Adoption of innovations: modelling the interplay of behavioural biases, incentives and network structure

Antoine Feylessoufi

Christ's College
University of Cambridge

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Declaration

I hereby declare that this thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except in Chapters 2 and 3. In Chapter 2, I collaborated with Professor Stylianos Kavadias and the large majority was my own contribution (idea, literature, and analysis). In Chapter 3, I collaborated with my advisors Professor Stylianos Kavadias and Professor Daniel Ralph. Again, the idea, literature review, methodology, and analysis are my own work. Chapters 4 and 5 are solo-authored papers.

I confirm that this thesis has not been submitted in whole or in part for an other degree or qualification at the University of Cambridge or any other institution. This dissertation contains fewer than 80,000 words and complies with the guidelines on length and format.

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Abstract

A crucial challenge faced by most large organisations concerns their ability to effectively adopt new operational practices. Many streams of literature have looked into this challenge and generally, two reasons have been given to explain the difficulty of adopting: the uncertain utility an individual gets by adopting the new practice and the social influences between adopters. Chapter 2 gives a detailed multi-disciplinary review (sociology, economics, marketing, organisational behaviour, operations management and operational research) exploring the main determinants and mechanisms of practice adoption identified over the years and opportunities for the field of operations management.

In particular, one key opportunity unexplored by the existing literature (highlighted by numerous examples and industry cases throughout the dissertation) is the importance of the relative benefits felt by adopters compared to others' choices due to behavioural considerations resulting from social interactions such as social comparisons. To study these effects fully, existing analytical methodologies, such as classic game theory or dynamic programming used in the field, prove to be limiting. Thus, I introduce a novel analytical methodology called evolutionary game theory. I propose a series of evolutionary game theoretic models in the following chapters to give novel insights in the adoption challenge by exploring the impact of these relative benefits in the decision-making process to adopt or not.

Chapter 3 is a seminal paper exploring the effects of these relative benefits to the adoption choice. I explore how (i) the types of reward systems (individual and/or collective) employed by an organisation to induce adoption, and (ii) the way social comparisons (namely behind-averse and ahead-seeking) affect individual employee utilities, shape the eventual adoption. Behind-averse social comparisons are felt by individuals when they experience a disutility of having a worse outcome than others. Ahead-seeking comparisons, on the other hand, are felt when individuals experience a utility boost by having a superior outcome than others. I find that under certain circumstances the *better* practice may not be fully adopted. Behind-averse social comparisons drive a bandwagon effect phenomenon whereby full adoption or

no-adoption occurs depending on the critical mass of initial adopters. In contrast, the initial mass of adopters does not have any effect in the presence of ahead-seeking comparisons. These lead to the coexistence of “competing” practices, because of the attempts of adopters to differentiate from each other. The organisational rewards moderate these two outcomes in non-intuitive ways. Specifically, collective rewards help moderate the coexistence of the “competing” practices under ahead-seeking comparisons and individual rewards play a key role to the adoption of high risk new practices under behind-averse social comparisons.

Chapter 4 further develops the concept of relative benefits of adoption introduced in Chapter 3 and proposes an evolutionary game theoretic model allowing heterogeneity in the teams of employees in their capabilities to successfully adopt the new practice, in the type of social comparisons and in the level of interactions between the two teams. Past literature in operations management advocates that information exchange and collaboration between teams help adoption. I mathematically model this collaboration concept in the form of wide and narrow bridges that represent the level of interactions between the two teams. I find that that these two types of bridges do not impact teams the same way due to the heterogeneous relative benefits. Contrary to past literature in operations management, I find that wide bridges may not always be the best solution to put in place in organisations. The choice that an organisation has to make between allowing wide or narrow bridges also depends on the upfront training investment it is willing to do. This analysis provides evidence for management on when adoption can benefit from increased collaboration between teams. This chapter also brings new theoretical insights to the current academic discussion on wide versus narrow bridges for diffusion of new practices in sociology and the ongoing debate on the creation of star teams in organisations for better performance.

Chapter 5 further investigates the impact of heterogeneous social interactions in the adoption of new practices introduced in Chapter 4 by introducing a network structure guiding the social interactions. I study two classic production network topologies, chain (decentralised) and hub-and-spoke (centralised), in the adoption of new practices in two distinct social settings, behind-averse and ahead-seeking. I find that the outcome in terms of average adoption differs between the two networks in each of the two social comparison regimes. Moreover, I find that the impact of economic incentives is heterogeneous among the network plants and depends on their connectivity. Interestingly, periphery nodes in the networks are the most sensitive to economic incentives. These findings give insights on the type of structure to promote for organisations (centralised or decentralised) and the placement of certain units in the network to ensure they stay innovative, such as the R&D departments. These have been significant concerns for manufacturing firms to which this chapter provides guidance.

In conclusion, I address in this dissertation a conceptual gap in the literature on the relative benefits experienced by individuals to adopt new practices and innovations. I model how key behavioural biases (ahead-seeking and behind-averse comparisons) trigger these relative benefits. Moreover, I use a novel methodology to the topic (evolutionary game theory) which grasps better the essence of the adoption challenge than existing methodologies. In addition, I study how the type of rewards (individual or collective) and the organisational structure (wide vs narrow bridges, decentralised vs centralised) can enhance or mitigate these behavioural effects.

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Chapter 1

Introduction

1.1 Motivation

This thesis is motivated by a research visit to an intergovernmental organisation during the summer of 2015. In my discussions with experts, I was struck by an anecdote about a failed project that was conducted a few years ago by the agency. The agency introduced new electrical terminals to charge batteries in an African village. While the introduction of the new technology initially helped some village members create small businesses as a segment of the population was using the electricity to power sewing machines to make bags and clothes to sell, the project ultimately failed as the villagers started comparing each other's successes, became envious, and even tried to undermine others' initiatives by damaging the terminals. Ultimately, the terminals were abandoned, not because they were not beneficial, but due to the social context and comparisons between villagers.

While not going as far as sabotage, similar adoption failures have been encountered in organisations where social considerations play a critical role. In the early 2000s, a famous home appliance manufacturing company implemented a new innovation ideation process in one of their teams. This team adopted this process and one of the ideas that was brought up led to a successful spin-off of the brand. Due to this success, the company decided to push all teams to adopt this new ideation practice by mixing members of the original successful team with the other teams to train them. Ultimately this failed, not only because other team members did not adopt the new practice but the original innovators went back to their old routine. The new ideation process did not always lead to great discussions and ideas did not always get enough traction. The innovators felt that they were losing their time as others were undermining their efforts. As their colleagues received no negative feedback of not adopting the ideation practice, the innovators decided to revert to their old routine as well and stop implementing the new ideation process (Chao et al. 2009).

Social considerations and comparisons with others can, however, have benefits in the adoption of new practices as recently observed in a recent study by Song et al. (2017) conducted in hospitals. Top performing physicians in an emergency department were hailed in weekly meetings as role models and asked to share their best practices (such as timing of radiology and laboratory test for patients). An increase of adoption of these practices were observed as low performers did not want to fall behind.

Understanding the adoption of new practices is of particular importance in organisations and key to their growth (Cool et al. 1997). In this dissertation, I define practice as a process or a technology that brings a value/benefit to the individual adopting it. This process bears some risk as it can fail or be wrongly adopted and this value is not received. This practice can be assimilated in operations management as an operational process or methodology such as the methods "kaizen", "lean six sigma", an ideation process or a best practice, in economics and marketing as a technology or product that offers an alternative way of executing a task (for example a new IT system/software or machinery such as the electrical terminal in the example above) or in organisations as a routine of performing a specific activity.

1.2 Original contributions of the dissertation

1.2.1 A cross-disciplinary review of determinants of adoption and opportunities in operations management

In Chapter 2, I provide an overview of practice adoption across a wide range of disciplines including sociology, economics, marketing, organisational behaviour, operations management and operational research. I present both empirical and theoretical works. From this review, I provide an original framework of adoption (see Figure 1.1) and identify the main determinants that these literatures have identified: individual characteristics and traits; the value of the new practice which can be influenced by incentives and the social context (externalities); and the information individuals gather on the value of adopting the new practice or technology (social learning mechanisms). This chapter also contributes to the scientific discussion by giving a *transversal* view of the topic of adoption of new practices as other existing reviews have been either focused on one methodology (Kiesling et al. 2012) or have been discipline specific (Libai et al. 2017).

As a result of this review, I suggest a number of opportunities in the field of operations management. Two of these will be developed in this dissertation: relative benefits due to social considerations that impact the choice of adoption and a mathematical modelling approach, evolutionary game theory, which provides novel insights to the topic of adoption.

1.2.2 A conceptual gap: relative benefits due to social considerations and interactions

From the review in Chapter 2, I find that all streams of research have considered the utility or threshold of adoption of practices as being evaluated in absolute value. This value is dependent on the type of practice or the individual adopting it. The social context has been playing a role only on the direct value or benefit of the practice or on the uncertainty surrounding its adoption.

However, strategic interactions and the relative choices of others can influence the adoption of practices due to social comparisons even though the absolute value of the practice stays constant (as illustrated in the example of electrical battery use or the hospital best practices cited above). This context-dependent (relative benefits based on others' actions) utility and relative threshold constitute a conceptual gap in the field on which this dissertation is shedding light (please see Figure 1.1). This relative utility evaluation based on others' choices is triggered by social interactions and has a behavioural root. In the adoption process, strategic interactions occur between employees in the organisation and the individuals with whom they interact (adopters or not). These social interactions can trigger social comparison effects, making utilities interdependent. Behind-averse and ahead-seeking social comparisons have been highlighted in the literature as the two most prominent behavioural effects that arise due to social interactions (Sobel 2005).

Chapter 3 of this dissertation focuses on the combined effect of economic incentives and behavioural effects such as social comparisons in adoption decisions. These social comparisons are distinct from economic incentives and can be influenced by an organisation management style or culture. In particular, I develop a model that sheds light on the impact of social comparisons on adoption patterns and how economic incentives can monitor these behavioural effects. Chapters 4 and 5 further develop the concept of relative benefits by including heterogeneity among the population in capabilities to adopt the new practice and social comparisons type (Chapter 4, please see Figure 1.1) and heterogeneity in strategic interactions by including a social network structure in the organisation (Chapter 5, please see Figure 1.1).

1.2.3 A behavioural view of practice adoption

It is important to note that, while this dissertation's topic and contributions are different in the research scope than other behavioural disciplines, it contributes to the effort initiated by other fields and schools of thought on the importance of behavioural considerations in decision-making. Seminal works in organisational behaviour (Cyert et al. 1963), evolutionary economics (Nelson 2009) and behavioural economics (Kőszegi and Rabin 2006) exposed a more "behavioural" (as opposite to a classic rationality assumption in economics) view of individuals and firms decisions. The organisational behaviour literature assumes individuals being bounded rational, decisions being myopic and rule-based as being driven by a personal or organisational target they wish to reach which they call aspiration levels. I assume similar behavioural assumptions regarding myopia and bounded rationality but the mechanism to adopt is very different. Adoption is not driven by a personal or organisational target but arises from dynamic strategic interactions as key triggers to behavioural phenomena which lead to adopt or not. Moreover, this stream has been traditionally more qualitative, driven by empirical analysis with a few simulation models considering individuals as rule driven automata. The evolutionary economics literature exposes a view at the firm level and assumes evolution of firm behaviour being driven by competition (industry sector dependent) which can push organisations to imitate others' choices or look for alternatives (problemistic search). As times passes, individuals actions within organisations and "routines" are built and adapt/evolve which lead the best ones to survive as the less successful will disappear. This stream of literature does not study the inherent mechanism creating adoption or imitation of the best routines which enables them to have a good descriptive analysis of firm behaviour and routines choice but does not provide key determinants and mechanisms to act on. Lastly, the behavioural economics stream provides behavioural models of decision making but the assumption that individuals are hyper-rational still holds and assumes static interactions, while I assume bounded rationality which is a key assumption in organisations and dynamic strategic interactions as key triggers of behavioural biases such as social comparisons.

1.2.4 A novel mathematical approach: evolutionary game theory

In addition to closing the gap conceptually, this dissertation contributes to the topic methodology-wise. Traditionally, five main modelling methodologies have been used to tackle the adoption problem: epidemiological, game theoretical, dynamic programming, Bayesian/ social learning models and agent-based simulations (Chapter 2 presents a discussion of these methodologies). In this work, I am proposing novel models to the topic by using a mathematical modelling approach new to the topic of adoption of new practices which has its roots in theoretical biology called evolutionary game theory. This modelling methodology is used in this dissertation as it provides a better fit to human decision-making in organisations compared to classic hyper-rational and optimisation models. It allows us to incorporate additional complex features such as bounded rationality, myopic behaviours and imitation phenomenons highlighted in the organisational behaviour literature (Cyert et al. 1963). Evolutionary game theory has rarely been used in the field of operations management, and never to investigate practice adoption in organisations. Similar to a classic game theory methodology, individuals are engaged in strategic interactions in which I include behavioural characteristics such as social comparisons in addition to the economic benefits of adoption. Important and novel features of the models in this dissertation, are that individuals are bounded rational, social interactions are dynamic and the individual utility to adopt is influenced by population effects.

1.2.5 A taxonomy of adoption for organisations: nature of the practice, economic incentives, network structure and culture

Another main focus of this dissertation is to provide managerial insights for organisations on the adoption patterns that could be observed along the following dimensions: the nature of the new practice (low risk vs high risk, best vs unethical practice), the type of social comparisons present in organisations (ahead-seeking and behind-averse), the rewards given by the organisation (individual and collective) and the social network structure in the organisation (centralised or decentralised).

Social comparisons can be heightened in certain organisations due to the type of activities in which they specialise (for example, engineering, sales, trading) or due to their management styles and culture within the organisation (Baldwin and Mussweiler 2018). For example, Huawei is known to have a more ahead-seeking culture as highlighted by its Chief Executive Officer Ren Zhengfei, "I will not judge whether each team has done a good job or not, because all of you are moving forward. If you run faster than others and achieve more, you are heroes. But, if you run slowly, I won't view you as underperformers." (Chun et al. 2018). On the other hand, a company such as General Electric (GE) under Jack Welch, cultivates a more behind-averse culture as the lowest performing 10% of employees are let go. Moreover, these social comparisons are triggered following social interactions. These interactions depend on the network structure in the organisation (Chapter 5) or collaborations between teams (Chapter 4) and have an impact on the level of these social comparisons.

An organisation may wish their whole employee base to adopt a new best practice such as six sigma or kaizen method as it benefits the organisation as a whole if implemented by everyone. However, other practices such as risky investment practices in finance may benefit the organisation if a few individuals adopt it but could have very heavy consequences if everyone starts taking too much risk. Therefore, depending on the nature of the new practice, having a few adopters and mainly non-adopters may be the best scenario for an organisation. Thus, the dissertation provides insights on the economic incentives to use such as individual or collective rewards for the desired adoption outcome of an organisation depending on the type of practice and the culture of social comparisons present in the organisation.

1.3 Plan of the dissertation

In Chapter 2, I provide an overview of practice adoption across a wide range of disciplines including sociology, economics, marketing, organisational behaviour, operations management and operational research. The purpose of this chapter is to identify the main determinants of adoption identified by these disciplines and the differences in their findings and modelling approaches. From this review, I integrate features from the other disciplines into operations management opportunities.

In Chapter 3, I introduce an evolutionary game theoretic model encompassing relative benefits due to social comparisons that affect the adoption of new management practices through their impact on utility perceptions and adoption thresholds. Firms may induce these behavioural biases through their management styles and the work environment, or be aware of their existence (Baldwin and Mussweiler 2018). I draw conditions by which full adoption of a new practice may occur depending on organisations possessing different social comparisons: behind-averse or ahead-seeking. I subsequently investigate how to advance adoption efforts through economic incentives such as collective levies (winner takes all schemes) and bonuses. Interestingly, social comparisons can significantly reduce the effectiveness of these economic incentives and it is therefore crucial for efficient allocation of resources to take the social context into consideration. I also find that "learning" to master the new practice over time (as uncertainty around the successful adoption diminishes) does not always guarantee full adoption.

Next, in Chapter 4, I further our understanding of the impact of relative benefits due to social comparisons on adoption patterns when there are heterogeneous teams in organisations. This heterogeneity can be driven by different types of social comparisons individuals experience or different proficiencies (successful adoption rate) to adopt a new operational practice. An organisation may have inherent barriers between parts of the organisation or they may have created such barriers on purpose such as when Google and Uber created respectively GoogleX and UberX in which the most innovative employees work.

In this chapter, I explore the effect of collaboration between heterogeneous teams in their ability to successfully adopt a new practice. I find that the conflict between teams with different types of social comparison environments or with different adoption proficiencies can give rise to unforeseen consequences with respect to the adoption of new practices. As a key operational lever, I introduce the notion of bridges between teams (Centola 2019). Bridges are levels of interactions between individuals, for example training exchanges between different parts of the organisation. Wide bridges are interactions where team members interact more with other teams than within their own, while narrow bridges describe interactions that occur more within teams.

In each of the settings studied, I investigate whether the organisation benefits more collectively in terms of adoption by creating wide or narrow bridges. In the first setting, it implies allowing collaboration between teams or not when groups have different social comparison cultures. In the other settings, I am exploring when it is more beneficial to create star teams with high capability separated from low ability teams or conversely when it is better to mix team members with different capabilities.

Lastly, in Chapter 5, I continue investigating the impact of relative benefits due to heterogeneous social interactions by exploring the effect of network structure on the adoption of new practices. Such scenario is particularly relevant in the case of firms' production networks consisting of multiple manufacturing plants. Often, firms encounter difficulties to diffuse knowledge of new operational practice standards (such as a new lean practice) in all the plants of the network. To highlight the impact of the structure of the production network, I explore two networks of identical densities but different topologies: chain and hub and spoke networks. I investigate how the average adoption rate differs between these networks and the role played by different social environments (behind-averse or ahead-seeking) in these adoption outcomes. Another important lever for management is to encourage adoption of the new practice by increasing its expected value through economic incentives. I examine if plants are affected differently by such an initiative due to their position in the network.

To summarise (please see Figure 1.1 for a visual summary of the dissertation contributions), I provide a series of evolutionary game theoretic models filling a contextual gap in the adoption literature which lead to novel insights for the field. In particular, I examine four main operational levers that firms can use to influence adoption: economic incentives, organisation cultures (which moderate behavioural biases of individuals - ahead-seeking and behind-averse), population effects through bridges between teams and network structure. In Chapter 6, I highlight the main theoretical and managerial contributions made in this dissertation and I suggest future research perspectives.

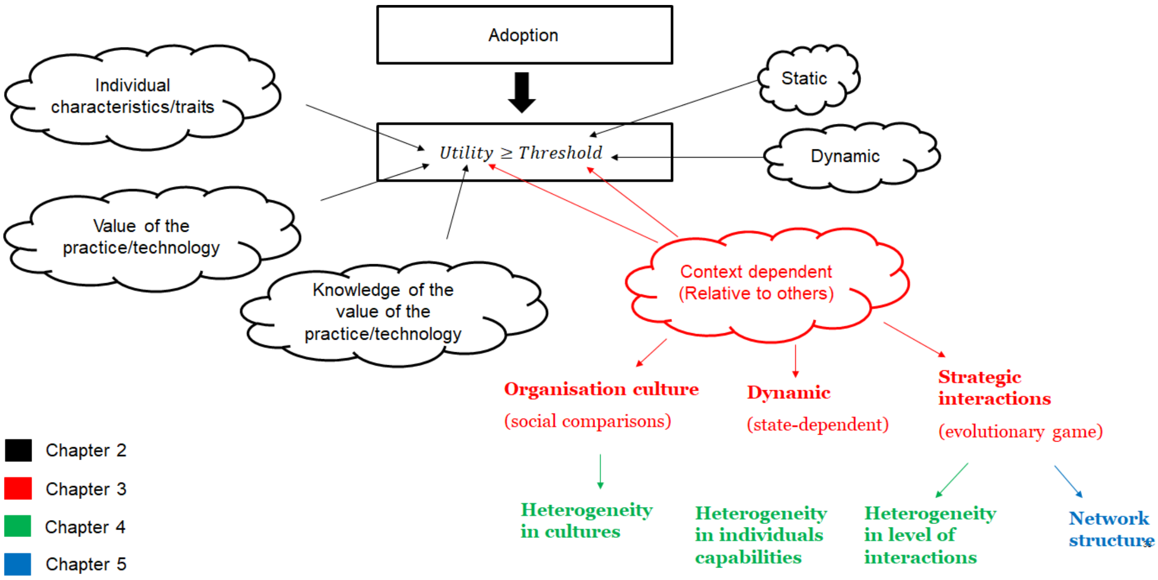

Fig. 1.1 Dissertation visual summary of contributions

Chapter 2

A cross-disciplinary review of models and determinants of practice adoption: opportunities in operations management

2.1 Introduction

Understanding how a new product, technology or practice is adopted and diffused in a market (the market being a community (Griliches 1957) or organisation (Mansfield 1961)) has been a key interest over the last 60 years. Adoption of new technologies and innovative practices is actively pursued because it is reflective of economic growth for companies and societies (Cool et al. 1997). In this chapter, I propose an adoption framework (Figure 2.1) and review the main determinants identified across various disciplines to explain practice adoption. I then identify a series of opportunities (conceptual and methodological) for the field of operations management.

2.1.1 Adopting new practices: a complex phenomenon

I define a practice as a novel way of executing a task or activity which bears some risk of being successfully adopted. This uncertainty of adoption can lead individuals to stick with already well mastered tasks or activities. Such a practice could be a new product or technology but not all products and technologies are practices.

2.1.1.1 Practice vs product and technology

Early works (Bass 1969, Rogers 1976) presented simple adoption models for new products. These simple adoption models are parametrised contagion models with three distinct parameters: an internal influence, an external influence and a market potential, and are linearly dependant on the previous number of adopters with the probability of adopting largely fixed. In such models, a single adopter can trigger adoption in the population until it reaches market saturation, which corresponds to the maximum number of potential adopters. The Bass model and other epidemiological models used in the field (Bass et al. 2001, Joshi et al. 2009, Libai et al. 2009, Savin and Terwiesch 2005) are examples of simple contagion models.

However, the adoption of new practices and certain types of technologies and products is often more complex. Adopting a new practice may require exposure to multiple adopters, or individuals may have behavioural characteristics that keep them from adopting at first contact with the new practice. Moreover, these interactions between adopters and non-adopters may have different effects depending on the existence of externalities or the overall environment. For example, the benefits to adopt increase with the number of adopters (communication technologies such as phones) when there are positive externalities or decrease if there are negative externalities.

2.1.1.2 Practice vs idea

The spread of idea and information (such as news spread for example), propagating effortlessly throughout populations, are also examples of simple contagion. A pioneering work in explaining the spread of ideas in a population is Granovetter's notion of weak ties (Granovetter 1977). Granovetter claimed that targeting weak rather than strong ties speeds up contagion. Weak ties are social circles and communities to which an individual is linked but with which he has little affinity. Thus, by targeting those relationships the information or idea will reach a large number of individuals who would otherwise not be exposed to it. Conversely, an idea may spread efficiently among strong ties but will stay within a community that would have been reached in any case.

Interestingly, transferring this notion of weak ties to adopting new practices can lead to inefficiencies (Beaman et al. 2018). Recent evidence shows that wide bridges between clusters and strong ties might better assist the adoption of complex behaviours (Centola 2019, Centola and Macy 2007). The main intuition behind this claim is that complex behaviours and practices are difficult to adopt. The more difficult they are, the more reinforcement and exposure are needed for them to be adopted. Strong ties come with some legitimacy, trust and influence. Moreover, the concern of targeting strong ties in Granovetter's theory, namely that an idea will circle around the same community, becomes a strength when a complex behaviour or practice must be adopted.

2.1.2 Approach and plan of the review

This review does not aim to discuss the patterns of adoption as the early work of Bass and the later empirical works tried to confirm or challenge the presence of an S-curve depending on the type of industries and technologies (Goldenberg et al. 2002). It, however, aims to identify key elements and mechanisms that influence these adoption on a more targeted, individual and collective level and in doing so, providing knowledge on how to influence them (Beaman et al. 2018).

In doing so, this review achieves the following three objectives. First, it reviews the topic of adoption of new practices across a variety of disciplines (which may have tackled this topic in their respective disciplines) ranging from sociology (Guilbeault et al. 2018, Strang and Soule 1998), marketing (Libai et al. 2017, Peres et al. 2010) and economics (Foster and Rosenzweig 2010, Hall and Khan 2003) as well as operations management. The findings reviewed fit our definition of practice regardless of the terminology they use in their paper (practice, process, technology or product). Second, it provides an original framework identifying the main determinants of adoption of new practices (Section 2.2) and the main modelling approaches used and their respective assumptions (Section 2.3). Lastly, it suggests a number of opportunities for the field of operations management in Section 3.

2.2 Determinants of adoption across different literatures

Phenomena observed by adoption curves, which consist of the slow take-off, saddles, asymptotic values of adoption followed by the decrease of adopters, have led academics and researchers from a large variety of disciplines to explore the factors that influence an individual's decision to adopt a new practice. From an extensive multi-disciplinary review (sociology, organisational behaviour, economics, marketing and operations management) I identify the key determinants of adoption and structure them in the framework in Figure 2.1 (see Table 2.1 for an overview of key papers and their research focus).

According to utility theory, individuals adopt a new technology when the utility derived from adoption outweighs both the cost and the opportunity cost of not adopting. This utility can depend on individual characteristics, the role of information that can be moderated through

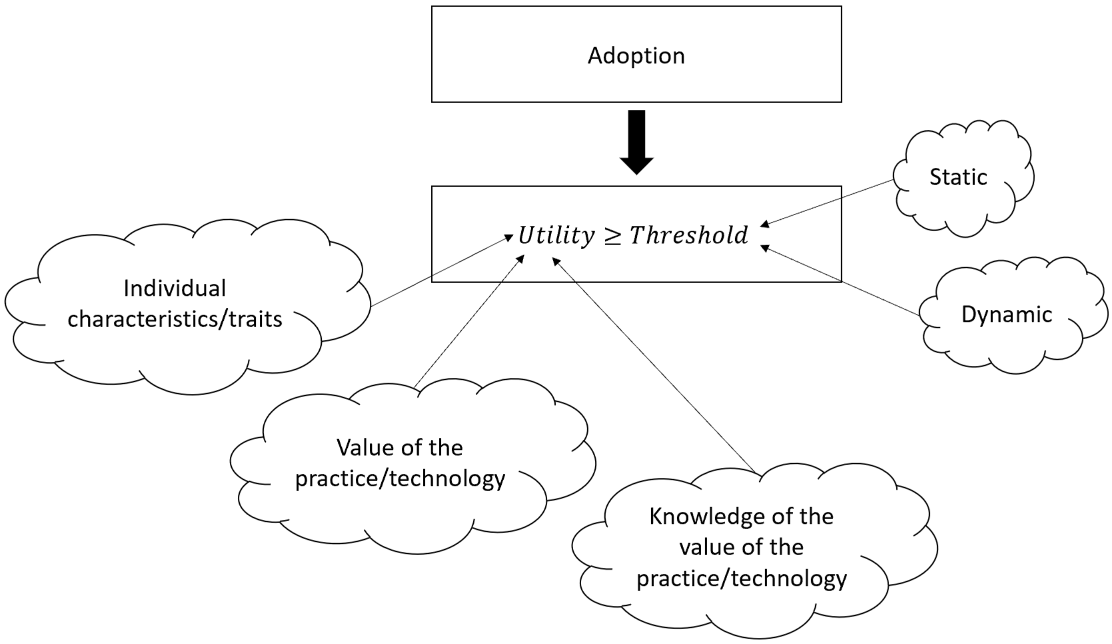

Fig. 2.1 Adoption framework

the social context, and interactions between both individuals and exogeneous interventions from the firm, the market, and regulations. Moreover, the utility to adopt can be functional, such as economic rewards, or psychological. Most of the work in practice and technology adoption has been done on the functional form of utility. A very recent stream of research has tried to incorporate certain individual behavioural assumptions into the utility function (Liu 2013, Smith and Ulu 2017) or disentangle the role of both types of utility in adoption behaviour (Huang et al. 2018). This section will cover the determinants of utility derived from adoption, and hence of the choice of adoption, identified across disciplines.

2.2.1 Individual characteristics/traits as determinants of utility

Early works in sociology argued that heterogeneity among individuals was the reason for the slow take-off of the technology in the population followed by a fast increase of adopters (Rogers 1976). The incorporation of heterogeneity in adoption models has provided new insights in a variety of research areas and can be explained by different risk appetites. For instance, Bass (1969) incorporates two classes of individuals who have different risk appetites: innovators (the first to adopt a new technology) and the subsequent imitators. This creates a first take-off which is followed by a large increase in adoption by the imitator population (a lot larger than the population of innovators), leading to the classic S-curve of adoption.

Some empirical evidence from marketing literature observes the existence of a saddle after the take-off of adoption, absent in the classic S-curve (Mahajan and Muller 1998, Moore and Benbasat 1991, Peres et al. 2010). This saddle reflects a sudden fast increase in the adoption of the new technology preceding a quick decrease before the adoption growth rate continues its S-trajectory. An explanation for this "saddle" is the existence of multiple groups of adopters with highly different rates of adoption, with a small group of individuals quickly fully adopting the new practice and the remainder exhibiting a slower adoption rate (Goldenberg et al. 2002, Libai et al. 2017, Van den Bulte and Joshi 2007).

The heterogeneity of individuals (innovators vs imitators) explaining the adoption curve found some traction in many different disciplines but with alternative explanations regarding the source of this heterogeneity.

Research in economics and organisational theory highlights the role of inertia in the slow process of adoption (Besley and Case 1993, Guillén 2002). For instance, some individuals may be more reluctant to adopt a new technology or risky practice. In the context of organisations instead of individual adoption behaviour, different organisations may have divergent evaluations of the benefits of adopting. For example, Tsikriktsis et al. (2004) find that "rational efficiency" which corresponds to their evaluation of the benefit of adopting a new e-process (such as a web-based process for transactions) and internal barriers specific to the firm can potentially negatively impact the adoption.

Another source of heterogeneity is the different skill levels and abilities of individuals to successfully adopt new technologies, leading them to evaluate the associated risk-return differently. Rosenberg (1972) examines factors influencing the adoption of new techniques or operational practices in firms and found it is heavily dependent on the skill levels and education of workers. If the new technique or practice introduced is too difficult or costly to implement, diffusion will be slow. Caselli and Coleman (2001) corroborate this finding in their study of computer adoption in OECD countries between 1970 and 1990. Kennickell and Kwast (1997) reach similar conclusions regarding the role of education and the capability of learning of individuals when studying the adoption of electronic banking in American households.

Marketing literature considers individuals' heterogeneity driven by their sensitivity to prices and willingness to buy a new product (Golder and Tellis 1998, Song and Chintagunta 2003). Traditionally, in operations management and operational research literature, individuals have different risk-return values of adopting a new practice as they evaluate the individual benefit (value) acquired through the adoption of the new practice either by its use or by reward systems. They adopt once a threshold of adoption (risk-return threshold) is reached (Chen and Ma 2017). Exogenous changes in technology or rewards may lead individuals to adopt as their threshold of adoption is reached (Loch and Huberman 1999, McCardle 1985). While most of the theoretical work in adoption assumes that individuals will evaluate the risk-return of adopting the new technology in expectation, a recent stream of research in operational research looks at incorporating notions from behavioural economics such as risk aversion in the evaluation of the risk return of the new technology (Chronopoulos and Lumbreras 2017, Smith and Ulu 2017).

2.2.2 Value of the practice/technology as determinant of utility

2.2.2.1 Incentives

Any decrease (saddle mentioned in Section 2.2.1) or increase of adoption in the Bass curve after reaching a local optimum, can also be explained by actions from firms (changes in prices through promotion or changes in incentives to adopt the new practice in the organisation). In particular, the saddle is contributed to by changes in the properties of the practice (cost, ease of use, etc.) that impact the expected adoption utility and thus influence the overall adoption behaviour (*moving equilibrium diffusion models*; see Loch and Huberman (1999) and Jensen (1982)).

The operations management and marketing literature both recognised changes in pricing strategies, for example via promotion campaigns, as a key influencer of adoption (Robinson and Lakhani 1975). While, the operations literature focused on finding optimal pricing strategies to help diffusion of innovation within a firm (Chenavaz 2012, Kamrad et al. 2005), the marketing literature explored the effect of various campaigns and pricing strategies on the diffusion of a new product (Lehmann and Esteban-Bravo 2006). Another key way in which a firm can encourage adoption is the introduction of an improvement or substitute of a previously adopted technology (for instance, next generation gaming console or phone). Heterogeneity in adoption can be explained by competition between different brands, leading one to be superior to the other at a particular moment in time (Norton and Bass 1987, Shi and Chumnumpan 2019).

In the organisational economics literature, Atkin et al. (2017) find experimentally that misalignment of incentives of workers to adopt a more profitable new practice for the firm was an important organisational barrier of adoption. In their experiment, the authors introduced a new way of cutting the primary raw material needed to produce soccer balls in a factory in Pakistan. The aim of this new practice was to reduce waste. This new practice was slowing them down at first and as they were paid per piece produced, they did not adopt it and lied to the firm managers regarding the benefit of this new practice. The authors then conducted another experiment and gave additional payment if they could show good mastery of the new practice. This incentivised them to master the new practice which then became the established way in the firm to cut the raw material.

2.2.2.2 Externalities (economic and social)

In addition to the actions of firms, the value of the new technology is also altered through social interactions (Centola 2019, Peres et al. 2010). In particular, in the organisation literature, there is a clear distinction between motivations to adopt a new technology driven by economic gain versus social gain (DiMaggio and Powell 1983, Strang and Macy 2001, Tolbert and Zucker 1983). The latter can involve notions such as legitimacy or aesthetic need (Kennedy and Fiss 2009). In this section, I investigate the different types of social influence that affect the risk return trade-off of the new technology experienced by adopters.

