the industry around $\hat{n}$.

Finally, the timeline of the model is as follows.

1. Firms compete in quantities and Cournot profits are determined.

2. Firms simultaneously choose their locations.

3. Imitation and innovation take place.

4. All qualities are updated according to Equation (2).

5. Industry exit and entry occur and the entrant (if any) makes its location choice.

3.5 Baseline Parametrization

The remainder of this paper is based on numerical simulations carried out for a baseline parametrization of our model. We focus on an oligopolistic industry with an average number of $\hat{n} = 6$ firms. Initially half of the firms are innovators and half are imitators, and each firm has one random location. Each entering firm is equally likely to be an innovator or an imitator. In all simulations we assume that there are $|\mathcal{L}| = 5$ locations. We show later in the paper that our main qualitative findings carry over to a scenario with a higher number of locations.

An important goal underlying the design and parametrization of our model is to account for the different stylized facts about firms' entry/exit decisions and location strategies that have been highlighted in the pertinent literature. No empirical studies of a single industry covering all the different indicators we are targeting are available. Hence, in what follows, we rely on empirical insights from different industries to derive a parametrization (see Table 1) that is broadly consistent with the available empirical evidence. We rely on a discount factor corresponding to an annual discount rate of 4%, which is a standard value in the literature. The entry probability χ^{en} is chosen such that the average annual entry rate (i.e. the number of entering firms relative to the number of firms in the industry) for the target number of firms in the industry ($\hat{n} = 6$)

is 8.4%, which corresponds to the mean of the range of values reported in Geroski (1995) for the UK. The lead time after which innovations become generally available in the industry, ω, is set to 40 months consistent with evidence reported in Grant (2010) [p. 304]. The value of the innovative ability of innovators is set to $\Psi^{in} = 0.04$, which induces average innovation development cycle times of less than 25 months (depending on the number of locations a firm is active in). Such cycle times are in line with observations in different innovation oriented industries, see e.g. Griffin (1997). Using U.S. data, Warusawitharana (2015) estimates the average increase of profitability from a product innovation to be about 23%. The parameter $\bar{\eta}$ has been calibrated such that, in a setting in which all firms have identical qualities, the profit of an innovator whose quality increases by the average factor $1 + \bar{\eta}/2$ grows by 23%. The imitators' monthly imitation probability is set at $\xi^{im} = 0.05$, which corresponds to the median of the distribution of times to imitation reported for the mobile phone industry in Giachetti and Lanzolla (2016). The chosen values for the probability that a firm considers a change in location (ρ) as well as for location and entry costs (ϑ^{loc}, ϑ^{en}), together with the value of the consumption budget (β), give rise to an annual location exit rate of 5.7% on average, which approximates the value of 5.4% reported by Livanis and Lamin (2016) for the exit rates of R&D laboratories.[12] Finally, the parameters α and γ – describing market demand – have been chosen in a way to model industries in which competitors offer close substitutes ($\gamma = 0.7$) and the market is sufficiently large to allow all competitors to sell positive quantities even under considerable heterogeneity of the product quality. Whereas in our setting some firms (innovators) are mainly focused on innovative activities and other firms (imitators) rely mainly on imitation, we assume that each type of firm is also to some extent active in the complementary activity (imitation/innovation). More precisely, we assume that the ability of imitators to innovate is at a level of 5% of that of innovators and viceversa. This choice of parameter values guarantees a clear distinction between the two types of firms, at the same time generating model outcomes that are consistent with the available empirical evidence, as it is shown in the next section.

4 Validation of the Model: Industry Analysis

As a first step in our analysis, we check that the outcomes of our model in terms of firms' location choices are consistent with the patterns highlighted in the empirical lit-

[12] Strictly speaking the number reported in Livanis and Lamin (2016) applies to firms who have multiple laboratories, which seems to be the relevant case for our setup given that the mean number of locations of firms in our sample is larger than one.

Par.	Description	Value
δ	discount factor	0.9967
χ^{en}	rate of entry into the industry	0.042
Ψ_i	innovative ability (innovators/imitators)	0.04 / 0.002
σ	cross regional R&D substitutability/complementarity	0.11
$\bar{\eta}$	quality improvement per innovation	0.07
ω	lead time for innovators	40
ξ_i	imitation probability (innovators/imitators)	0.0025 / 0.05
ρ	probability of considering location change	0.02
ϑ^{loc}	operating costs in a location	0.01
ϑ^{en}	costs of entering a location	3.0
α	market size	2.0
β	consumption budget	5.0
γ	degree of horizontal differentiation	0.7

Table 1: Baseline parametrization of the model (the time unit is one month)

erature. In particular, we check whether our model is able to replicate the key stylized facts that have been identified in the pertinent literature with respect to firms' location decisions.

Stylized Fact 1. When entering an industry, less technologically advanced firms favor locations with high levels of industrial innovative activity, whereas technologically advanced firms locate apart from other firms to prevent spilling knowledge to competitors (Alcacer and Chung (2007)).

In the context of our model, the statement of Stylized Fact 1 amounts to the observation that upon entering the industry an imitator (i.e. a technologically less advanced firm) is more likely to choose a specific location the larger is the number of firms in that location.[13] Conversely, the probability of an innovator to enter a location is negatively affected by the number of potential imitators. In order to check whether this pattern is reproduced by our model, we rely on a set of 200 batch-runs for 1000 periods under our baseline parametrization. To avoid dependence on initial conditions,

[13] Alcacer and Chung (2007) distinguish between technological leaders and laggards based on R&D intensity, which in our framework corresponds to the innovation ability parameter Ψ_i. Since by definition in our setup innovators have a higher value of Ψ_i than imitators, we refer to innovators as the technologically more advanced, and to imitators as the technologically less advanced, firms.

we disregard the first 400 periods as a burn-in phase. For the purpose of this industry analysis we assume that all firms follow a rule consistent with a standard NPV criterion. In particular, all firms set their strategy parameters to zero, i.e. $K_i^{en} = K_i^{ex} = K_i^{sw} = 0,\ \forall i \in \mathcal{N}_t$. Despite the symmetry with respect to the strategy parameters, as it will become clear below, the induced actions of innovators and imitators differ significantly. We explore later in the paper how the individually optimal choices of these strategy parameters differ across the different types of firms.

In Table 2, we show the results of two logit regressions based on our simulation data, each carried out separately for innovators and imitators, with the probability of entering a location as the dependent variable. In the first regression, we focus on two explanatory variables only: the total number of firms in a location, and a dummy indicating whether the location is empty (i.e. whether there are no firms in that location). In the second regression, we further decompose the total number of firms distinguishing between the number of imitators and innovators in a location. Considering the entry probabilities of innovators, we conclude from the first column that they strongly prefer locations where no other firms are present, while the number of firms in non-empty locations hardly matters as long as one does not distinguish between imitators and innovators. The second column shows, however, a strong negative correlation between the number of imitators in a location and the entry probability of an innovator. Turning to an imitator's entry probability we find a strongly positive correlation with the number of firms active in a location, where the effect is much stronger if these firms are innovators rather than imitators. Overall, both the tendency of innovators to locate apart from other firms as well as that of imitators to cluster are qualitatively fully consistent with the evidence provided by Alcacer and Chung (2007).

Since both innovators and imitators share the same strategy parameter value, these differences in location choices must be due to differences in the estimated net present values associated with locations that are more or less populated by each of the two types of firms. In particular, an entering innovator who expects to gain a quality advantage through her own innovations foresees that sharing a location with imitating competitors fosters the prospects of the latter to catch-up with respect to product quality. Such catching-up increases competition on the market, thereby reducing the innovator's profit. Hence, she has an incentive to avoid regions in which imitators are present. This reasoning is fully in line with the narrative of Alcacer and Chung (2007) that technologically advanced firms fear outgoing spillovers.[14] In this respect, our

[14] Alcacer and Chung (2007) use the level of industrial patent activity to measure the potential of spillovers, finding a negative impact on leaders' entry probability. Furthermore, they also find a positive impact of academic patenting in a region on leaders' entry probability. Our model does not

	Entry Prob. Innovator		Entry Prob. Imitator	
No. firms in location	0.054^{**}		1.2^{***}	
	(0.013)		(0.03)	
No. imitators in location		-2.96^{***}		1.52^{***}
		(0.096)		(0.08)
No. innovators in location		2.09^{***}		6.07^{***}
		(0.072)		(0.28)
Non-zero firms in location	-0.44^{***}	-0.54^{***}	4.33^{***}	1.37
	(0.067)	(0.11)	(1.0)	(1.04)
No. observations	2538		2562	
R^2	0.006	0.51	0.66	0.89
Significance Levels: $^{***}0.001$; $^{**}0.01$; $^{*}0.05$				

Table 2: Results of a logit regression on the probability of location choice at market entry

model does not only reproduce the stylized fact but also captures the main underlying mechanism. Imitators are less concerned about outgoing spillovers; moreover, imitating other imitators in a region is a potentially profitable activity for them. Therefore, the presence of imitators (as well as of innovators) makes a region attractive for imitating firms, as is shown in the second column of Table 2.

Stylized Fact 2. Multi-location of R&D activity is positively associated with imitative innovation output, but not to new-to-the-market innovations (Leiponen and Helfat (2011)).