Network externalities/ effects have been identified as important social influences on adoption. Generally, a technology can exhibit positive or negative network effects. When these are positive, the utility of adopting the new technology increases with the number of adopters, whereas in the presence of negative network effects, the utility to adopt decreases with the number of adopters. These effects can impact an individual's utility to adopt economically (positive for networked goods and negative for services) or psychologically (positive for conformity or negative for exclusivity behaviours) (Huang et al. 2018). In addition to being positive or negative, externalities can be of two types: direct and indirect. For example, software such as Microsoft Office exhibits direct network externalities: a new user benefits directly from others using it as it eases file exchanges and communication. Technologies exhibiting indirect network externalities are influenced by the number of adopters of a complementary good. For example, if a company such as Sony offers numerous exclusive media on DVD, consumers purchasing a DVD player will in turn trigger the development of more film distribution on a DVD platform. New users of the platform (DVD player) indirectly benefit from old users that have spurred previous development (Karaca-Mandic 2011).

Examples of positive externalities are networked goods. A characteristic of a networked good is that the utility to use it increases as more individuals utilise it, one example being a telephone (Katz et al. 1985). A high number of empirical studies have been conducted to explain the impact of such externalities. Saloner and Shepard (1992) show that banks started implementing ATMs in various locations between 1971 and 1979 while users were making more deposits due to the improved convenience. Karsai et al. (2014) conducted a study on the adoption of Skype, showing that the likelihood of an individual to adopt depends on a percentage of close neighbours in their social network adopting. A technology may also exhibit positive externalities that impact the psychological utility of an individual. For example, as more individuals adopt a certain good or practice, the individuals may feel a need to conform (Abrahamson and Rosenkopf 1993), triggering a bandwagon effect. In the strategy literature, Zhu et al. (2006) analyse the adoption of open-standard systems put in place between firms. They find that firms coordinating to use the system (positive network effect) plays a key role in the adoption of the system by each firm.

On the other hand, new technologies can exhibit negative externalities. In service operations management, such negative externality scenarios arise in services where too many users create congestion, leading to more time spent in queues, ultimately discouraging an individual from using the service. Such scenarios are well-known in road traffic management (Sandholm 2002) as too many users on a single road can create congestion. In the supply chain literature, negative externalities exist when suppliers have to manage inventory for substitute products (Netessine and Zhang 2005). The authors find that competing retailers tend to overstock their inventory under substitutability. However, as highlighted in the previous paragraph, externalities can also affect the behavioural/psychological utility of an individual. In the marketing literature, the utility of acquiring a luxury good decreases as the number of people purchasing it increases. Gao et al. (2016) explain that such a negative externality exists because individuals seek exclusivity. Thus, as more people adopt, the less interesting adoption becomes.

Over the last decade, several lines of research have further explored the role of network effects/externalities and structure in adoption. This stream of literature has been of both of theoretical (Goyal et al. 2014) and empirical natures (Beaman et al. 2018). The network framework extends the concept of externalities by suggesting a more complex dependence between the number of adopters and the utility to adopt.

This theoretical research has mainly focused on the idea that the utility to adopt a new practice may depend on the number of connections an individual has and the position the individual has in the network thus the importance of the network topology. A nascent stream of research has tried to identify network topology characteristics (Peres 2014) that enable adoption of new products. Integrating network considerations allows firms to price their product optimally (Candogan et al. 2012) or target the right individuals. For example, Beaman et al. (2018) find empirically that when multiple individuals in the same clusters of a network adopt a new practice, it helps overall diffusion. In their extensive review on this topic, Muller and Peres (2019) highlight many research studies studying how to predict the penetration of an innovation process through different network metrics such as average degree (Mukherjee 2014), clustering (Choi et al. 2010), degree distribution (Dover et al. 2012), strength (Aral and Walker 2014) and location characteristics such as centrality and social hubs measures (Goldenberg et al. 2009a). Muller and Peres (2019) observe that a network possessing the three following characteristics, cohesion, connectedness and conciseness, can achieve an efficient adoption of innovation.

2.2.3 Knowledge of the value of the practice/technology as determinant of utility

2.2.4 Firms' actions

Another key determinant of adoption is the level of information or knowledge about the value of the new practice. This knowledge can be made accessible to individuals through firms' actions and different disciplines focused on different types of actions.

An organisation may invest upfront on the development of the new technology with advertising campaigns to reach a high number of individuals, or through training their employees to learn about the new practice. However, it may require a certain time before information on the new technology reaches the consumer market or the knowledge about it to be assimilated. When it does, the subsequent information cascade leads to the aforementioned saddle dynamic (Chandrasekaran and Tellis 2011, Golder and Tellis 1997, 2004). The operations and marketing literature has traditionally focused on finding optimal advertising strategies (Dockner and Jørgensen 1988, Kamrad et al. 2005) for a better adoption of new products and these campaigns do not always have to alter prices to have an important effect on the adoption of new products (Horsky and Simon 1983).

In the organisation literature, Gaba and Dokko (2016) highlight an example of the influence of staff training in practice adoption in the IT industry. They find evidence that managers' experience with Corporate Venture Capital practices positively impacts the continued use of this type practice within the firm. In addition, Zhu et al. (2006) show that the high cost of adopting a new technology may be driven by a lack of experience or training in the new practice.

2.2.4.1 Social learning mechanisms

Targeting individuals is costly and to spread the information about the new product, firms can also use individuals' social context as the same information can be passed by other individuals through social learning mechanisms (Van den Bulte and Lilien 2001).

The more information an individual has on a new technology, the higher the chances of successful adoption, thus increasing the utility to adopt. The different shapes of adoption curves aforementioned can also be solely explained by information about the new practice being available at different rates to individuals (Strang and Soule 1998).

Social learning mechanisms have been closely linked to externalities concepts but are conceptually different. Social learning is a process through which individuals infer information based on own and others' experiences and update their beliefs accordingly (Abrahamson and Rosenkopf 1993, Herriott et al. 1985). On the other hand, as seen in the previous section, the effect of externalities is not due to information gathering but is proportional to the number of adopters.

Traditionally, the empirical and theoretical literatures in economics, marketing and operations management have difficulty in separating both types of social influences (Moretti 2011, Peres et al. 2010) as arguments could be given to explain an adoption outcome either in terms of externalities or social learning. Recent works in operations management and economics are, however, starting to test and disentangle these two concepts. Papanastasiou and Savva (2016) analyse the effects of online reviews on individuals to help them infer the quality of a product. Banerjee et al. (2013) find empirical evidence that individuals trained to adopt a micro-financial service were able to diffuse better in the rest of the population as non-adopters were able to learn from them.

In the economics literature, social learning models have a long tradition on explaining adoption decision (Banerjee 1992, Chamley 2004). Adopting a new practice is very uncertain and over time, individuals update their information and beliefs on the profitability of this new practice (Jensen 1982). This updating can be heterogeneous in the population and be based on an individual's risk attitude and initial preference (Chatterjee and Eliashberg 1990). Empirical evidence of social learning explaining adoption have also been investigated.

Bandiera and Rasul (2006) find that individuals learn from each other to adopt a new type of crop. They find an interesting U-shaped adoption pattern highlighting that when there are few adopters, individuals adopt but when there are too many they tend not to. The intuition behind it is that the positive effect of having individuals adopting due to information gathering can be overpowered by strategic delay to adopt in order to free-ride when there are too many adopters. Individuals then postpone their decision to adopt until they observe whether the risky bet of others is paying off.

In the organisation literature, social learning is depicted as the key factor of adoption, as organisation environments are myopic and the benefits of adopting new practices or technologies are consequently uncertain. This mechanism leads individuals to infer that there is value in imitating others' choices and thus mimic their practice choices (Levinthal and March 1993, March 1991). Sun (2013) conducts a longitudinal study looking at the adoption and continued use of an information systems technology. Using a herding approach, the author argues that when facing a new technology, individuals tend to discount their own information about it and imitate others to reduce the regret of not having adopted. This also makes the adoption state fragile and reversible. Gaba and Dokko (2016) look at the abandonment of organisational practices within firms and find that the utilization of the practice within the organisation impacts its long-term adoption and its susceptibility to adopt another one due to social influences.

Such mechanisms also happen between firms and there are two categories explaining imitation between organisations (see extensive review for imitation mechanisms between firms in Lieberman and Asaba (2006)): 1) adopting due to a risk of being left behind, even if the new practice does not currently show great promise and 2) imitating others because they are successful. Tsikriktsis et al. (2004) find empirical evidence suggesting that bandwagon effects play a critical role in the adoption of e-processes among service firms. Angst et al. (2010) look at the adoption of electronic medical records among hospitals. The authors highlight the impact of social contagion effects from adopters to non-adopters. Certain hospitals have more influence than others and interactions of individuals between hospitals play a significant role in the adoption process. Similarly, in terms of influence, Guler et al. (2002) highlight that states and multinationals impact other companies' adoption of ISO 9000 standard certification as they play a powerful role in the market due to their dependence on them in terms of resources. The strategy literature also highlights imitation behaviour among firms when facing a new disruptive technology (Semadeni and Anderson 2010). On the one hand, the earlier the firm adopts, the more competitive advantages it can get (Suarez and Lanzolla 2007). On the other hand, there are risks associated with being the first to adopt, possibly leading to early failures (Boulding and Christen 2008, Christensen 2013). Henisz and Delios (2001) conduct an extensive analysis of Japanese multinationals that opened plants abroad. They found empirical evidence that firms tend to imitate other firms' actions to gather information when they lack experience in the specific market they want to penetrate. Similarly, Guillén (2002) conducts an empirical analysis on the choice of South Korean firms to start expansion in foreign countries. He finds evidence highlighting the need to gather knowledge of such processes by imitating other firms in their inter-organisational network when they first start expanding.

2.2.4.2 The role of networks

Networks are a more detailed framework to explain how information on a new practice is made available to individuals. A nascent stream of research in theoretical economics and operational research model how individuals update their beliefs on the new practice based on their local interactions in the network due to information exchange (BenYishay and Mobarak 2018, Miller and Mobarak 2014, Sadler 2020), and targeted advertising from firms (Bimpikis et al. 2016). This stream of research in economics is related to the impact of externalities in networks on the adoption decision. However, this stream does not necessarily explain adoption because of the number of adopters but their influence on the process of updating information about the new practice. As some individuals may be more influential, implying that certain seeding strategies may help the adoption of the whole network or certain individuals may be more central to and thus hold more power in the network (Burkhardt and Brass 1990, Katona et al. 2011). For example, Bandiera and Rasul (2006) find that the adoption pattern of a sunflower crop was dependent on the community that the initial adopters were in. The new crop was better adopted within family/friends social networks than within social networks based on same religious faith.

Empirically, a number of recent studies have been exploring how to engineer social interactions and thus the adoption of new practices in networks. One study finds that if the first-informed adopters of a microfinance loan are central, it helps the diffusion in the whole social network (Banerjee et al. 2013). Another study by Miller and Mobarak (2014) shows that targeting opinion leaders in villages leads to easier adoption of cooking stoves in the community. BenYishay and Mobarak (2018) hypothesize that the diffusion of a new innovation is more effective when its first adopters belong to a similar community.

In the context of problem-solving/ideation process, Lazer and Friedman (2007) find through simulations that depending on the complexity of the problem, even if well-connected networks are the most efficient to share information, they do not always perform the best at the organisational level. This is because inefficiencies can increase the diversity of ideas and lead to a better performance in the long run. In related work, Masini and Pich (2001) simulate the diffusion of competing technologies within organisations and define how different types of network structures (central, dense or linear) impact performance measures and the trade-off between exploration and exploitation. They find that the network that maximises information exchange is not always the most effective depending on the complexity of the technology environment. Further, Sykes et al. (2009) conduct an experiment in an organisational unit to evaluate the peer effects in efficiently using a new information system. They look at characteristics of the network, such as density and centrality, that can explain why certain individuals are slow to efficiently use the system and the overall efficient use of the system.

Numerous studies have also looked at the role that social networks play within organisations and between firms in the adoption of technologies. Coleman et al. (1957) and Burt (1987) look at the role of cohesion and structural holes (cohesive ties make a network rigid which can hamper coordination on complex tasks) in the adoption of a medical innovation among a population of doctors. Abrahamson and Rosenkopf (1997) propose a computer simulation model of the spread of a single innovation and highlights how certain characteristics of a network (such as density) affects the impact of bandwagon effects on adopting a single innovation. DeCanio et al. (2000) propose a model where exogenous factors influence the profitability of a firm which is defined by its adopters. Organisational structure plays a key role in the profitability of the firm, as the innovation may diffuse differently. Lee et al. (2006) highlight that the network structure can help the least advanced technology to survive within the organisation while the general literature on networks suggests that the technology with the larger base will win over the whole organisation.

In their study on social contagion of an Electronic Medical Record (EMR), Angst et al. (2010) find evidence that the proximity of the different hospitals leads to easier interactions between individuals, which lead to a better adoption of the new technology. Connelly et al. (2011) explore empirically how the social network of directorate boards members of a company with other companies' boards impact the likelihood of a firm to adopt a strategic initiative. They find that ties to successful companies impact positively the likelihood to adopt the initiative within the firm while ties to unsuccessful adopters or non-adopters impact negatively.

In the manufacturing literature, targeting specific plants and factories in the global production network to help dissemination of better operational practices has a long history (Holweg et al. 2018). Numerous research studies examined empirically the importance of hosting network factories and the effect of the topology of the network enabling the flow of knowledge among all plants in the network (Ferdows et al. 2016, Vereecke et al. 2006). Some findings of this stream of research are that the more connected the factory network is, the more information about the new practice is accessible which ultimately helps adoption. However, creating links between factories and units is costly and the firm is faced with a cost-information trade-off. Moreover, some factories may have different roles in the production network and targeting certain plants such as hosting factories can have more impact on the overall adoption.

2.2.5 The threshold value of adoption

The threshold value has been traditionally evaluated in absolute value as either static/fixed or dynamic.

Individuals may have a threshold of adoption depending on their own risk preferences or specific traits or their threshold may depend on the number of connections they have (Acemoglu et al. 2011) or repeated exposure to certain individuals (Centola 2018, Centola et al. 2018). Generally, a mixture of internal and external influences will determine an individual's threshold of adoption.

The threshold value can be dynamic which has been well developed in the operational research literature. One of the key features and concerns of this stream of research has been the timing of adoption given the risk-return to adopt and how to speed up this process (Reinganum 1989). These studies conclude that individuals adopt the new practice once their expected utility from adoption becomes greater than a risk dependent threshold related to the information gathered (McCardle 1985). In these studies, information is gathered until enough uncertainty is resolved (Chen and Ma 2014, Cho and McCardle 2009, McCardle 1985, Smith and Ulu 2012). For example, Huang et al. (2018) study at what point firms should disclose the number of adopters to the non-adopters in order to reduce their uncertainty/threshold to adopt. Operational research literature has recognised the importance of external information for risk resolution and lowering the threshold to adopt. To resolve such risk uncertainty, traditionally in the operations literature, individuals can either invest in costly search for more information, or wait for others to acquire it and receive a positive or negative signal to adopt (Smith and Ulu 2012).

Table 2.1 Overview of key articles across disciplines and research focus

Discipline	Individual characteristics/traits	Value of the practice/technology		Knowledge of the value of the practice/technology		
		Incentives	Externalities	Firms' actions	Social learning mechanisms	The role of networks
Sociology and organisational behaviour	Guillén (2002) Moore and Benbasat (1991) Bass (1969) Rogers (1976)	Centola (2018) Strang and Soule (1998)	Kennedy and Fiss (2009) Tolbert and Zucker (1983) DiMaggio and Powell (1983)	Gaba and Dokko (2016) Zhu et al. (2006) Van den Bulte and Lilien (2001)	Sun (2013) Christensen (2013) Semadeni and Anderson (2010) Suarez and Lanzolla (2007) Lieberman and Asaba (2006) Guler et al. (2002) Guillén (2002) Henisz and Delios (2001) Levinthal and March (1993) Abrahamson and Rosenkopf (1993) March (1991)	Karsai et al. (2014) Connelly et al. (2011) Sykes et al. (2009) Lazer and Friedman (2007) Masini and Pich (2001) Burkhardt and Brass (1990) Burt (1987) Coleman et al. (1957)
Economics	Caselli and Coleman (2001) Kennickell and Kwast (1997) Besley and Case (1993) Rosenberg (1972)	Atkin et al. (2017) Jensen (1982) Griliches (1957)	Beaman et al. (2018) Karaca-Mandic (2011) Goyal et al. (2014) Sandholm (2002) Saloner and Shepard (1992) Katz et al. (1985)	/	Moretti (2011) Bandiera and Rasul (2006) Chamley (2004) Banerjee (1992) Herriott et al. (1985)	Sadler (2020) BenYishay and Mobarak (2018) Banerjee et al. (2013) Lee et al. (2006) DeCanio et al. (2000)
Marketing	Van den Bulte and Joshi (2007) Song and Chintagunta (2003) Goldenberg et al. (2002) Golder and Tellis (1998) Mahajan and Muller (1998)	Lehmann and Esteban-Bravo (2006) Norton and Bass (1987) Robinson and Lakhani (1975)	Muller and Peres (2019) Huang et al. (2018) Mukherjee (2014) Gao et al. (2016) Peres (2014) Aral and Walker (2014) Dover et al. (2012) Choi et al. (2010) Goldenberg et al. (2009a)	Chandrasekaran and Tellis (2011) Golder and Tellis (1998) Golder and Tellis (1997) Horsky and Simon (1983)	Boulding and Christen (2008) Chatterjee and Eliashberg (1990)	Muller and Peres (2019) Libai et al. (2017) Miller and Mobarak (2014) Katona et al. (2011) Peres et al. (2010)
Operational research and operations management	Chen and Ma (2017) Smith and Ulu (2017) Chronopoulos and Lumbreras (2017) Tsikriktsis et al. (2004) McCardle (1985)	Shi and Chumnumpan (2019) Chenavaz (2012) Cho and McCardle (2009) Kamrad et al. (2005) Loch and Huberman (1999)	Candogan et al. (2012) Netessine and Zhang (2005)	McCardle et al. (2018) Savin and Terwiesch (2005) Kamrad et al. (2005) Dockner and Jørgensen (1988)	Papanastasiou and Savva (2016) Branco et al. (2012) Angst et al. (2010) Tsikriktsis et al. (2004)	Holweg et al. (2018) Ferdows et al. (2016) Bimpikis et al. (2016) Angst et al. (2010) Vereecke et al. (2006)

2.3 Main modelling assumptions and methodologies

One of the key assumptions in all models of adoption is that individuals evaluate the risk-return trade-off of adopting a practice or technology (see Table 2.2 for a comparison overview of the main methodologies). In early works and many current works in marketing, operations management, and economics, the evaluation of a risk-return trade-off is usually assumed to be dependent on the individual (see Section 2.4.1 of this review) and calculated in expectation (Von Neumann et al. 2007). Recently some theoretical works try to include behavioural economics notions on risk aversion to the evaluation of risk (Chronopoulos and Lumbreras 2017, Smith and Ulu 2017). The benefit to adopt the new practice can also change because individuals update their information and beliefs about the practice. In economics, this stream of research has usually modelled such information updating process using Bayesian social learning models (Jensen 1982, Sadler 2020).

Moreover, most of the theoretical works on adoption in economics and operations management have assumed individuals to be "hyper-rational", in that they are forward-looking and able to optimise their benefits when adopting technologies (Huang et al. (2018) and other similar game theoretical research works; see also operational research literature using dynamic programming methods). But, a few recent mathematical modelling works started making bounded rationality assumptions (see Ren and Huang (2018) for a review). This assumption is not new in the organisation and strategy literature (Puranam et al. 2015) as a large body of empirical evidence suggests that in general, when adopting, individuals are unable to optimise their decisions by looking forward and only take into account the current state of the system (March 1991). This theoretical work has traditionally used agent-based simulations to highlight the behavioural characteristics of individuals, dynamics and temporal effects (Kiesling et al. 2012).

2.3.1 Epidemiological models

Epidemiological models have been used to predict the spread of diseases and famously adapted in the technology adoption literature by Bass (1969). They are considered simple contagion models (see discussion earlier in section 2.1 of the review). They describe at the aggregate level the diffusion of innovation in a population. The Bass model and its variations are still widely used in sociology and marketing as they generally fit well the data observed, and exhibit an S-curve. Such models have three fixed parameters describing the diffusion of innovation: p which represents the internal influence in the population, q corresponds to the external influence and m the market potential. Researchers in marketing and economics generally use this type of model for descriptive purposes. Due to the very broad nature of these parameters, recent works have tried to express them as function of a range of composite variables (for example price etc.) (Peres et al. 2010) but these are difficult to use for policy scenarios and drive managerial insights.

2.3.2 Game theoretical models

Epidemiological models are macro-models of diffusion and adoption of innovation. As seen in the paper so far, social interactions and strategic decision-making between individuals play a very important role in the adoption of new technology but epidemiological models have not taken that into account. To close the gap, a stream of research has explored the role of strategic interactions in adoption decisions (Arthur 1989, Fudenberg and Tirole 1985, Huang et al. 2018, Huisman and Kort 2004). In particular, these allow policy insights for firms to analyse the potential behaviour of individuals when facing exogenous changes in the technology or decisions by firms, such as pricing or advertising.

A downside of this methodology is that it does not take into account dynamics and temporal effects of adoption and it assumes individuals to be hyper-rational and able to optimise their decision by looking forward. However, a concurrent body of literature indicates that individuals are not able to optimise their decisions and are bounded rational.

2.3.3 Dynamic programming models

Dynamic programming is an optimization method used for problems that can be divided into substages, where optimal solutions to the subproblems lead to the optimal solution of the global problem. The system can be found in each stage and a decision policy can lead to another stage. Each stage can, for example, correspond to a decision by the firm to exert an exogenous change in the technology such as pricing/advertising policy, or to consumers choosing to adopt, wait for more information, or pay a fee to get more information. By backward induction, the firm can find the optimal pricing/advertising policy to implement the practice (Savin and Terwiesch 2005), or individuals can find the right time to adopt the new practice (McCardle et al. 2018).

2.3.4 Bayesian social learning models

This type of models are used to describe social learning mechanism and focuses on changing agents beliefs on the information about the new practice following Bayes' rules, then updating the expected utility to adopt it (Jensen 1982). They are sometimes combined with dynamic programming (Branco et al. 2012) approaches in operational research and game theoretical (Jordan 1991) methodologies in economics.

This information updating process can be heterogeneous in the population as dependant on risk attitudes or preferences towards the new practice (Chatterjee and Eliashberg 1990). Recent promising research, using this type of models, explores how information about a new practice or technology is updated based on the number of connections an individual may have and their initial beliefs (Acemoglu et al. 2011, Sadler 2020) in a social network.

2.3.5 Agent-based models

Agent-based simulation methods have also been used to describe adoption of new technologies. This methodology incorporates more complexity and heterogeneity in the behaviours of both, individuals at the micro level, and dynamics at the macro level.

There are two basic features in agent-based modelling: 1) the individual adoption behaviour, and 2) the social influence modelled via pairwise interactions (see Kiesling et al. (2012) for an in-depth review of agent-based modelling papers in innovation).

In the literature, the adoption decision at the individual level has been modelled either as based on simple rules such as contagion, when a threshold of adopters is reached (Alkemade and Castaldi 2005, Valente and Davis 1999) using heterogeneous cost thresholds/reservation prices (Faber et al. 2010) or based on heterogeneous preferences included in individuals' expected utility calculations (Delre et al. 2007). Other agent-based models have studied the adoption through a probabilistic sequence of stages completed before adopting the new innovation (Goldenberg et al. 2007). Finally, a few agent-based models have included parameters involving social psychology characteristics of individuals (Kaufmann et al. 2009).

Another key characteristic of agent-based models is the ease of modelling dynamic effects over time and pairwise social interactions through simulations. Studies have looked at the impact of topology of the network that individuals interact in, as well as different social influence processes, such as word-of-mouth phenomenon (Goldenberg et al. 2001, 2009b).

Table 2.2 Comparisons of modelling methodologies on key characteristics

Model type	Dynamic population effects	Strategic interactions	Rule-driven decision	Information update	Network effects	Hyper rationality	Bounded rationality	Analytically tractable
Epidemiological	✓		✓		✓		✓	✓
Game Theoretical		✓	✓		✓	✓		✓
Dynamic Programming			✓	✓		✓		✓
Bayesian learning			✓	✓	✓	✓	✓	✓
Agent-based	✓		✓	✓	✓		✓	

2.4 Opportunities in operations management

In this section, I draw some opportunities for the field of operations management derived from the previous review and analysis (see Figure 2.1, Table 2.1 and Table 2.2).

2.4.1 A more behavioural view of practice adoption

2.4.1.1 Bounded rationality vs hyper rationality

Seminal works in decision-making within organisations such as a behavioural theory of the firm (Cyert et al. 1963) advocated that individuals are bounded rational and make decisions following sets of rules which depends on the current competitive environment and firm expectations. Later, more focused on the problem of practice and innovation adoption, studies in the organisation literature suggested that individuals can not optimise the impact of their decisions regarding adopting innovations and practices as the adoption benefit can be very uncertain which leads employees to imitate others' choices thus being bounded rational (Abrahamson and Rosenkopf 1993). Most of this literature points to the fact that individuals tend to make decisions either through imitation of others or based on the current information they have obtained.

However, most of the theoretical works in operations management and operational research either use dynamic programming or game theoretical methods to tackle the topic of technology adoption. Both methodologies assume that individuals are hyper-rational and able to optimise their decisions being forward looking. The topic of practice adoption would benefit by taking into consideration bounded rationality assumptions present in the organisation literature and build novel types of mathematical models. Recent effort in operations management have highlighted that decision-making models assuming more bounded rational individuals, start emerging (Ren and Huang 2018). In this dissertation, a series of bounded rational models are proposed to address this gap in the field of practice adoption and more should follow.

2.4.1.2 Decision-making driven by psychological considerations

The wider literature has been mostly focused on economic incentives that impact the utility of an individual to adopt. Recently, the operations management literature started to include behavioural and psychological elements to the utility function in supply chain problems (Avcı et al. 2014, Netessine and Zhang 2005). An interesting research avenue would be to find and include behavioural effects that impact the process of adoption. This has been done in the following chapters of this dissertation introducing the impact of social comparisons in the utility to adopt a new practice and more work is needed in this vein. Such behavioural effects can be found in literature from social psychology, neuroscience and decision under uncertainty. It would enable management and organisations to better impact and control adoption of new practices among individuals.

2.4.1.3 Behavioural decision-making

Adopting new practices is a risky decision and a large amount of work in operations has focused on the evaluation of risk in making the adoption decision. A rational modelling view would be to evaluate adoption in expectation (Von Neumann et al. 2007) but different types of utility functions have been introduced to focus on risk preferences such as risk taking and risk aversion. This stream of work focuses on the impact of such risk preferences in the adoption of new practices and optimal policy for organisations (Smith and Ulu 2017).

While extensive modelling work exists in this field, these papers assume that individuals' traits lead them to be risk averse or risk taking. An interesting research avenue would be to make these risk preferences context dependent, in other words influenced and moderated by the social structure in which these individuals interact. Experimental work on risky decisions and social structure are not numerous and such modelling work may need to be combined with empirical works to understand the inherent mechanisms.

2.4.2 Social learning vs externalities

Social learning is the process of updating one's belief and gather information through social interactions. Externalities correspond to a situation in which the number of adopters impact the utility of adopting a certain practice. Both concepts of social learning and externalities are interrelated and may cause similar phenomena and research in operations, economics and sociology/organisation behaviour, have rarely mixed both concepts in a single study. In the operational research tradition, gathering information about a new practice is one of the main factors influencing adoption. As network externalities are a proxy of how good a new practice is as it hints at the number of adopters, it is understandable why the operations literature did not disentangle both phenomenons.

However, these two phenomena have different roots and thus, may create opposite effects. In particular, recent advancements in social network science find that externalities and social learning processes may act in opposite ways. Certain characteristics such as an individual position in the network and social hubs influence adoption as the information exchanged is of different quality than other members of the network. Thus, network externalities and social learning processes may not have the same effect on individuals depending on their position in the network. An interesting research avenue would be to disentangle both effects in operations models, in particular if they act in opposite ways.

2.4.3 Relative vs absolute benefit and threshold of adoption

To adopt a new practice, individuals evaluate the functional benefit to adopt the practice and if this value is above a threshold, it is adopted.

Generally, this benefit of adoption has been evaluated in absolute value. Externalities increase or decrease the benefit to adopt and social learning enables to uncover information about this new practice. But, this benefit can have other sources than functional. Other mechanisms (psychological or behavioural, see section above) can influence adoption and may impact the utility to adopt even though the functional value does not change (conformity, exclusivity, jealousy, etc.). Thus, to understand adoption, these benefits may change depending on others' choices and with whom an individual interacts. Differentiating between absolute and relative benefits of adoption may enable organisations and communities to promote more efficiently the adoption of new practices. The following chapters focus on modelling such relative benefits and their effects on adoption.

Similarly, the threshold value has been evaluated in absolute value and fixed as dependant on the type of practice or individuals' characteristics. A stream of literature in decision-making has been interested in choices made based on reference points. These reference points similar to thresholds are usually exogeneous and fixed, constant or dynamic (evolving over time). However, individuals' utilities can be interdependent to others' choices of practices which can lead the threshold of adoption to be relative to others' decisions. An interesting research avenue would be to explore what happens when the threshold value is evaluated in relative terms.

2.4.4 Dynamical systems and strategic interactions

The main modelling methodologies used in operations management to look into adoption phenomena have been game theory and dynamic programming. These methodologies allow to analyse the effects of strategic interactions on adoption patterns. However, these are static methods that do not take into account dynamic effects of adoption. The other main modelling method used in marketing research has been the use of parameter-driven differential equations. While, being very effective at fitting the data, they do not allow strategic interactions and the parameters definitions are very broad (internal influence, external influence, for instance, see section “Epidemiological models”). Agent-based simulations have been used to include more sophisticated behaviours of agents as well as population dynamics. Unfortunately, such methods are not ideal to analyse trade-offs of adoption due to their lack of transparency and very specific to the initial state of the population of agents as agents act as automata.

Modelling strategic interactions roles on absolute and relative benefits of adoption as well as population dynamics to take into account changing environments are critical for further research into adoption of new practice. An exciting research area in operations management could be to combine both approaches. This dissertation explores another methodology that takes its origin in theoretical biology called evolutionary game theory that fills this gap. This mathematical modelling approach allows for social interactions and dynamic effects over time, while being tractable. Evolutionary games show great promise to draw more insights in the topic of adoption and should be explored further by the operational research community.

2.5 Conclusion

In this review, I proposed a framework of determinants of adoption of new practices. I review findings on the topic that fits our definition of “practice” given in Section 2.1.1, across numerous disciplines (sociology, economics, organisational behaviour, marketing and operations). This review is original as it looks across these disciplines to identify similarities and differences in findings, assumptions and modelling methods. This review also suggests numerous opportunities for the field of operations management and some of which are tackled in the remaining chapters of this dissertation (bounded rationality, psychological considerations, network structure, relative benefits and evolutionary games).

Chapter 3

The Role of Social Comparisons in the Adoption of Innovative Operational Practices

3.1 Introduction

The adoption of new operational practices, methods and technologies by large organisations has been coined as a classic and complex problem that companies face across the different stages of their growth (Centola 2019, Jacobs et al. 2015). The number of cases that describe failures in the adoption of practices[1] but also the magnitude of the failures can barely go unnoticed. Yet, it is not as if senior managers are unaware of these difficulties, or fail to identify good new practices. Quite the contrary: in many cases the upfront expectations (i.e., the start of these adoption attempts) tend to be very positive. Still, it is repeatedly recorded that such new practices encounter resistance during roll out (Barley 1986, Vermeulen 2018).

Two main reasons that explain the adoption failures in organisations have been identified: expected return and the social context. First, adoption decisions tend to be guided by risk-return trade-offs. Adoption of a certain practice will generate some utility, which I refer to as the value of adoption. As these practices are often new, there exists a risk that adoption is unsuccessful, reducing the expected return. Second, the social context plays a critical role in adoption. One example is network effects, where the value of adoption depends on the

[1] I use the term 'practices' in the article as the unifying term describing operational practices, methods and new technologies that bear a risk of being wrongly adopted and brings a high benefit if successfully adopted.

number of adopters. As more people adopt, the practice will become more attractive in the case of positive externalities, or less attractive when these are negative. Another example is social imitation. If the value of adopting is highly uncertain, people can be inclined to reduce that risk by basing their decision on others' choices which lead to the appearance of a well-known S-curve (Bass 1969). Adoption patterns can therefore be subject to myopic and bounded rational behaviour (Levinthal and March 1981, Ren and Huang 2018).

These studies show how social and monetary considerations can affect the value of adoption, but have been silent on the influence of relative benefits on practice adoption. This paper takes a unique look at the practice adoption problem by proposing a novel evolutionary game model that combines three important factors that all past approaches have not fully recognized in a unified framework: (1) the strategic interactions that may take place between adopters as they contemplate whether to adopt or not, given the interdependence of their respective utilities and others' choices; (2) the relative benefits, expressed in the form of social comparisons, affect whether to adopt or not given that the organisation culture has an impact in moderating these effects; (3) I model the adoption decision dynamical and dependent on the frequency of meeting an adopter and a non-adopter.

Numerous examples in practice highlight that relative benefits, in the form of social comparisons, impact adoption decisions. Some organisational studies (Charness et al. 2013) show that status seeking behaviour can lead to make unethical choices (such as cheating or sabotaging others) in order to perform better than others. But status seeking behaviour can also lead an organisation to make safer choices as individuals choose safe actions to enjoy being better by seeing others failing in their risky endeavour (Kramer et al. 2011). In hospitals, Song et al. (2017) observe that the lower ranked physicians imitated the best practices (timing of radiology and laboratory test order and discharge instruction practices) used by the best top performers in an emergency department when top management highlighted them as the role models during weekly meetings. The authors argue that adoption of these practices were triggered as the lower performing physicians wished to avoid being behind the others by copying these practices.

The literature has broadly classified social comparisons into two categories: *behind-averse* (also called *social regret* and *envy*) and *ahead-seeking* (also called *status seeking* and *gloating*). The literatures in behavioural economics (Ashraf and Bandiera 2018, Sobel 2005) and operations management (Avcı et al. 2014, Roels and Su 2013), have considered that social comparisons arise based solely on a difference in outcomes and have looked at how these trigger more or less effort. But, recent experimental evidence in neuroscience and social psychology provide evidence that differential choices leading to different outcomes (in our context different choices of practices) between interacting individuals trigger the highest level of social comparisons (Bault et al. 2011, Corcoran et al. 2011, Coricelli and Rustichini 2010, Lahno and Serra-Garcia 2015) which I am the first to model in this paper.