Within our framework, the statement of Stylized Fact 2 translates into the observation that on average imitators are located in a larger number of locations than innovators, which in our setting are mainly responsible for quality improvements going beyond the technological frontier ('new-to-the-market innovations'). In order to check this conjecture, in Table 3 we estimate by means of an OLS the average number of locations of a firm over its life cycle as a function of a dummy variable indicating whether the firm is an imitator, as well as of the length of the firm life span. We find a significant positive coefficient of the imitator dummy, which means that imitators are on average

explicitly incorporate differences in academic activity across locations. However, in light of the fact that innovators generate knowledge but hardly engage in imitation, the positive correlation between the number of innovators in a location and an innovator's probability to enter that location seems qualitatively consistent with this finding.

	No locations
Imitator	0.36***
	(0.007)
Length of Life-Cycle	0.0009***
	(0.00002)
Constant	0.88***
	(0.006)
No. observations	8029
R^2	0.37
Significance Levels: ***0.001; **0.01; *0.05	

Table 3: Results of a linear regression on the average number of locations of a firm over its life cycle

active in more locations than innovators.[15] The fact that the number of locations of imitators is persistently higher than that of innovators is fully consistent with Stylized Fact 2.

The economic intuition behind this finding is closely related to the arguments developed above. Considering innovators first, it should be noted that due to the cross-location complementarity in the R&D success function (see Equation (1)), diversifying their R&D activity to several locations is potentially profitable. However, in the calculation of the present values of different location options, these firms take into account the negative implications of outgoing spillovers associated with multiple locations. Being present in several locations makes it more likely to share locations with imitators, thereby improving the chances for the latter to successfully imitate the new products an innovator brings to the market. Our results show that this second indirect effect dominates the direct incentives to choose multiple locations.

Conversely, for imitators, there is no trade-off between the direct incentive to diversify induced by the complementarity of the innovation process and the indirect effect driven by the benefits of imitating successful innovators and imitators. The fact that imitators regularly choose more than one location indicates that no single cluster emerges in our setting. Although each innovator typically chooses a single location, these locations tend to differ among innovators, such that it is attractive for imitators

[15] Accounting for systematic differences in average lifetime between innovators and imitators, we find that the actual average number of locations over the life cycle for these two types of firms are 1.02 and 1.4, respectively.

to be in several locations at the same time.

Stylized Fact 3. The location exit rate of R&D labs (i.e. closing a lab in a specific location) of technological laggards depends negatively on the presence of other firms in the same location whereas the exit rate of technological leaders depends positively on it (Livanis and Lamin (2016)).

In the framework of our model, interpreting R&D labs as firms, Stylized Fact 3 amounts to check that the number of firms in a location has a negative impact on the exit rate of imitators and a positive one on that of innovators. To check Stylized Fact 3 we record, for each innovator and imitator in each period and for each location the firm is in, the binary decision exit/no exit, the number of innovators and imitators in that location, as well as the quality of the firm's product relative to the average quality in the industry, the number of the firm's locations, the number of firms in the industry, and the number of locations with no other firms. Again relying on 200 batch runs, we use these data to estimate by means of logit regressions the probability that innovators and imitators exit a region.

Focusing on innovators' exit probability, Table 4 reveals a positive effect of the number of imitators (consistently with Stylized Fact 3), but a negative effect of the number of innovators. Two observations contribute explaining this last finding, which is at odds with Stylized Fact 3. First, if other innovators are present in the same location, the exit of an innovator is likely to have a relatively mild impact on imitators. Therefore, leaving a location populated by other innovators does not substantially reduce imitation opportunities, so that the gains of leaving the location are likely to be smaller than the associated costs. Second, being endowed with some (albeit small) imitation ability, in our setup innovators can profitably imitate other innovators, which makes locations densely populated by innovators potentially attractive. The combination of these two observations explains the negative effect of the number of innovators in a location on the exit probability of an innovator. As far as the exit probabilities of imitators are concerned, we find a negative effect of the number of both imitators and innovators, which is in full accordance with Stylized Fact 3.

It is worth noting that other factors contribute explaining the probability of a firm exiting a location. Unsurprisingly, the quality of the firm's product relative to the average quality in the industry has a strong positive effect on the exit rate of an innovator, as the firm tries to escape competitors in the attempt to maintain its quality advantage. Instead, for imitators there is no significant correlation between

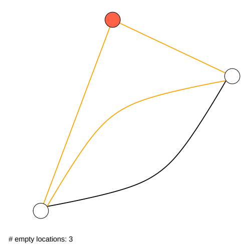
	Exit Prob. Innovator			Exit Prob. Imitator		
No. imitators in region	1.95***	2.01***	2.10***	−0.73***	−0.74***	−0.73***
	(0.07)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
No. innovators in region	−0.54***	−0.55***	−0.82***	−8.07***	−8.08***	−8.17***
	(0.05)	(0.05)	(0.06)	(0.28)	(0.28)	(0.27)
Interaction innovators - imitators	−0.47***	−0.48***	−0.35***	0.54***	1.71***	0.58***
	(0.02)	(0.02)	(0.03)	(0.16)	(0.16)	(0.15)
Relative quality		9.25***	8.98***		1.71	−0.86
		(0.53)	(0.52)		(1.17)	(1.26)
No. firm's locations			0.54*			0.40***
			(0.24)			(0.05)
No. firms in industry			−0.77***			0.33***
			(0.03)			(0.03)
No. empty locations			0.04*			−0.28***
			(0.02)			(0.03)
Constant	−2.73***	11.96***	−8.41***	3.03	1.31	1.77
	(0.06)	(0.53)	(0.61)	(0.05)	(1.18)	(1.25)
No. observations		21466			23063	
R^2	0.427	0.472	0.472	0.72	0.72	0.73
Significance Levels: ***0.001; **0.01; *0.05						

Table 4: Results of a logit regression on the probability of location exit

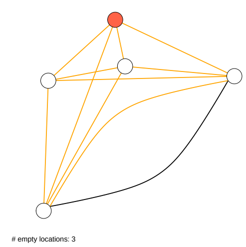
relative quality and exit rate, since imitators with high relative quality are typically co-located with innovators and hence have no incentives to exit that location. The overall number of firms in the industry has a negative effect on the exit probability of an innovator, and a positive one on the exit probability of an imitator. Indeed, this covariate is essentially capturing the effects of competition in the industry. As the number of firms in the industry grows larger, the profits accruing to each firm become smaller, which reduces the benefits of imitating and the costs of being imitated. In turn, this increases the probability that an imitator leaves a location and reduces the probability that an innovator does so. The more locations a firm is active in, the less significant are the opportunities it gives up by exiting a location, and hence the larger is the exit probability. Finally, the number of locations with no competitors is positively correlated to the exit probability of innovators, since moving to an empty location allows to avoid outwards spillovers. On the contrary, the exit rate of imitators is negatively correlated to the availability of empty locations, because such locations do not offer inwards spillovers and therefore are not attractive for them.

In order to illustrate the dynamic mechanisms generating the patterns highlighted above, we show the actual evolution of the location choices of the different firms in an industry for a part of a representative single run carried out under our baseline parametrization. Figure 1 shows six snapshots for selected periods of this run. Each node corresponds to a firm, where red nodes depict innovators and white nodes imitators. Whenever two firms share the same location, a link between the nodes is shown, with different colors corresponding to different locations. The starting point of our illustration, depicted in panel (a), is a situation with one innovator and two imitators. All firms share one location and the two imitators also share a second location. This is consistent with our finding that on average imitators are active in more locations than innovators. Up to the period depicted in panel (b), two imitators have entered the industry, and consistent with our insights from Table 2, both of them enter at the location with the largest number of firms. This generates a cluster (yellow links) consisting of one innovator and four imitators in one location. To avoid the resulting outwards spillovers, the innovator moves out of the cluster into a location without competitors (see panel (c)). Panel (d) shows the entry of an additional innovator into the industry, who consistently with Table 2 does not choose the location in which imitators are present. The reason for sharing the location with the other innovator rather than entering into an empty location is that although the firm is mainly focused on innovation it also has some ability to imitate, which makes co-locating with an innovator attractive. The reasons why the imitators remain in their cluster rather than immediately following the innovator to her new location are threefold. They face switching costs, the other imitators in their cluster might potentially be equally or even more advanced than the innovator, and opportunities to relocate arrive only in random periods. However, as can be seen in panels (e) and (f), eventually the imitator's cluster 'dissolves' because several imitators follow the innovators to their new location in order to gain from potential inwards spillovers. Finally, panel (f) shows that in the presence of a cluster consisting of both innovators and imitators an additional innovator entering the industry chooses an empty location.

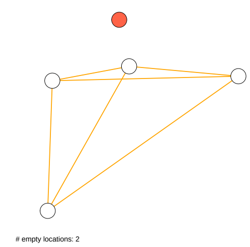
Summarizing, clusters emerge in this model as innovators enter an empty location and other firms, mainly imitators, follow them with some delay. At that stage, the location becomes less and less attractive for the innovators who eventually exit it, often moving to another location without imitators (consistently with Stylized Fact 1). This pattern clearly explains that the exit probabilities of innovators increase with the number of firms that are present in a location. Furthermore, this shows that imitators have no incentives to exit locations in which innovators are present. Hence, the negative



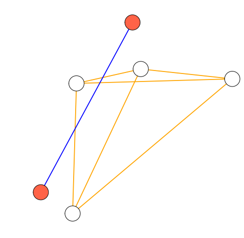
(a)



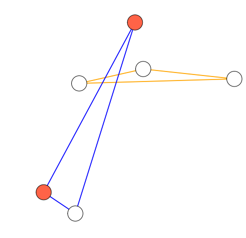
(b)



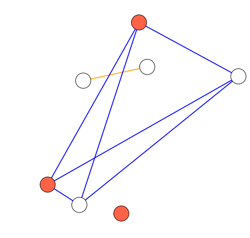
(c)



(d)



(e)



(f)

Figure 1: Six snapshots of a single run illustrating the determinants of the location choices of innovators (red) and imitators (white)

dependence of the exit rate of imitators on the number of firms in a location is mainly related to a strong dependence on the number of innovators in that location. Finally, our illustrative example further highlights that imitators entering the industry tend to select locations heavily populated by other firms. In this respect the dynamics of cluster formation in our model resembles the observed pattern by which the entry of key firms in an area prompts the formation of new industrial districts there (c.f. Footnote 1 for notable examples). It is also important to recall that all these patterns emerge from firms using a relatively simple heuristic decision rule relying on estimated future profits under naive expectations about competitors' future location choices.