It is well accepted among companies' top management that different types of social comparisons emerge as manifestations of distinct organisational norms and affect employees' behaviours (Chun et al. 2018). I will refer to it as the social comparison culture in the organisation which can be observed and potentially measured (Baldwin and Mussweiler 2018). For example, Huawei tries to encourage employees not to fear falling behind their peers and encourage any form of success even though being ahead is very well rewarded as highlighted by Ren Zhengfei, "I will not judge whether each team has done a good job or not, because all of you are moving forward. If you run faster than others and achieve more, you are heroes. But, if you run slowly, I won't view you as underperformers." (Chun et al. 2018). But, other companies such as General Electric (GE) under Jack Welch or Amazon, cultivate the fear of being behind as the lowest performing 10% of employees are let go. Thus, Huawei seems to cultivate a more *ahead-seeking* culture, while GE under Jack Welch and Amazon are cultivating a more *behind-averse* culture.

The population affects adoption decisions due to frequency-dependent strategic interactions. Past literature modelled population effects on adoption decision either in terms of externalities impacting the value of the practice in the individual utility or without any strategic considerations using epidemiological models where adoption occurs proportional to the remaining proportion of potential adopters. But, the multiple examples shown above and the specific nature of social comparisons suggest that adoption decisions are strategic and are dependent on others' choices. This leads us to propose a novel framework where adoption occurs strategically due to frequency-dependent interactions that change as the population states of adopters and non-adopters change over time.

The model presented in this paper accounts for social comparisons and utility interdependencies at an individual level, and population level effects on the dynamics of adoption are derived. The individual utilities comprise two components; these map onto utility due to reward systems, and utility from social comparisons. The results offer guidelines to organisations when faced with introducing a new practice among their employees. First, I show how the same practice introduced in two organisations with the same reward systems but different social comparison regimes may exhibit a different pattern of adoption. In particular, I highlight that social comparisons can act against a collective reward system put in place by management, and inhibit adoption. Second, I characterise two adoption patterns that emerge in the presence of social comparisons: *co-existence* and *bi-stability*. *Co-existence* represents a situation where both practices continue to be used in the organisation at equilibrium. *Bi-stability* corresponds to the case where full adoption of the new practice rests critically upon the upfront adopters of the new practice; at equilibrium, 100% of the employees will adopt if the initial number of adopters is above a determined threshold, i.e. a critical mass phenomenon. It is important to understand the circumstances that determine which adoption patterns emerge; for example, a manager cannot achieve full adoption under *coexistence* circumstances, irrespective of the level of initial effort to recruit or train or induce employees to adopt the new practice. Lastly, I characterise the impact of three key levers: culture of social comparisons, reward systems and training/hiring initial critical mass of adopters, on the adoption patterns in the coexistence and bi-stability regions identified.

These findings have important managerial insights as they provide insights for organisations on how to influence practice adoption. Training/hiring individuals can lead the whole organisation to adopt in a behind-averse organisation such as Amazon, while it has no impact in a ahead-seeking organisation such as Huawei in which rewards will have more impact. Moreover, as you may recall the examples provided earlier, depending on the type of practice (safe vs risky, sustainable vs unsustainable, ethical vs unethical), the desired outcome for an organisation might not be to drive full adoption of the practice in the organisation. Environmentally speaking, the will to be ahead can lead to a good outcome at the societal level as more sustainable practices were used. But seeking status can also lead to a less righteous outcome for an organisation when unethical practices were adopted. Imitation behaviour can be beneficial for organisations such as the sharing of best practices in hospitals or the reduction of antibiotics prescription among GPs but it can also lead to a bad outcome when farmers decided to imitate the other farmers who were consuming more water.

After reviewing the relevant literature in the next section, I present the model set-up in Section 3.3. I then show, in Section 3.4, the dynamic adoption behaviour in an organisation and define how the social comparisons effects interact with the reward systems to drive adoption. In Section 3.4.3, I provide an extension of the model to show how the improvement of individuals' capabilities to adopt the new practice impacts adoption (i.e. the practice becomes less risky over time). Finally, in conclusion, I discuss the theoretical contributions of this novel model in the broad adoption literature and the managerial implications for organisations.

3.2 Literature review

The adoption of new practices and innovations has emerged, early on, as an important research topic attempting to describe and explain its evolution observed in social systems. These research efforts have been undertaken across different disciplines ranging from sociology (Burt 1987), to organisational behaviour (Henderson Rebecca and Clark Kim 1990), economics (Griliches 1957, Hannan and McDowell 1984), marketing (Bass 1969), operations management (Loch and Huberman 1999) and the history of the technology (Rosenberg 1972). Independently of their different approaches all streams have converged to a robust finding: adoption accumulates over time in an S-shaped curve, as in Rogers (1962). The prevalence of the S-shaped adoption curve has prompted researchers to focus on identifying the mechanisms that determine the dynamics of adoption (Hall and Khan 2003), e.g., how the rate of adoption changes, what are the resulting numbers of adopters at any point in time, etc. A related goal is to understand the adoption patterns, i.e., the proportion of the population engaging in a new practice as time goes by.

A key factor highlighted in the literature that speaks directly to the challenge of adoption is the trade-off between a highly uncertain but more rewarding new practice and the riskless but limited-value old practice. This fundamental risk-return trade-off governs the decision to adopt, and reveals the two dimensions in which management can influence adoption: the individual benefit (value) acquired through the adoption of the new practice, and the risk associated with the successful implementation of the new practice.[2] The literature has considered these dimensions of risk and return explicitly. With respect to the risk of adoption, the literature has recognized the importance of external information for risk resolution. Such information can emerge from costly investments (as advocated by the operations research technology adoption literature, see McCardle (1985)).

Another main factor driving adoption decisions has been the role of the social context in the form of social imitation and externalities to which this paper contributes.

[2]Research in the adoption of new technologies in the Operations Research literature has concentrated on the individual decisions to adopt given the risk-return trade-off (McCardle 1985). These studies conclude that individuals adopt the new practice once their expected value from adoption grows higher than a risk dependent threshold. As such these studies question primarily how the resolution of uncertainty affects this adoption threshold (Chen and Ma 2014, Cho and McCardle 2009, Hagspiel et al. 2015, Ma 2010, McCardle 1985, Smith and Ulu 2012), or whether exogenous changes in the properties of the practice (cost, ease of use, etc.) prompt individuals to adopt (*moving equilibrium diffusion models*; see Loch and Huberman (1999) and Jensen (1982)). I do not consider stand-alone individual decisions. I explore adoption patterns in social settings, as these emerge at a population level, being the result of multiple *interacting* individual decisions and individuals decisions being made based on these interactions.

It has long been accepted in the literature (Abrahamson and Rosenkopf 1993, Bass 1969, Granovetter 1978, Levinthal and March 1981) that in social settings individuals adopt new practices from observations on the adoption choices of their peers, e.g., co-workers and co-consumers. While this early literature has attributed the propensity to imitate as a trait of individuals (e.g., see the distinction between innovators and imitators in Bass (1969)), the sociology literature has demonstrated that imitation can take place even in social settings with a homogeneous population (see review of Strang and Soule (1998)). These streams of literature have modelled the influence of population on employees' adoption decisions through imitation and evolves proportional to the remaining share of potential adopters similar to epidemiological contagion phenomenons. But, this approach does not take into account the strategic component of adoption decisions due to interactions which I introduce in my model using an evolutionary game theoretic approach. I consider adoption of new practices in a firm where imitation by individuals is driven by the magnitude of the value differential between adopting the new practice or staying with the old one, and that value differential depends on the proportion of adopters at a given time and the frequency of meeting an adopter or a non-adopter, thereby inducing interdependence between individuals. This evolutionary game approach also supports the existing literature that argues that in organisations, individuals are bounded rational and do not make decisions by being forward-looking (Levinthal and March 1981, Ren and Huang 2018).

The wider literature also addresses the notion of externalities to model value interdependence in which an individual's successful adoption decision induces either a positive or negative effect on others (Eckles et al. 2016, Jovanovic and Nyarko 1994, Tucker 2008). I borrow conceptually from those studies to consider a form of value dependency which is, however, put in place by management. Indeed, senior management induces such externalities upon the introduction of the new practice through their choice of *collective rewards* which could be either be a *bonus*, i.e., a positive externality of successful innovation, or a *levy* which is a negative externality in that rewards of success are diluted by the number of successful innovators. "Levies" can be encountered in innovation (that is "winner-takes-all") systems in the form of, for example, innovation tournaments.

Beyond accumulating the effects of population externalities on any individual, the goal is to identify and analyse another form of value interdependency in the context of new practice adoption that has a social root, namely *social comparison* effects (Festinger 1954). To my knowledge, this study is the first to explicitly account for relative utility specifications in the adoption decision, and I deem this as a key contribution of this study. Social comparisons induce also utility gains (losses) that individuals realise when their outcomes end up being relatively superior (inferior) with respect to other adopters.[3] Social comparison relativizes an individual's utility and decisions; I say that the individual makes *relative choices* and explore how such social comparisons shape the patterns of adoption in the population. I focus on two main types of social comparisons, *behind-averse* and *ahead-seeking*, as these have been identified by research in neuroscience, behavioural economics and decision making under uncertainty (Ashraf and Bandiera 2018, Bault et al. 2011, Charness and Rabin 2002, Fehr and Schmidt 1999, Lahno and Serra-Garcia 2015, Sobel 2005). These terms have also been called in these other literatures status-seeking or gloating for ahead-seeking and social regret or envy for behind-averse. *Ahead-seeking* implies an increase in utility when performing better than another, whereas *behind-averse* results in lower utility when performing worse. Interestingly, these social comparison effects, though related, are somewhat independent of each other. The interdependencies driven by social comparison stand differentiated from the classic concept of externalities, because their effect on value depends on the relative choices of the individuals, which in this setting is approximated by the balance between adopters and non-adopters in the entire population. Thus, the same type of social comparison (say *ahead-seeking*) can act as either a positive or negative externality *depending* on the relative choices of the individuals in the population.

Recent research has shown that the intensity of the social comparisons felt by individuals is often shaped by the overall organisational norms (Chun et al. 2018), i.e., the set of common underlying values and beliefs as to what is positive or negative contribution to an organisation, good or bad individual behaviour etc. (Schein 1996). Huawei seems to possess a *ahead-seeking* culture as it rewards high performers but will not consider lower performers, underperformers (Chun et al. 2018). Therefore, being behind is not seen badly. On the other hand, organisations such as Amazon, GE under Jack Welch or Microsoft under Steve Ballmer put in place a ranking system where the lowest performers were fired. It created a *behind-averse* culture where employees did not want to be at the bottom.

Closer to this study from a conceptual viewpoint but different compared to this paper's context (adoption of practices) and the underlying methodology (evolutionary game), the operations management normative literature has recorded a handful of studies that account for social comparisons between different actors (Avcı et al. 2014, Loch and Wu 2008). These studies analyse the effects of social comparisons on profitability between two main actors either in a newsvendor setting, or from a supply chain performance perspective. Roels and

[3] Corcoran et al. (2011), Dvash et al. (2010) note that "even failures might suddenly appear to be successes in comparisons with others who performed even worse than oneself".

Su (2013) study the effect of social comparisons on individual performances within a group and show how the manipulation of the relative position of an individual's performance with respect to a reference point (which can be the average overall performance or a specific performance distribution of the group) can influence the individuals' contributions.

To summarize, I contribute to the existing literature in the following ways. First, I investigate the impact of relative benefits in the form of social comparisons on the adoption of new practices. Indeed, this paper breaks ground by considering social comparisons with reference to both the individual choices and the outcome of those choices, based on a recent neuroscience literature (Bault et al. 2011).

Secondly, I analyse the interplay of social comparisons with reward systems, a type of externality set by senior management, to understand what form of reward supports adoption under each social comparison culture.

Lastly, I widen research horizons on the adoption of new practices and technologies by looking at social influence through the lens of evolutionary game theory. The model (i) accounts for strategic interactions between individuals (as opposed to their predetermined traits) and (ii) expresses the dynamic evolution of individual choices via frequency-dependent population effects. Within that context I am able to offer closed form representations of the stable equilibria and derive striking managerial insights, e.g., the co-existence of multiple practices that serve the same organisational goal, or pointers to how social comparisons dynamics and rewards may combine to defeat adoption of a valuable innovation. Some of these findings can corroborate different situations and examples observed in practice and bring novel insights of potential scenarios that could occur.

3.3 Model set-up

In this section, I develop a model to describe an organisational setting whereby employees choose to either adopt a "new" or novel management practice, represented by the subscript N and delivering utility U_N to each employee, or continue with the "old" or conventional practice, with subscript O and utility U_O. I elaborate the model for these utilities in three layers. The first two layers describe the micro level of adoption; employees decide whether to adopt (the new practice) based on their utility which depends on their direct economic benefit but also on the choice and/or the outcome of their peers. Economic benefit, in the first layer, stems from the reward systems that senior management may establish with respect to both individual rewards (e.g., bonus schemes that depend on the assumed risk). The second layer accounts for the social comparison effects which emerge when employees undertake similar or different practices. Two important dimensions determine these social effects. First, the mechanics of social comparisons, and second the types of social comparisons. The former is formally captured through a random "matching" between employees. The random pairing modelling choice is not new and it has been widely employed in the literature (Sandholm 2010). The latter builds upon the concepts of ahead-seeking and behind-averse to define whether better/worse performance than the random counterpart increases/decreases the focal adopter utility. The third layer models how the entire population mediates social influence at the micro level, and therefore how the adoption of new practice, or retention of old practice, evolves dynamically. This represents approximately — and over time — as expressed in Theorem 1 an *average* influence that the rest of the peers have on a focal adopter.

3.3.1 Payoffs at the micro-level

Economic benefits as rewards at the micro level.

Individual utilities are determined by a combination of factors. First, the adoption of the new practice holds uncertainty as to a successful outcome. Denote by V_N the positive and fixed value received by an employee upon successful adoption of new practice, and by $p \in [0,1]$ the probability of success, whereas he receives 0 if the new practice fails. At the same time, sticking with the existing practice bears no risk (probability of success is 1) and the value of such practice received by an employee is denoted V_O. I define $V_O = kV_N$ where $k \in]0,1[$ is chosen such that $\frac{1}{k}$ captures the reward differential the organisation puts forward for the employees to adopt the new practice. I take the viewpoint of an organisation that promotes the adoption of the new practice:[4] $k < 1$ so that $0 < V_O = kV_N < V_N$.

Social influence through social comparisons at the micro level.

Beyond the economic benefits considerations, I broaden the utilities' definition by including social comparison effects as follows: employees care whether they have made the "right" choice of practice (the one that leads to a better outcome) or the "wrong" choice. Interestingly, right and wrong might be determined as much by what others are doing as by the own outcome. That is, the right or wrong choice is determined by both whether an individual engages in social comparison, which depends both on whether an individual's choice differs from his peers, and how his outcome compares with others' outcomes.

[4]In fact the model set-up is valid for an organisation that prefers the old, or suppresses the new, practice.

My representation of such social comparisons is based on recent research that describes the fundamental neurology that triggers such effects. Bault et al. (2011) show experimentally that individuals exhibit significant utility gains or losses when the outcomes are attributed to *visibly* different choices.[5] Two important findings of their work are instrumental for my theory: first, the individual response to a loss or gain of having chosen wrongly or rightly, relative to the outcome of the unchosen lottery, is higher in the social context, i.e., in the presence of others. Second, the strongest perception of such a relative loss or gain occurs in the social context *when others made a different choice of lottery*. To put it another way, the same choice leading to differential outcomes due to uncertainty invokes fewer behind-averse or ahead-seeking utility effects compared to differential choices resulting in different outcomes; Lahno and Serra-Garcia (2015) also experimentally find that peer effects increase significantly due to peer choices; the latter invokes the notion of a "correct" choice and triggers stronger utility effects (Coricelli and Rustichini 2010, Lahno and Serra-Garcia 2015, Luttmer 2005, Zeelenberg et al. 1996).

Such social comparisons occur when employees interact in randomly matched pairs, and they are triggered when both employees make different choices. Should employees make the same choices, then I assume that no social comparison is triggered, to indicate the relatively smaller social comparison effect. To illustrate the social comparison dynamics in more detail, consider the situation when one employee is paired with another who undertakes a *different* practice: depending on the outcomes the former may feel ahead (if his outcome exceeds that of the other), or feel behind otherwise.

I introduce the parameters $\alpha > 0$ and $\gamma > 0$ that moderate respectively the ahead-seeking social comparison and the behind-averse social comparison effects. As supported by the literature (Baldwin and Mussweiler 2018, Chun et al. 2018), I posit that α and γ are organisational parameters which captures the firm's broader norms towards social comparisons. Specifically, α weights the ahead-seeking or celebratory feeling of coming out ahead of someone who has undertaken a different practice (in case of success), while γ weights the feeling of behind-averse, for achieving less when undertaking a different practice (relative failure).

[5] In particular, they investigate how striatal activity, in a reward-related brain structure, and skin conductance are affected positively or negatively when individuals make choices between two risky lotteries, before they discover the outcome of their choice and the unchosen lottery. The authors conduct experiments when the choice is in a private context (the individual is the only person to make a choice) and in a social context (another individual also makes a choice between the two lotteries)

To model this, consider an employee who chooses to adopt the new practice, and he is paired with someone who sticks with the old practice. If the former's strategy is successful then, because his reward V_N exceeds that of the other, kV_N, he perceives a utility uplift of $\alpha(V_N - kV_N)$ which I assume to be proportional to the difference; whereas if he fails, his reward of 0 is further decremented by an behind-averse-based loss of $\gamma(kV_N - 0)$. As successful adoption is risky (with a probability p), the expected utility including the rewards and the social comparison utility effects is $p[V_N + \alpha(V_N - kV_N)] - (1-p)\gamma kV_N$.

A similar calculation applies in the case of an employee who sticks to the old practice and is paired with someone who attempts the new practice. Should the latter party fail, the former will feel a ahead-seeking utility $\alpha(kV_N - 0)$ but if the latter succeeds, the former will then suffer a utility loss due to behind-averse of $\gamma(V_N - kV_N)$.

Given the risk of adopting the new practice, the expected utility including rewards and social comparisons felt by the employee is $kV_N + (1-p)\alpha kV_N - p\gamma(V_N - kV_N)$.

The following table summarises the utilities realised by the employees depending on the random matching:

Table 3.1 General payoff matrix

	N	O
N	$U_{NN} = pV_N$	$U_{NO} = p[V_N + \alpha(V_N - kV_N)] - (1-p)\gamma kV_N$
O	$U_{ON} = kV_N + (1-p)\alpha kV_N - p\gamma(V_N - kV_N)$	$U_{OO} = kV_N$

3.3.2 The population game and revision protocol

The payoff matrix above represents the micro structure of the strategic interactions. Scaling that effect at the population level, I define the population game $U(x) = \begin{pmatrix} U_N(x) \\ U_O(x) \end{pmatrix}$ such that the utility of undertaking either a new practice, U_N, or old practice, U_O, must account for the social influence of the entire population. Thus, I calculate the employee utility of choosing one of the two practices in expectation as a linear combination of the utilities the agent would get by being paired with an employee making the same choice and by being paired with an employee making the opposite choice. I denote x the proportion of employees choosing to adopt the new practice and $1-x$ the share of employees sticking with the old practice.

Hence, I can write the population game utilities of an agent depending on whether he engages in a new or old practice:

$$U(x) = \begin{pmatrix} U_N(x) \\ U_O(x) \end{pmatrix} = \begin{bmatrix} U_{NN} & U_{NO} \\ U_{ON} & U_{OO} \end{bmatrix} \times \begin{pmatrix} x \\ 1-x \end{pmatrix} = \begin{pmatrix} xU_{NN} + (1-x)U_{NO} \\ xU_{ON} + (1-x)U_{OO} \end{pmatrix} . \quad (3.1)$$

Employees choose when and which practice to adopt following a protocol ρ defined by an alarm clock of rate R and a conditional probability of switching between practices O and N, ρ_{ij}. Each employee is equipped with a rate R Poisson alarm clock and when this clock rings, each employee re-evaluates their current strategy by picking randomly another employee to play the game. If the employee was adopting the old practice O and he picks an individual adopting the new practice N, he will adopt the new practice with a probability: $\rho_{ON} = x[U_N(x) - U_O(x)]_+$. Such protocol is one of the classic imitation protocols described in the literature in game theory as *pairwise proportional imitation* (Sandholm 2010). In this formulation it is important to note that the choice made by employees at any moment is based on the state of the organisation at the time of evaluation; decisions do not take into account a forward-looking optimization mechanism, e.g., dynamic programming, but the employees act myopically, a consistent assumption made in the organisational literature due to the existence of bounded rationality (Levinthal and March 1993).

3.3.3 The stochastic evolutionary process and its deterministic approximation

Building upon precedent works in evolutionary games (Sandholm 2010, Weibull 1997), the population game U, the revision protocol ρ, the rate R of each employee's clock satisfying $max_{x,i\in(O,N)} \sum_{j\neq i} \rho_{ij}(U(x),x) \leq R < \infty$ and the finite size n of the population define a Markov process $\{X_t^n\}$ on the feasible social states of the population χ^n with a jump rate $\lambda_x^n = nR$ and transition probabilities:

$$P^n_{x,x+z} = \begin{cases} x(1-x)\dfrac{[U_N(x)-U_O(x)]_+}{R} & \text{if } z = \dfrac{1}{n} \\ x(1-x)\dfrac{[U_O(x)-U_N(x)]_+}{R} & \text{if } z = -\dfrac{1}{n} \\ 1-(1-x)x\dfrac{|U_N(x)-U_O(x)|}{R} & \text{if } z = 0 \end{cases}$$

Theorem 1 *When the population size n is sufficiently large, the Markov process $\{X^n_t\}$ is well approximated aver a finite horizon by solutions of the following differential equation:*

$$\frac{dx}{dt} = x(1-x)(U_N(x)-U_O(x)). \tag{3.2}$$

Proof: All proofs are listed in a separate Appendix to enhance the paper's readability

In the following section, I study the deterministic approximation of the stochastic model. Since equilibrium implies zero on the left of (3.2), I see from the right that an equilibrium implies one of three outcomes: no adoption ($x = 0$), full adoption ($x = 1$), or equality of utilities of new and old practices ($U_N = U_O$, which may occur for $0 < x < 1$). To establish these results, I analyse the asymptotic stability of the equilibria, i.e., the evolutionary stable strategies that emerge from the dynamical system 3.2. This approach is of importance for senior managers; the emerging adoption equilibria reflect the potential of overall productivity improvement.

3.4 Analysis

3.4.1 Adoption patterns: the key role of the social comparisons

In this section I analyse the evolutionary stable adoption equilibria that emerge within organisations as represented in the model setup above. I describe these equilibria and then seek to understand how the contextual parameters, e.g., type of social comparisons, shape them. I identify four archetypical patterns of adoption that may occur:

- A *bi-stability* pattern, where any of the two asymptotic stable states (full adoption or no adoption) may emerge depending on the initial number of the practice adopters.

- A *co-existence* pattern, which results in an asymptotic stable state where a percentage of the organisation workforce adopts the new practice, while the rest continues with the current practice.
- In the *full adoption* pattern, the entire organisation adopts the new practice, $x^* = 1$, independent of the initial number of new practice adopters.
- In the *non-adoption* pattern, everyone in the organisation forgoes the adoption of the new practice, i.e., $x^* = 0$, independent of the initial number of new practice adopters.

Proposition 1 highlights a key finding of the paper illustrated in Figure 3.1. It explicitly defines the adoption patterns that emerge in the organisation depending on the type of social comparisons parameters α and γ. The organisation can be more ahead-seeking ($\alpha > \gamma$) or more behind-averse ($\alpha < \gamma$). In particular, I find that the bi-stability region occurs only when the organisation is more behind-averse than ahead-seeking and the coexistence region, when the organisation is more ahead-seeking than behind-averse. I will denote by x_0 the fraction of the population which attempts the new practice initially and by x^* the fraction of adopters at equilibrium. The former may be set by management, e.g., a high x_0 may result from investing heavily upfront through either training of existing employees or recruitment of expert employees. For some settings, x^* will depend on whether x_0 is below or above the threshold x_0^*. I also introduce the following notation to simplify the presentation of my results: $\varepsilon_1 = \mid \frac{p(1-p)(\alpha-\gamma)}{1+\alpha p+(1-p)\gamma} \mid$ and $\varepsilon_2 = \mid \frac{p(1-p)(\alpha-\gamma)}{1+\gamma p+(1-p)\alpha} \mid$.

Proposition 1 *For any implementation risk of the new practice $p \in]0,1[$:*

- *Bi-stability occurs when the organisation exhibits behind-averse social comparisons ($\alpha < \gamma$) and $p - \varepsilon_1 < k < p + \varepsilon_2$. The resulting adoption pattern is full adoption (no-adoption) when the initial proportion of adopters x_0 is $x_0 > x_0^* = \frac{k-p+\gamma k-\alpha p-kp(\gamma-\alpha)}{(\gamma-\alpha)(p-k(2p-1))}$ ($x_0 < x_0^*$).*
- *Co-existence occurs when the organisation exhibits ahead-seeking social comparisons ($\alpha > \gamma$) and $p - \varepsilon_2 < k < p + \varepsilon_1$; the asymptotically stable fraction of the new practice adopters is $x^* = \frac{k-p+\gamma k-\alpha p-kp(\gamma-\alpha)}{(\gamma-\alpha)(p-k(2p-1))}$.*
- *Full adoption occurs when $0 < k < p - \varepsilon_1$ in a behind-averse organisation and when $0 < k < p - \varepsilon_2$ in a ahead-seeking organisation.*
- *No-adoption occurs $p + \varepsilon_2 < k < 1$ in a behind-averse organisation and when $p + \varepsilon_1 < k < 1$ in a ahead-seeking organisation.*

Proof: All proofs are listed in a separate Appendix to enhance the paper readability.

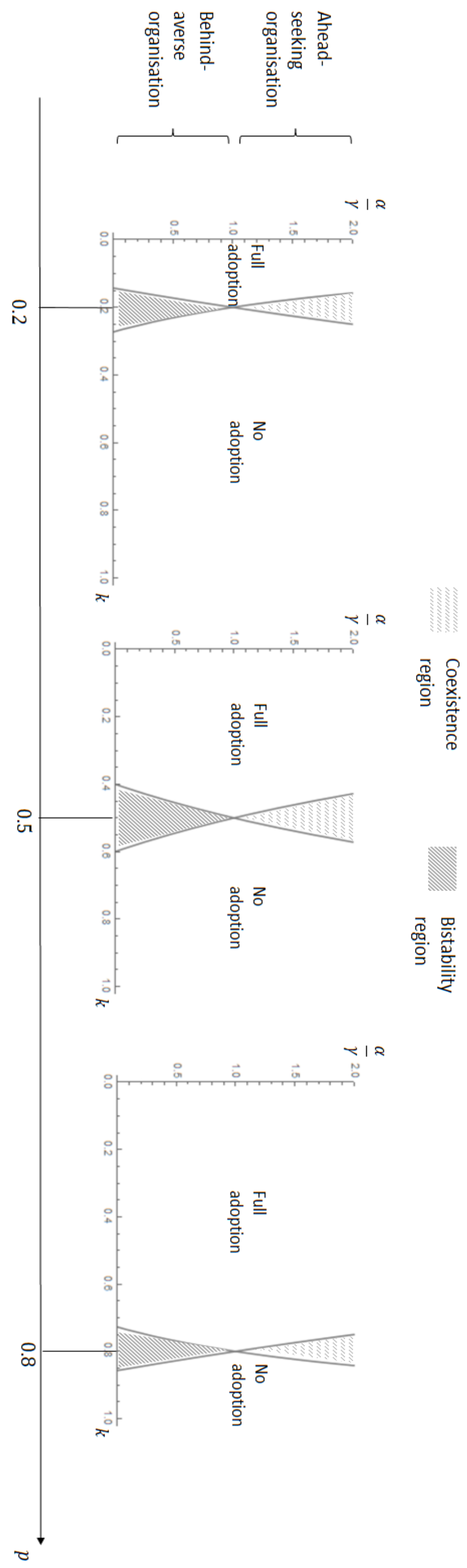

Fig. 3.1 Regions of adoption depending on α/γ, p and k

Proposition 1 highlights that under ahead-seeking social comparison dynamics, organisations fail to achieve full adoption, even when they invest significantly upfront on the initial number of adopters through training of existing employees, or through the recruitment of expert employees (thus increasing x_0). The social comparison dynamics lead to co-existence equilibria, that is, a certain percentage of the organisational workforce stays with the existing practice. Moreover, this happens despite the fact that employees who dare to try the new practice (and succeed) enjoy additional utility in the form of a social comparison bonus. Although this result appears puzzling at first, the model shows how the adoption dynamics might give rise to such an adverse reaction from a part of the organisation. The reason is that beyond a level x of adopters of the new practice, social comparisons end up rewarding more the fewer non-adopters, compared to the employees that choose to adopt. This can be directly observed by the comparison of the U_N, U_O (Section 3.3). As more employees adopt, benefits from social comparison due to success drop on average for the adopters of the new practice. This happens because social comparison happens less often (adopters rarely "pair" with proponents of the current practice while they still face the risk of failure); in mathematical terms the $(1-x)p$ effect diminishes. In contrast, the fewer non-adopters observe a higher likelihood of benefiting from social comparison (as they "pair" more often with an adopter) while they still face a good chance to succeed in relative terms and therefore benefit from the comparison; in mathematical terms the $x(1-p)$ effect becomes sizeable.

All in all, social comparisons that exhibit ahead-seeking dynamics would, *a priori* seem to motivate employees to pursue riskier new practices, “let’s celebrate success” or “let’s create the successful examples to instigate adoption” are often recommendations that populate the business press; yet they may be the underlying factor that prevents the eventual full adoption. The model analysis captures structurally an important social effect which has been experimentally shown recently in the social psychology and neuroscience literatures. They find that the social context plays a key role in assessing gains and losses. In particular, they find that relative incomes have greater effect than absolute ones to the point that a loss can be as rewarding as a gain, if others experienced a greater loss (Dvash et al. 2010). As in my model, individuals may choose opportunities that lead (on average) to a lesser outcome, as long as they ensure relative success.

Proposition 1 also reflects the respective effect of a “punishing” context of social comparisons, i.e., the behind-averse type of social comparisons on the adoption patterns. In organisational contexts where the failure of implementing a new practice is perceived as an additional personal loss, i.e., employees who fail to implement the new and riskier practice realise a "social cost", I may still achieve full adoption of the new practice. This result requires further elaboration as the mere notion of failure being socially "punished", but eventually resulting in full adoption, appears counter-intuitive. One would expect that in such punishing social contexts, adoption of the new practices would have been a guaranteed failure! The intuition behind this result lies in the role of the social dynamics of the context of study: a sufficient initial population of proponents of the new practice renders the utility loss from the behind-averse type of social comparison higher, when one chooses to stick with the current practice (the xp effect in U_O), as opposed to someone that chooses the new practice (the $(1-x)(1-p)$ effect in U_N). In fact, the difference between the two quantities can be higher for relatively riskier practices because of the additional benefit that $p-\varepsilon_1 < k < p+\varepsilon_2$ brings in the loss utility (see term $V_N - kV_N$).

These two results showcase in greater detail the intricacies that the dynamics of social comparisons impose. As such they offer a plausible explanatory mechanism for the persistent challenges often observed in companies regarding the adoption of new practices. For example, one can draw a parallel with the examples mentioned in the introduction. In the context of the adoption of best practices in the emergency department, I could argue that after top management highlighted them as role models, and the culture being behind-averse, the lower performers started to adopt the best practices. Similarly, in the case of the practice of antibiotics prescription, being aware of other physicians' behaviour, led them to imitate what the majority was doing highlighting a behind-averse environment. On the other hand, ahead-seeking behaviour can lead individuals to differentiate their choices form others. As mentioned in the introduction, it led some individuals to adopt sustainable practice to signal a higher status, make unethical choices to perform better than others or to choose safe practices ans hope others will fail their endeavours. While, these studies have been conducted in a short horizon of time which highlighted the differentiation effect, a dynamic view as suggested in this model, leads to the appearance of an equilibrium where both practices will coexist.

The two adoption patterns of coexistence and bi-stability appear when the implementation risk of the new practice p and k associated with sticking with the old practice are close in range ($p-\varepsilon_1 < k < p+\varepsilon_2$ in the bi-stability region and $p-\varepsilon_2 < k < p+\varepsilon_1$ in the coexistence region) as seen in Figure 3.1. The existence of these two regions for these ranges reflect a recurrent reality of practice adoption of "high risk, high return" rule. That is, senior management recognizes that the riskier a new practice is (as reflected by the lower values of p), the higher the reward ($\frac{1}{k}$) given to the successful employees should be. This assumption reflects standard outcomes of agency theory where reward premia are passed on to agents by the principal in order to perform riskier tasks (Holmstrom et al. 1979).

In the rest of the analysis, to focus on the most interesting cases and for simplicity without loss of generality, I position k in this range and assume $k = p$. This condition also allows us to normalise the effect of social comparisons again without loss generality such that $\alpha \in [0,1]$ and the behind-averse social comparison parameter γ is equal to $1-\alpha$ which gives a payoff matrix corresponding to Table 3.2:

Table 3.2 Payoff Matrix when $k = p$.

	N	O
N	$U_{NN} = pV_N$	$U_{NO} = pV_N(p+2\alpha(1-p))$
O	$U_{ON} = pV_N(p+2\alpha(1-p))$	$U_{OO} = pV_N$

Observe that an agent who is matched with someone attempting the same strategy is indifferent between attempting the new or old practices. In fact since pV_N is a common factor of all payoffs, an agent's preferences are determined by the relative size of the coefficients of pV_N.

Under this assumption, Proposition 1 leads to Corollary 1.

Corollary 1 $\forall p \in]0,1[$ *and* $k = p$*:*

- *Bi-stability occurs when the social comparisons exhibit behind-averse dynamics (*$\alpha < \frac{1}{2}$*). The resulting adoption pattern is full adoption (no-adoption) when the initial proportion of adopters* x_0 *is* $x_0 > x_0^* = \frac{1}{2}$ *(*$x_0 < x_0^*$*).*
- *Co-existence occurs when the social comparisons exhibit ahead-seeking dynamics (*$\alpha > \frac{1}{2}$*); the asymptotically stable fraction of the new practice adopters is* $x^* = \frac{1}{2}$*.*

Proof: All proofs are listed in a separate Appendix to enhance the paper readability.[6]

3.4.2 The Effect of collective rewards

Up to this point, I have modelled senior management influences via the individual rewards for the adoption of practices (the fraction by which 1 exceeds $\frac{1}{k}$), and the preparatory effort as approximated by, e.g., training or recruitment needed to set up the initial proportion of

[6]Note that I here and throughout avoid boundary situations, such as $p = 0$ or 1, or $x_0 = x_0^*$, which are associated with multiple equilibria.