5 Strategy Analysis

The benchmark version of our model assumes that firms decide to enter, exit, or switch locations if the expected change in future (discounted) firm profit associated with that action is larger than the corresponding entry, exit, or switching costs; i.e. $K_i^{en} = K_i^{ex} = K_i^{sw} = 0$ for all $i \in \mathcal{N}_t$. Expected future profits are calculated under the naive expectation that the other firms will not change their location profiles. Although all firms use identical decision rules, our discussion in the previous section has clearly demonstrated that the induced actions differ systematically between innovators and imitators. The benchmark rule can be seen as a plausible NPV-based heuristic, although it is not clear that $K_i^{en} = K_i^{ex} = K_i^{sw} = 0$ is indeed the profit maximizing choice of a firm even within the class of strategy rules that we consider in our model.

In this section, we examine the characteristics of *optimal* location strategies for imitators and innovators. In particular, we analyze how the optimal rules of these two types of firms differ, and also how the optimal location choice strategies are influenced by the degree of industry innovativeness. To address these questions, we systematically vary the strategy parameters of Firm 1 in the industry, denoted as the 'strategic firm', while keeping the strategy parameters of the other firms at the benchmark level $K_i^{en} = K_i^{ex} = K_i^{sw} = 0, i > 1$. The strategy of Firm 1 is parameterized by a single parameter κ in a way that $K_1^{en} = \kappa, K_1^{ex} = -\kappa, K_1^{sw} = \max[0, \kappa]$. Intuitively, a firm using $\kappa > 0$ has a low diversification location strategy in the sense that it is less willing to enter and more willing to exit a location compared to a benchmark firm. This suggests that such a firm on average should be present in a smaller number of locations than a benchmark firm. Furthermore, also a higher requirement for switching locations implies a larger degree of inertia with respect to the firm's location choice relative to the benchmark. The larger the value of κ, the stronger these effects are. A negative value of κ, on the contrary, stands for a location strategy of strong diversification with numerous entries and few exits. The reason why the value of K^{sw} is set to zero if $\kappa < 0$ is that for negative values of K^{sw} it is possible that for two regions the NPVs of the switches in both directions are above the threshold, resulting in long sequences of back and forth switching. Hence, we do not consider negative values of K^{sw} to be reasonable strategy choices and rule them out here.

In order to gain a sound understanding of how the type of the strategic firm (innovator vs. imitator) and the innovativeness of the industry are interacting to influence the optimal strategy choice, we distinguish between four scenarios. Each scenario is characterized by an exogenously given and constant number of the two types of firms in the industry, as well as by the type of the strategic firm.

(i) Scenario **INS**: the strategic firm is an innovator operating in a strongly innovative industry consisting of 4 innovative and 2 imitative firms.

(ii) Scenario **INW**: the strategic firm is an innovator operating in a weakly innovative industry consisting of 2 innovative and 4 imitative firms.

(iii) Scenario **IMS**: the strategic firm is an imitator operating in a strongly innovative industry consisting of 4 innovative and 2 imitative firms.

(iv) Scenario **IMW**: the strategic firm is an imitator operating in a weakly innovative industry consisting of 2 innovative and 4 imitative firms.

In each scenario we vary the κ-value of the strategic firm in the interval $\kappa \in [-0.15, 0.3]$ with a stepsize of 0.025.[16] For each considered value of κ we carry out a batch of $n = 200$ simulation runs. Each run lasts for $T^{tot} = 1000$ periods and we assume that the strategic firm enters the industry in period $t = 200$, i.e. at a point in time when potential initial transient effects have disappeared. For each run the discounted profit stream of the strategic firm over the time interval $t = 200$ to $t = 1000$ is determined and stored. Furthermore, we also record for each run the average number of locations the strategic firm is present in during its 800 periods in the industry. Due to this procedure we obtain for each value of κ a set of n realizations of the strategic firm's discounted profit and average number of locations. The following analysis is based on the comparison of these data across the different values of κ for each of the four scenarios. In order to be able to fully control the type distribution in the industry and to keep it constant over time, for the purpose of the strategy analysis we abstract from entry and exit into the industry apart from the single entry of the strategic firm at

[16] The interval is chosen in a way to guarantee that in all considered scenarios the profit maximizing value is in the interior of the interval. All non-strategic firms are assumed to use $\kappa = 0$, corresponding to the standard NPV rule.

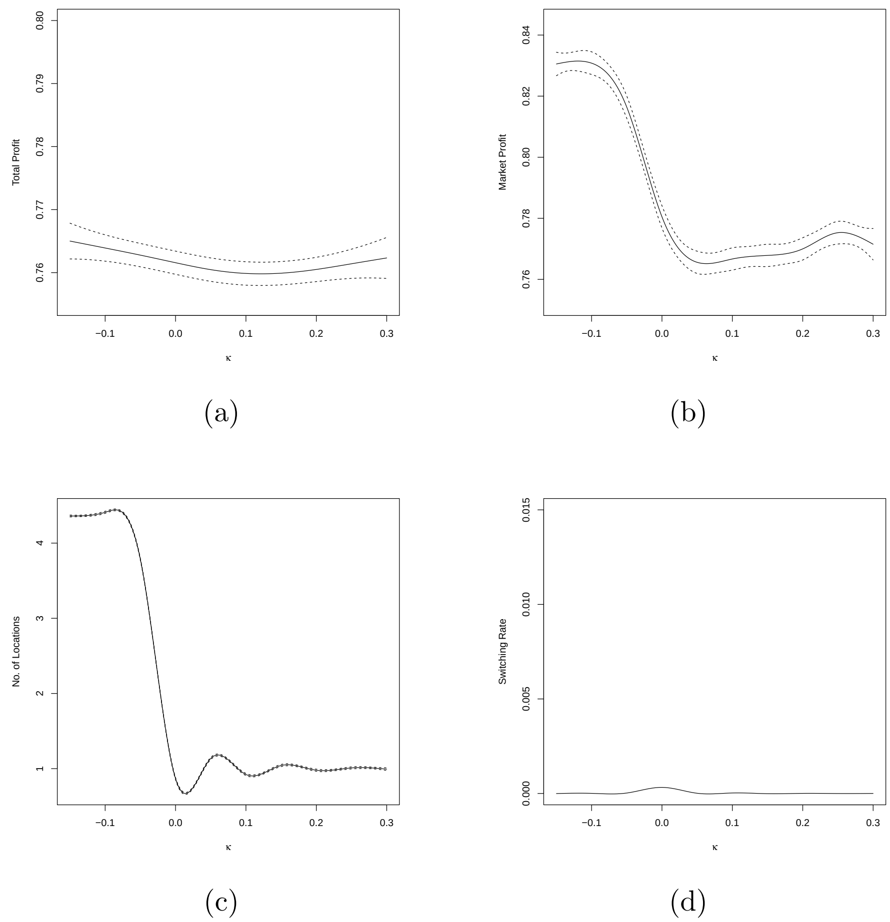
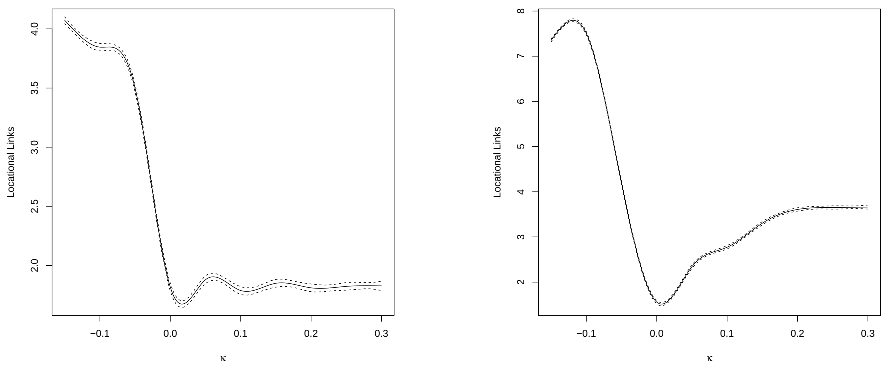


Figure 2: Penalized spline estimations of the expected discounted profits (a), market profits (b), the average number of locations (c) and the switching rate (d) of the strategic innovator in strongly innovative industry

$t = 200$. The graphical representations of the dependence of the key indicators from the parameter κ in the remainder of this section rely on estimated non-linear models using penalized spline methods (see, e.g., Kauermann et al., 2009).