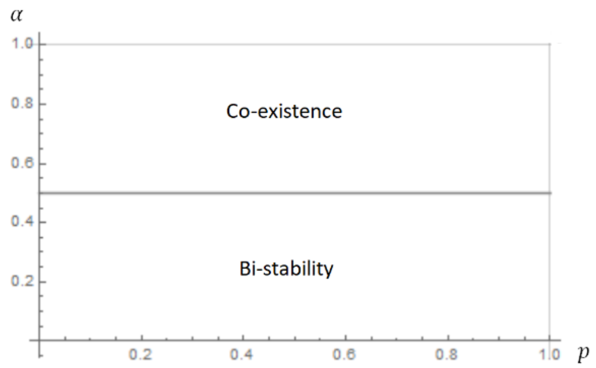

Fig. 3.2 Regions of adoption depending on α and p

adopters x_0. In this section I consider an additional management lever which I call a *collective reward*; I represent this by a parameter $\beta > 0$, and I contemplate that collective rewards also affect remuneration at the micro level when employees collectively choose the new practice (i.e., in modelling terms when employees keen to adopt are paired together and they are successful).

The collective reward system for successful adoption of the new practice can be set as a group bonus, which further increases the remuneration of employees, or a winner-takes-all system which may act as a levy and reduce the remuneration. In a sense, the type of collective rewards acts as a utility externality that is controlled by management. A bonus seems to suggest that management tries to incentivise innovative behaviour through collaborative benefits. A promotion system reflects a management perspective that promotes individual initiative, e.g., career advancement schemes for successful adopters with limited places awarded or a bonus pool of fixed size to be shared amongst successful adopters.

I represent such collective rewards by $\beta > 0$, to understand how managers influence the eventual adoption patterns. Consider a pair of employees who both attempt a new practice. Under a collective reward policy, if both succeed then they each receive payment $\frac{V_N}{\beta}$ instead of V_N (with probability p^2). Note that the case where $\beta < 1$ corresponds to a bonus, and promotion system if $\beta > 1$, while $\beta = 1$ reduces to the situation of Section 3.3 of Corollary 1. If the employee is successful and her counter-party is not, the former receives V_N (with probability $p(1-p)$). However if the employee is unsuccessful, she receives 0 (with probability $1-p$), irrespective of the outcome of his counter-party.

Table 3.3 Payoff Matrix under collective rewards when $k = p$.

	N	O
N	$U_{NN} = pV_N(\frac{p}{\beta} + (1-p))$	$U_{NO} = pV_N(p + 2\alpha(1-p))$
O	$U_{ON} = pV_N(p + 2\alpha(1-p))$	$U_{OO} = pV_N$

3.4.2.1 Adoption scenarios under collective rewards

Propositions 2 and 3 highlight two important results of this analysis for the settings where management induces collective rewards and the risk-return condition $k = p$ remains in force (I show in appendix that this assumption is without loss of generality as the effect of collective rewards is qualitatively the same for any value of k in the regions of bi-stability and coexistence found in the previous section respectively $p - \varepsilon_1 < k < p + \varepsilon_2$ and $p - \varepsilon_2 < k < p + \varepsilon_1$). They delineate the contingent nature of the adoption patterns in the organisation's reward systems (individually, via $k = p$ and collectively through the value of β) and the behavioural types of social comparisons captured by α).

I introduce the following notation to simplify the presentation of the results:

$$
\begin{aligned}
\hat{\alpha}_1 &= \left[1 + \frac{p(1-2\beta)}{\beta}\right] / [2(1-p)] \\
\hat{\alpha}_2 &= \frac{1}{2} \\
x^*_{\text{co-ex}} &= \left(2 + \frac{p(1-\beta)}{(1-p)\beta(1-2\alpha)}\right)^{-1} \\
x^*_0 &= \left(2 + \frac{p(1-\beta)}{(1-p)\beta(1-2\alpha)}\right)^{-1} \\
\hat{p}_1 &= \beta \\
\hat{p}_2 &= \frac{\beta}{2\beta - 1}
\end{aligned}
\tag{3.3}
$$

Proposition 2 *Collective bonus rewards ($\beta < 1$) associated with a new practice lead to the following adoption patterns:*

- *Bi-stability occurs when there exist behind-averse social comparisons ($\alpha < \hat{\alpha}_2$), for any new practice ($\forall p \in]0,1[$). Whether the result is full adoption or non-adoption* *depends on the initial proportion of adopters* x_0*: for* $x_0 > x_0^*$ *everyone adopts the new practice (*$x^* = 1$*), while all employees stick to the old practice (*$x^* = 0$*) for* $x_0 < x_0^*$*.*

- *Co-existence occurs when there exist strong ahead-seeking social comparisons (*$\alpha > \hat{\alpha}_1 > \hat{\alpha}_2$*), and the new practice exhibits relatively high implementation risk (*$0 < p < \hat{p}_1$*); the asymptotically stable fraction of the adopters of the new practice is* $x^* = x^*_{\text{co-ex}}$*.*
- *Full adoption (*$x^* = 1$*) occurs when either (i) the social comparisons are strongly ahead-seeking and the new practice has low implementation risk (*$p > \beta$*), or (ii) the social comparisons are weakly ahead-seeking (*$\hat{\alpha}_2 < \alpha < \hat{\alpha}_1$*).*

Proof: All proofs are listed in a separate Appendix[7] *to enhance the paper's readability*

The introduction of collective rewards impacts the adoption patterns. In particular, a collective bonus reward, which increases the remuneration from the successful implementation of the new practice, effectively acts as a positive externality of adoption. Therefore, it should promote the adoption of the new practice.

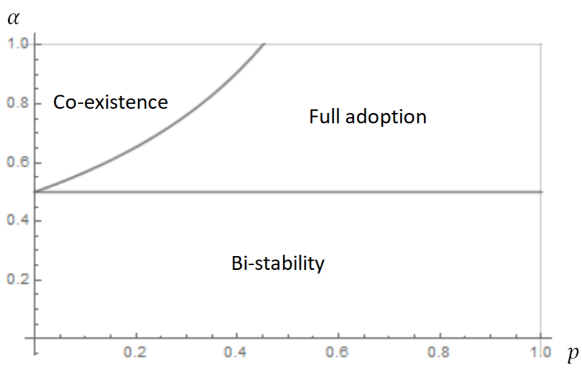

Fig. 3.3 Regime of adoption for innovative practices with collective bonus rewards ($\beta < 1$)

In addition, if the organisational context is characterised by *ahead-seeking* social comparisons, performing better than others when making the right choice is encouraged. This should enhance the effect of the collective bonus rewards and promote full adoption. Yet, surprisingly, I observe that a group of non-adopters will persist in the organisation for high risk high return practices. It is explained as follows: if the collective bonus reward is not sufficient to offset the risk of implementation failure from adopting the new practice, which makes the adopting employee perform better than her non-adopting peers, then employees might stick

[7] As in Section 3.3. I avoid boundary situations such as $x_0 = x_0^*$ in part 1 of the proposition, which are associated with multiple equilibria.

to the existing practice, to enjoy the “ahead-seeking” of having made the right choice and outperformed the adopters. For higher numbers of adopters, it becomes more beneficial to stick with the old practice, as there is a higher chance of experiencing the better performance compared to the adopters. It is also important to note that the collective bonus reward has a positive effect on the utility to adopt only if all employees adopt successfully. However, the riskier the new practice, the less likely it is for all employees to successfully adopt (likelihood p^2) which renders the collective bonus reward less effective.

Proposition 3 *Collective levy rewards ($\beta > 1$) yield the following patterns for the adoption of new practices:*

- *Bi-stability occurs when there exist strong behind-averse social comparisons ($0 \leq \alpha \leq \hat{\alpha}_1$) and the new practice has a high implementation risk (i.e., $0 < p < \hat{p}_2$); then, all employees adopt the new practice if the initial proportion of adopters x_0 is at least x_0^*, otherwise they all stick with the current practice.*
- *Non-adoption occurs when either (i) social comparisons exhibit strong behind-averse and the new practice has a low implementation risk ($p > \hat{p}_2$), or (ii) there exists weakly behind-averse social comparisons ($\hat{\alpha}_1 < \alpha < \hat{\alpha}_2$).*
- *Co-existence occurs under a context of ahead-seeking social comparisons ($\alpha > \hat{\alpha}_2$); the asymptotic stable fraction of the new practice adopters is $x^*_{\text{co-ex}}$, and it is independent of the initial proportion of adopters $x_0 \in]0,1[$.*

Proof: All proofs are listed in a separate Appendix to enhance the paper’s readability

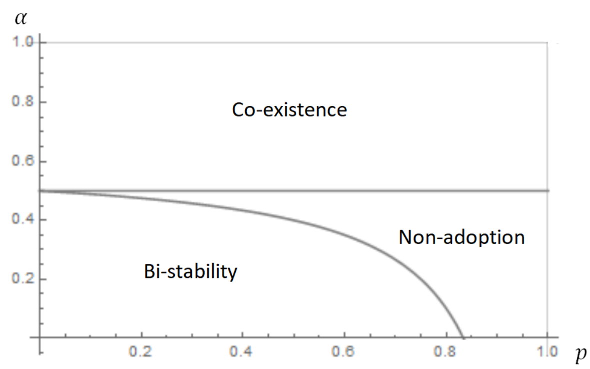

Fig. 3.4 Regime of adoption for innovative practices with collective levy rewards ($\beta > 1$)

Levies (i.e., “winner-takes-all”) systems have been advocated to help innovation, e.g., innovation tournaments. Introducing an adoption “levy” reduces the effective remuneration by allocating the success remuneration between adopters (e.g., only one of the good performers becomes the group leader). This decreases the attractiveness of adopting the new practice and explains the appearance of a non-adoption region.

Moreover, behind-averse social comparisons punish further failure when the wrong choice is made. These types of social comparison push for conformism. Combined with the disincentive to adopt, they should prompt everyone to stick with the old practice. Still, I observe that it is possible to push everyone to adopt if *enough* individuals are upfront induced positively for adoption. This is due to the nature of the social comparisons. If enough individuals try the new practice, the conformism effect can overpower the disincentive to adopt, and thus lead everyone in the organisation to adopt.

To further interpret the impact of the collective rewards on the different patterns of adoption, I define the coexistence region, $C(\beta)$, and bi-stability region, $B(\beta)$, in the (α,p)-space of different organisational contexts. These allow us to visually represent the relative magnitude of the emerging equilibria.

$$\begin{cases} C(\beta) := & \left\{(\alpha,p) \in]0,1[\times]0,1[: \alpha \in]\hat{\alpha}_1, 1[\text{ and } p \in]0,\hat{p}_1[\right\}, \\ B(\beta) := & \left\{(\alpha,p) \in]0,1[\times]0,1[: \alpha \in]0,\hat{\alpha}_1[\text{ and } p \in]0,\hat{p}_2[\right\}. \end{cases}$$

Proposition 4 *The coexistence region $C(\beta)$ is a convex set in the rectangle $]0,1[\times]1/2,1[$ and the full adoption region is the complement of $C(\beta)$ in that rectangle. Collective bonus rewards ($\beta < 1$), enlarge $C(\beta)$ in β and, as a result, the full adoption region shrinks in β: $C(\beta_1) \subsetneq C(\beta_2)$ when $0 < \beta_1 < \beta_2 < 1$.*
The bi-stability region $B(\beta)$ is a convex set in the rectangle $]0,1[\times]0,1/2[$ and the non-adoption region is the complement of $B(\beta)$ in that rectangle. Collective levy rewards ($\beta > 1$), reduce $B(\beta)$ in β and, as a result, the non-adoption region increases: $B(\beta_1) \subsetneq B(\beta_2)$ when $1 < \beta_1 < \beta_2$.

Proof: All proofs are listed in a separate Appendix to enhance the paper's readability

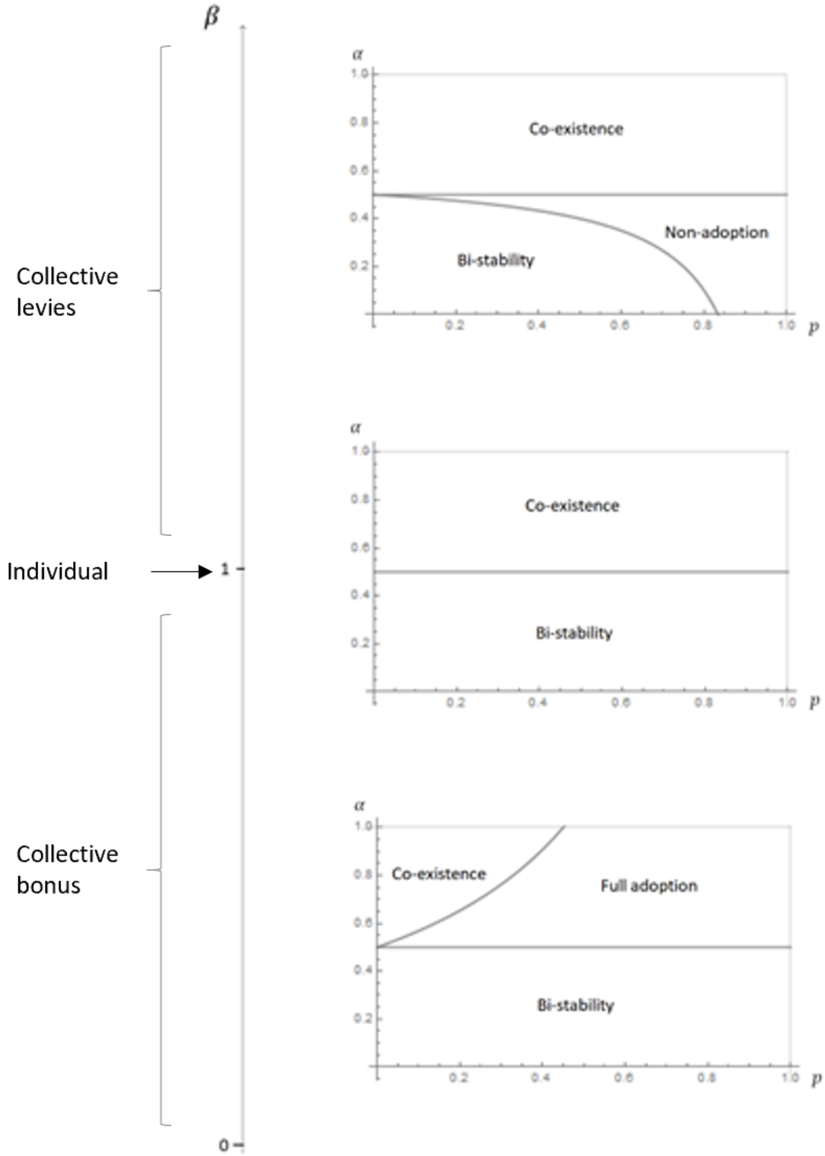

Fig. 3.5 Regions of adoption depending on β, α and p

Surprisingly, I find from Propositions 2, 3 and 4 that collective rewards only impact adoption when a firm faces a new practice that is low risk (large p) and thus low return. For high risk, high return practices, coexistence and bi-stability adoption patterns will persist for any type of collective reward.

Corollary 2 *Irrespective of the collective reward (any $\beta > 0$), there always exists an interval of risk-return p such that when the social comparisons are highly ahead-seeking, the adoption pattern will be coexistence: old practices and new practices will coexist. Similarly, there always exists an interval of risk-return for which highly behind-averse social comparisons* *drive a bi-stable adoption pattern: the organisation will either fully adopt the new practice if a critical mass of initial adopters exists, or will otherwise fully conform to the old practice.*

I also observe that even if the collective levy reward gets so high that the reward of successfully implementing the new practice is zero, i.e., $\beta \to \infty$, there will always exist a region of bi-stability for a range of risky practices.

This again seems surprising as I would assume that increasing the collective levy makes adopting the new practice less attractive. However, for high risk and high return practices ($k = p$ is high), the effect of the levy becomes negligible. On the other hand, the reward of an old practice is relatively low compared to high-return new practices. And as the social comparisons in the organisation gets more behind-averse, the perceived social loss in mathematical terms $(1-\alpha)p(V_N - kV_N)$ can offset the reward of sticking with the old practice as it is proportional to the difference in expected choice outcomes. Therefore choosing to stick with the old practice becomes less attractive than adopting the new practice, thus creating the bi-stability phenomenon.

3.4.2.2 Coexistence and bi-stability equilibria

In settings whereby organisational adoption results in a coexistence scenario, the equilibrium behaviours are characterised by the fraction x^* of adopters in the organisation. Alternatively, when organisations observe a bi-stability setting, full adoption takes place if the initial adopters exceed a critical mass, x_0^*.

Proposition 5 characterises these two key quantities with respect to the collective innovation reward parameter β and the implementation risk p.

Proposition 5 *Lower collective rewards (β increases) lead to a lower number of adopters at equilibrium (x^*) in coexistence settings, and higher upfront critical mass (x_0^*) to ensure full adoption in bi-stability settings.*

Proof: See in Appendix

Increasing β means decreasing the attractiveness of adopting the new practice as the utility that an adopter extracts when meeting another adopter decreases, *ceteris paribus*. Thus, there will be less adopters in co-existence settings and more upfront adopters would be needed to make the new practice attractive enough to push everyone to adopt.

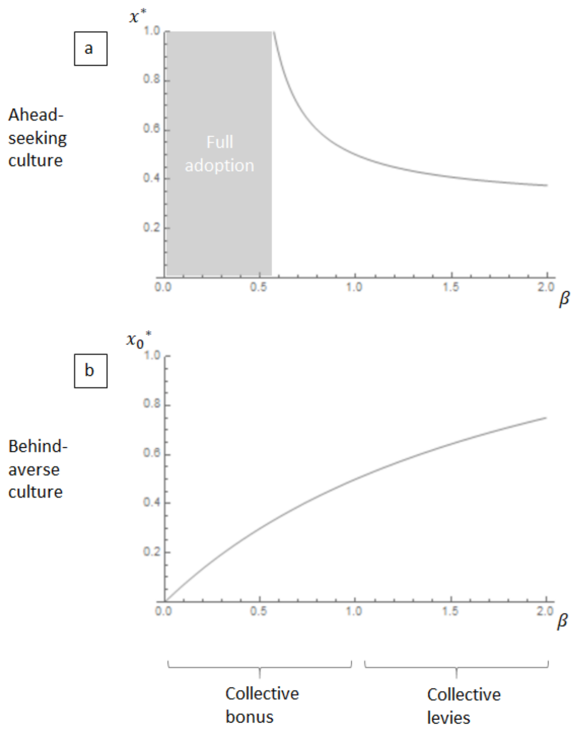

Fig. 3.6 Effect of collective rewards on the share of adopters at equilibrium (x^*) in a ahead-seeking organisation (top, numerical example: $\alpha = 0.75$) and upfront critical mass (x_0^*) needed for full adoption in a behind-averse organisation (bottom, numerical example: $\alpha = 0.25$) for a fixed practice (numerical example: $p = 0.4$)

3.4.2.3 The effect of the implementation risk p on the adoption equilibria

The next proposition illustrated in Figure 3.7 characterises the effect of the implementation risk on the coexistence and bi-stability adoption equilibria. Recall that I assume an efficient agency mechanism whereby higher risk practices would imply higher individual incentives for adoption, namely $p = k$.

Proposition 6 *Under a collective bonus reward scheme ($\beta < 1$), lower implementation risk (larger p) increases the fraction of adopters at equilibrium x^* in coexistence settings, when social comparisons are ahead-seeking, and decreases the upfront critical mass x_0^* necessary for adoption in bi-stability settings, when the social comparisons are behind-averse. Under collective competitive rewards of adoption ($\beta > 1$), the opposite effects occur.*

Proof: See in Appendix

The result illustrates the involved nature of the interactions between a cultural dimension (i.e., social comparisons), on one hand, and management intervention, (i.e., collective rewards), on

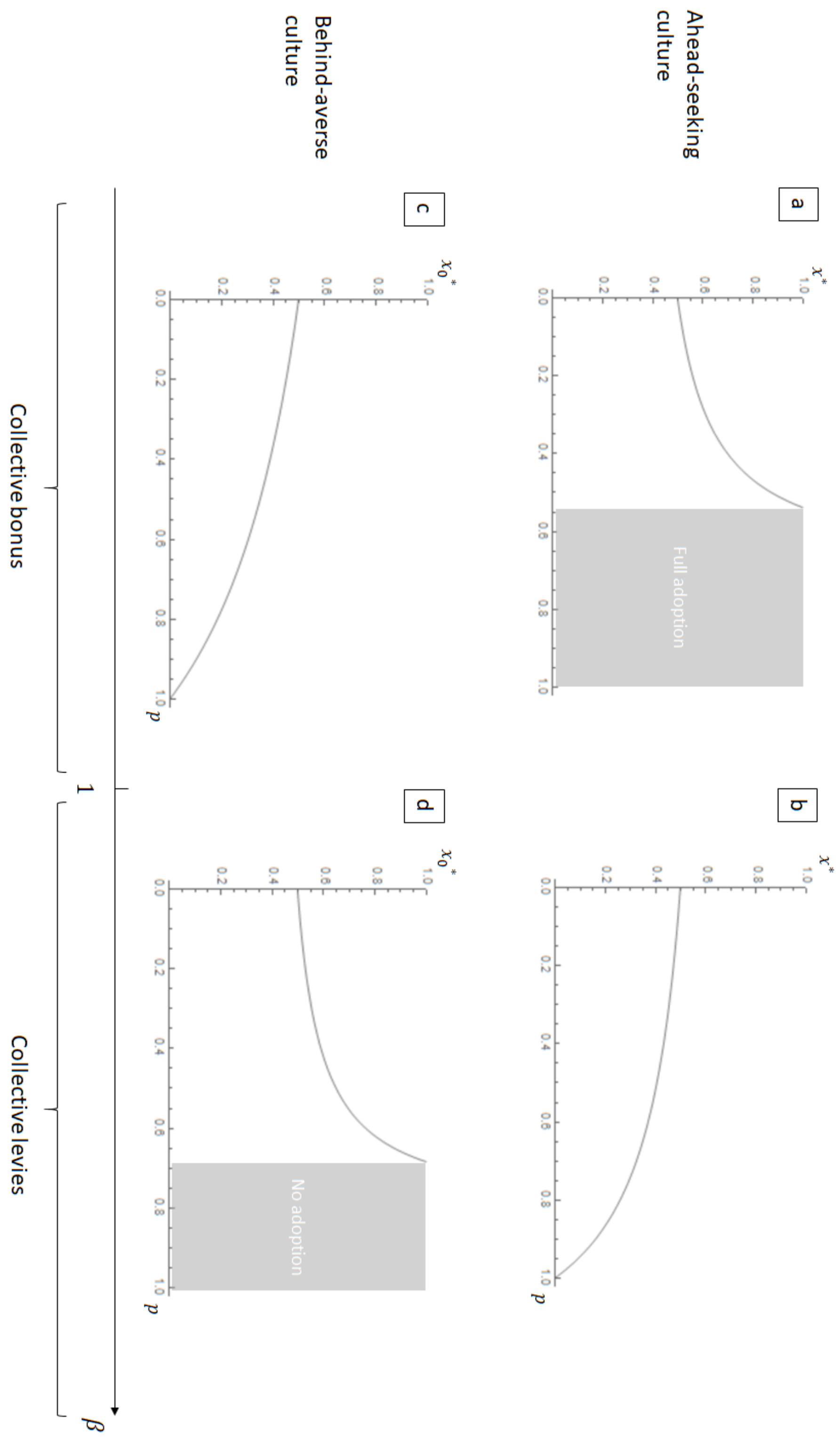

Fig. 3.7 Effect of the type of practice (risk return p) on the share of adopters at equilibrium (x^*) in a ahead-seeking organisation (top, numerical example=$\alpha = 0.75$) and upfront critical mass (x_0^*) needed for full adoption in a behind-averse organisation (bottom, numerical example=$\alpha = 0.25$) when there are collective bonuses (numerical example: $\beta = 0.7$) and collective levies (numerical example: $\beta = 1.3$)

the other. The result depends on the tension between the implementation risk, that determines success or failure from adoption, and the utility from social comparisons, which may leave you feeling either ahead-seeking or behind-averse when you succeed or fail to implement a practice that is different from your neighbour. Proposition 6 points to the careful analysis required to determine how management promotes innovative new practices in a certain culture. The choice of collective reward should align with the risk of the new practice in the case of ahead-seeking social comparisons, for example, low risk practice adoption benefits while (somewhat counter intuitively) high risk practice adoption benefits from collective levies. Hence, in the former setting management should enhance collaboration whereas in the latter enforce competitiveness and individualism. The opposite promotes innovation in an behind-averse culture.

3.4.3 Impact of "learning" on adoption patterns

In preceding sections I assumed that the uptake of new practices in a firm evolves through social influence of adopters and non-adopters on each other, while the ability of an individual to successfully implement the new practice at any time is fixed as the probability p.

In this section I ask how *learning*, in which p increases over time, affects the adoption equilibria that emerge. In particular, when the practice is such that the organisation is in full adoption, no-adoption or bi-stability, the organisation will end up either fully adopting or non-adopting and "learning" can only occur if the practice subsists in the organisation. In other words, individuals will not improve their capability to adopt if they ended up in one of the two steady states (full adoption or non-adoption). Therefore, the region of interest for us is when the new practice is still not fully adopted at equilibrium, ie. organisation is in a coexistence scenario. I abandon the risk-return condition $p = k$, and instead I posit $p = p(t)$ where initially $p(0) = k$ and increases to $\bar{p} \leq 1$ over time while being in the coexistence region such that $\alpha > \gamma$. Hence, the probability of successful adoption evolves as an exogenous process, e.g., a spillover effect from industry learning about this practice outside the focal organisation to the eventual point that there is no risk of failure [8].

The population dynamics model introduced in Section 3.3 retains the same formal structure although p varies:

[8] I could also assume that the implementation risk depends on the number of adopters such that $p(t, x(t))$ but I shall leave it for future research

$$\frac{dx}{dt} = x(1-x)(U_N(x,p) - U_O(x,p)). \tag{3.4}$$

I model $p(t)$ as an S-curve running from 0 to 1 as t becomes large, via its own differential equation,

$$\frac{dp}{dt} = \varepsilon p(\bar{p} - p), \text{ where } p(0) = k, \text{ and } k < \bar{p} <= 1$$

for an arbitrary constant $\varepsilon > 0$ that controls the "steepness" of the S-curve.

I analyse the local stability of the dynamic system and draw out the stable equilibria that emerge.

Proposition 7 *If a new practice is "learned" by all the employees over time when the organisation is initially in a coexistence scenario,*

- *There still exists a stable coexistence equilibrium* $x^* = \frac{\beta(-(1+\alpha)\bar{p}+k(1+\gamma+\bar{p}(\alpha-\gamma)))}{\bar{p}^2(1-\beta)+\beta(\gamma(k+\bar{p}-2k\bar{p})+\alpha(-\bar{p}+k(2\bar{p}-1)))}$ *for a range of collective rewards* $\beta > \frac{\bar{p}^2}{k(1+\alpha)+\bar{p}(\bar{p}+k(\gamma-\alpha)-\gamma-1)}$ *such that* $\frac{\bar{p}(1+\gamma-\bar{p})}{1+\alpha+\bar{p}(\gamma-\alpha)} < k = p(0) < \bar{p}$ *and* $0 < \gamma < \alpha$.
- *Full adoption occurs otherwise.*

Proof: See in Appendix

When individuals in the organisation learn and there are high collective bonuses when meeting an adopter, it creates quite intuitively full adoption. On the other hand, under low collective bonuses, if the new practice is not fully mastered or under collective levies when meeting an adopter reduces the expected reward, it might still be of value to stick with the old practice when meeting an adopter in a ahead-seeking organisation which explains the persistence of a coexistence scenario.

3.5 Discussion and conclusion

In this paper, I introduce an evolutionary game theory model in which bounded rational employees are involved in strategic interactions and choose to adopt a new practice that bears some risk or stick with a well established practice. Over time, they make choices based on the relative utility they get compared to others' choices and the state of the population is updated throughout the evolutionary game. I incorporate and theorise the individuals' utility as dependent on behavioural considerations such as the social comparisons, that take place between individuals in all organisational and social settings, on the eventual adoption patterns of novel and innovative practices that are introduced in organisations. For that purpose, I consider an explicit form of social comparisons introduced in the literature: ahead-seeking versus behind-averse (Bault et al. 2011, Sobel 2005). I account for the utility form that such comparisons take, and I explore their interactions with the monetary reward systems that senior management might introduce to induce adoption. Reward systems are categorised into collective *bonus* systems (where management rewards the collective adoption above and beyond individual rewards) and collective *levy* systems (where management might promote a more competitive recognition and therefore collective adoption may limit the individual utility).

I show that adoption patterns might admit steady states that do not achieve full adoption depending on the type of social comparisons an organisation cultivates. In a ahead-seeking culture, both the old and the new practice might end up co-existing; this offers a plausible explanation for the often observed co-existence of different legacy practices in large organisations. In a behind-averse culture, the organisation may end up fully adopting the new practice but this depends on the upfront critical mass of adopters; this phenomenon is similar to herding or bandwagon behaviour. These results make apparent that the behavioural characteristics play a significant role in the eventual level of adoption of a new practice.

In addition, I identify some interesting interactions between management settings (a collective bonus reward or a collective bonus levy), the type of new practices (low risk-low return or high risk-return) and type of social comparisons (behind-averse or ahead-seeking) present in the organisation. First, for a given practice, in a ahead-seeking organisation, providing collective bonus will increase the number of adopters at equilibrium and collective levies will diminish it. In a behind-averse organisation, collective bonuses will decrease the critical mass of employees to train to induce adoption of the new practice and collective levies will increase it thus making adoption of the new practice at the organisation level harder. Second, in a ahead-seeking organisation, if an organisation puts in place collective bonus rewards, the low risk-low return practices will exhibit a higher adoption of the new practices than the high risk-high return practices, while, if it puts in place collective levies rewards, the high risk-high return practices will exhibit a higher adoption than the low risk low return practices. On the other hand, in a behind-averse organisation, if the organisation implements collective bonuses, low risk-low return practices needs a lower critical mass to induce full adoption in the organisation than high risk-high return practices. However, if the organisation puts in place collective levies, low risk-low return practices demand a higher critical mass (and may not be adopted) compared to high risk-high return practices.

Lastly, I explore the impact of learning while the organisation is in a coexistence scenario, i.e., with time as the organisation exhibits both practices at equilibrium, the new practice may become less risky as individuals learn more about it. I find that getting better at implementing the new practice (i.e., lower risk of adoption) does not always guarantee full adoption under collective levy rewards or low collective bonus. As the new practice gets less risky, the gain to adopt the old practice when meeting an adopter due to the ahead-seeking culture, diminishes which leads to full adoption. High collective bonuses reinforce this effect but collective levies decrease the benefit of adopting when meeting an adopter and the coexistence scenario can thus persist.

3.5.1 Theoretical contributions

This paper makes several contributions in the literature on technology management, practice adoption and behavioural decision-making. First, motivated by recent empirical findings and examples of adoption failures and successes in organisations, I identify and model a key behavioural mechanism that has been overlooked by the existing literature. Social comparisons moderated by an organisation culture can impact the adoption of practices and these are enhanced when the choices made that led to a different of performance are due to a difference in choice (Bault et al. 2011). In certain conditions the role of social comparisons is essential in determining whether adoption can be influenced by the initial investment in assembling a critical mass of employees to adopt the new practice. But, the organisation can decide to influence adoption through collective rewards (bonus or levies) to have the desired outcome. To my knowledge, this is also the first study that considers the combined effect of rewards mechanisms and social comparisons.

The second contribution is to propose an evolutionary game to model practice adoption. Past approaches have modelled it either in a static way through classic game theoretic modelling or dynamically using epidemiological models or simulations that do not take strategic interactions into account. Using a methodology with dynamic strategic interactions is critical for two main reasons. First, the nature of the key mechanism of social comparisons depends on choices made by other individuals. Therefore, as the state of adopters changes in the organisation, the way social comparisons and subsequent adoption or non-adoption are triggered, change endogenously with the state of the population. Secondly, the analytical model presented, incorporates key important features of decision-making highlighted in the organisation literature such as bounded rationality, myopic decisions influenced by feedback mechanisms but most analytical models tackling this problem assumes static decision-making, hyper-rationality, forward looking optimisation. This paper contributes in the broader sense to the effort of providing a more behavioural view of decision-making within organisations that some streams of the management and economics literature initiated, such as a behavioural theory of the firm (Cyert et al. 1963), the exploration vs exploitation literature (March 1991), evolutionary economics (Nelson 2009) and ambidexterity within firms (O'Reilly III and Tushman 2013). Some key assumptions of these streams are shared with this work such as bounded rationality and imitation mechanisms. While, these streams usually have been using simulations considering individuals as automata, I contribute to the broad behavioural literature by providing novel analytical models incorporating dynamic strategic interactions with individuals' choices changing depending on others' actions (relative dependent utility) even so the individuals are modelled as homogeneous.

The third contribution is that the results derived from this model could explain multiple empirical findings and bring novel insights. For example, ahead-seeking behaviour can create a scenario where both risky and safe practices can co-exist. This result unifies two empirical findings that may be seen as different but could in fact highlight a similar effect if a longer horizon would have been taken in the experiments. When many individuals stick with a safe practice, in a ahead-seeking organisation, individuals will start taking risky practices similar to the findings of Charness et al. (2013) who finds that unethical practices such as cheating and sabotaging to perform better than others were undertaken in such environment. On the other hand, when too many individuals undertake risky practices, it becomes advantageous to choose the old practice which is corroborated by Kramer et al. (2011) who finds that individuals tend to choose to stick with a safe choice and hope others will fail.