We first consider the implications of different choices of the location strategy of an innovator both in strongly and weakly innovative industries. Panels (a) and (b) of Figure 2 show the estimated discounted profit and the estimated discounted market profit of the strategic innovator in a strongly innovative industry (scenario **INS**). Whereas optimality is determined with respect to the discounted profit, considering also the market profit – which does not account for location-, entry-, exit- and switching-costs – is helpful to better understand the main determinants of the firm's optimal strategy. From panel (a) it is immediate to see that if the strategic innovator operates in a strongly innovative industry, the choice of the strategy parameter is of little relevance for the firm's discounted profits. Whereas with a negative value of the strategy parameter κ the firm is typically active in several locations (see panel (c)), which induces high market profits (see panel (b)), these additional market profits are exactly offset by the additional location costs. Hence, the firm's total discounted profit under such a diversification-oriented strategy is virtually identical to that obtained with a non-negative value of κ, which induces concentration in a single location only and reduces the number of links with imitators (see Figure 3(a)). Furthermore, the innovator in a strongly innovative environment refrains from switching between locations. The reason why in this industry environment the strategic innovator does not switch locations regardless of the value of κ is closely related to the arguments put forward in Section 4 to explain the negative dependence of innovators' exit rate on the number of innovators in that location. In a strongly innovative industry, the location of an innovator is typically shared with other innovators as well as with imitators. Therefore, even if the strategic innovator leaves this location (e.g. by switching to another location) the imitators have the possibility to improve their product quality by imitating other innovative firms. Hence, the competitive advantage that the strategic innovator can achieve by leaving such a densely populated location is relatively small. As we elaborate below, this is quite different from the case of a weakly innovative industry, where in many cases the strategic innovator does not share its location with other innovators. Since for our parametrization the value of κ does not substantially influence the strategic firm's expected profit, the scenario with a strategic innovator in a strongly innovative industry can be considered as a benchmark. Starting from this benchmark, in what follows we explore how varying the industry environment and the type of the strategic firm affects the optimal choice of the strategy parameter κ.

We start this investigation by considering the optimal location strategy of an innovator in a weakly innovative industry environment (scenario **INW**). Figure 4(a) shows that in such an environment the innovator's expected profit is largest if its strategy corresponds to a positive value of κ above a level of about 0.15. As can be seen in panel (c), this strategy choice induces the firm to be in a single location. Furthermore, comparing the rate at which the strategic innovator switches between locations (see panel (d)) shows a distinctive difference between the case of $\kappa = 0$ and the optimal choice of $\kappa = 0.15$. Whereas in the former case the innovator switches regularly, in the latter almost no switching occurs. Considering the instances in which the innovator shares a location with imitators (Figure 3(b)), we see that the active switching behavior under $\kappa = 0$ results in an average number of less than two imitators in the same region as the strategic innovator, while the corresponding number for $\kappa = 0.15$ strongly increases



(a) (b)

Figure 3: Penalized spline estimations of the locational links between the strategic innovator and imitators in a strongly (a) and weakly (b) innovative industry

to about three imitators. The discussion above explains why an innovator in such an industry environment should systematically deviate from the NPV criterion and enter a new location only if the NPV of doing so is above a strictly positive threshold. The key observation is that by moving into a location the innovator triggers the future entry of imitators (attracted by potential spillovers) into that location, which reduces the actual present value of moving compared to the NPV estimated under naive expectations (i.e. under the current distribution of firms across locations). The firm should take this systematic bias into account by setting a positive value of κ.

The bias incurred by a firm setting $\kappa = 0$ becomes evident by observing that, in order to reduce the risk of being imitated, it keeps leaving regions populated by many imitators (see again panel (d) of Figure 4). Whereas this behavior indeed induces relatively high market profits (panel (b)), the resulting switching costs are so high that the strategic firm's profit is lower than under $\kappa = 0.15$, in which case the strategic innovator refrains from switching between locations and accepts the risk of being imitated. The key difference between this scenario and the one of a strongly innovative industry is that, due to the much smaller number of imitators in the INS scenario, the bias of the NPV under naive expectations is negligible and therefore there is no systematic reason to correct for it. This is illustrated by the fact that almost no location switching occurs even when $\kappa = 0$, corresponding to a strategy which aims at avoiding co-location with imitators (see Figure 2(d)).[17]

We now turn to the analysis of the optimal location strategy of an imitator. In

[17] The scale used in panel (d) is identical across the four scenarios we consider in the section in order to allow a better comparison of the size of switching rates.

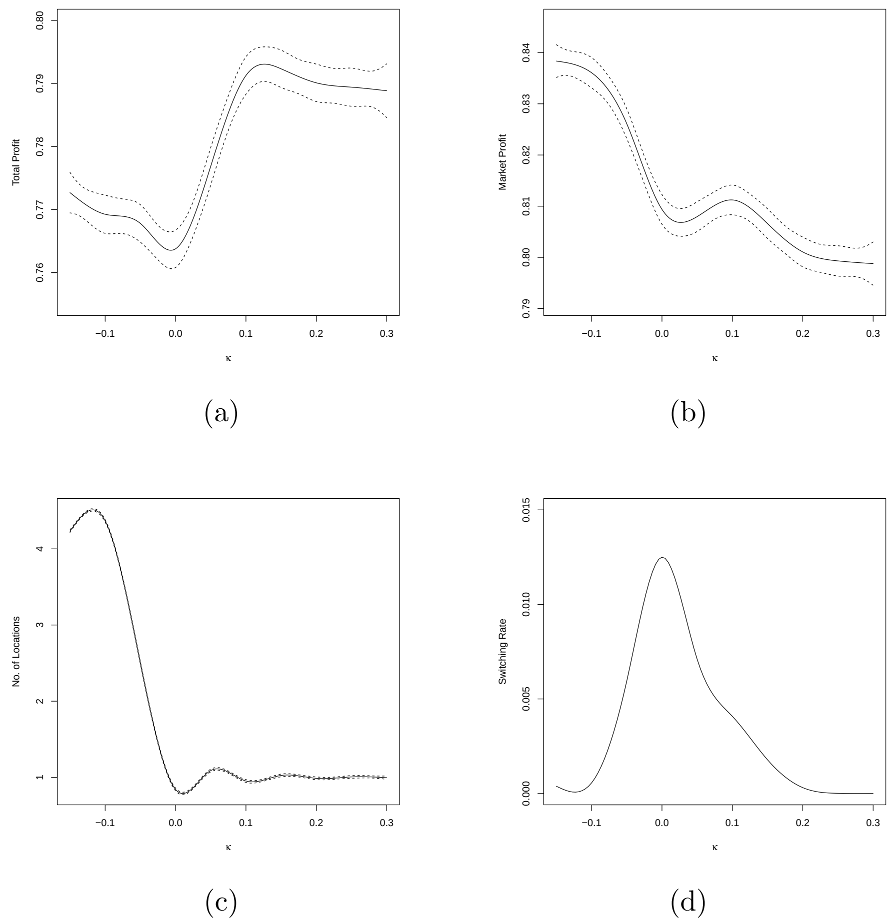


Figure 4: Penalized spline estimations of the expected discounted profits (a), market profits (b), the average number of locations (c) and the switching rate (d) of the strategic innovator in weakly innovative industry

Figure 5 we focus on the case of a strongly innovative industry (scenario **IMS**). Panel (a) of Figure 5 clearly shows that for an imitator operating in a strongly innovative environment it is optimal to choose $\kappa = 0$, which is in accordance with our benchmark case. The key intuition why using the NPV criterion introduces no systematic bias in the location decision is that in an industry mainly populated by innovative firms the location decision of a single imitator does not have a systematic impact on the future location choices of its competitors, having no substantial effect on their inwards and outwards spillovers. Panel (c) shows that for this strategy choice the strategic imitator on average operates in about two locations. Choosing a negative value of κ, which leads to a more diversified location portfolio, would induce higher market profits for the firm. However, the location and entry costs associated to such a broader portfolio

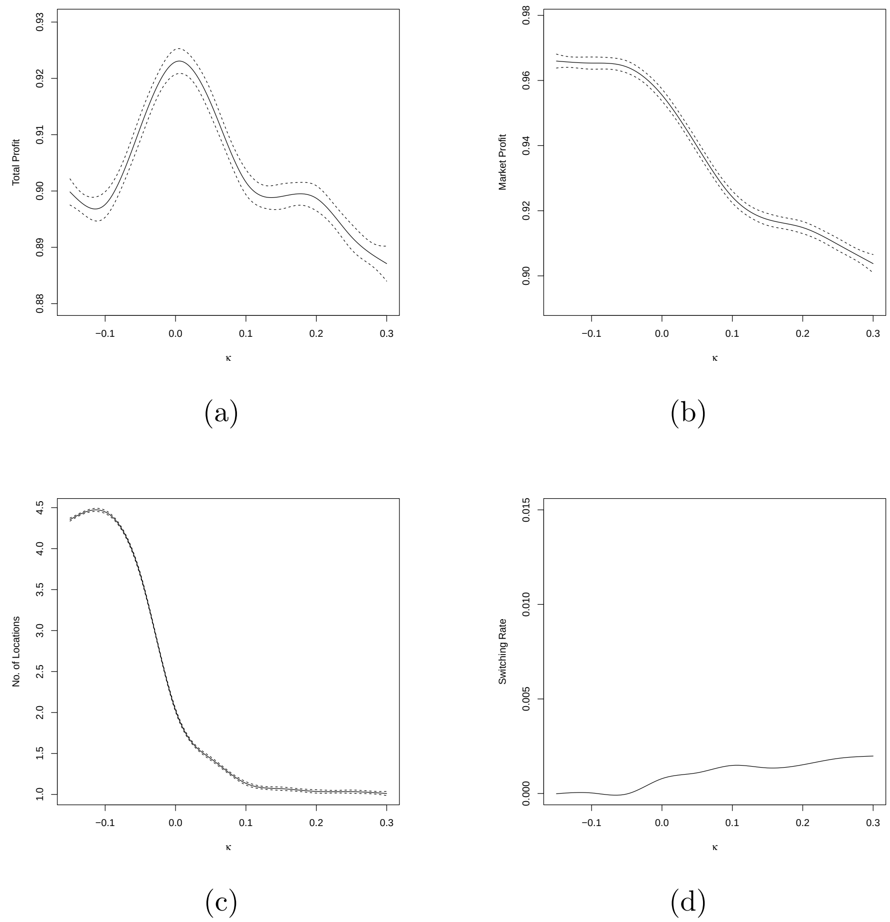


Figure 5: Penalized spline estimations of the expected discounted profits (a), market profits (b), the average number of locations (c) and the switching rate (d) of the strategic imitator in strongly innovative industry