This model also supports the example mentioned in introduction regarding the adoption of medical practices. Based on this model, I could argue that these studies were conducted in a behind-averse environment as social comparisons led on one hand to conform to the other physicians by adopting the best practices performed by the top physicians in emergency departments (Song et al. 2017). The medical sector seems to exhibit a behind-averse environment and it may be due to the high pressure from society on the healthcare staff. Similarly, in an other medical study conducted among General practitioners (GPs) in England (Hallsworth et al. 2016), the authors studied the GPs prescription quantity of antibiotics to patients. To fight against the over prescription of antibiotics, the authors conducted experiments showing these high prescribers how much more compared to the average of all prescriptions, they were prescribing. This feedback on the use of others pushed the high-prescribers to conform to the lower prescribers and diminish their prescriptions.

The agricultural sector seems to exhibit both types of social comparisons. Organic farming is sometimes adopted by farmers in order to signal to other farmers that they possess a higher status (Dessart et al. 2019, Michel-Guillou and Moser 2006). Another study finds that farmers having reduced their water consumption may increase their usage if they are aware that peers have a higher consumption, leading to imitating less sustainable practices (Chabé-Ferret et al. 2019).

3.5.2 Managerial implications

This study provides a novel model describing a key mechanism of practice adoption and this normative analysis provides ways on which organisations can act. In this section, I discuss three main operational levers the organisation can choose from to influence adoption and I discuss how certain types of practices may benefit from one social comparison culture over another.

It is common to read in the press that organisations should influence adoption of new practices through training and by disseminating innovation champions in the organisation. But, I find that such strategy will not have the desired effect on employees in an organisation with a ahead-seeking culture. Organisations such as Huawei can expect the new and established practices to coexist. If the company wants to influence the adoption of the new risky practice, training or hiring individuals to influence others will not have the desired effect and providing additional benefits to employees to adopt such as collective bonus rewards is the best strategy to increase the adoption towards the new practice. On the other hand, in organisations such as Amazon or GE (under Jack Welch), a behind-averse culture can help the imitation of the new risky practice if a critical of mass is reached. In this context, disseminating innovation champions may work only if they are enough initially. In such situations, the organisation has a trade-off between using monetary rewards or training/hiring enough adopters of the new practice. But in such a culture, the whole organisation will adopt one of the two practices.

If the new practice presents only upside such as executing a task better e.g., the lean six sigma practice but is difficult to adopt at the beginning, an organisation may wish that all the employees adopt it in the long term. For this kind of practice, companies like Huawei need to be prepared to provide collective bonus rewards to increase adoption of the new practice, while organisations such as Amazon could use critical mass effects to reach their goal.
However, top management may not want everyone to adopt a novel practice. For example, the organisation may have a core activity which they need to continue developing thus they want their employees to continue using more classic practices in their work to produce value.

On the other hand, they want a few individuals to be able to take risky choices and enable some outside of the box thinking. In such scenario, a behind-averse culture is to avoid as it either creates an organisation that sticks to well established practices or on the other hand to adopting only risky practices. A ahead-seeking culture will allow the organisation to have both adopters and non-adopters of the new practice. But, this culture can also lead to the use of unethical practices as seen in one of the examples given in introduction. If such unfortunate scenario occurs, top management can use collective levy rewards to help reduce the adoption of the unethical practice. In an organisation with a behind-averse culture, such unethical practices can take over the whole organisation which can lead to a disastrous situation but the organisation can put in place collective levy rewards such that the critical mass needed for this unethical practice to take over, becomes very high.

3.5.3 Limitations and further research

The model presented in this paper could potentially be extended by overlapping an organisational structure that mediates the interactions of the individuals; in contrast, the current model assumes a very flat organisation in which individuals know the number of adopters and non-adopters in the organisation and the frequency of interactions is the same for all. Moreover, I assume homogeneity in this paper, in terms of culture present in the organisation and individuals' capability to successfully adopt the new practice. The effects of ahead-seeking and behind-averse cultures on individuals' performance, is the same throughout the organisation, as is their capability in successfully adopting new practices. Further research could examine the diffusion of new practices given heterogeneous staff, allowing individuals to have different capabilities, and given heterogeneous cultures, depending on the department in which the individual works (finance, engineering, human resources, etc.).

3.6 Appendix

3.6.1 Proof of Theorem 1

To prove that this differential equation approximates well the Markov process $\{X_t^n\}$, I adapt, to my model, a proof by Sandholm (2010) using conditions stated in Kurtz (1970) theorem on approximations of Markov jump processes.

Following Sandholm (2010) theorem, I calculate three functions of interest, the expected increment per unit of the Markov process $V^n(x)$, the expected absolute displacement per time unit, $A^n(x)$ and the expected absolute displacement per time unit due to jumps travelling further than δ, $A^n_{\delta^n}(x)$.

I define ζ_x^n a random variable whose distribution describes the stochastic increment of $\{X_t^n\}$ from state x such that $P(\zeta_x^n = z) = P^n_{x,x+z}$.

With e_i being the vector of population state of strategy i and $e_j - e_i$ being the displacement vector of state between two strategies j and i.

I compute the expected increment per unit the Markov process $\{X_t^n\}$: $V^n(x)$.

$$
\begin{aligned}
V^n(x) &= \lambda_x^n E[\zeta_x^n] \\
&= nR \sum_{i\in(O,N)} \sum_{j\neq i} \frac{1}{n}(e_j - e_i)P(\zeta_x^n = \frac{1}{n}) \\
&= nR \sum_{i\in(O,N)} \sum_{j\neq i} \frac{1}{n}(e_j - e_i)\frac{x_i\rho_{ij}(U(x),x)}{R} \\
&= nR \sum_{i\in(O,N)} \sum_{j\neq i} \frac{1}{n}(e_j - e_i)\frac{x_i x_j[U_j(x) - U_i(x)]_+}{R} \\
&= (e_O + e_N)(x(1-x)(U_N(x) - U_O(x))
\end{aligned}
$$

Thus, I have, $V^n(x) = x(1-x)(U_N(x) - U_O(x)$ (the differential equation of the paper) which is Lipschitz continuous so ensure existence and uniqueness of the solutions of the differential equation.

For the pair of new and old practice strategies, $|e_N - e_O| = \sqrt{2}$, thus leading the increments of the Markov process to be either of length $\frac{\sqrt{2}}{n}$ or 0.

I define the expected absolute displacement per time unit as, $A^n(x) = \lambda_x^n E[|\zeta_x^n|]$ and the expected absolute displacement per time unit due to jumps travelling further than δ as, $A^n_{\delta^n}(x) = \lambda_x^n E[|\zeta_x^n 1_{|\zeta_x^n > \delta^n|}|]$.

By setting, $\delta^n = \frac{\sqrt{2}}{n}$, I have that $A^n(x) \leq \frac{\sqrt{2}}{R}$ and $A^n_{\delta^n}(x) = 0$.

Thus obtaining the conditions given by Kurtz (1970) that prove that the Markov process is well approximated by $V^n(x)$.

3.6.2 Proof of Proposition 1

It is known following previous works in evolutionary game theory (Sandholm 2010, Weibull 1997) that for any symmetric 2x2 populations games, a population state is asymptotic stable in the corresponding mean dynamic iff the corresponding mixed strategy is evolutionary stable.

There exists a unique stable equilibria which corresponds to a mix of adopters and non adopters in the organisation (i.e., coexistence) x^* iff,

$$\begin{cases} pV_N < kV_N + \alpha(1-p)kV_N - \gamma(1-k)pV_N \\ \qquad pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N > kV_N \end{cases}$$
$$\Leftrightarrow \begin{cases} 0 < p < 1 \\ \alpha > \gamma > 0 \\ p - \dfrac{p(1-p)(\alpha-\gamma)}{1+\gamma p+(1-p)\alpha} < k < p + \dfrac{p(1-p)(\alpha-\gamma)}{1+\alpha p+(1-p)\gamma} \end{cases}$$

The stable interior fixed point is such that:
$U_N(x^*) = U_O(x^*) \Leftrightarrow x^* = \frac{k-p+\gamma k-\alpha p-kp(\gamma-\alpha)}{(\gamma-\alpha)(p-k(2p-1))}$

There exist two stable equilibria (bi-stability scenario) which correspond to the whole organisation to adopt the new practice if a critical mass is initially adopting otherwise no one adopts in the organisation iff,

$$\begin{cases} pV_N > kV_N + \alpha(1-p)kV_N - \gamma(1-k)pV_N \\ \qquad pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N < kV_N \end{cases}$$

$$\Leftrightarrow \begin{cases} 0 < p < 1 \\ \gamma > \alpha > 0 \\ p - \dfrac{p(1-p)(\gamma-\alpha)}{1+\alpha p+(1-p)\gamma} < k < p + \dfrac{p(1-p)(\gamma-\alpha)}{1+\gamma p+(1-p)\alpha} \end{cases}$$

The unstable interior fixed point is such that:
$U_N(x_0^*) = U_O(x_0^*) \Leftrightarrow x_0^* = \frac{k-p+\gamma k-\alpha p-kp(\gamma-\alpha)}{(\gamma-\alpha)(p-k(2p-1))}$

The full adoption scenario occurs, iff,

$$\begin{cases} pV_N > kV_N + \alpha(1-p)kV_N - \gamma(1-k)pV_N \\ pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N > kV_N \end{cases} \Leftrightarrow$$

$$\begin{cases} 0 < p < 1 \\ \alpha > \gamma > 0 \\ 0 < k < p - \dfrac{p(1-p)(\alpha-\gamma)}{1+\gamma p+(1-p)\alpha} \end{cases} \text{and} \begin{cases} 0 < p < 1 \\ \gamma > \alpha > 0 \\ 0 < k < p - \dfrac{p(1-p)(\gamma-\alpha)}{1+\alpha p+(1-p)\gamma} \end{cases}$$

The no-adoption scenario occurs,iff,

$$\begin{cases} pV_N < kV_N + \alpha(1-p)kV_N - \gamma(1-k)pV_N \\ pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N < kV_N \end{cases} \Leftrightarrow$$

$$\begin{cases} 0 < p < 1 \\ \alpha > \gamma > 0 \\ p + \dfrac{p(1-p)(\alpha-\gamma)}{1+\alpha p+(1-p)\gamma} < k < 1 \end{cases} \text{and} \begin{cases} 0 < p < 1 \\ \gamma > \alpha > 0 \\ p + \dfrac{p(1-p)(\gamma-\alpha)}{1+\gamma p+(1-p)\alpha} < k < 1 \end{cases}$$

3.6.3 Proof of Corollary 1

I find the evolutionary stable strategies of the game in the case when $k = p$ (high risk high return assumption) which also allow us to normalise $\alpha \in [0,1]$ and $\gamma = 1-\alpha$.

There are two evolutionary stable strategies (asymptotic stable states) that occur for the game studied: coexistence and bi-stability.

There exists a unique stable equilibria which corresponds to a mix of adopters and non adopters in the organisation (i.e., coexistence) iff,

$$\begin{cases} pV_N + \alpha(1-p)pV_N - (1-\alpha)p(1-p)V_N > pV_N \\ pV_N + \alpha p(1-p)V_N - (1-\alpha)(1-p)pV_N > pV_N \end{cases} \Leftrightarrow \begin{cases} \alpha > \dfrac{1}{2} \\ \alpha > \dfrac{1}{2} \end{cases}$$

$\forall \alpha > \frac{1}{2}$, $\forall p \in [0,1[$, it is a coexistence scenario and there exists a stable mix of adopters and non adopters $x^*_{\text{co-ex}} = \frac{1}{2}$.

There exist two stable equilibria (bi-stability scenario) which correspond to the whole organisation to adopt the new practice if a critical mass is initially adopting otherwise no one adopts in the organisation iff,

$$\begin{cases} pV_N + \alpha(1-p)pV_N - (1-\alpha)p(1-p)V_N < pV_N \\ pV_N + \alpha p(1-p)V_N - (1-\alpha)(1-p)pV_N < pV_N \end{cases} \Leftrightarrow \begin{cases} \alpha < \dfrac{1}{2} \\ \alpha < \dfrac{1}{2} \end{cases}$$

Thus $\forall p \in]0,1[$, $\forall \alpha < \frac{1}{2}$, it is a bi-stability scenario and the critical mass is equal to $x^*_0 = \frac{1}{2}$.

3.6.4 Proofs of Proposition 2 and Proposition 3

Similar to the proof of Proposition 1 and Corollary 1, I derive the evolutionary stable strategies.

There exists a unique stable equilibrium which corresponds to a mix of adopters and non adopters in the organisation (i.e., coexistence) iff,

$$\begin{cases} pV_N + \alpha(1-p)pV_N - (1-\alpha)p(1-p)V_N > \dfrac{p^2V_N}{\beta} + p(1-p)V_N \\ pV_N + \alpha p(1-p)V_N - (1-\alpha)(1-p)pV_N > pV_N \end{cases}$$

$$\Leftrightarrow \begin{cases} \alpha > \dfrac{\frac{p^2}{\beta} - p^2 + 2p - p(1+p)}{p + p(1-2p)} \\ \alpha > \dfrac{2p - p(1+p)}{p + p(1-2p)} \end{cases} \forall p \in [0,1[$$

$$\Leftrightarrow \begin{cases} \alpha > \dfrac{1 + p\frac{1-2\beta}{\beta}}{2(1-p)} = \alpha_1 \\ \alpha > \dfrac{1}{2} \end{cases}$$

$\forall \beta \geq 1, \alpha_1 \leq \frac{1}{2}$
$\forall \beta \in]0,1[\alpha_1 > \frac{1}{2}$ $\alpha_1 \leq 1 \Leftrightarrow p < \beta$

Thus $\forall \beta \in]0,1[$, $\forall \alpha > \alpha_1$, $\forall p < \beta$ and $\forall \beta \geq 1$, $\forall \alpha > \frac{1}{2}$, $\forall p \in [0,1[$, it is a coexistence scenario and there exists a stable mix of adopters and non adopters $x^*_{\text{co-ex}} = \frac{1}{2+\frac{p(1-\beta)}{(1-p)\beta(1-2\alpha)}}$.

There exist two stable equilibria (bi-stability scenario) which correspond to the whole organisation adopting the new practice if a critical mass initially adopts and otherwise no one in the organisation adopts iff,

$$\begin{cases} pV_N + \alpha(1-p)pV_N - (1-\alpha)p(1-p)V_N < \dfrac{p^2V_N}{\beta} + p(1-p)V_N \\ pV_N + \alpha p(1-p)V_N - (1-\alpha)(1-p)pV_N < pV_N \end{cases}$$

$$\Leftrightarrow \begin{cases} \alpha < \dfrac{\frac{p^2}{\beta} - p^2 + 2p - p(1+p)}{p + p(1-2p)} = \alpha_1 \\ \alpha < \dfrac{2p - p(1+p)}{p + p(1-2p)} = \dfrac{1}{2} \end{cases} \forall p \in [0,1[$$

$\forall \beta \in]0,1], \alpha_1 > \frac{1}{2}$
$\forall \beta > 1$, $\alpha_1 \leq \frac{1}{2}$ and $\alpha_1 > 0 \Leftrightarrow p < \frac{\beta}{2\beta-1} (< 1)$

Thus $\forall \beta \in [0,1]$, $\forall p \in]0,1[$, $\forall \alpha < \frac{1}{2}$ and $\forall \beta > 1$, $\forall 0 < p < \frac{\beta}{2\beta-1}$,$\forall \alpha < \alpha_1$, it is a bi-stability scenario and the critical mass is equal to $x^*_0 = \frac{1}{2+\frac{p(1-\beta)}{(1-p)\beta(1-2\alpha)}}$.

There exists a unique stable equilibrium which corresponds to full adoption in the organisation iff,

$$\begin{cases} pV_N + \alpha(1-p)pV_N - (1-\alpha)p(1-p)V_N < \dfrac{p^2V_N}{\beta} + p(1-p)V_N \\ pV_N + \alpha p(1-p)V_N - (1-\alpha)(1-p)pV_N > pV_N \end{cases}$$

$$\Leftrightarrow \begin{cases} \alpha < \dfrac{\frac{p^2}{\beta} - p^2 + 2p - p(1+p)}{p + p(1-2p)} = \alpha_1 \\ \alpha > \dfrac{2p - p(1+p)}{p + p(1-2p)} = \dfrac{1}{2} \end{cases} \forall p \in [0,1[$$

$\forall \beta \geq 1$, this system of equations is not feasible so full adoption does not exist.
$\forall \beta \in]0,1[, \alpha_1 \geq \frac{1}{2}$ and $\alpha_1 < 1, \forall p < \beta$.

Thus, $\forall\beta \in]0,1[\forall\alpha$ such as $0<\alpha<\alpha_1$ when $p<\beta$ and $\forall\alpha$ such as $\frac{1}{2}<\alpha\leq 1$ when $\beta\leq p<1$, there is full adoption in the organisation.

There is a unique stable equilibrium where no one adopts in the organisation iff,

$$\begin{cases} pV_N+\alpha(1-p)pV_N-(1-\alpha)p(1-p)V_N > \dfrac{p^2V_N}{\beta}+p(1-p)V_N \\ pV_N+\alpha p(1-p)V_N-(1-\alpha)(1-p)pV_N < pV_N \end{cases}$$

$$\Leftrightarrow \begin{cases} \alpha > \dfrac{\frac{p^2}{\beta}-p^2+2p-p(1+p)}{p+p(1-2p)} = \alpha_1 \\ \alpha < \dfrac{2p-p(1+p)}{p+p(1-2p)} = \dfrac{1}{2} \end{cases} \quad \forall p \in [0,1[$$

$\forall\beta \in]0,1]$, this system of equations is not feasible so the no-adoption scenario does not exist. $\forall\beta>1$, it follows that $\alpha_1<\frac{1}{2}$, $\alpha_1\geq 0 \Leftrightarrow p\leq\frac{\beta}{2\beta-1}$.

Thus, $\forall\beta>1$, $\forall\alpha$ such as $\alpha_1<\alpha<\frac{1}{2}$ when $0<p\leq\frac{\beta}{2\beta-1}$ and $\forall\alpha$ such as $0\leq\alpha<\frac{1}{2}$ when $\frac{\beta}{2\beta-1}\leq p<1$, there is no adoption in the organisation.

3.6.4.1 Robustness analysis

Without any collective rewards in place ($\beta=1$), coexistence occurs when $\alpha>\gamma>0$, $0<p<1$ and $p-\frac{p(1-p)(\alpha-\gamma)}{1+\gamma p+(1-p)\alpha}<k<p+\frac{p(1-p)(\alpha-\gamma)}{1+\alpha p+(1-p)\gamma}$.

In this region, when collective rewards β are introduced, the coexistence region stills exists, ie,

$$\begin{cases} pV_N+\alpha(1-p)kV_N-\gamma p(1-k)V_N > \dfrac{p^2V_N}{\beta}+p(1-p)V_N \\ pV_N+\alpha p(1-k)V_N-\gamma(1-p)kV_N > pV_N \end{cases}$$

when $\beta>1$ and $\frac{p^2}{k(1+\alpha)-p(1+\gamma+\alpha k-\gamma k-p)}<\beta<1$

as well as the full adoption region,ie.,

$$\begin{cases} pV_N+\alpha(1-p)kV_N-\gamma p(1-k)V_N < \dfrac{p^2V_N}{\beta}+p(1-p)V_N \\ pV_N+\alpha p(1-k)V_N-\gamma(1-p)kV_N > kV_N \end{cases}$$

when $0<\beta<\frac{p^2}{k(1+\alpha)-p(1+\gamma+\alpha k-\gamma k-p)}$.

Bi-stability and no-adoption do not occur when collective rewards are introduced when $\alpha > \gamma > 0$, $0 < p < 1$ and $p - \frac{p(1-p)(\alpha-\gamma)}{1+\gamma p+(1-p)\alpha} < k < p + \frac{p(1-p)(\alpha-\gamma)}{1+\alpha p+(1-p)\gamma}$.

Without any collective rewards in place ($\beta = 1$), bi-stability occurs when $0 < \alpha < \gamma$, $0 < p < 1$ and $p - \frac{p(1-p)(\gamma-\alpha)}{1+\alpha p+(1-p)\gamma} < k < p + \frac{p(1-p)(\gamma-\alpha)}{1+\gamma p+(1-p)\alpha}$.

In this region, when collective rewards β are introduced, the bi-stability region stills exists, ie,

$$\begin{cases} pV_N + \alpha(1-p)kV_N - \gamma p(1-k)V_N < \dfrac{p^2V_N}{\beta} + p(1-p)V_N \\ pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N < kV_N \end{cases}$$

when $0 < \beta < 1$ and for a range of values $\beta > 1$ (exact expression found using a software such as Mathematica but too heavy algebrically to put in this appendix).

as well as the no-adoption region, ie.,

$$\begin{cases} pV_N + \alpha(1-p)kV_N - \gamma p(1-k)V_N < \dfrac{p^2V_N}{\beta} + p(1-p)V_N \\ pV_N + \alpha p(1-k)V_N - \gamma(1-p)kV_N < kV_N \end{cases}$$

for a range of values $\beta > 1$ (exact expression found using a software such as Mathematica but too heavy algebrically to put in this appendix).

Coexistence and full adoption do not exist when collective rewards are introduced when $0 < \alpha < \gamma$, $0 < p < 1$ and $p - \frac{p(1-p)(\gamma-\alpha)}{1+\alpha p+(1-p)\gamma} < k < p + \frac{p(1-p)(\gamma-\alpha)}{1+\gamma p+(1-p)\alpha}$.

3.6.5 Proof of Proposition 4

I introduce first two auxiliary Lemmas which qualitatively describe the behaviour $\hat{\alpha}_1(p,\beta)$ and $\hat{\alpha}_2(p,\beta)$ from (3.3).

Lemma 1 *When the organisation establishes collective bonus rewards for the adoption of a practice , i.e., $\beta < 1$, then $\hat{\alpha}_1(p,\beta)$ decreases in β, and is convex and increasing in p. However under collective levy rewards ($\beta > 1$), $\hat{\alpha}_1(p,\beta)$ decreases in both β and p, and $\hat{\alpha}_1$ is concave with respect to p.*

Proof of Lemma 1

$\frac{d\alpha_1}{d\beta} = -\frac{p}{2(1-p)\beta^2} < 0 \; \forall \beta$
$\frac{d\alpha_1}{dp} = \frac{2(1+\frac{1-2\beta}{\beta})}{4(1-p)^2}$

$\frac{d\alpha_1}{dp} > 0\ \forall\beta < 1$ and $\frac{d\alpha_1}{dp} < 0\ \forall\beta > 1$
$\frac{d^2\alpha_1}{dp^2} < 0\ \forall\beta < 1$ and $\frac{d^2\alpha_1}{dp^2} > 0\ \forall\beta > 1$

Lemma 2 *When an organisation establishes collective bonus rewards for the adoption of a new practice, i.e., $\beta < 1$, then $\hat{p}_1$ increases in β.*
However under collective levy rewards ($\beta > 1$), $\hat{p}_2$ decreases in β.

Proof of Lemma 2

$\frac{d\overline{p_1}}{d\beta} = \frac{d\beta}{\beta} = 1 > 0$
$\frac{d\overline{p_2}}{d\beta} = \frac{d(\frac{\beta}{2\beta-1}}{d\beta} = -\frac{1}{(2\beta-1)^2} < 0\ \forall\beta$

It follows from lemmas 1 and 2 that the coexistence region diminishes when the collective bonus reward decreases while the bi-stability region decreases when the collective levy reward increases.

3.6.6 Proof of Corollary 2

This corollary is a direct consequence of Propositions 2 and 3.
As $\beta \to 0$, the coexistence region will always exist iff $p < \beta$ and $\alpha > \hat{\alpha}_1$.
As $\beta \to \infty$, the bi-stability region will always exist iff $p < \frac{1}{2}$ and $\alpha < \hat{\alpha}_1$.

3.6.7 Proof of Proposition 5

When $\alpha < \frac{1}{2}, \frac{dx_0^*}{d\beta} > 0$ and when $\alpha > \frac{1}{2}, \frac{dx^*_{\text{co-ex}}}{d\beta} < 0$ which lead to the results highlighted by the proposition.

3.6.8 Proof of Proposition 6

When $\alpha < \frac{1}{2}, \frac{dx_0^*}{dp} < 0$ if $\beta < 1$ and $\frac{dx_0^*}{dp} > 0 if \beta > 1$
When $\alpha > \frac{1}{2}, \frac{dx^*_{\text{co-ex}}}{dp} < 0$ if $\beta > 1$ and $\frac{dx^*_{\text{co-ex}}}{dp} > 0$ if $\beta < 1$

3.6.9 Proof of Proposition 7

I study here the local stability of the dynamical system presented in Section 3.4.3. This system admits 6 fixed points but as $\varepsilon > 0$, p increases over time so I can simplify my analysis and study the stability of the following 3 fixed points: $(0,\bar{p})$, $(1,\bar{p})$ and $(x^* =$

$\frac{\beta(-(1+\alpha)\bar{p}+k(1+\gamma+\bar{p}(\alpha-\gamma)))}{\bar{p}^2(1-\beta)+\beta(\gamma(k+\bar{p}-2k\bar{p})+\alpha(-\bar{p}+k(2\bar{p}-1)))}, \bar{p})$. x^* is defined in the boundary of the problem ($k = p(0) < \bar{p} \leq 1$ and $\alpha > \gamma$, ie. in the coexistence region) when:

$$\begin{cases} \dfrac{\bar{p}(1+\gamma-\bar{p})}{1+\alpha+\bar{p}(\gamma-\alpha)} < k < \bar{p} \\ \qquad\qquad\qquad \beta > \dfrac{\bar{p}^2}{k(1+\alpha)+\bar{p}(\bar{p}+k(\gamma-\alpha)-\gamma-1)} \end{cases}$$

I assume in the following analysis $\varepsilon = 1$ without loss of generality. The Jacobian of the system at each of the 3 fixed points is a triangular matrix thus the eigenvalues can be read in the diagonal:

$J(0,\bar{p}) = \begin{bmatrix} V_N((1+\alpha)\bar{p}+k(\gamma(\bar{p}-1)-1-\alpha\bar{p})) & 0 \\ 0 & -1 \end{bmatrix}$ This fixed point is unstable (eigenvalues of opposite sign) in the boundary of the problem.

$$J(1,\bar{p}) = \begin{bmatrix} (-\frac{\bar{p}^2}{\beta}+\bar{p}(-1-\gamma+\bar{p})+k(1+\alpha+\bar{p}(\gamma-\alpha)))V_N & 0 \\ 0 & -1 \end{bmatrix}$$

The above fixed point is stable (both eigenvalues real negative) for the following conditions and unstable otherwise:

$$\begin{cases} 0 < k \leq \dfrac{\bar{p}(1+\gamma-\bar{p})}{1+\alpha+\bar{p}(\gamma-\alpha)} \\ 0 < \beta \end{cases} \quad \text{and} \quad \begin{cases} \dfrac{\bar{p}(1+\gamma-\bar{p})}{1+\alpha+\bar{p}(\gamma-\alpha)} < k < \bar{p} \\ \qquad\qquad 0 < \beta < \dfrac{\bar{p}^2}{k(1+\alpha)+\bar{p}(\bar{p}+k(\gamma-\alpha)-\gamma-1)} \end{cases}$$

$$J(x^*,\bar{p}) = \begin{bmatrix} V_N \frac{(\beta(1+\gamma-\bar{p})\bar{p}+\bar{p}^2+\beta k(-1+\alpha(\bar{p}-1)-\gamma\bar{p}))(-(1+\alpha)\bar{p}+k(1+\gamma+\bar{p}(\alpha-\gamma)))}{\bar{p}^2(1-\beta)+\beta\gamma(k+\bar{p}-2k\bar{p})+\alpha\beta(-\bar{p}+k(-1+2\bar{p}))} & C \\ 0 & -1 \end{bmatrix}$$

The constant C in the Jacobian is a heavy algebric expression and is not expressed as it is not needed to find the stability of the fixed point due to its triangular Jacobian. This fixed point is stable (both eigenvalues are real negative) under the following conditions and unstable otherwise:

$$\begin{cases} \dfrac{\bar{p}(1+\gamma-\bar{p})}{1+\alpha+\bar{p}(\gamma-\alpha)} < k < \bar{p} \\ \qquad\qquad\qquad \beta > \dfrac{\bar{p}^2}{k(1+\alpha)+\bar{p}(\bar{p}+k(\gamma-\alpha)-\gamma-1)} \end{cases}$$

Chapter 4

Wide vs narrow bridges. Can collaboration between teams hurt the adoption of new practices?

4.1 Introduction

The adoption of new operational practices in organisations is critical to firms for their growth of capabilities and ultimately to their survival (Cool et al. 1997). Yet, it is not an easy task. As discussed in Chapter 2, the topic has been explored extensively in the literature across different fields to explain its underlying mechanisms. In particular, the broad literature highlights two keys factors influencing adoption in an organisation: the uncertainty surrounding a new practice (Abrahamson and Rosenkopf 1993, Levinthal and March 1993) and the social context/interactions between members of the organisation. As seen in Chapter 3, the social context has a critical effect on the relative benefits of adoption between individuals created by behavioural biases such as social comparisons.

Past literature has advocated that encouraging collaborations between teams that successfully adopted a new practice and other teams that did not adopt yet, help adoption due to the sharing of knowledge. However, there are instances where adoption still does not happen. A striking and one of the most infamous examples of such instances comes from General Motors (GM) when they entered into an alliance with Toyota Motor Co. in their Freemont, CA, plant, named New United Motor Manufacturing (NUMMI) in 1984. Their objective was to induce their personnel into adopting Toyota's lean manufacturing and total quality management practices, through imitation and learning-by-doing (Adler et al. 1997). Interestingly, while at the start, Toyota's practices effectively disseminated from the Japanese experts' team to the US teams in NUMMI, constituting a temporary success, the subsequent efforts at other GM plants provoked strong reactions, which made further adoption extremely limited. The eventual failure to replicate NUMMI's success became a legendary story of failure to modernise GM, and at some level synonymous with the decline of America's auto industry (Langfitt 2010).

This practical example shows the importance of group interactions in the context of adoption as collaboration first helped adoption within NUMMI but failed between NUMMI's teams and other US plants' teams. A plausible explanation of such failure may have been that the NUMMI teams and the teams in the other US plants experienced different relative benefits to adopt the new practice due to their heterogeneities in capabilities and attitudes towards the new practice (type of social comparisons). In this paper, I investigate how the level of group interactions (wide or narrow bridges (Centola 2018)) between two teams with different characteristics (heterogeneous in their capabilities to adopt and in the type of social comparisons they experience) monitor the level of relative benefits experienced by individuals and thus the overall adoption outcome.

The notion of bridges between teams has been deemed critical to the adoption of new practices (Centola 2019) as well as between communities to enhance cooperation (Fotouhi et al. 2018). Bridges are links between two teams or groups in terms of social connections. For example, bridges are said to be narrow if team members mainly interact within their own team. But, if individuals from each team have multiple contacts with members of the other team then these two units have wide bridges. Wide bridges have been deemed beneficial for diffusion of innovations as they create social reinforcement which is needed for adopting new practices (complex contagion, see Centola (2018) and Centola and Macy (2007)).

However, the uncertain utility in adopting successfully the new practice may be felt differently by individuals in an organisation. Some teams may be composed of individuals of higher capability to adopt successfully a new practice due to their training or education background. For example, organisations such as Google and Uber create star teams with high performing individuals (GoogleX and UberX respectively) and isolate them from the rest of the organisation. Heterogeneity can also occur when teams exhibit different types of social comparisons due to management styles or the type of work they perform (finance vs engineering). One may be more likely to reward individuals who outperform others (ahead-seeking) and another may have a more punishing culture that does not allow individuals to fail (behind-averse) (Baldwin and Mussweiler 2018).

My results offer guidelines to organisations trying to diffuse new practices between teams that are heterogeneous, highlighting the effect of social comparisons on the adoption outcome. They answer some interesting questions for management on whether it is beneficial for the organisation to isolate star teams with high capabilities and if encouraging collaboration between teams with different cultures or management styles is beneficial. I find that when heterogeneous teams interact, wide and narrow bridges have different effects on these teams. In certain circumstances, wide bridges can benefit adoption overall or in only one of the teams. In other cases, narrow bridges can help better adoption but depends on the number of adopters initially present in the two teams thus, upfront training investment may be needed to drive overall adoption.

After reviewing the related literature in the next section, I present the model set-up in Section 4.3. After, I analyse the model and present my results in Section 4.4 to finally conclude with the main insights and limitations of the study in Section 4.5.

4.2 Related literature

This study contributes mainly to three streams of research: practice adoption under heterogeneity and diversity, peer effects and social comparisons, and team staffing management.

The literature on practice adoption highlights that heterogeneity in skills has an impact on the adoption of a new uncertain practice (Caselli and Coleman 2001, Rosenberg 1972) as individuals may have different thresholds of adoption. Moreover, empirical evidence suggests that diversity in a population helps adoption of a new technology. In particular, the literature on new technology adoption also highlights that the social context enables individuals to update their beliefs or imitate the action of others to gather information when the environment is too uncertain. The organisation literature points out that individuals tend to discount their own beliefs in organisation and value more others' actions. Recent research in economics finds that seeding high capability individuals to adopt the new practice helps the practice to diffuse well in the community rather than seeding the new practice randomly (BenYishay and Mobarak 2018).

A number of research studies from various disciplines have emphasized the role of inter-team or inter-group interactions in the adoption of new practices and the performance of an organisation. In the operations management literature there has traditionally been a focus on inter-factory/plant communication and training exchanges to help employees gain knowledge about new know-how practices and ultimately advance the diffusion process (Ferdows et al. 2016, Vereecke et al. 2006). The manufacturing literature defines in particular two types of plants: *isolated* and *active* factory (De Meyer and Vereecke 2009). This classification is given by the authors to define the role they play in transferring knowledge (about an innovation or new practice as well as level of communication between members of the plants). In an isolated plant, employees tend to have most of their interactions within the plant and limited interactions with other plants. Members of an active network factory, on the other hand, have most of their interactions with other plants' members.

The organisation literature has also highlighted the role of social interactions within and between teams and how to manage this human resource capital. Employees may interact a lot within their unit and little with other units or on the contrary, they may interact very little within their team and mainly with other teams. This stream of research emphasizes the importance of understanding the relational ties of team members as well as the existence of formal or informal groups within the organisation as a competitive advantage to achieve greater organisational performance through better information flow (Hollenbeck and Jamieson 2015).