outweigh the profit gains in the market and therefore such a strategy is dominated by $\kappa = 0$. Conversely, a positive value of κ induces a substantial loss in market profits (see panel (b)), mainly due to a reduction in the firm's locations and the associated loss in imitation opportunities. As can be seen in panel (a) of Figure 6, an increase from $\kappa = 0$ to $\kappa = 0.1$ is associated with a strong decrease in the number of instances in which the strategic imitator shares a location with an innovator. This reduces the opportunities for the strategic firm to quickly adopt successful innovations. Due to this effect, following a strategy associated with a too small number of locations (positive κ) is not optimal for the strategic imitator in this industry environment. As can be seen in panel (d) of Figure 5, the optimal strategy of an imitator in this market environment requires that it does not switch across locations. The fact that we consider a strongly

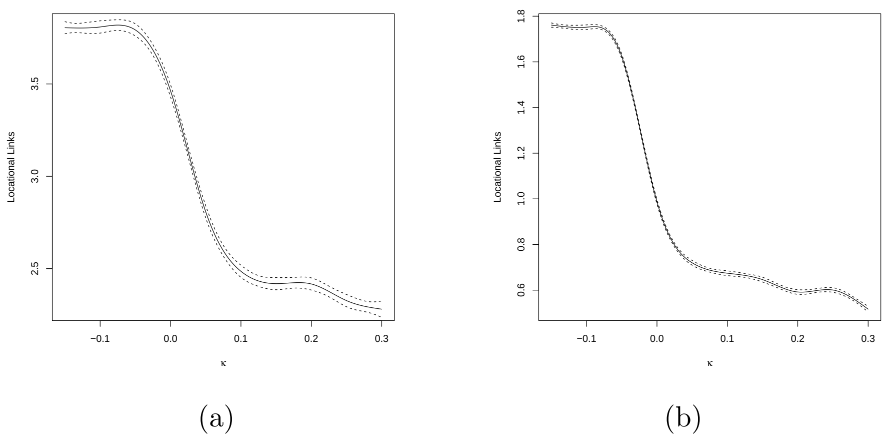


Figure 6: Penalized spline estimations of the locational links between the strategic imitator and innovators in a strongly (a) and weakly (b) innovative industry

innovative industry is crucial for the absence of location switching under $\kappa = 0$. In this industry environment, innovators are spread across several locations such that an imitator is likely to share a location with an innovator even if its own number of locations is relatively small and it is not attempting to chase innovators by switching locations.

Finally, Figure 7 focuses on the case of a weakly innovative industry (scenario **IMW**). The optimal choice of the strategy parameter in this scenario is $\kappa = -0.1$, which corresponds to a highly diversified location strategy inducing the firm to be present in almost all available locations (see panel (c)). Intuitively, similar to the INW scenario also here the NPV under naive expectations introduces a systematic bias. In particular, the fact that a location is attractive for the strategic imitator implies that it is also attractive for all other imitators in the industry. Hence, it should be expected that the number of imitators in that region increases, which makes that region even more attractive for the strategic imitator, since it increases the number of potential sources of inwards spillovers. Taking this into account, it is optimal for the strategic imitator to enter a location even if the NPV under naive expectations is negative. Relative to the case of $\kappa = 0$, choosing a negative value of κ has several implications. First, due to the larger number of locations in which the firm is active (4.4 vs. ≈ 1.5, see panel (c)) the strategic firm has more opportunities for imitation. Figure 6(b) illustrates the point by showing that the number of instances in which the strategic imitator shares a location with an innovator grows considerably as κ is decreased from the benchmark case to $\kappa = -0.1$. This results in higher market profits (Figure 7 (b)). However, the higher number of locations is also associated with larger location costs. As can be seen in panel (d) of Figure 7, relative to the case of $\kappa = 0$ setting the strategy parameter to $\kappa = -0.1$ substantially reduces the instances in which the strategic firm switches locations. This entails a strong reduction in switching costs. Intuitively, using this strategy, the firm is highly diversified location-wise, such that – regardless where innovators decide to locate – the firm has the possibility to imitate through local spillovers. On the contrary, for the benchmark value $\kappa = 0$ the strategic firm has only a small number of active locations, which is associated to a relatively high switching rate. A small number of active locations, in turn, makes it necessary for the strategic firm to 'chase' (by switching locations) the few innovators in the industry in order to have opportunities for successful imitation. Similar arguments apply to even more restrictive location strategies associated to a positive value of κ.

The key insight from our strategy analysis is that for a given parameter constellation the optimal location strategy differs significantly between innovators and imitators, and between the different industry environments in which they operate. To highlight that this insight carries over beyond our benchmark parameter setting, in Appendix B we compare the optimal values of κ across our four scenarios for different values of the location costs, entry costs and number of locations. It turns out that the optimal value of κ does not qualitatively change compared to the benchmark parameter setting. In particular, for all considered parameter settings the optimal κ varies across the four scenarios, confirming our key insight that the optimal location strategy depends on firm and industry type.[18]

6 Concluding Remarks

We provide a theory of firms' R&D location choices emphasizing the role of knowledge flows as key determinants of that choice. We show that firms' heterogeneity in terms of the relevance of potential inwards and outwards spillovers systematically affects firms' optimal location strategies in different industry environments, as well as the dynamics of location patterns over time.

Our theory is able to replicate a number of stylized facts that have been documented by the recent empirical literature, highlighting also the key underlying driving forces that are associated to their emergence. Consistently with e.g. Alcacer and Chung (2007), we find that technologically advanced firms distance themselves from locations with significant industrial activity (preferring area characterized by high levels of aca-

[18]It should be noted that we restrict attention to parameter constellations where neither location nor entry costs are too large, as this would obviously imply that all firms stick to only one location regardless of their type and industry environment.

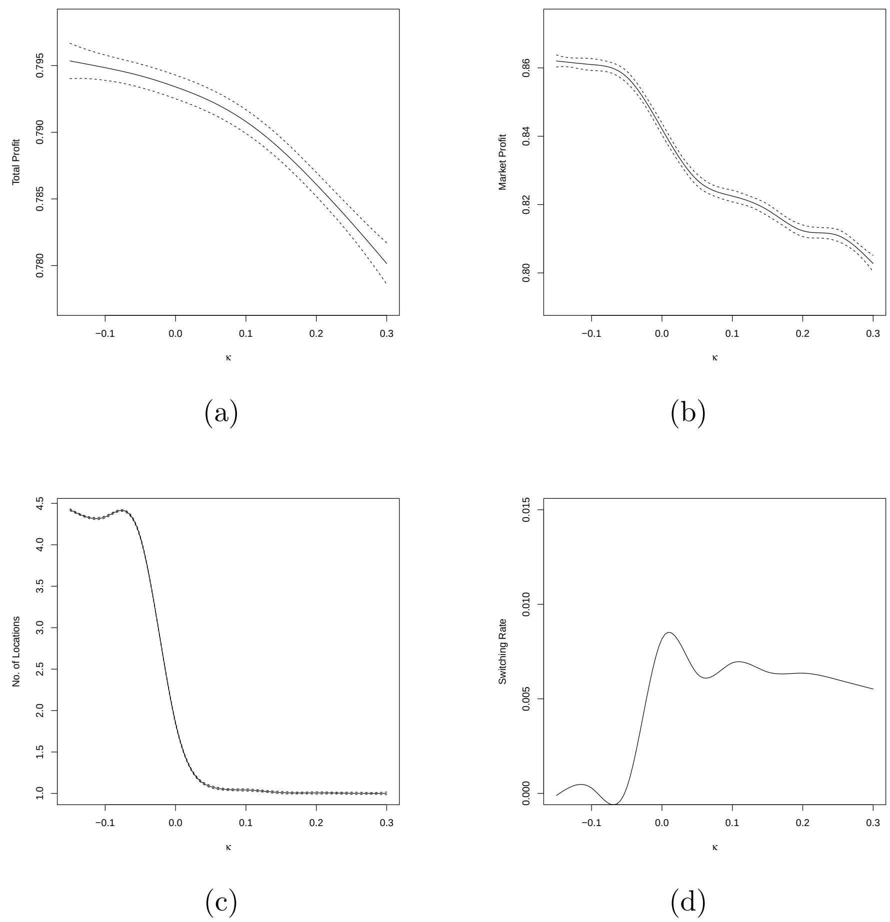


Figure 7: Penalized spline estimations of the expected discounted profits (a), market profits (b), the average number of locations (c) and the switching rate (d) of the strategic imitator in weakly innovative industry

demic activity), while less technologically advanced firms tend instead to favor such locations. Furthermore, we obtain that technological laggards tend to operate in a larger number of locations than more advanced firms, which resonates with the observation (see e.g. Leiponen and Helfat (2011)) that multi-location of R&D is associated with imitative innovation activities rather than with new-to-the-market innovations. Finally, in accordance with the evidence reported by Livanis and Lamin (2016) on the exit rates of R&D facilities, we document the existence of a strong negative correlation between the probability of an imitative firm leaving a location and the number of other firms operating in that location, as well as a positive correlation between the probability of a technological leader leaving a location and the number of competitors operating there.