In the management and sociology literature (Centola 2018), social interactions have been deemed to play a key role to the adoption of new behaviour and new practices in general. One of the first main concepts on the topic has been Granovetter's notion of weak ties (Granovetter 1977) which is broadly similar to the notion of narrow bridges Centola (2019). According to Granovetter, targeting weak ties to spread an idea help individuals reach communities outside of your circle, improving the diffusion of information or ideas in the population. However, such diffusions are called simple contagion, whereas adopting a new practice or a new technology is considered a complex contagion (Beaman et al. 2018). The complex contagion literature stream argues that creating wide bridges and strong ties may lead to better adoption than narrow bridges and weak ties (Centola 2019). Social reinforcement through multiple links and trust through strong ties are crucial in new practice adoption.

Complexity in adopting new practices is also due to the impact of the social context on individual decisions. As mentioned above, the social context plays an important role in the adoption of new practices. Empirical evidence shows that adoption of new practices can be driven by considerations such as internal competition. Certain practices that bring less value to the individual are sometimes adopted because outperforming another matters more. This literature hints at the effect of social comparisons on adoption of new technologies. Social comparisons have been recently studied theoretically (Ashraf and Bandiera 2018, Roels and Su 2013) and empirically (Tan and Netessine 2019) in performance comparisons between workers. Tan and Netessine (2019) show that they can schedule teams of waiters by taking into account peer effects that arise in order to improve their performance. The literature on peer effects highlights two main areas: ahead-seeking and behind-averse social comparisons (Sobel 2005). As highlighted in Chapter 3, most of the literature focuses on social comparisons that arise when there is a difference in performances. However, recent studies in decision making under uncertainty (Lahno and Serra-Garcia 2015) and neuroscience (Bault et al. 2011) highlight that social comparisons are heightened when a different decision leads to a different outcome. Similar to Chapter 3, I model social comparisons in such a way and evaluate adoption patterns that arise from dynamic strategic interactions between individuals. However, contrary to Chapter 3 that assumes all individuals homogeneous in their capability and the type of social comparisons (ahead-seeking or behind-averse) experienced, I allow, in this paper, social interactions between heterogeneous teams that trigger heterogeneous social comparisons effects.

I contribute to the literature in the following aspects. First, I broaden the impact of social comparisons in adoption of new practices (Chapter 3) by including social interactions between heterogeneous groups in capabilities and in the type of social comparisons they experience. Secondly, this paper provides insights on how to social engineer adoption of new practices with the use of wide and narrow bridges as an important operational lever for organisations and the adoption benefits for the organisation. Lastly, this paper adds new elements to the debate on complex contagion of new practice in organisations and the use of wide vs narrow bridges to enhance the diffusion of innovations (Centola 2019, Fotouhi et al. 2018). While the argument given to promote wide bridges for diffusion is due to social reinforcement of information, I argue that by taking the social comparisons into account, wide bridges may not always be the best way to promote adoption.

4.3 Model set-up

In this section, I develop an evolutionary game theoretical model to describe an organisational setting where two teams interact. Employees from both teams can choose either to adopt a novel operational practice denoted with the subscript N and delivering a utility U_N or to stick with the previous well mastered operational practice with subscript O and utility U_O.

Following the tradition in evolutionary games, my model has two main components: the utility that each individual receives based on interactions with individuals (games) and the population dynamic tracking the evolution of the use of each practice over time that arises from these interactions (Weibull 1997).

The utility that each employee perceives has three layers: economic benefits which an individual receives in the form of rewards induced by the organisation, social comparisons which are triggered when individuals undertake different practices which lead to a difference in outcomes, and finally the random pairwise matching which mediates the value of the utility depending on the current amount of employees who have chosen the new or the old practice. The pairwise matching may induce an interaction between two members of the same team or members of different teams[1]. I define the parameter $\delta \in [0,1]$ as the level of interactions employees have within their own team and $1-\delta$, the level of interactions employees have with members of the other team. At the extreme, $\delta = 1$ corresponds to narrow bridges in which there are no interactions between the two teams. On the other hand, $\delta = 0$ corresponds to the extreme case of wide bridges in which individuals of a team only interact with individuals of the other team.

I explore the adoption of new practices in the organisations when two teams, denoted by the respective subscripts i and j, are heterogeneous in their capabilities and in the way they experience social comparisons.

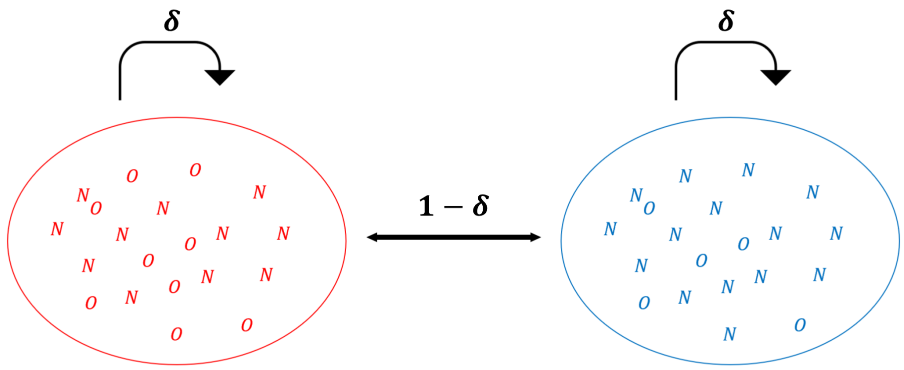

Fig. 4.1 Organisation with 2 teams interacting

[1]This model contributes to the growing literature in theoretical economics on evolutionary games with heterogeneous levels of of interactions (Khalifa et al. 2017).

In the following two sections, I explore three different scenarios which lead to three different game set-ups. In Section 4.3.1, both teams have same capabilities, i.e., $p_i = p_j = p$ and experience different social comparisons. In Section 4.3.2, both teams have same social comparisons, in one case both are ahead-seeking and in the other case both are behind-averse. In each of these two scenarios, the two teams have different capabilities, i.e., $p_i \neq p_j$.

4.3.1 Payoff matrix at the micro-level when teams have heterogeneous social comparisons but the same capabilities

Economic benefits in the form of rewards

Employees in both teams can choose to adopt a new uncertain practice N whose value is V_N if successfully adopted with a probability $p \in]0,1[$. If the successful adoption of the new practice fails, the members of the teams receive 0. The employees can decide to stick with the old practice O that they have already mastered, thus being rewarded V_O with a likelihood of success equal to 1. We define $V_O = kV_N$ where $k \in]0,1[$ such that $0 < V_O = kV_N < V_N$.

Social comparisons

In this setting, the members of team i experience ahead-seeking social comparisons. I introduce the parameter α as the degree to which the employees in team i enjoy being ahead and having made the correct choice of practice compared to the employee they are paired with.

On the other hand, the members of team j experience behind-averse social comparisons. I denote the parameter γ which weighs the behind-averse feeling of being behind against an employee who made a different choice of practice.

Table 4.1 displays the utility an employee of team i interacting with a member of his team i, or with a member of team j receives depending on the random matching. Table 4.2 displays the utility an employee of team j interacting with another member of team i or j receives depending on the random matching.

Table 4.1 Payoff matrix when a member of team i interacts with another member of team i or j (heterogeneity in social comparisons setting)

		Team i/j	
		N	O
Team i	N	$U_{NN}^{ii} = U_{NN}^{ij} = pV_N$	$U_{NO}^{ii} = U_{NO}^{ij} = pV_N + \alpha p(1-k)V_N$
	O	$U_{ON}^{ii} = U_{ON}^{ij} = kV_N + \alpha(1-p)kV_N$	$U_{OO}^{ii} = U_{OO}^{ij} = kV_N$

Table 4.2 Payoff matrix when a member of team j interacts with another member of team i or j (heterogeneity in social comparisons setting)

		Team j/i	
		N	O
Team j	N	$U_{NN}^{jj} = U_{NN}^{ji} = pV_N$	$U_{NO}^{jj} = U_{NO}^{ji} = pV_N - \gamma(1-p)kV_N$
	O	$U_{ON}^{jj} = U_{ON}^{ji} = kV_N - \gamma p(1-k)V_N$	$U_{OO}^{jj} = U_{OO}^{ji} = kV_N$

4.3.2 Payoff matrices at the micro-level when teams have heterogeneous capabilities but same social comparisons

Economic benefits in the form of rewards

In this setting, team j members have a better aptitude to successfully adopt the new practice than members of team i. In other words, team i members have a likelihood p_i of successfully adopting the new practice and extracting the value V_N while team j members have a probability of success p_j with $p_i < p_j$. Similarly to the previous setting, all team members can choose to stick with the old practice O that they have already mastered (probability of success equal to 1) and get a value V_O. We define respectively for team i members and team j members $V_O^i = k_i V_N$ and $V_O^j = k_j V_N$ with $k_i < k_j \in]0,1[$. As the team members have different capabilities of successfully adopting the new practice, we also assume that they do not extract the same value from choosing the old practice.

Social comparisons

I look at two separate scenarios: when the organisation environment is ahead-seeking and when it is behind-averse. Due to the heterogeneity in capabilities between the two teams, an individual will not experience the same utility when interacting with a fellow team member or interacting with a member from the other team (because of the social comparisons), thus leading to the following payoff matrices.

In a ahead-seeking organisation:

Table 4.3 displays the utility two members of the same team i receive by interacting with each other depending on the random matching. Table 4.4 displays the utility a member of team i receives when interacting with a member of team $j \neq i$ depending on the random matching.

Table 4.3 Payoff matrix when two members of team i interact in a ahead-seeking organisation (heterogeneity in capabilities setting)

		Team i: N	Team i: O
Team i	N	$U^{ii}_{NN} = p_i V_N$	$U^{ii}_{NO} = p_i V_N + \alpha p_i (1-k_i) V_N$
	O	$U^{ii}_{ON} = k_i V_N + \alpha (1-p_i) k_i V_N$	$U^{ii}_{OO} = k_i V_N$

Table 4.4 Payoff matrix when a member of team i and a member of team j interact in a ahead-seeking organisation (heterogeneity in capabilities setting)

		Team j: N	Team j: O
Team i	N	$U^{ij}_{NN} = p_i V_N$	$U^{ij}_{NO} = p_i V_N + \alpha p_i (1-k_i) V_N$
	O	$U^{ij}_{ON} = k_i V_N + \alpha (1-p_j) k_i V_N$	$U^{ij}_{OO} = k_i V_N$

Similarly, by replacing j with i in Tables 4.3 and 4.4, the payoff matrices when two members of team j interact and when a member of team j interacts with a member of team i can be obtained.

In a behind-averse organisation:

Table 4.5 displays the utility members of the same team i receive when interacting with each other depending on the random matching. Table 4.6 displays the utility a member of team i interacting with a member of team $j \neq i$ receives depending on the random matching.

Similarly, by replacing j with i in Tables 4.5 and 4.6, the payoff matrices when two members of team j interact and when a member of team j interacts with a member of team i can be obtained.

Table 4.5 Payoff matrix when two members of team i interact in a behind-averse organisation (heterogeneity in capabilities setting)

		Team i	
		N	O
Team i	N	$U^{ii}_{NN} = p_i V_N$	$U^{ii}_{NO} = p_i V_N - \gamma p_i (1-k_i) V_N$
	O	$U^{ii}_{ON} = k_i V_N - \gamma(1-p_i) k_i V_N$	$U^{ii}_{OO} = k_i V_N$

Table 4.6 Payoff matrix when a member of team i and a member of team j interact in a behind-averse organisation (heterogeneity in capabilities setting)

		Team j	
		N	O
Team i	N	$U^{ij}_{NN} = p_i V_N$	$U^{ij}_{NO} = p_i V_N - \gamma p_i (1-k_i) V_N$
	O	$U^{ij}_{ON} = k_i V_N - \gamma(1-p_j) k_i V_N$	$U^{ij}_{OO} = k_i V_N$

4.3.3 The population game and population dynamics

The payoff matrices in the previous section represent the micro structure of the strategic interactions. Scaling that effect at the population level, I define the population game for team i with x^N being the proportion of adopters of the new practice: $U(x^N) = \begin{pmatrix} U^i_N(x^N) \\ U^i_O(x^N) \end{pmatrix}$.

I define δ the interaction level within a team (i and j) and $(1-\delta)$ the level of interactions between the two teams i and j:

$$\begin{aligned} U^i(x^N) &= \begin{pmatrix} U^i_N(x^N) \\ U^i_O(x^N) \end{pmatrix} \\ &= \delta \begin{bmatrix} U^{ii}_{NN} & U^{ii}_{NO} \\ U^{ii}_{ON} & U^{ii}_{OO} \end{bmatrix} \times \begin{pmatrix} x^N_i \\ 1-x^N_i \end{pmatrix} + (1-\delta) \begin{bmatrix} U^{ij}_{NN} & U^{ij}_{NO} \\ U^{ij}_{ON} & U^{ij}_{OO} \end{bmatrix} \times \begin{pmatrix} x^N_j \\ 1-x^N_j \end{pmatrix}, \\ &= \begin{pmatrix} \delta(x^N_i U^{ii}_{NN} + (1-x^N_i) U^{ii}_{NO}) + (1-\delta)(x^N_j U^{ij}_{NN} + (1-x^N_j) U^{ij}_{NO}) \\ \delta(x^N_i U^{ii}_{ON} + (1-x^N_i) U^{ii}_{OO}) + (1-\delta)(x^N_j U^{ij}_{ON} + (1-x^N_j) U^{ij}_{OO}) \end{pmatrix} \end{aligned} \tag{4.1}$$

I study one of the classic dynamics in evolutionary game theory, the replicator dynamics (Weibull 1997). An individual will adopt the new practice N if his utility to adopt is higher than the average of practices used in the team. Thus, following this dynamic, in each team the population of adopters will increase/decrease proportional to the difference between the utility to adopt the new practice and the average utility between using the two practices within the team.

I define the average performance of the two practices in team i by:
$\bar{U}_i(x^N) = x_i^N U_N^i(x^N) + (1 - x_i^N) U_O^i(x^N)$.

This leads to the following dynamical system for two teams with $i = 1$ and $j = 2$:

$$\begin{cases} \dfrac{dx_1^N}{dt} = x_1^N(U_1^N - \bar{U}_1^N) \\ \quad = x_1^N(1 - x_1^N)(\delta(x_1^N(U_{NN}^{11} - U_{ON}^{11}) + (1 - x_1^N)(U_{NO}^{11} - U_{OO}^{11})) \\ \quad + (1 - \delta)(x_2^N(U_{NN}^{12} - U_{ON}^{12}) + (1 - x_2^N)(U_{NO}^{12} - U_{OO}^{12}))) \\ \dfrac{dx_2^N}{dt} = x_1^N(U_2^N - \bar{U}_2^N) \\ \quad = x_2^N(1 - x_2^N)(\delta(x_2^N(U_{NN}^{22} - U_{ON}^{22}) + (1 - x_2^N)(U_{NO}^{22} - U_{OO}^{22})) \\ \quad + (1 - \delta)(x_1^N(U_{NN}^{21} - U_{ON}^{21}) + (1 - x_1^N)(U_{NO}^{21} - U_{OO}^{21}))) \end{cases}$$

4.4 Analysis

Definition 1 *Two teams have wide bridges when the level of interactions of each team with another is higher than within any one team ($\delta < \frac{1}{2}$); and they have narrow bridges when the team members interact more within their own team than with members of another ($\delta > \frac{1}{2}$).*

4.4.1 Social comparisons heterogeneity

In this section of the analysis, I assume, similar to Chapter 3, that the individual reward system used by management is such that adopting new practices follows a high risk-high return rule: the higher the likelihood to succeed in adopting the new practice (p high), the higher the value of sticking with the old practice given by senior management $V_O = kV_N$ is high (k high). For simplification of this trade-off, I assume in the rest of the analysis $k = p$ leading to the following: $pV_N = V_O = kV_N$.

Proposition 8 *If an organisation creates wide bridges ($\delta < \frac{1}{2}$) between two teams with different types of social comparisons, there exists an asymptotically stable mix of adopters and non-adopters in each of the two teams, iff employees in the behind-averse team are less susceptible to social comparisons than the employees in the ahead-seeking team ($\gamma < \alpha$).*

Proof: See in Appendix

Corollary 3 *Inducing wide bridges between the two teams when one team is relatively less ahead-seeking than the other is behind-averse ($\alpha < \gamma$), will lead to a diverging and unstable oscillating pattern in the organisation between adopting and non adopting.*

Proof: See in Appendix

When the organisation puts in place wide bridges between the two teams, employees tend to interact more with the other team members than with their own. Thus, they are more impacted by a change in practices of the other team than within their team.

In a ahead-seeking team, employees will have the need to differentiate themselves in order to feel a rise in their utility so if too many individuals adopt the risky practice, the utility of sticking with the old practice will increase (see Table 4.1).

In an behind-averse team, individuals will tend to conform to the behaviour of others if enough individuals choose one of the two practices (see Table 4.2).

The wide bridges can create a very interesting oscillation phenomenon between adopting the new practice and sticking with the old in both teams. When the number of employees adopting the new practice in the behind-averse team decreases, ahead-seeking team members are more impacted by the decrease of adoption of the behind-averse team members which will lead them to adopt the new practice. However, as the number of adopters of the ahead-seeking team increases, the behind-averse team members will conform and start adopting the new practice. Similarly, as the behind-averse team members adopt the new practice, the ahead-seeking team members will try to differentiate themselves and go back to the old practice as a safer option and hope the other team members fail. As they stick with the old practice, the utility of going back to the old practice increases for the behind-averse team members which lead the number of adopters to decrease.

However, this oscillating pattern is heavily influenced by the payoffs of the game thus the social comparisons. If the ahead-seeking team feels relatively more strongly the social comparisons than the members of the behind-averse team ($\alpha > \gamma$), the ahead-seeking team members will differentiate faster than the behind-averse team members conform, thus leading the oscillation to converge to an asymptotic stable state where there is a mix of both adopters and non-adopters in both teams. In this scenario, management can expect both teams (even the behind-averse one!) to have a mix of adopters and non-adopters at equilibrium. This scenario is illustrated in Figure 4.2 on the left-hand side.

But, if behind-averse team members are relatively more behind-averse than the other team members are ahead-seeking ($\alpha < \gamma$), the need to conform will be stronger which will make the oscillations diverge. Given the need to differentiate from the ahead-seeking team, as the oscillations diverge they never stabilise and both teams end-up oscillating between adopting and non-adopting. This scenario is illustrated in Figure 4.2 on the right-hand side. In this case, management should prefer narrow over wide bridges.

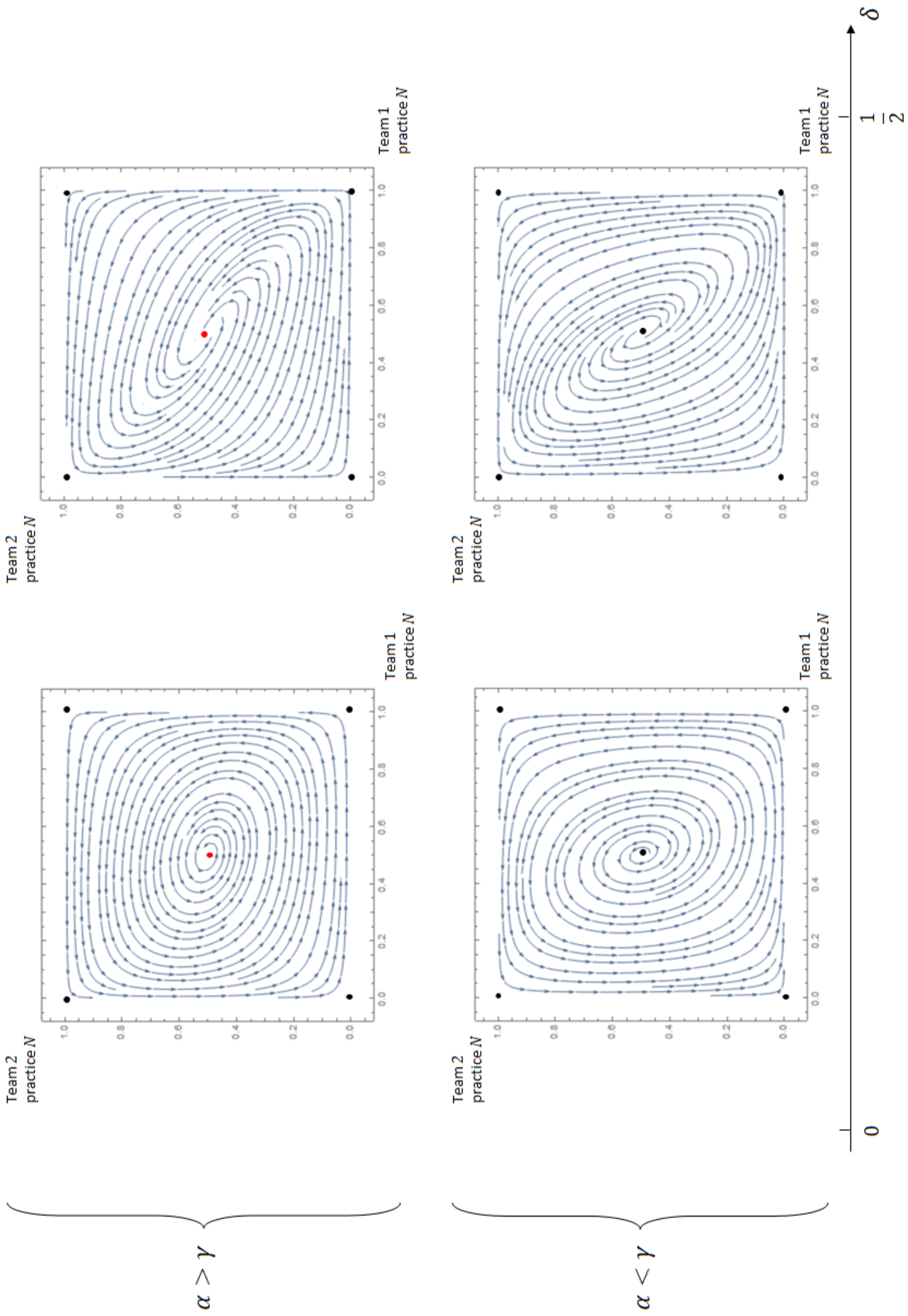

Fig. 4.2 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (ahead-seeking α) and in team 2 (behind-averse γ) in the presence of wide bridges ($0 < \delta < \frac{1}{2}$)

Proposition 9 *If an organisation creates narrow bridges between teams ($\delta > \frac{1}{2}$), the ahead-seeking team will always exhibit a stable mix of adopters and non-adopters while the behind-averse team will either adopt the new practice or stick with the old practice as a whole.*

Proof: See in Appendix

When the organisation puts in place narrow bridges, the team members are more impacted by members of their own team switching practices than by actions of the other team. The overall pattern of adoption in each team is thus led by the social comparisons present in the team. In behind-averse teams, members will conform to their team members' behaviour. If there are enough initial adopters of the new practice, individuals of the behind-averse team will fully adopt the new practice. If not, they will stick with the old practice. On the other hand, the ahead-seeking team differentiates which leads to a mix of adopters and non-adopters in the team. These patterns are illustrated in Figure 4.3.

Even so the bridges are narrow, team members can still interact with the other team. As the behind-averse team members interact with the other team, the mix of adopters and non-adopters in the ahead-seeking team is influenced by the number of adopters at equilibrium of the behind-averse team (even if it is not dominant). As the bridges become less narrow ($\delta > \frac{1}{2}$ but decreases), the number of adopters in the ahead-seeking team decreases when the behind-averse team fully adopts the new practice and increases when the behind-averse team sticks with the old practice, due to differentiation.

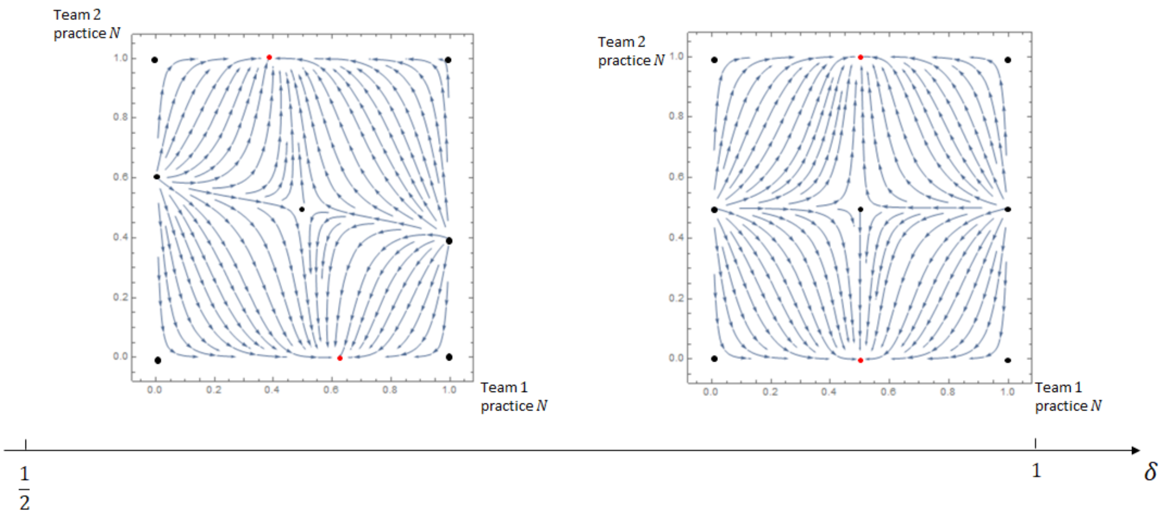

Fig. 4.3 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (ahead-seeking) and in team 2 (behind-averse) in the presence of narrow bridges ($\frac{1}{2} < \delta < 1$)

4.4.2 Capabilities' heterogeneity

In this section of the analysis, similar to the previous section, I assume that management induces rewards such that the new practice follows a "high risk-high return" rule: the higher the likelihood to succeed in adopting the new practice (p high), the higher the value of sticking with the old practice given by senior management $V_O = kV_N$ is high (k high). Thus, I state that $p_1 = k_1$ and $p_2 = k_2$ with team 1 corresponding to the low-capability team (L) and team 2 being the high capability team (H). This also suggests that H team members also extract more value from performing an old practice than the L team members.

4.4.2.1 A ahead-seeking organisation

Proposition 10 *If the organisation creates a:*
- low level of narrow bridges ($\frac{1}{2} < \delta < \delta_3^{as} = \frac{p_1+p_2-2}{p_1+3p_2-4}$), the members of the high capability (H) team will stick with the old practice and both practices will co-exist in the low capability (L) team $(x_1^*, 0)$.
- high level of narrow bridges ($\delta_3^{as} < \delta < 1$), the two practices will co-exist in both teams (x_1^*, x_2^*).

Proof: See in Appendix

When the organisation puts narrow bridges in place, the team members interact more within their own team than with other teams.

In a ahead-seeking team, employees value being better than others. As many employees adopt an uncertain practice, other employees may choose to stick with an old practice and wait for the adopters to fail to receive a ahead-seeking utility. But, as too many employees stick with the old practice, adopting the new practice may enable them to feel some ahead-seeking and employees will start adopting again. This creates some coexistence patterns in both teams.

There are two interesting remarks to be made.

First, I observe that at equilibrium there are more adopters in team L than in team H. We could have expected that the H team would adopt more. But, as the H team's likelihood of adopting is higher than the L team's, adopting the new practice for H team members will bring them relatively less ahead-seeking utility than L team members adopting the new practice (see Table 4.3).

Second, interestingly, I observe that as the bridges become wider but are still narrow, the number of adopters in the team H decreases at equilibrium while the L team adopters of the new practice increases at equilibrium (see Figure 4.4). It is due to the interactions which the H team members start having with the L team members. As the employees in the team L fail more in expectation, H employees will feel more utility when interacting with a L employee when choosing to adopt the old practice compared to when they chose to adopt the new practice. This leads H employees to prefer adopting the old practice when there are many L team members adopting the new practice. On the other hand, the team L receives less ahead-seeking utility when sticking with the old practice compared to adopting the new practice, as the H team members succeed more at adopting the new practice in expectation (see Table 4.4).

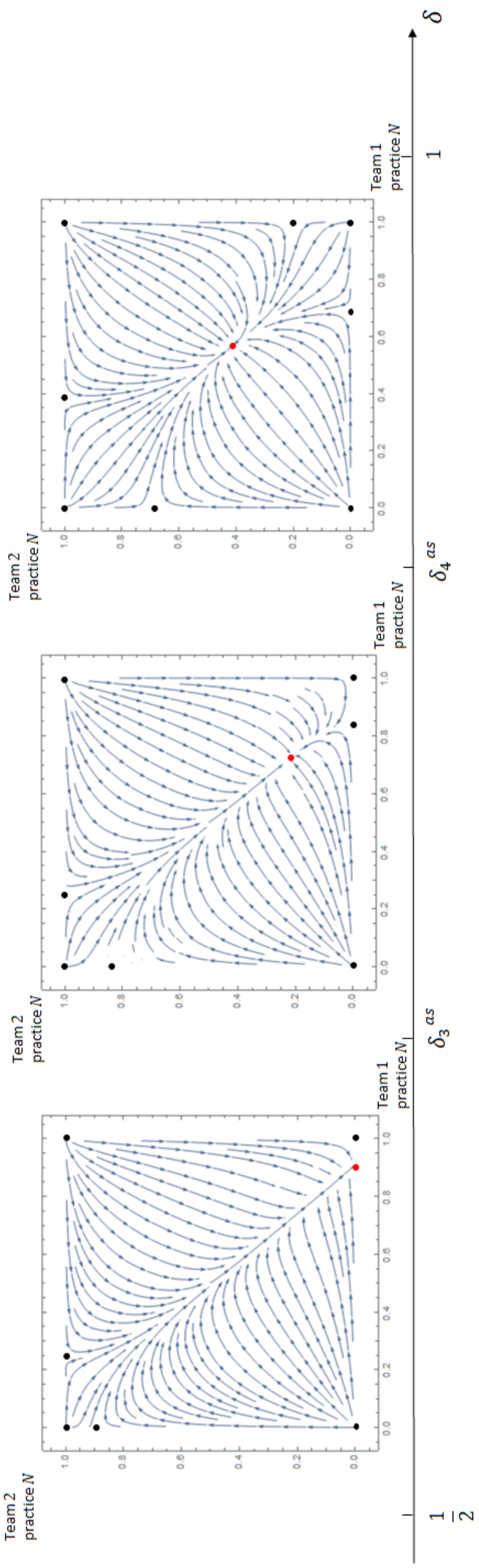

Fig. 4.4 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (low-capability) and in team 2 (high-capability) in a ahead-seeking organisation in the presence of narrow bridges ($\frac{1}{2} < \delta < 1$)

Proposition 11 *If the organisation allows a:*
- high level of wide bridges ($0 < \delta < \delta_1^{as} = \frac{p_2-1}{p_1+p_2-2}$)*, there are two asymptotic stable equilibria where one team is cannibalized by the other:* $(0,1)$ *or* $(1,0)$.
- mid level of wide bridges ($\delta_1^{as} < \delta < \delta_2^{as}$) *there are two asymptotic stable equilibria where either the low capability team cannibalizes the high capability team* $(1,0)$ *or the high capability team fully adopts and the two practices coexist in the low-capability team* $(x_1^*, 1)$.
- low level of wide bridges ($\delta_2^{as} < \delta < \frac{1}{2}$)*, the only asymptotic stable equilibrium is when the low capability team cannibalises the high capability team* $(1,0)$.

Proof: See in Appendix.

When the organisation puts very wide bridges in place, two scenarios arise when one of the team fully adopts while the other sticks with the old practice.

When L team members interact with H employees, they enjoy more utility when choosing the new practice than sticking with the old practice. On the other hand, H team members enjoy more utility to stick with the old practice than adopting the new practice. This leads the L team to fully adopt the new practice while the H team will stick with the old practice (see Table 4.4).

However, if the number of L team members adopting the new practice is initially low, the utility of adopting the new practice is higher for H team members than the utility to stick with the old practice, which will lead the number of adopters in the H team to increase. As the H employees adopt more, the utility of sticking with the old practice increases, which leads the number of adopters in the L team to decrease. The H team ends up fully adopting the new practice while the L team sticks with the old practice.

As the bridges become narrower but still wide ($\delta < \frac{1}{2}$), team members start interacting more within their own team. Due to the differentiation effect, H team members (who were initially adopting) start differentiate and stick with the old practice. As the interactions with L team members are still present, the utility to stick with the old practice increases even more! On the other hand, the L team wants to differentiate as well and as more team members adopt, the more they stick with the old practice. But, as the bridge with the H team is still too wide and H team members stick with the old practice, the employees L are pushed to adopt the new practice. This leads to a single scenario where the L team fully adopts the new practice while the H team sticks with the old practice (see in Figure 4.5).

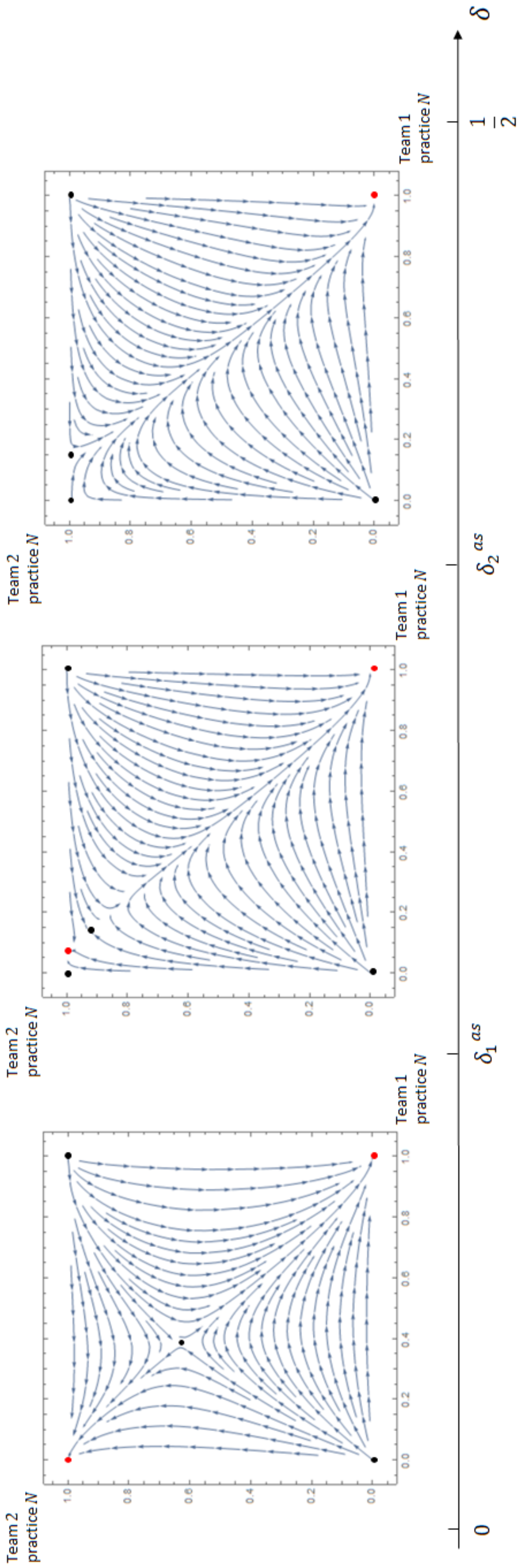

Fig. 4.5 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (low-capability) and in team 2 (high-capability) in a ahead-seeking organisation in the presence of wide bridges ($0 < \delta < \frac{1}{2}$)

4.4.2.2 A behind-averse organisation

Proposition 12 *If the organisation creates:*
- a low level of narrow bridges ($\frac{1}{2} < \delta < \delta_4^{ba} = \frac{p_1-1}{p_1+p_2-2}$), there are 3 asymptotic stable equilibria possible: both teams will stick to the old practice $(0,0)$, the high capability team will fully adopt the new practice while the low capability team will stick with the old practice $(0,1)$ or both teams will fully adopt the new practice $(1,1)$.
- a high level of narrow bridges ($\delta_4^{ba} < \delta < 1$), an additional stable equilibrium appears in which the high capability team ends up sticking with the old practice while the low capability employees fully adopt the new practice $(1,0)$.