Besides being able to explain key stylized facts and the underlying driving forces, our theoretical model also allows for a careful normative investigation of heterogeneous firms' location strategies in different environments. In this respect, the key managerial implication of this paper is that there are situations in which a firm should be willing to enter a location even though the net present value of doing so under the current location pattern is negative (this is the case of an imitation oriented firm in a weakly innovative industry), while there are other circumstances in which a firm should not enter a location even for (slightly) positive net present values (an innovation oriented firm in a weakly innovative industry).

The dynamic dimension of our analysis allows us to study how firms' location strategies shape the formation of industry agglomerations and their spatial dynamics. In this respect, our study sheds light on how knowledge flows affect the decisions of heterogeneous firms to join – or to escape – industry clusters. Furthermore, it helps understanding the reasons why clusters move across locations over time and why technologically advanced firms act as 'anchors' for the formation of new spatial agglomerations within and across industries.

Several caveats to our results need to be acknowledged, which paves the way for further research. On normative ground, our theory suggests that – in the presence of strategic uncertainty that cannot be eliminated about competitors' future location choices – firms' strategies, based on simple heuristics, may vary significantly depending on firm and industry characteristics, often entailing a significant departure from the application of a standard NPV rule. The merits of relying on heuristics to take decisions in complex environments have been highlighted in the recent managerial literature (see e.g. Joo et al. (2019) and Cui et al. (2018)). Notwithstanding, although the simple heuristic decision rule we consider appears to be quite reasonable, alternative mechanisms to handle fundamental uncertainty may be used by different firms, which calls for a deeper investigation of the robustness of our results to alternative heuristics specifications.

Overall, this work enhances our understanding of the role of knowledge spillovers – as a mechanism for accessing external knowledge – in driving firms' location strategies. As effectively noted by Alcacer and Chung (2007), while this channel is important for some firms, other strategic mechanisms may turn out to be more effective in accessing external knowledge for other firms, the location choices of which are then likely to be less affected by the presence of knowledge spillovers. Furthermore, the characteristics of local labor markets, the availability of specialized suppliers, the quality of infrastructures and more generally of the local environment are all factors that may carry a large weight on firms' location decisions. Exploring the relevance of strategic mechanisms other than spillovers for accessing external knowledge, and investigating the interplay between knowledge sourcing and other factors potentially affecting firms' location strategies, are important avenues for future research.

References

Alcacer, J. and W. Chung (2007): "Location Strategies and Knowledge Spillovers," *Management Science*, 53, 760–776.

Alcacer, J. and M. Zhao (2012): "Local R&D Strategies and Multi-location Firms: The Role of Internal Linkages," *Management Science*, 58, 734–753.

Almazan, A., A. De Motta, and S. Titman (2007): "Firm Location and the Creation and Utilization of Human Capital," *Review of Economic Studies*, 74, 1305–1327.

Belderbos, R., B. Leten, and S. Suzuki (2017): "Scientific research, firm heterogeneity, and foreign R&D locations of multinational firms," *Journal of Economics and Management Strategy*, 26, 691–711.

Belderbos, R., E. Lykogianni, and R. Veugelers (2008): "Strategic R&D location by multinational firms: spillovers, technology sourcing, and competition," *Journal of Economics and Management Strategy*, 17, 759–779.

Belderbos, R. and D. Somers (2015): "Do Technology Leaders Deter Inward R&D Investments? Evidence from Regional R&D Location Decisions in Europe," *Regional Studies*, 49, 1805–1821.

Cassiman, B. and R. Veugelers (2006): "In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition," *Management Science*, 52, 68–82.

Chesbrough, H. (2003): *Open Innovation: The New Imperative for Creating and Profiting from Technology*, Harvard Business School Press: Boston, MA.

Colombo, L. and H. Dawid (2014): "Strategic Location Choice Under Dynamic Oligopolistic Competition and Spillovers," *Journal of Economic Dynamics and Control*, 48, 288–307.

Cui, Y., I. Duenyas, and O. Sahin (2018): "Pricing of Conditional Upgrades in the Presence of Strategic Consumers," *Management Science*, 64, 3208–3226.

Dawid, H. and M. Reimann (2011): "Diversification: A Road to Inefficiency in Product Innovations?" *Journal of Evolutionary Economics*, 21, 191–229.

De Beule, F. and J.-L. Duanmu (2012): "Locational determinants of internationalization: A firm-level analysis of Chinese and Indian acquisitions," *European Management Journal*, 30, 264–277.

Ellison, G. and E. L. Glaeser (1997): "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, 105, 889–927.

Geroski, P. (1995): "What Do We Know about Entry?" *International Journal of Industrial Organization*, 13, 421–440.

Gersbach, H. and A. Schmutzler (1999): "External spillovers, internal spillovers and the geography of production and innovation," *Regional Science and Urban Economics*, 29, 679–696.

——— (2011): "Foreign direct investment and R&D-offshoring," *Oxford Economic Papers*, 63, 134–157.

Giachetti, C. and G. Lanzolla (2016): "Product Technology Imitation Over the Product Diffusion Cycle: Which Companies and Product Innovations do Competitors Imitate More Quickly?" *Long Range Planning*, 49, 250–264.

Giarratana, M. S. and M. Mariani (2014): "The Relationship between Knowledge Sourcing and Fear of Imitation," *Strategic Management Journal*, 35, 1144–1163.

Gigerenzer, G. and W. Gaissmaier (2011): "Heuristic decision making," *Annual Review of Psychology*, 62, 451–482.

Grant, R. M. (2010): *Contemporary Strategy Analysis*, Wiley & Sons.

Griffin, A. (1997): "Modeling and Measuring Product Development Cycle Time across Industries," *Journal of Engineering and Technology Management*, 14, 1–24.

Grillitsch, M. and M. Nilsson (2017): "Firm Performance in the Periphery: on the Relation between Firm-internal Knowledge and Local Knowledge Spillovers," *Regional Studies*, 51, 1219–1231.

Joo, M., M. L. Thompson, and G. M. Allenby (2019): "Optimal Product Design by Sequential Experiments in High Dimensions," *Management Science*, 65, 3235–3254.

Katz, B. and J. Wagner (2014): "The Rise of Innovation Districts: A New Geography of Innovation in America," *Brookings Institution*, 1–33.

Kauermann, G., G. Claeskens, and J. D. Opsomer (2009): "Bootstrapping for penalized spline regression," *Journal of Computational and Graphical Statistics*, 18, 126–146.

Klepper, S. (1996): "Entry, Exit, Growth, and Innovation Over the Product Life Cycle," *American Economic Review*, 86, 562–583.

Landini, F., K. Leec, and F. Malerba (2017): "A history-friendly model of the successive changes in industrialleadership and the catch-up by latecomers," *Research Policy*, 46, 431–446.

Lee, J. and E. Mansfield (1996): "Intellectual Property Protection and US Foreign Direct Investment," *Review of Economics and Statistics*, 78, 181–186.

Leiponen, A. and C. E. Helfat (2011): "Location, Decentralization, and Knowledge Sources for Innovation," *Organization Science*, 22, 641–658.

Li, D., G. Caponec, and F. Malerba (2019): "The long march to catch-up: A history-friendly model of Chinas mobile communications industry," *Research Policy*, 48, 649–664.

Livanis, G. and A. Lamin (2016): "Knowledge, Proximity and R&D Exodus," *Research Policy*, 45, 8–26.

Mariotti, S., L. Piscitello, and S. Elia (2010): "Spatial agglomeration of multinational enterprises: the role of information externalities and knowledge spillovers," *Journal of Economic Geography*, 10, 519–538.

Shaver, J. and F. Flyer (2000): "Agglomeration Economics, Firm Heterogeneity, and Foreign Direct Investment in the United States," *Strategic Management Journal*, 21, 1175–1193.

Smith, E. B. and W. Rand (2018): "Simulating Macro-Level Effects from Micro-Level Observations," *Management Science*, 64, 5405–5421.

Symeonidis, G. (2003): "Comparing Cournot and Betrand Equilibria in a Differentiated Duopoly with Product R&D," *International Journal of Industrial Organization*, 21, 39–55.

Wang, S. and M. Zhao (2018): "A Tale of Two Distances: a Study of Technological Distance, Geographic Distance and Multilocation Firms," *Journal of Economic Geography*, 18, 1091–1120.

Warusawitharana, M. (2015): "Research and Development, Profits, and Firm Value: A Structural Estimation," *Quantitative Economics*, 6, 531–565.

Appendix A: Derivation of Cournot Equilibrium Profits

The optimization problem of the representative consumer in period t is given by

$$\max_x U(x,q) \qquad \text{s.t. } \sum_{i \in N_t} p_i x_i \leq \beta,$$

where $U(x,q)$ is defined in Equation (3). Formulating the first order conditions of the associated Lagrangian immediately yields the inverse demand (4), with θ being the multiplier of the budget constraint. Taking into account that $\sum_{i \in N_t} p_i x_i = \beta$ holds for the optimal consumption choice, we obtain

$$\theta(x_t, q_t) = \frac{\beta}{\alpha \sum_{k \in \mathcal{N}_t} x_{k,t} - \sum_{k \in \mathcal{N}_t} \frac{x_{k,t}^2}{q_{k,t}^2} - \gamma \sum_{k \in \mathcal{N}_t} \sum_{j \in \mathcal{N}_t \setminus \{k\}} \frac{x_{k,t} x_{j,t}}{q_{k,t} q_{j,t}}}.$$

The quantity choice problem of firm i is given by

$$\max_{x_{i,t}} \tilde{\pi}_{i,t} := x_{i,t} p_i(x_t, q_t),$$

where we have used that marginal costs are normalized to zero. This yields the first order condition

$$\begin{aligned}\frac{\partial\tilde{\pi}_{i,t}}{\partial x_{i,t}} &= \theta(x_t,q_t)\left(\alpha-\frac{2x_{i,t}}{q_{i,t}^2}-\gamma\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}\right)+\frac{\partial\theta(x_t,q_t)}{\partial x_{i,t}}\left(\alpha-\frac{x_{i,t}}{q_{i,t}^2}-\gamma\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}\right)x_{i,t}\\ &=0.\end{aligned}$$

Taking into account that

$$\frac{\partial\theta(x_t,q_t)}{\partial x_{i,t}}=-\theta(x_t,q_t)\frac{\alpha-\frac{2x_{i,t}}{q_{i,t}^2}-\gamma\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}}{\alpha\sum_{k\in N_t}x_{k,t}-\sum_{k\in N_t}\frac{x_{k,t}^2}{q_{k,t}^2}-\gamma\sum_{k\in N_t}\sum_{j\in N_t\setminus\{k\}}\frac{x_{k,t}x_{j,t}}{q_{k,t}q_{j,t}}},$$

we obtain that

$$\begin{aligned}\frac{\partial\tilde{\pi}_{i,t}}{\partial x_{i,t}} &= \left(\alpha-\frac{2x_{i,t}}{q_{i,t}^2}-\gamma\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}\right)\theta(x_t,q_t)\left(1-\frac{\alpha-\frac{x_{i,t}}{q_{i,t}^2}-\gamma\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}}{\alpha\sum_{k\in N_t}x_{k,t}-\sum_{k\in N_t}\frac{x_{k,t}^2}{q_{k,t}^2}-\gamma\sum_{k\in N_t}\sum_{j\in N_t\setminus\{k\}}\frac{x_{k,t}x_{j,t}}{q_{k,t}q_{j,t}}}\right)\\ &=0.\end{aligned}$$

Considering the second order condition shows that in order to maximize $\tilde{\pi}_{i,t}$ the first bracket has to be zero, which gives the following best response function for firm i:

$$x_{i,t}=\frac{\alpha q_{i,t}^2}{2}-\frac{\gamma q_{i,t}}{2}\sum_{j\in N_t\setminus\{i\}}\frac{x_{j,t}}{q_{i,t}q_{j,t}}.$$

Based on this best response, standard arguments give equilibrium quantities and prices; i.e.

$$\begin{aligned}x_{i,t}^* &= \frac{\alpha q_{i,t}\left((2-\gamma)q_{i,t}+\gamma\sum_{j\in N_t\setminus\{i\}}(q_{i,t}-q_{j,t})\right)}{(2-\gamma)(2+\gamma(n_t-1))},\\ p_{i,t}^* &= \theta(x_t^*,q_t)\frac{\alpha\left((2-\gamma)q_{i,t}+\gamma\sum_{j\in N_t\setminus\{i\}}(q_{i,t}-q_{j,t})\right)}{q_{i,t}(2-\gamma)(2+\gamma(n_t-1))}=\theta(x_t^*,q_t)\frac{x_{i,t}^*}{q_{i,t}^2}.\end{aligned}$$

Hence, equilibrium profits are given by (5).

Appendix B: Robustness

In this Appendix, we check the robustness of our findings with respect to variations in key parameters. In particular, we focus on those parameters that most directly affect the location choices of firms, namely the number of available locations as well as the costs of entering (ϑ^{en}) and operating (ϑ^{loc}) in a location.

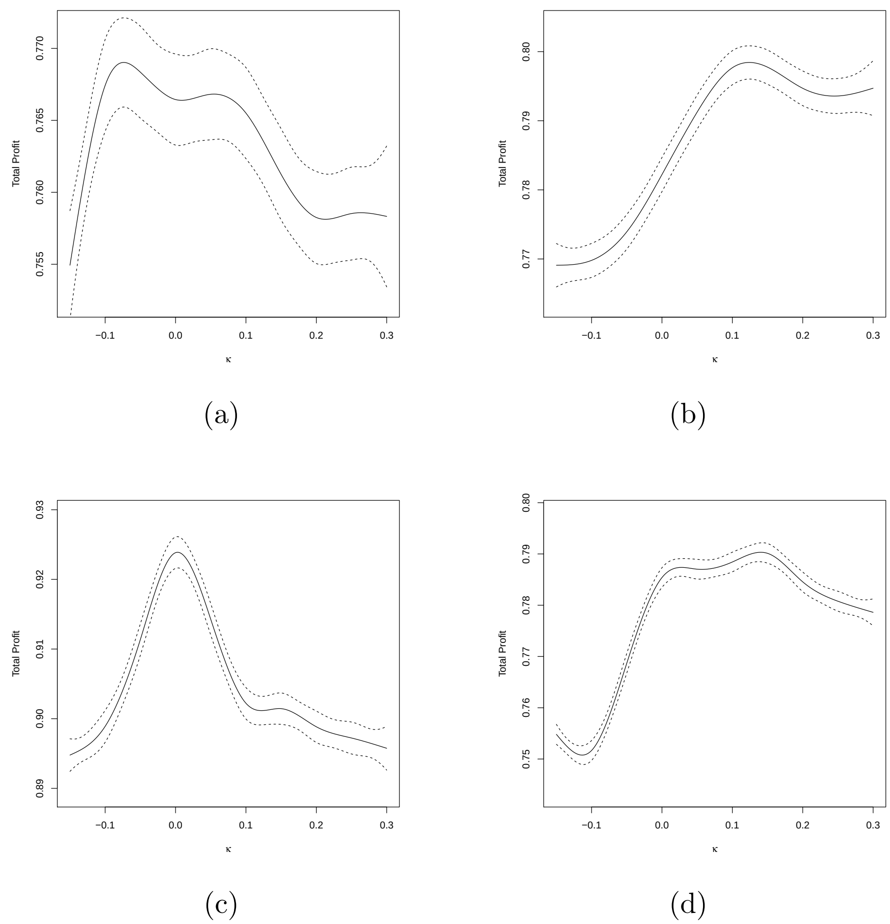


Figure 8: Penalized spline estimations of the strategic firm's expected discounted profits for a scenario with $|\mathcal{L}| = 10$ locations in cases of a strategic innovator in a strongly (a) and weakly (b) innovative industry as well as for a strategic imitator in a strongly (c) and weakly (d) innovative industry

Number of Locations

All results in this paper have been obtained for an industry in which the number of available locations is $|\mathcal{L}| = 5$. As it turns out, in such a scenario there are cases in which all locations are inhabited by at least one firm, so that an entering or moving firm does not have the option to choose an empty location. In order to assess whether our findings about the firms' optimal strategy are affected by this property, we also carry out simulations for $|\mathcal{L}| = 10$. Our simulations show that for such a setting there is always at least one empty location available for a switching or entering firm. Figures 8 and 9 depict the expected total profits and the switching rate, respectively, of the strategic firm for $\kappa \in [-0.15, 0.3]$ in all the four cases INS, INW, IMS and IMW. It turns out that our characterization of the optimal location strategy is fully robust for the first three of these cases. Only for the scenario of an imitative strategic firm in a weakly innovative industry (IMW) we obtain that the optimal value of the strategy parameter changes from $\kappa = -0.1$ to $\kappa = 0.15$. Not surprisingly, if the number of available locations becomes too large, a strategy aiming at 'covering all bases', i.e. being present in all locations where innovators might move to, becomes too costly. Hence, a strategy focusing on one location and following innovators if they move (see panel (d) in Figure 9) becomes the optimal choice of the strategic imitator. In any case, these results highlight that the optimal value of κ for the strategic innovator differs significantly between a strongly and weakly innovative industry (panel (a) versus panel (b) of Figure 8) and also that in a strongly innovative industry the optimal location strategy of an innovator is significantly different from that of an imitator (panel (a) versus panel (c)).

Location and Entry Costs

There are two types of direct costs related to the R&D location choice of firms. On the one hand, the firm has to pay recurring location costs ϑ^{loc} for every location it operates in. On the other hand, there are entry costs ϑ^{en} occurring either when the firm enters an additional location, or switches between locations. Given that both types of costs are taken into account by the firm in the estimation of the net present values of alternative location patterns, it should be clear that these costs can have considerable effects on the outcome of firm's decision making.