Proof: See in Appendix

When the organisation puts in place narrow bridges, individuals tend to interact more within their own team. In an behind-averse environment, employees will conform to other team members' choice of practices.

For very narrow bridges, the effect of the practice used by the members of the other team is negligible. This leads to four distinctive scenarios. If H team members mainly use the new practice and the L team uses the old practice initially, members will conform to each other in each team. This will create an asymptotic stable state where the H team fully adopts the new practice and the L team sticks with the old practice. Due to this conformity effect being present in each team, the organisation can also end up at equilibrium in situations where both the H and L teams fully adopt, where both teams stick with the old practice and where the L team fully adopts while the H team sticks with the old practice (see Table 4.5).

Interestingly, as the bridges become wider but stay narrow ($\delta > \frac{1}{2}$), the equilibrium where the L team fully adopts while the H team sticks with the old practice becomes unstable. This is explained by the increased level of interactions between teams and due to the H team's greater likelihood of adopting the new practice. Because of the narrow bridges, team members interact more within their own team, which should lead H team members to stick with the old practice if not many of them initially adopt the new practice. But as the bridges get wider, when a member of the H team interacts with a member of the L team, he will feel relatively more behind-aversion by choosing to stick with the old practice when the L team member successfully adopts the new practice compared to the behind-aversion he could feel by failing to adopt the new practice while the employee L stuck with the old practice (see Table 4.6). Therefore, H team members will tend to adopt the new practice which make the equilibrium $(1,0)$ unstable. The adoption pattern is illustrated in Figure 4.6.

This is of particular interest, as in such situation, both teams can end up fully adopting the new practice if only the L team fully adopted it first. However it is important to notice that employees L cannot drive the H team to adopt in all circumstances. If not enough employees L adopt initially, the interactions within their own team will push them to stick with the old practice. As they stick with the old practice, the wider the bridges become, the less likely the H team will want to try the new practice and risk under-performing compared to the L employees, which will lead the H employees to stick with the old practice.

Proposition 13 *If the organisation allows wide bridges ($0 < \delta < \frac{1}{2}$), there exist two asymptotic stable states. The two teams can either fully adopt the new practice ($1,1$) or both teams will stick with the old practice ($0,0$).*

Proof: See in Appendix

When the organisation puts in place wide bridges ($\delta < \frac{1}{2}$), employees tend to interact more often with members of the other team. We observe that in this case, there are only two stable scenarios that can occur in the two teams compared to four in the case of narrow bridges: the H team fully adopts while L team sticks with the old practice, and the L team fully adopts and the H team sticks with the old practice.

Due to the difference in both teams' capabilities, when interacting with a L team member, the H employee will feel more behind-aversion when choosing to stick with the old practice when meeting a L adopter than when choosing to adopt the new practice when meeting one that stuck with the old practice. On the other hand, a L team member will feel more behind-aversion adopting the new practice while the employee H sticks with the old practice. This opposing effect from each team towards the other team's choice creates instability when the two teams fully adopt different practices. The adoption pattern is illustrated in Figure 4.7.

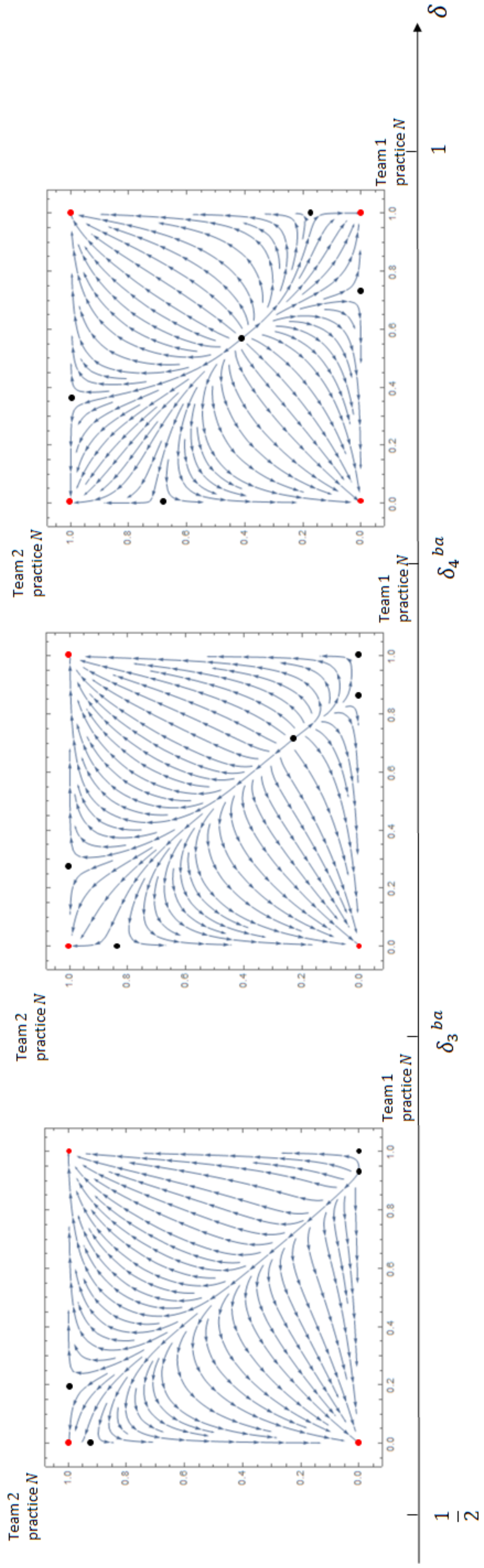

Fig. 4.6 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (low-capability) and in team 2 (high-capability) in a behind-averse organisation in the presence of narrow bridges ($\frac{1}{2} < \delta < 1$)

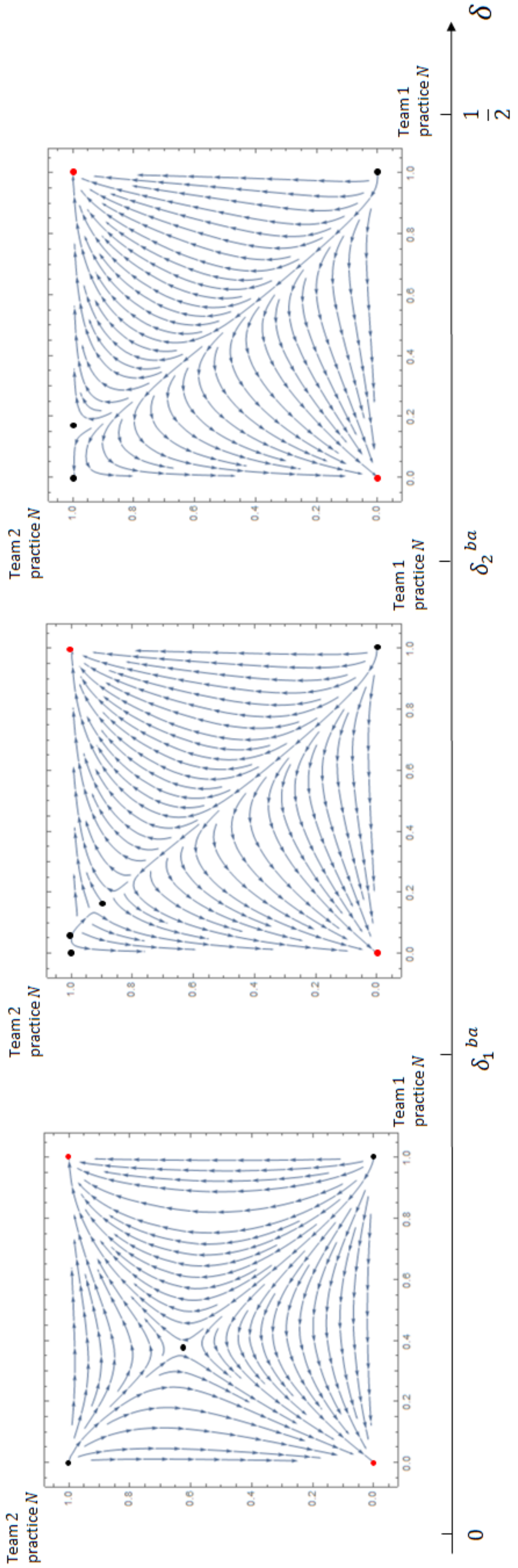

Fig. 4.7 Phase portraits of adoption equilibria (stable in red and unstable in black) of the new practice in team 1 (low-capability) and in team 2 (high-capability) in a behind-averse organisation in the presence of wide bridges ($0 < \delta < \frac{1}{2}$)

4.5 Discussion and conclusion

In this paper I provide a model of practice adoption extending the work presented in Chapter 3 by allowing heterogeneous interactions between groups in the organisation with heterogeneous capabilities and heterogeneous types of social comparisons. I study how heterogeneity of the two teams in their capabilities or in their social comparisons type (behind-averse and ahead-seeking) have an impact on the overall adoption in the organisation. In doing so, I introduce a new operational lever, wide/narrow bridges, that an organisation could use to monitor adoption. The findings presented in the paper lead to interesting managerial insights and theoretical contributions for the field of management of technology.

4.5.1 Managerial contributions

First, this paper provides novel insights on the decision of organisations to create star teams or to mix teams with different capabilities regarding the adoption of practices. These have interesting implications for companies such as Google and Uber that isolate their top teams, GoogleX and UberX, respectively. If the organisation has a ahead-seeking culture, separating both teams will create a mix adopters and non-adopters in each team (similar to Chapter 3). Creating wide bridges (mixing both teams) will ensure that one of the two teams fully adopts while the other will not adopt. The organisation can ensure that the high capability team is fully adopting if there is initially relatively more adopters in the high capability team than in the low capability team which will require some upfront training in the high capability team. Similar to the discussion in Chapter 3, depending on the type of practice (risky vs non risky, ethical vs non ethical), an organisation may want to increase or diminish the overall adoption. In the case of a risky but beneficial practice for the organisation, the organisation may consider wide bridges and some upfront training in the high capability team to make sure that the best employees try the risky practice, while the low capability team sticks with the well mastered practice. On the other hand, in a behind-averse organisation, the outcome in each team will depend on some upfront training. Mixing teams will either allow both teams to adopt or no team to adopt.

Second, top management is often faced with decisions to merge units or departments in the organisation which may have behavioural consequences on the adoption of new practices. Past work on collaborations between units in manufacturing has justified that enhancing collaboration between units was good for information exchange or knowledge sharing about the new practice (Ferdows et al. 2016). However, this literature did not take into account the behavioural consequences of this decision when these two units have different social comparisons cultures in place (one ahead-seeking and one behind-averse). In this paper, I find that enhancing collaboration and merging units that have different social comparisons can lead to an unstable outcome when the behind-averse team is relatively more behind-averse than the other team is ahead-seeking. In this case, oscillations will occur in both teams with the organisation not being able to influence any of the two teams. A similar oscillation pattern was observed in the design performance evolution, observed in complex engineering team projects (Mihm et al. 2003) and this mechanism could also be a potential explanation of such phenomenon. In this case, to avoid this uncertainty, the organisation may be better off keeping the two units separated as the adoption in each unit can be influenced when separated. On the other hand, mixing both units when the ahead-seeking team is relatively more ahead-seeking than the other team is behind-averse creates a stable outcome for both units. There is a mix of adopters and non-adopters in the ahead-seeking team (similar without mixing it) but more surprisingly in the behind-averse team as well. Thus, creating wide bridges between the two teams benefits the behind-averse team to have a mix of adopters and non-adopters without any initial training. Therefore, organisations could benefit to mix these two teams in this scenario if they want to avoid the practice to be fully adopted (unethical or too risky) or if they want to create adoption without spending on initial training.

4.5.2 Theoretical contributions

This paper also makes several theoretical contributions in the field of practice adoption and technology management. First, in the management literature, an important operational lever that firms possess is the level of interactions between teams and factories. The manufacturing management literature argues that such interactions can help the exchange of information and imitation mechanisms to learn new practices such as know-how best techniques or new lean practices introduced by some experts similar to the NUMMI case. These interactions are generally put in place through training exchange or geographical proximity (Ferdows et al. 2016). In addition to information exchange, the organisation sociology literature emphasises the importance of interactions between teams in the form of wide bridges as a mean to reinforce the exposure of the new practice to be better adopted. However, as seen in the example of NUMMI, such exchanges do not always lead to adoption and I propose in this paper a behavioural mechanism that could explain this failure. I find that overexposure of the new practice may have opposite effects when individuals compare their relative benefits of adoption thus showing that enabling bridges between teams does not always help adoption.

Second, this paper is extending the work presented in Chapter 3 on the impact of social comparisons in the adoption of new management practices. Chapter 3 assumed an homogeneous population in their capabilities and social comparisons type (ahead-seeking or behind-averse) in which every individual had the same likelihood of interacting with others. In this analysis, I am proposing an evolutionary game theoretical model in which I allow the presence of two classes of individuals either in their capability to adopt successfully the new practice or in their social comparisons type. In addition, I allow some heterogeneity of interactions through wide and narrow bridges. A few results of this paper differ qualitatively from Chapter 3's analysis and we are discussing how the role of heterogeneity impacts the overall adoption of the new practice.

Lastly, these results also support qualitatively some findings in the field of research on cooperation. Fotouhi et al. (2018) finds that in certain conditions, conjoining groups and communities which were not initially cooperating can enhance cooperation. If I make a parallel between cooperation and adoption of the new practice, I also find that creating bridges between two groups not initially adopting can be beneficial for adoption. In particular, I find that a behind-averse team can adopt the new practice with no initial upfront training if wide bridges are created with a ahead-seeking team more sensitive to social comparisons.

4.5.3 Limitations

This study brings new insights into the effects of wide bridges between heterogeneous teams but it has limitations.

First, I focus on the effect of heterogeneity in different settings, either when individuals have similar capabilities but the teams experience different social comparisons, or by looking at a difference in capabilities when both teams experience the same type of social comparisons. Combining both types of heterogeneity in the same setting could be an interesting extension.

Secondly, the formal utility that individuals extract in my model is simplified. The literature highlights that externalities could impact the formal value individuals extract from using the new practice (modelled in Chapter 3), which could increase or decrease with the number of adopters. Including more sophisticated formal utilities in my model could be an interesting research avenue.

Lastly, I study the evolution of practice choice and team members' interactions with a classic imitative protocol called replicator dynamics. Replicator dynamics ask for a high level of information which could be made available by the organisation through a social planner. An interesting research avenue would be to study the impact of other dynamic protocols that make less information of the system available to employees. However, using other protocols may prove challenging and lead to non-analytical tractable solutions which may require only numerical simulations to analyse.

4.6 Appendix

4.6.1 Proofs of Corollary 2 and Propositions 8 and 9

In the case of the two teams interacting with different social comparisons, one with ahead-seeking social comparisons and the other with behind-averse social comparisons.

Let's introduce the following variables as function of the model parameters:

$$\begin{cases} A_1 = -\alpha V_N(p(1-k)+(1-p)k) \\ A_2 = \gamma V_N((1-p)k+p(1-k)) \\ B_1 = V_N(p-k+\alpha p(1-k)) \\ B_2 = V_N(p-k-\gamma(1-p)k) \end{cases}$$

In the case of $p = k$ (assumption of the paper), we have:

$$\begin{cases} A_1 = -2\alpha V_N p(1-p) \\ A_2 = 2\gamma V_N 2p(1-p) \\ B_1 = V_N \alpha p(1-p) \\ B_2 = -V_N \gamma(1-p)p \end{cases}$$

The dynamical system can be written as follows:

$$\begin{cases} \dfrac{dx_1^N}{dt} = x_1^N(1-x_1^N)(A_1(\delta x_1^N+(1-\delta)x_2^N)+B_1) \\ \dfrac{dx_2^N}{dt} = x_2^N(1-x_2^N)(A_2(\delta x_2^N+(1-\delta)x_1^N)+B_2) \end{cases}$$

This system admits nine stationary points (x_1^*, x_2^*): $(0,0)$, $(0,1)$, $(1,0)$, $(1,1)$, $(0,-\frac{B_2}{\delta A_2})$, $(-\frac{B_1}{\delta A_1},0)$, $(1,-\frac{(1-\delta)A_2+B_2}{\delta A_2})$, $(-\frac{(1-\delta)A_1+B_1}{\delta A_1},1)$, $(\frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2}, \frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2})$.

By linearising this system around each of these stationary points, we study the asymptotic stability of these equilibria. These equilibria are asymptotic stable iff,

$$\begin{cases} tr[J(x_1^*, x_2^*)] < 0 \\ det[J(x_1^*, x_2^*)] > 0 \end{cases}.$$

We linearise the system with this change of variables $\begin{cases} x_1^N = x_1^* + y_1^N \\ x_2^N = x_2^* + y_2^N \end{cases}$

For $(x_1^*, x_2^*) = (-\frac{B_1}{\delta A_1}, 0)$, we obtain the following dynamic system:

$$\begin{cases} \frac{dy_1^N}{dt} = (x_1^* + y_1^N)(1 - x_1^* - y_1^N)A_1(\delta y_1^N + (1-\delta)y_2^N) \\ \frac{dy_2^N}{dt} = y_2^N(1 - y_2^N)(A_2(\delta y_2^N + (1-\delta)(x_1^* + y_1^N)) + B_2) \end{cases}$$

$$\Leftrightarrow \begin{pmatrix} \frac{dy_1^N}{dt} \\ \frac{dy_2^N}{dt} \end{pmatrix} = \begin{pmatrix} x_1^*(1-x_1^*)\delta A_1 & x_1^*(1-x_1^*)(1-\delta)A_1 \\ 0 & (1-\delta)x_1^* A_2 + B_2 \end{pmatrix} \times \begin{pmatrix} y_1^N \\ y_2^N \end{pmatrix} = J(x_1^*, x_2^*) \times \begin{pmatrix} y_1^N \\ y_2^N \end{pmatrix}$$

I obtain:

$$\begin{cases} tr[J(-\frac{B_1}{\delta A_1}, 0)] = \frac{-B_1}{\delta A_1}(A_1\delta(1 + \frac{B_1}{A_1\delta}) + A_2(1-\delta)) + B_2 \\ det[J(-\frac{B_1}{\delta A_1}, 0)] = \frac{-B_1}{\delta A_1}(A_1\delta(1 + \frac{B_1}{A_1\delta})(\frac{-B_1}{\delta A_1}A_2(1-\delta) + B_2) \end{cases}$$

and

$$\begin{cases} tr[J(-\frac{B_1}{\delta A_1}, 0)] = \frac{-B_1}{\delta A_1}(A_1\delta(1 + \frac{B_1}{A_1\delta}) + A_2(1-\delta)) + B_2 & < 0 \\ det[J(-\frac{B_1}{\delta A_1}, 0)] = \frac{-B_1}{\delta A_1}(A_1\delta(1 + \frac{B_1}{A_1\delta})(\frac{-B_1}{\delta A_1}A_2(1-\delta) + B_2) & > 0 \end{cases} \Leftrightarrow \frac{1}{2} < \delta < 1$$

In a very similar manner, I derive for the remaining eight equilibria (x_1^*, x_2^*) the conditions such that $\begin{cases} tr[J(x_1^*, x_2^*)] < 0 \\ det[J(x_1^*, x_2^*)] > 0 \end{cases}$

- $(0,0)$ is stable $\Leftrightarrow \begin{cases} tr[J(0,0)] = B_1 + B_2 & < 0 \\ det[J(0,0)] = B_1 B_2 & > 0 \end{cases}$
- $(0,1)$ is stable $\Leftrightarrow \begin{cases} tr[J(0,1)] = A_1 + B_1 - B_2 - \delta(A_1 + A_2) & < 0 \\ det[J(0,1)] = -((1-\delta)A_1 + B_1)(\delta A_2 + B_2) & > 0 \end{cases}$

- $(1,0)$ is stable $\Leftrightarrow \begin{cases} tr[J(1,0)] = A_2 + B_2 - B_1 - \delta(A_1 + A_2) & < 0 \\ det[J(1,0)] = -((1-\delta)A_2 + B_2)(A_1\delta + B_1) & > 0 \end{cases}$

- $(1,1)$ is stable $\Leftrightarrow \begin{cases} tr[J(0,0)] = -(A_1 + A_2 + B_1 + B_2) & < 0 \\ det[J(0,0)] = (A_1 + B_1)(A_2 + B_2) & > 0 \end{cases}$

  Those conditions can not be met so the four equilibria above are always unstable for any parameter values.

- $(0, -\frac{B_2}{\delta A_2})$ is stable $\Leftrightarrow \begin{cases} tr[J(0, -\dfrac{B_2}{\delta A_2})] = \dfrac{-B_2}{A_2\delta}(A_1(1-\delta) + A_2\delta(1 + \dfrac{B_2}{A_2\delta})) + B_1 & < 0 \\ det[J(0, -\dfrac{B_2}{\delta A_2})] = \dfrac{-B_2}{A_2\delta}(1 + \dfrac{B_2}{A_2\delta})A_2\delta(A_1(1-\delta)\dfrac{-B_2}{A_2\delta} + B_1) & > 0 \end{cases}$

  $\Leftrightarrow 0 < \delta < \frac{1}{2}$

- $(1, -\frac{(1-\delta)A_2 + B_2}{\delta A_2})$ is stable

$$\Leftrightarrow \begin{cases} tr[J(1, -\dfrac{(1-\delta)A_2 + B_2}{\delta A_2})] = -\dfrac{(1-\delta)A_2 + B_2}{\delta A_2}((1 + \dfrac{(1-\delta)A_2 + B_2}{\delta A_2})A_2\delta \\ \qquad -(1-\delta)A_1) - A_1\delta - B_1 & < 0 \\ det[J(1, -\dfrac{(1-\delta)A_2 + B_2}{\delta A_2})] = -(A_1(\delta + (1-\delta) - \dfrac{(1-\delta)A_2 + B_2}{\delta A_2}) + B_1) \\ \qquad -\dfrac{(1-\delta)A_2 + B_2}{\delta A_2}(1 + \dfrac{(1-\delta)A_2 + B_2}{\delta A_2})A_2\delta & > 0 \end{cases}$$

$\Leftrightarrow 0 < \delta < \frac{1}{2}$

- $(-\frac{(1-\delta)A_1 + B_1}{\delta A_1}, 1)$ is stable

$$\Leftrightarrow \begin{cases} tr[J(-\dfrac{(1-\delta)A_1 + B_1}{\delta A_1}, 1)] = -\dfrac{(1-\delta)A_1 + B_1}{\delta A_1}(A_1\delta(1 + \dfrac{(1-\delta)A_1 + B_1}{\delta A_1}) \\ \qquad -A_2(1-\delta)) - a_2\delta - B_2 & < 0 \\ det[J(-\dfrac{(1-\delta)A_1 + B_1}{\delta A_1}, 1)] = \dfrac{(1-\delta)A_1 + B_1}{\delta A_1}(1 + \dfrac{(1-\delta)A_1 + B_1}{\delta A_1})A_1\delta(A_2(\delta \\ \qquad +(1-\delta) - \dfrac{(1-\delta)A_1 + B_1}{\delta A_1}) + B_2) & > 0 \end{cases}$$

$\Leftrightarrow 0 < \delta < \frac{1}{2}$

- $(\frac{(1-\delta)A_1B_2 - \delta A_2B_1}{(2\delta-1)A_1A_2}, \frac{(1-\delta)A_2B_1 - \delta A_1B_2}{(2\delta-1)A_1A_2})$ is stable

$$\Leftrightarrow \begin{cases} tr[J(\frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2}, \frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2})] = \frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2} \\ \qquad (1-\frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2})\delta A_1 + \\ \qquad \frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2} \\ \qquad (1-\frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2})\delta A_2 \\ \qquad < 0 \\ det[J(\frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2}, \frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2})] = \frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2} \\ \qquad (1-\frac{(1-\delta)A_1B_2-\delta A_2B_1}{(2\delta-1)A_1A_2}) \\ \qquad \frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2} \\ \qquad (1-\frac{(1-\delta)A_2B_1-\delta A_1B_2}{(2\delta-1)A_1A_2})A_1A_2(2\delta-1) \\ \qquad > 0 \end{cases}$$

$$\Leftrightarrow \begin{cases} 0 < \delta < \frac{1}{2} \\ 0 < \gamma < \alpha < 1 \end{cases}$$

4.6.2 Proofs of Propositions 10 and 11

In the case of the two teams interacting in a ahead-seeking environment with heterogeneous capabilities .

Let's introduce the following variables as function of the model parameters:

$$\begin{cases} A_1 = -V_N\alpha(p_1(1-k_1)+(1-p_1)k_1) \\ A_2 = -V_N\alpha(p_2(1-k_2)+(1-p_2)k_2) \\ A_{12} = -V_N\alpha(p_1(1-k_1)+(1-p_2)k_1) \\ A_{21} = -V_N\alpha(p_2(1-k_2)+(1-p_1)k_2) \\ B_1 = V_N(p_1-k_1+\alpha p_1(1-k_1)) \\ B_2 = V_N(p_2-k_2+\alpha p_2(1-k_2)) \end{cases}$$

In the case of $p_1 = k_1$ and $p_2 = k_2$ (assumption of the paper), I have:

$$\begin{cases} A_1 = -V_N\alpha 2p_1(1-p_1) \\ A_2 = -V_N\alpha 2p_2(1-p_2) \\ A_{12} = -V_N\alpha p_1(2-p_1-p_2) \\ A_{21} = -V_N\alpha p_2(2-p_1-p_2) \\ B_1 = V_N\alpha p_1(1-p_1) \\ B_2 = V_N\alpha p_2(1-p_2) \end{cases}$$

The dynamical system can be written as follows:

$$\begin{cases} \dfrac{dx_1^N}{dt} = x_1^N(1-x_1^N)(\delta A_1 x_1^N + (1-\delta)A_{12}x_2^N) + B_1) \\ \dfrac{dx_2^N}{dt} = x_2^N(1-x_2^N)(\delta A_2 x_2^N + (1-\delta)A_{21}x_1^N + B_2) \end{cases}$$

This system admits nine stationary points (x_1^*, x_2^*): $(0,0)$, $(0,1)$, $(1,0)$, $(1,1)$, $(0, -\frac{B_2}{\delta A_2})$, $(-\frac{B_1}{\delta A_1}, 0)$, $(1, -\frac{(1-\delta)A_{21}+B_2}{\delta A_2})$, $(-\frac{(1-\delta)A_{12}+B_1}{\delta A_1}, 1)$, $(\frac{(1-\delta)A_{12}B_2-\delta A_2B_1}{\delta^2 A_1A_2-(1-\delta)^2A_{12}A_{21}}, \frac{(1-\delta)A_{21}B_1-\delta A_1B_2}{\delta^2 A_1A_2-(1-\delta)^2A_{12}A_{21}})$.

In order to find, the asymptotic stability of the stationary points, I linearise the dynamical system around these equilibria and obtain the following dynamical system:

$$\begin{cases} \dfrac{dy_1^N}{dt} = (x_1^*+y_1^N)(1-x_1^*-y_1^N)(\delta A_1(x_1^*+y_1^N) + (1-\delta)A_{12}(x_2^*+y_2^N) + B_1) \\ \dfrac{dy_2^N}{dt} = (x_2^*+y_2^N)(1-x_2^*-y_2^N)(\delta A_2(x_2^*+y_2^N) + (1-\delta)A_{21}(x_1^*+y_1^N) + B_2) \end{cases}$$

In a similar manner to the proofs of the propositions above, I derive for the remaining eight equilibria (x_1^*, x_2^*) the conditions such that $\begin{cases} tr[J(x_1^*, x_2^*)] < 0 \\ det[J(x_1^*, x_2^*)] > 0 \end{cases}$

Trivial calculations of the trace and determinant lead to the following stability conditions for each equilibrium:

- $(0,0)$ and $(1,1)$ are unstable.
- $(0,1)$ is stable $\Leftrightarrow 0 < \delta < \frac{p_2-1}{p_1+p_2-2} = \delta_1^{as} (< \frac{1}{2})$

- $(1,0)$ is stable $\Leftrightarrow 0 < \delta < \frac{1}{2}$
- $(0, -\frac{B_2}{\delta A_2})$ is unstable but exists when $\Leftrightarrow \frac{1}{2} < \delta < 1$
- $(-\frac{B_1}{\delta A_1}, 0)$ exists when $\frac{1}{2} < \delta < 1$ and is stable

  $\Leftrightarrow \frac{1}{2} < \delta < \frac{p_1+p_2-2}{p_1+3p_2-4} = \delta_3^{as}(< 1)$
- $(1, -\frac{(1-\delta)A_{21}+B_2}{\delta A_2})$ exists when $(\frac{1}{2} <)\delta_4^{as} = \frac{p_1-1}{p_1+p_2-2} < \delta < 1$ but is unstable
- $(-\frac{(1-\delta)A_{12}+B_1}{\delta A_1}, 1)$ is stable $\Leftrightarrow \delta_1^{as} = \frac{p_2-1}{p_1+p_2-2} < \delta < \delta_2^{as}(< \frac{1}{2})$
  but exists when $\delta_1^{as} < \delta < 1$
- $(\frac{(1-\delta)A_{12}B_2-\delta A_2 B_1}{\delta^2 A_1 A_2-(1-\delta)^2 A_{12}A_{21}}, \frac{(1-\delta)A_{21}B_1-\delta A_1 B_2}{\delta^2 A_1 A_2-(1-\delta)^2 A_{12}A_{21}})$ is stable $\Leftrightarrow \delta_3^{as} < \delta < 1$

  and exists (but is unstable) when $0 < \delta < \delta_3^{as}$.

4.6.3 Proofs of Propositions 12 and 13

In the case of the two teams interacting in a behind-averse environment with heterogeneous capabilities .

Let's introduce the following variables as function of the model parameters:

$$\begin{cases} A_1 = V_N\gamma(p_1(1-k_1)+(1-p_1)k_1) \\ A_2 = V_N\gamma(p_2(1-k_2)+(1-p_2)k_2) \\ A_{12} = V_N\gamma(p_1(1-k_1)+(1-p_2)k_1) \\ A_{21} = V_N\gamma(p_2(1-k_2)+(1-p_1)k_2) \\ B_1 = V_N(p_1-k_1-\gamma p_1(1-k_1)) \\ B_2 = V_N(p_2-k_2-\gamma p_2(1-k_2)) \end{cases}$$

In the case of $p_1 = k_1$ and $p_2 = k_2$ (assumption of the paper), we have:

$$\begin{cases} A_1 = V_N\gamma 2p_1(1-p_1) \\ A_2 = V_N\gamma 2p_2(1-p_2) \\ A_{12} = V_N\gamma p_1(2-p_1-p_2) \\ A_{21} = V_N\gamma p_2(2-p_1-p_2) \\ B_1 = -V_N\gamma p_1(1-p_1) \\ B_2 = -V_N\gamma p_2(1-p_2) \end{cases}$$

The dynamical system can be written as follows:

$$\begin{cases} \dfrac{dx_1^N}{dt} = x_1^N(1-x_1^N)(\delta A_1 x_1^N + (1-\delta)A_{12}x_2^N) + B_1) \\ \dfrac{dx_2^N}{dt} = x_2^N(1-x_2^N)(\delta A_2 x_2^N + (1-\delta)A_{21}x_1^N + B_2) \end{cases}$$

This system admits nine stationary points (x_1^*, x_2^*): $(0,0)$, $(0,1)$, $(1,0)$, $(1,1)$, $(0, -\frac{B_2}{\delta A_2})$, $(-\frac{B_1}{\delta A_1}, 0)$, $(1, -\frac{(1-\delta)A_{21}+B_2}{\delta A_2})$, $(-\frac{(1-\delta)A_{12}+B_1}{\delta A_1}, 1)$, $(\frac{(1-\delta)A_{12}B_2-\delta A_2 B_1}{\delta^2 A_1 A_2-(1-\delta)^2 A_{12}A_{21}}, \frac{(1-\delta)A_{21}B_1-\delta A_1 B_2}{\delta^2 A_1 A_2-(1-\delta)^2 A_{12}A_{21}})$.