In order to demonstrate that the qualitative findings of our strategy analysis are robust with respect to a variation of these costs within a reasonable range around their default values (see Table 1), we report two additional robustness checks in each of which we show the dependence of a firm's expected discounted profit from the strategy

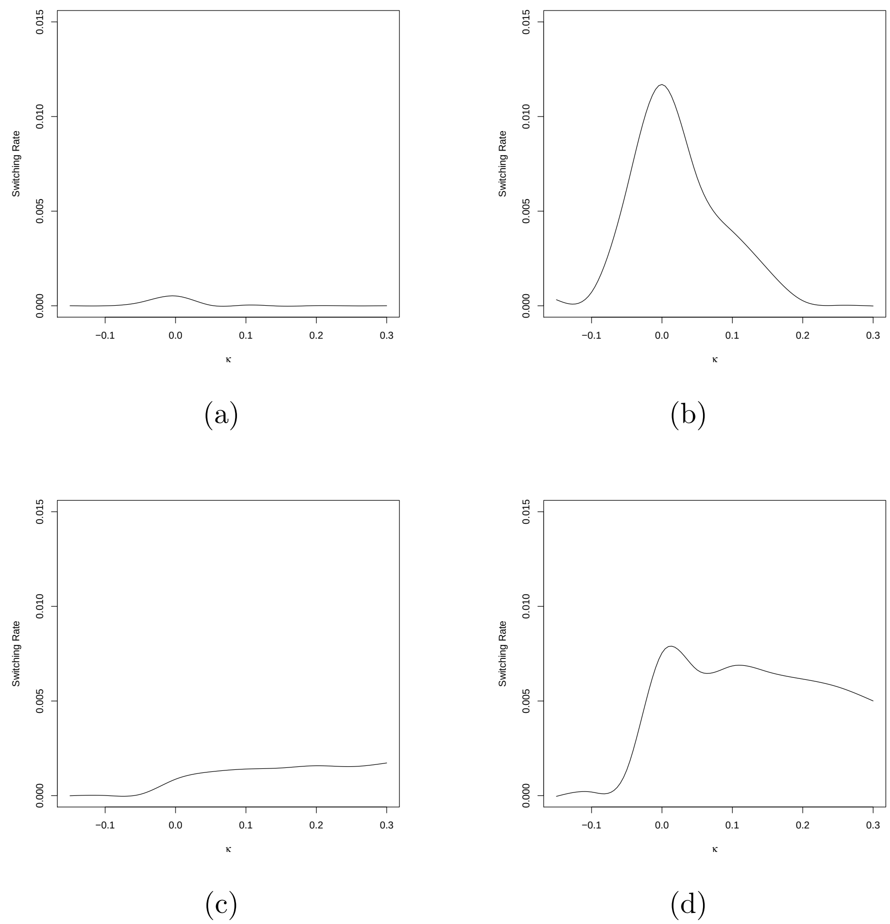
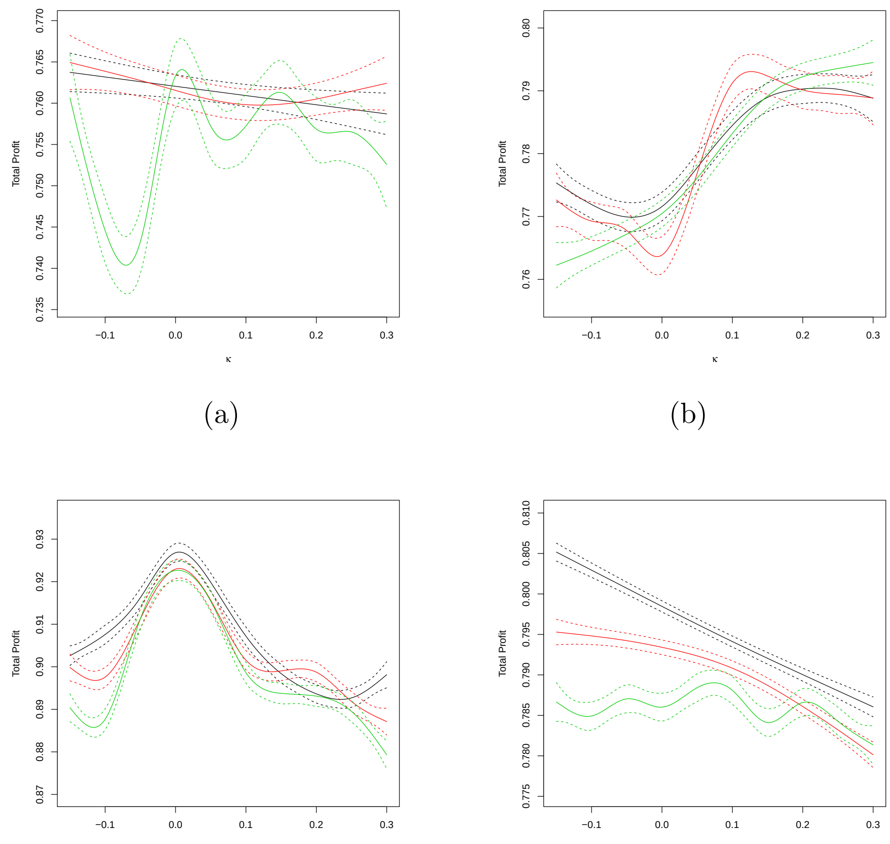


Figure 9: Penalized spline estimations of the strategic firm's switching rate for a scenario with $|\mathcal{L}| = 10$ locations in cases of a strategic innovator in a strongly (a) and weakly (b) innovative industry as well as for a strategic imitator in a strongly (c) and weakly (d) innovative industry

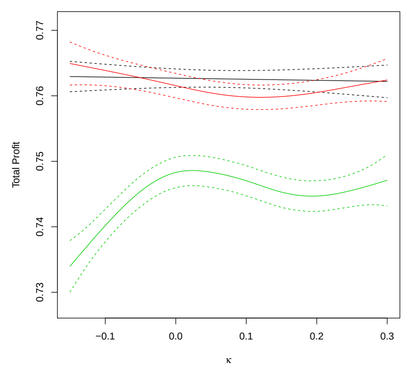
parameter κ under different levels of the corresponding cost parameter. In particular, we consider an interval $[0.0075, 0.0125]$ for the location costs ϑ^{loc}, whereas we focus on the interval $[2.25, 3.75]$ for the entering costs ϑ^{en}. In both cases, this corresponds to a significant variation of 25% in each direction from the default values that we obtain from our calibration ($\vartheta^{loc} = 0.01$, $\vartheta^{en} = 3.0$).



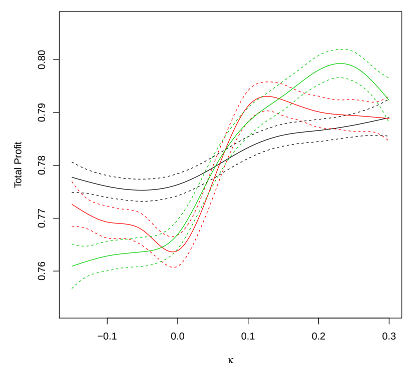
(a) (b) (c) (d)

Figure 10: Penalized spline estimations of the strategic firm's total profit a scenario with locations costs $\vartheta^{loc} = 0.0075$ (black), $\vartheta^{loc} = 0.01$ (red, default value) and $\vartheta^{loc} = 0.0125$ (green) in cases of a strategic innovator in a strongly (a) and weakly (b) innovative industry as well as for a strategic imitator in a strongly (c) and weakly (d) innovative industry

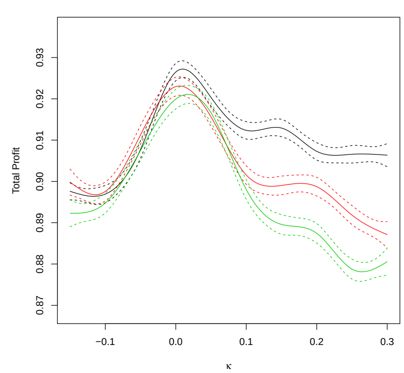
In Figure 10, we show the results of the robustness check for alternative specifications of location costs. Not surprisingly, a change in location costs induces level effects on the profitability of the strategy profiles, which are more pronounced for $\kappa < 0$. Nevertheless, the characterization of the optimal strategy profiles does not change qualitatively within the considered interval. In particular, for an innovator in a strongly innovative industry, no clear normative statements about the optimal value of κ can be made, which is consistent with our observation for the baseline case (panel (a)). In the same environment, instead, using $\kappa = 0$ is optimal for an imitator, again consistently with our baseline finding (panel (c)). In a weakly innovative industry, the innovator should always choose a positive κ value (panel (b)), whereas for an imitator in such an environment a negative value of κ is optimal under all considered parameter values (panel (d)).



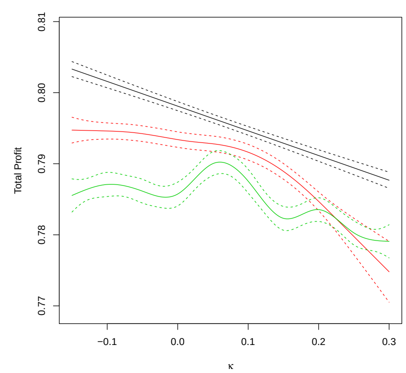
(a)



(b)



(c)



(d)

Figure 11: Penalized spline estimations of the strategic firm's total profit a scenario with entering costs $\vartheta^{en} = 2.25$ (black), $\vartheta^{en} = 3.0$ (red, default value) and $\vartheta^{en} = 3.75$ (green) in cases of a strategic innovator in a strongly (a) and weakly (b) innovative industry as well as for a strategic imitator in a strongly (c) and weakly (d) innovative industry

A similar conclusion is confirmed by Figure 11 considering different values of entry costs ϑ^{en}. Again, a change of this parameter induces level effects, but the characteristics of the firm's optimal strategy qualitatively do not change across the considered values of entry costs. The only exception in this respect is the case of a strategic innovator in a strongly innovative industry, where for a large entry cost negative values of κ can be ruled out as the optimal choice. Nonetheless, consistently with our baseline analysis, in this scenario there is still a whole range of κ values maximizing the expected profit of the strategic firm.