In order to find the asymptotic stability of the stationary points, I linearise the dynamical system around these equilibria and obtain the following dynamical system:

$$\begin{cases} \dfrac{dy_1^N}{dt} = (x_1^* + y_1^N)(1-x_1^*-y_1^N)(\delta A_1(x_1^*+y_1^N) + (1-\delta)A_{12}(x_2^*+y_2^N) + B_1) \\ \dfrac{dy_2^N}{dt} = (x_2^* + y_2^N)(1-x_2^*-y_2^N)(\delta A_2(x_2^*+y_2^N) + (1-\delta)A_{21}(x_1^*+y_1^N) + B_2) \end{cases}$$

In a similar manner to the proofs of the propositions above, I derive for the remaining eight equilibria (x_1^*, x_2^*) the conditions such that $\begin{cases} tr[J(x_1^*, x_2^*)] < 0 \\ det[J(x_1^*, x_2^*)] > 0 \end{cases}$

Trivial calculations of the trace and determinant lead to the following stability conditions for each equilibrium:

- $(0,0)$ is stable $\Leftrightarrow 0 < \delta < 1$
- $(0,1)$ is stable $\Leftrightarrow \frac{1}{2} < \delta < 1$
- $(1,0)$ is stable $\Leftrightarrow (\frac{1}{2} <)\delta_4^{ba} = \frac{p_1-1}{p_1+p_2-2} < \delta < 1$
- $(1,1)$ is stable $\Leftrightarrow 0 < \delta < 1$
- $(0, -\frac{B_2}{\delta A_2})$ is unstable but exists when $\frac{1}{2} < \delta < 1$
- $(-\frac{B_1}{\delta A_1}, 0)$ is unstable but exists when $\frac{1}{2} < \delta < 1$
- $(1, -\frac{(1-\delta)A_{21}+B_2}{\delta A_2})$ is unstable but exists when $(\frac{1}{2} <)\delta_4^{ba} = \frac{p_1-1}{p_1+p_2-2} < \delta < 1$
- $(-\frac{(1-\delta)A_{12}+B_1}{\delta A_1}, 1)$ is unstable but exists when $(\frac{1}{2} <)\delta_1^{ba} = \frac{p_2-1}{p_1+p_2-2}(\frac{1}{2} <) < \delta < 1$

- $\left(\frac{(1-\delta)A_{12}B_2-\delta A_2B_1}{\delta^2A_1A_2-(1-\delta)^2A_{12}A_{21}}, \frac{(1-\delta)A_{21}B_1-\delta A_1B_2}{\delta^2A_1A_2-(1-\delta)^2A_{12}A_{21}}\right)$ is unstable but exists

$$\Leftrightarrow \begin{cases} 0 < \delta < \delta_2^{ba} (< \dfrac{1}{2}) \\ \delta_3^{ba} = \dfrac{p_1+p_2-2}{p_1+3p_2-4} < \delta < 1 \end{cases}$$

Chapter 5

Adoption of practices in production networks: decentralised vs centralised.

5.1 Introduction

The adoption of new innovative know-how operational practices within manufacturing plants has been deemed critical to firm competitiveness and growth (Doering and Parayre 2000). Employees from these manufacturing plants face the dilemma of sticking with an operational practice they have already mastered or adopting a new operational practice that enables them to better perform a specific task or allows an alternative way to perform it (e.g., a lean practice (six sigma, kaizen) or the use of a new technology in the plant such as smart manufacturing equipment). The new operational practice may present some risk and full adoption of such new practice may not occur (see a review in Chapter 2).

The literature in organisational behaviour and manufacturing highlights that the social context plays a critical role in adoption as individuals tend to imitate each other (Sun 2013). Thus, the design of the manufacturing network and the position of R&D plants are important considerations for organisations. As highlighted by De Meyer and Vereecke (2009), "decisions about the design of a company's manufacturing network are not limited to what it should produce and where, and how to organise the resulting logistics flows; they are also about the design and management of flows of innovation and know-how. Executives must not leave this to chance. Facilitating, building, maintaining, balancing, and managing network relations among factories may prove to be the key to competitiveness." Such phenomenon is not only observed in manufacturing management but also in healthcare network operations with hospitals instead of plants. Angst et al. (2010) find empirically that hospitals' proximity help individuals interact which lead to a better adoption of electronic medical records systems due to social influence.

This paper is related to the work presented in Chapter 4 on the role of social comparisons (ahead-seeking and behind-averse) and heterogeneous social interactions in the adoption of new practices. Chapter 4 looks at social engineering interactions between two teams and this paper extends this aspect by including a network structure in which each plant's level of social interactions is defined by its position in the production network. It contributes to the literature of adoption in manufacturing networks as I study two main structures that the global production networks literature sees as the stylised network models of decentralised and centralised structures (Lanza et al. 2019): the chain and the hub-and-spoke networks. Such configurations can be engineered by a firm through exchanges and program training between plants or are naturally present due to geography. These two network structures suggest two different ways that information can flow between plants which trigger different types of strategic interactions.

This paper's findings bring novel insights to the manufacturing literature. First, I find that a certain topology can enable better adoption of a know-how practice under each regime of social comparisons (ahead-seeking or behind-averse). In particular, I find that more adoption of the new practice can be achieved in a ahead-seeking organisation with a hub-and-spoke network compared to a chain network if periphery plants are targeted. On the other hand, a chain network allows more diverse patterns of adoption in a behind-averse organisation compared to a hub-and-spoke if the organisation wishes to enable a mix level of adoption. Such scenario can benefit an organisation when the value of the new system for the organisation is not clear yet. An example is smart factory equipment. A full adoption may not help an organisation perform better if these new solutions do not mesh correctly with existing processes in the organisation or if the technology of such new equipment requires large hardware investment and becomes obsolete before bringing enough value to the organisation. In such circumstances, having existing practices and new "smart" practices co-exist can be beneficial for manufacturing plants. Secondly, management can encourage employees to adopt a new know-how practice even if it presents a risk of failure by increasing the economic benefit of successful adoption through rewards (Atkin et al. 2017). I find that the higher connected the plant is, the less impacted by the rewards change they are. This suggests that if an organisation wants to have more control on specific plants such as R&D departments, they should position them in the lowest connected nodes (at the periphery of the chain and hub-and-spoke).

The remainder of this paper is organised as follows. In Section 5.2, I review the literature on the topic. In Section 5.3, I present the evolutionary game model set-up applied to the two network structures: chain and hub-and-spoke. Section 5.4 contains the analysis and the main results. I conclude the chapter by summarising the main managerial insights drawn from the analysis and the main theoretical contributions to the field of operation management.

5.2 Related literature

The current paper contributes to the literature on adoption of new operational practices in production networks and the growing literature initiated in Chapters 3 and 4 on the impact of relative benefits in adoption decisions.

The design of global production networks is a complex problem for firms and has attracted a large body of research in the operations management literature (see Lanza et al. (2019) for a review). Two main approaches have been taken regarding the design of production plants. The first typically focuses on cost minimisation and profit maximisation of implementing factories to meet a certain demand, by attaining a reduction in labour costs or improving proximity to partners or raw material providers (Cheng et al. 2015). The second approach, to which this paper contributes, has focused on the role manufacturing plants' networks play in knowledge sharing. This stream argues that an improvement in information flow can allow people in these plants to adopt new innovations or become acquainted with better practices (Holweg et al. 2018). Knowledge can be directly shared about a product or a new process by mentioning it explicitly, but it is also often implicitly communicated, especially when different managers from different plants have high levels of interaction. The latter approach has emphasized "the role of individual facilities in fostering and disseminating innovation across a manufacturing network" and how “the strength of a multinational manufacturing company lies precisely in its ability to exploit a network of knowledge to spread process innovations and best practices and, ultimately, to create innovative products and services.” (De Meyer and Vereecke 2009).

Two of the main types of manufacturing plant networks investigated in this literature are the chain (linear) and the hub-and-spoke (star) networks (Lanza et al. 2019). This literature has generally used a few key metrics to describe the influence of the plants in the network as well as knowledge flows. Some of the most used have been the density, the average path length and the degree of centralization (see Wasserman et al. (1994), Watts (1999, 2002)). Density highlights the number of links in the network over potential links possible. Dense networks are usually more costly due to the creation of multiple links but their benefits are that they encourage individuals' interactions. The level of centralization and the average short path length are features that look at the importance of the topology of the network and how links are positioned. Due to the difference in their degree distribution, certain nodes have more influence and social power than others.

The extant literature has advocated that social interactions are key to adoption, due to information sharing or social influence due to proximity with others or number of links in the network. However, the impact of two main behavioural effects (ahead-seeking and behind-averse social comparisons[1]) have been absent in the manufacturing literature. Therefore, I contribute to the literature on production networks by incorporating social comparisons considerations in the decision to adopt.

I show, first, that contrary to past literature well-connected networks can be less efficient in terms of adoption of innovation compared to less connected networks due to the nature of the relative benefits arising from knowledge sharing that depend on the type of social comparisons. Different types of social comparisons (ahead-seeking or behind-averse) can lead to very different adoption patterns of know-how practices which can influence firms to choose the type of production network they want to promote (decentralised vs centralised). A similar phenomenon has been observed by Lazer and Friedman (2007) and Masini and Pich (2001) but their underlying mechanism is different. They argue that well connected networks indeed help innovation due to knowledge sharing but suggest that less connected network can give rise to more innovation breakthroughs due to better exploration of ideas.

Second, current literature also suggests that alignment of incentives allow adoption of new practices (Atkin et al. 2017). I find, however, that the effectiveness of these incentives will differ depending on the plant's position in the network. In the light of these findings, I provide new insights on how management should place their innovation plants, such as the Research and Development centres, in the network to optimise the effectiveness of rewards schemes.

[1]Other terms have been used in the literature instead of ahead-seeking such as gain seeking or gloating and instead of behind-averse, social regret or envy.

Lastly, this paper also contributes methodology-wise to the work presented in Chapter 3 on the impact of heterogeneous social interactions on adoption of new practices by including network structures guiding the level of social interactions. The model proposed in this paper also differs from approaches in economics and organisational behaviour. Traditionally, the organisational behaviour literature has studied the diffusion of innovations in organisations through agent-based simulations (Abrahamson and Rosenkopf 1993, Lazer and Friedman 2007, Masini and Pich 2001) with individuals acting as automata with rule-based behaviours. On the other hand, the theoretical literature in economics of networks investigated how a behaviour can spread depending on the network structure and the characteristics of the new behaviour (strategic complements or substitutes). Most of these works have been looking at static equilibria that emerge in graphical games and how equilibria of adoption or non-adoption depend on a threshold that is usually fixed and the same for all or dependent on the degree distribution. Another stream of works has been looking at the adoption behaviour dynamically over time and the equilibria stability assuming usually forward looking individuals and the adoption when it occurs being definitive (Jackson and Yariv 2007). This stream has been interested at characterising how the structure of the network is linked to the number of nodes to target for achieving full adoption (Morris 2000). Contrary to these streams of research, I propose a population game in which individuals are bounded rational and the behaviour analysed (adoption of a new practice) can act as both a strategic complement and substitute depending on the number of adopters, due to the effect of social comparisons.

5.3 Model set-up

In this section, I introduce an evolutionary game theoretic model on two particular network settings, chain and hub-and-spoke, which are the classic structures studied in the global production network literature (Lanza et al. 2019).

The network consists of nodes which correspond to plants. In each plant, there is a clique of employees. Employees can choose either to adopt the new practice N for which the individual will get the utility U_N or to stick with the old practice O and get a utility U_O.

5.3.1 Payoffs at the micro-level: economic benefits and social influence through social comparisons

The utility is composed of a utility driven by economic benefits of adoption and social comparisons.

Employees in the organisation can choose to try a new operational practice with a likelihood p of successfully adopting it and extract a value V_N. They can also decide to stick with the old well-mastered practice O and extract a value $V_O = kV_N$ with $k \in]0,1[$.

The utility driven by social comparisons is triggered when employees who made different choices interact and experience a difference in outcomes. In an organisation where ahead-seeking social comparisons are present, individuals will gloat and get an *increase* in their utility when they made the right choice that led to extracting more value than the employee they interact with. I model this boost in utility proportional to the difference of outcomes observed and a parameter $0 < \alpha < 1$, characteristic to the organisation controlling the magnitude of this utility boost. Thus, in an ahead-seeking organisation, two employees interacting will receive the utilities displayed in Table 5.1 depending on random matching where the level of ahead-seeking is characterised by $\alpha \in [0,1]$.

Table 5.1 Payoff matrix when a member of plant i interacts with another member of plant i or j adjacent to i

		Plant i/j	
		N	O
Plant i	N	$U_{NN} = pV_N$	$U_{NO} = pV_N + \alpha p(1-k)V_N$
	O	$U_{ON} = kV_N + \alpha(1-p)kV_N$	$U_{OO} = kV_N$

While, in an organisation where behind-averse social comparisons are predominant, individuals will feel behind-averse and will get a *decrease* in their utility due to having made the wrong choice while their counterpart extracted more value by having chosen a different practice. I model this decrease in utility proportional to the difference that arises in outcomes and an organisational parameter $0 < \gamma < 1$ mediating the magnitude of this utility decrease. Thus, in a behind-averse organisation, two employees interacting will receive the utilities displayed in Table 5.2 depending on random matching where the level of behind-aversion is characterised by $\gamma \in [0,1]$.

Table 5.2 Payoff matrix when a member of plant i interacts with another member of plant i or j adjacent to i

		Plant i/j N	Plant i/j O
Plant i	N	$U_{NN} = pV_N$	$U_{NO} = pV_N - \gamma(1-p)kV_N$
Plant i	O	$U_{ON} = kV_N - \gamma p(1-k)V_N$	$U_{OO} = kV_N$

5.3.2 The production network structures

Each plant of the network corresponds to a cluster of employees and employees can interact within the plant or with an employee from an adjacent plant. I study which structure, a chain (linear) or a hub-and-spoke (star), may be best to promote adoption of the new practice depending on the type of social comparisons present in the organisation.

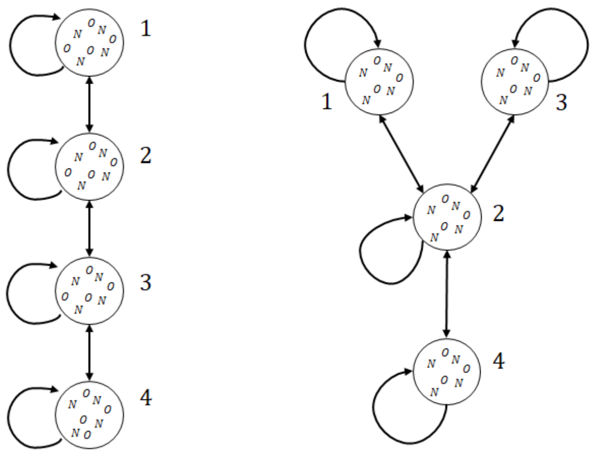

Fig. 5.1 Chain (left) and hub-and-spoke (right) production networks

The management literature usually uses density or centrality (Sykes et al. 2009) as key measures to compare the efficiency and performance of various observed social networks to determine which may perform better. In Table 5.3, I present the following three topology characteristics of these two types of networks shown in Figure 5.1: density, average path length and centralisation degree. The density of a network is defined as the proportion of links over the total number of possible links in the network. The average path length is a measure of how efficiently an information can pass in the network and corresponds to the average distance of all the shortest paths between any pair of nodes in the network. Lastly, the centralisation degree is a measure on how evenly distributed the degrees of the nodes in the network are.

Table 5.3 Chain and hub-and-spoke topology characteristics

Network type	Density	Average path length	Centralisation degree
chain ($n = 4$)	0.7	$\frac{5}{3}$	$\frac{1}{3}$
hub-and-spoke ($n = 4$)	0.7	$\frac{3}{2}$	1

Both networks have the same density but the hub-and-spoke network allows better information sharing due to it shorter average path length and plants exhibit a more hierarchical structure due to its higher centralisation. These features lead the existing literature to consider the hub-and-spoke network more performant than the chain network in terms of information sharing. In Section 5.4, we show that this is not always beneficial for the organisation.

5.3.3 The population game and population dynamics on networks

The payoff matrices in Section 5.3.2 represent the micro structure of the strategic interactions. Scaling that effect at the population level, I define the population game for plant i members with x^N the proportion of adopters: $U^i(x^N) = \begin{pmatrix} U_N^i(x^N) \\ U_O^i(x^N) \end{pmatrix}$.

I define d_{ij} as the interaction level between plants i and j and $c(i)$ the number of connections of plant i such that for any plant i, $d_{ij} = \frac{1}{c(i)}$ and $\sum_j = d_{ij} = 1$:

$$\begin{aligned} U^i(x^N) &= \begin{pmatrix} U_N^i(x^N) \\ U_O^i(x^N) \end{pmatrix} \\ &= d_{ii} \begin{bmatrix} U_{NN} & U_{NO} \\ U_{ON} & U_{OO} \end{bmatrix} \times \begin{pmatrix} x_i^N \\ 1 - x_i^N \end{pmatrix} + \sum_{j \neq i} d_{ij} \begin{bmatrix} U_{NN} & U_{NO} \\ U_{ON} & U_{OO} \end{bmatrix} \times \begin{pmatrix} x_j^N \\ 1 - x_j^N \end{pmatrix} \\ &= \begin{pmatrix} d_{ii}(x_i^N U_{NN} + (1 - x_i^N) U_{NO}) + \sum_{j \neq i} d_{ij}(x_j^N U_{NN} + (1 - x_j^N) U_{NO}) \\ d_{ii}(x_i^N U_{ON} + (1 - x_i^N) U_{OO}) + \sum_{j \neq i} d_{ij}(x_j^N U_{ON} + (1 - x_j^N) U_{OO}) \end{pmatrix}. \end{aligned} \tag{5.1}$$

One of the most studied dynamics in evolutionary game theory has been the replicator dynamics (Weibull 1997). The replicator dynamic is a type of imitative dynamic where the use of a practice increases in a population i when the utility of adopting this practice is greater than the average performance of all practices in the population i.

I define the average performance of the two practices in population i by:
$\bar{U}_i(x^N) = x_i^N U_N^i(x^N) + (1-x_i^N)U_O^i(x^N)$.

In each plant i, the number of adopters of the new practice evolves according to the following dynamic:

$$\begin{aligned}\frac{dx_i^N}{dt} &= x_i^N(U_N^i(x^N) - \bar{U}_i(x^N)) \\ &= x_i^N(1-x_i^N)(U_{NO} - U_{OO} + \frac{x_i^N + \sum_{j\neq i} x_j^N}{c(i)}(U_{NN} - U_{ON} - U_{NO} + U_{OO})).\end{aligned}$$

In the case of $n = 4$, I derive the following dynamical system for the chain production network:

$$\begin{cases}\frac{dx_1^N}{dt} = x_1^N(1-x_1^N)(U_{NO} - U_{OO} + \frac{x_1^N + x_2^N}{2}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_2^N}{dt} = x_2^N(1-x_2^N)(U_{NO} - U_{OO} + \frac{x_1^N + x_2^N + x_3^N}{3}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_3^N}{dt} = x_3^N(1-x_3^N)(U_{NO} - U_{OO} + \frac{x_2^N + x_3^N + x_4^N}{3}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_4^N}{dt} = x_4^N(1-x_4^N)(U_{NO} - U_{OO} + \frac{x_3^N + x_4^N}{2}(U_{NN} - U_{ON} - U_{NO} + U_{OO}))\end{cases}$$

In the case of $n = 4$, I derive the following dynamical system for the hub-and-spoke production network:

$$\begin{cases}\frac{dx_1^N}{dt} = x_1^N(1-x_1^N)(U_{NO} - U_{OO} + \frac{x_1^N + x_2^N}{2}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_2^N}{dt} = x_2^N(1-x_2^N)(U_{NO} - U_{OO} + \frac{x_1^N + x_2^N + x_3^N + x_4^N}{4}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_3^N}{dt} = x_3^N(1-x_3^N)(U_{NO} - U_{OO} + \frac{x_2^N + x_3^N}{2}(U_{NN} - U_{ON} - U_{NO} + U_{OO})) \\ \frac{dx_4^N}{dt} = x_4^N(1-x_4^N)(U_{NO} - U_{OO} + \frac{x_2^N + x_4^N}{2}(U_{NN} - U_{ON} - U_{NO} + U_{OO}))\end{cases}$$

In the following section, I analyse the stable equilibria that emerge from these two dynamical systems.

5.4 Analysis

5.4.1 The effect of network topology on adoption outcomes

In this section, to highlight the role of social comparisons, I assume new practices follow a "high risk-high return" rule. The more risky it is to adopt a new practice successfully (p low), the higher the reward will be compared to sticking with the old practice (k low). As a simplification of this rule, I assume $p = k$. This condition is relaxed in the following sections of the analysis.

5.4.1.1 In an ahead-seeking environment

In an ahead-seeking environment, a member of the organisation enjoys an ahead-seeking effect if his choice leads to a better outcome than the individuals he interacts with. These individuals can be working at his plant or work at connected other plants. Given the assumption of $p = k$, he gains more utility in expectation when he meets individuals choosing opposite practices and therefore has an incentive to differentiate. Thus, employees stick with the old practice when too many other employees adopt the new practice, whereas adopting the new practice becomes more attractive if too many others stick with the old practice. This phenomenon has been observed in practice when individuals do not necessarily choose the practice that leads to a better personal performance, but prefer to perform better than their peers.

Proposition 14 *In the chain network, two stable adoption patterns exist where the plants that adopt fully alternate with the ones that stick to the old practice.*

Proof: See in Appendix

In the chain network, I observe a stable adoption pattern where employees differentiate between plants but not within as illustrated in Figure 5.2. This phenomenon is due to the different level of connectivity of the peripheral plants (degree of centrality of 2) and the more central plants in the network (degree of centrality of 3). Through social interactions, an employee in plant 2 wants to differentiate from the adoption behaviour of his direct colleagues and those that work in the neighbouring plants (1 and 3). With two strategies (adopt and non-adopt), he will choose the strategy that is pursued by the lowest proportion of people in his network at that point in time. Let's imagine he chooses to adopt. Using the same decision process, employees in plant 1 and 3 will respond by non-adopting, after which this change feeds back into the decision-making process of people in plant 2, exacerbating their incentive to adopt. Due to the feedback loop that arises when employees in a plant are pushed to differentiate with respect to two directions (plant 2 and 3), the only stable equilibrium is where they can differentiate with respect to both neighbours. This will push these employees and those at the periphery to conform to each other within.

It is important to note that the difference in connectivity also impacts the rate of change. Individuals in a peripheral plant are more sensitive to changes in adoption behaviour that occur in their environment simply because that change comprises a relatively large part of their network. More central nodes are slower in adapting to a change because their large network mitigates the effect.

Figure 5.2 displays the unique stable adoption patterns that arise in the chain network. Note that in Figure 5.2 and the subsequent Figures of this chapter, additional adoption patterns can be displayed by argument of symmetry.

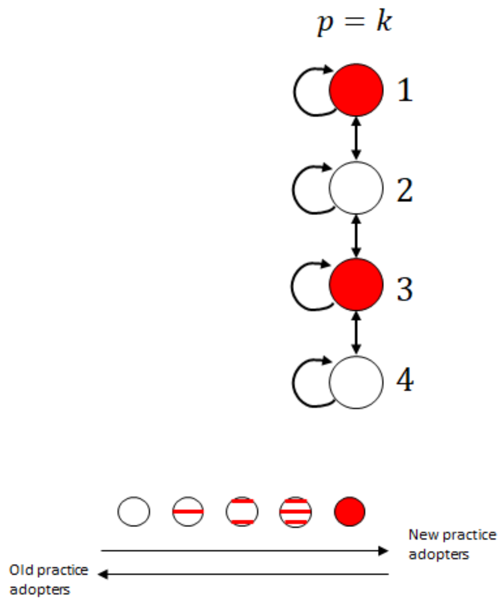

Fig. 5.2 Stable adoption patterns in the chain network in a ahead-seeking environment when $p = k$

Proposition 15 *In the hub-and-spoke network, two stable adoption patterns exist where either the centre of the network fully adopts the new practice while the periphery plants stick with the old practice, or the periphery plants adopt fully and the plant at the centre sticks with the old practice.*

Proof: See in Appendix

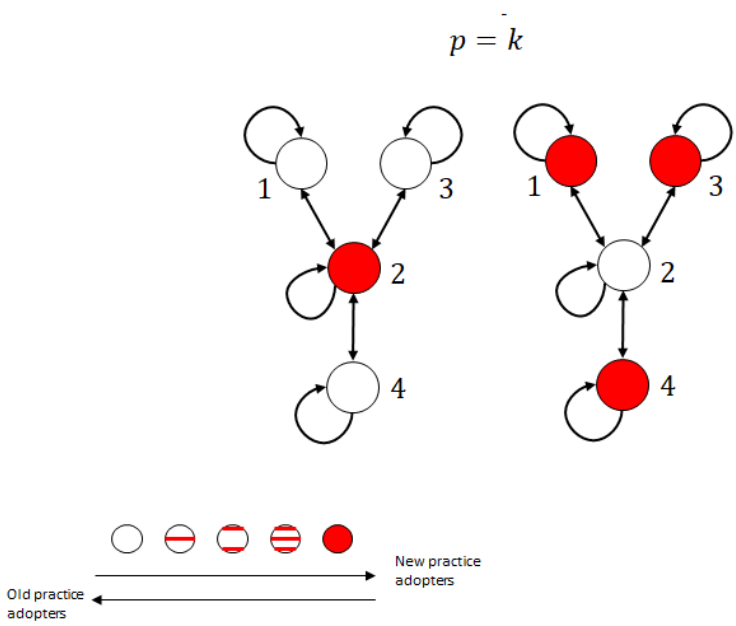

Fig. 5.3 Stable adoption patterns in the hub-and-spoke network in a ahead-seeking environment when $p = k$

In a more centralised network such as the hub-and-spoke, the central plant exhibits a higher level of connectivity (degree of centrality of 4) than the peripheral plants (degree of centrality 2) as illustrated in Figure 5.3. As in the previous example, the plants will either adopt fully or not at all. For instance, as the central node has complete information the employees will decide to adopt if the overall proportion of adopters in the network is low. The employees in the peripheral plants are only connected to the central node. As a result, they perceive a high proportion of adopters in their network and decide to stick with the old practice, even though the proportion of adopters in the total network is very low (left-hand side of Figure 5.3).

In terms of the rate of change, the central plant will differentiate more slowly than the peripheral plant due to its higher level of connectivity. In other words, the employees within the central plant are being pushed to adopt from three directions and therefore any small change in behaviour in one of these plants will comprise a very small proportional change of their total network. Conversely, a change in behaviour in the central node carries a much larger weight in the network of a peripheral plant.

5.4.1.2 In a behind-averse environment

In a behind-averse setting, employees receive a negative utility if they interact with individuals who performed better by choosing a different practice. In the case where $p = k$, the employee always receives less utility when choosing an opposite practice from the individual he interacts with. This pushes employees to conform to the practice choice of others. Behind-averse social comparisons create a herding/bandwagon behaviour from employees in the organisation.

Proposition 16 *In the chain network, three stable adoption patterns exist where either all plants fully adopt the new practice, all plants stick with the old practice, or half of the plants adopt the new practice while the other half sticks with the old practice, with the plants choosing the same practice being adjacent.*

Proof: See in appendix

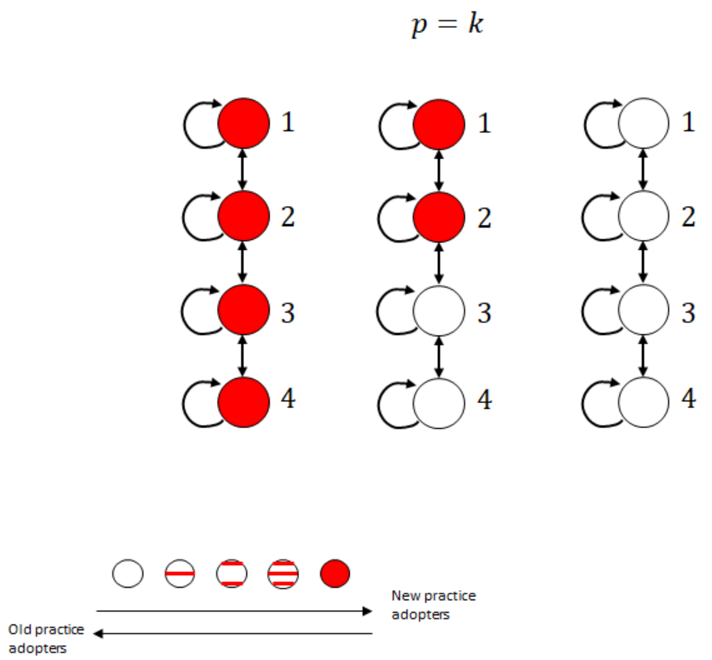

Fig. 5.4 Stable adoption patterns in the chain network in a behind-averse environment when $p = k$

Proposition 17 *In the hub-and-spoke network, two stable adoption patterns exist where all the plants adopt or none of them do.*

Proof: See in appendix

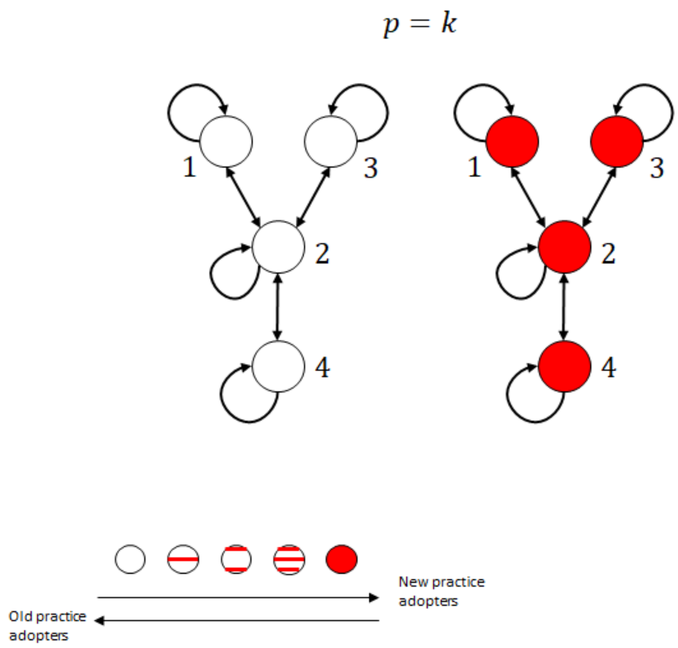

Fig. 5.5 Stable adoption patterns in the hub-and-spoke network in a behind-averse environment when $p = k$

Not surprisingly, as displayed in Figures 5.4 and 5.5, due to the herding effect, in the chain and the hub-and-spoke networks, I observe two stable adoption patterns that can occur where all the plants fully adopt the new practice or all the plants stick with the old practice.

Interestingly, the chain network (Figure 5.4) exhibits an additional stable adoption pattern where the herding effect comes from two directions. The two central plants preferably conform to both connected plants. However, if their neighbours exhibit opposite adoption patterns, given that these neighbours are not connected to each other, this equilibrium can arise and be stable. This means that high centrality nodes can resist a push towards non-adoption and enables a cascading effect in the other direction towards adoption.

5.4.2 The impact of change in rewards on the patterns of adoption

In this section, I extend the analysis to cases where $p \neq k$ which correspond to occurrences where the organisation changes the rewards to adopt the new practice. When $p > k$, the economic benefits to adopt the new practice are greater than the economic benefits of sticking with the old practice. It corresponds to cases where the new practice becomes "low risk high return". In contrast, $p < k$ corresponds to cases where the new practice is "high risk low return" practices.

Theorem 2 *The effect of changes in rewards is most effective in the least connected plants.*

Theorem 2 displays a key result of this paper. The level of connectivity of a plant highlights the level of interactions with other members within and of other plants. In our model, the risk-return of adopting or sticking with a new practice is not influenced by population effects while the magnitude of the effects of social comparisons depends on the state of the population (adopters or non-adopters) as being triggered by employees interacting having made opposite choices. Therefore, the more connectivity with others a plant has, the more influenced it will be by social comparisons effects. It follows that the effect of changes in rewards will be most effective in the least connected plants.

5.4.2.1 In an ahead-seeking environment

In Section 5.4.1.1, I found that under $p = k$ plants alternate in adopting and non-adopting the new practice, driven by the differentiation effect. We consider here cases when $p \neq k$.

When the economic benefits of adopting the new practice become greater than the economic benefits of sticking with the old practice, i.e., $p > k$, the utility of adopting the new practice increases. This can be introduced for example by the management of an organisation by increasing the expected reward of employees that decide to adopt the new practice. As a result, the plants which were fully adopting the new practice will want to continue to adopt, while the individuals in the plants that were sticking with the old practice can increase their utility by adopting the new practice instead. Interestingly, if the increase in rewards is not large enough, the ahead-seeking effect can continue to push people to differentiate and create a mix of adopters and non-adopters in the plant. Coming from the base scenario (Figure 5.2), this effect is illustrated on the left-hand side of Figure 5.6.

Proposition 18 *In the chain network, two stable adoption patterns occur for a range of changes in rewards:*
- $p > k$ cases: half the plants fully adopt while the other half have a mix of adopters and non-adopters with fully adopting plants being adjacent to mixed adoption plants.
- $p < k$ cases: half of the plants fully stick with the old practice while the other half have a mix of adopters and non-adopters, with plants fully sticking with the old practice being adjacent to mixed adoption plants.

Proof: See in Appendix

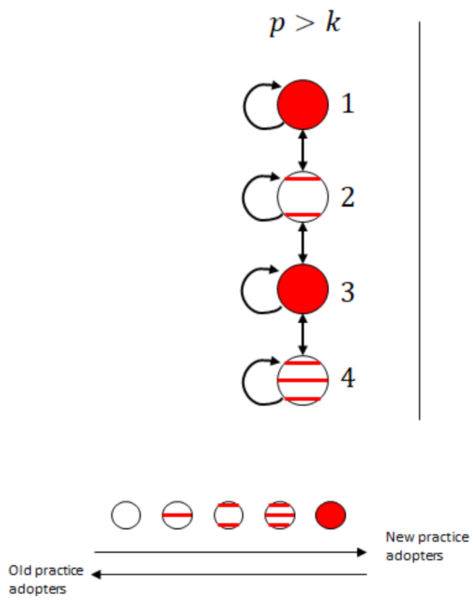

Fig. 5.6 Stable adoption patterns in the chain network in a ahead-seeking environment when $p \neq k$

On the other hand, when the reward of adopting the new practice is lower than sticking with the old practice, i.e., $p < k$, the utility of staying with the old practice is greater. This occurs for example when a new practice is very risky to adopt successfully and a significant amount of recognition is still given when an individual sticks with the old practice. Plants that chose the old practice will continue to do so, while plants that fully adopted want to switch to the old practice. If the differentiation effect is strong enough, a mix of adopters and non-adopters will exist within these plants that were initially only adopting. Coming from the base scenario (Figure 5.2), this effect is illustrated on the right-hand side of Figure 5.6.

The effect in the hub-and-spoke network is similar to the discussion above. An increase in the expected utility of adopting the new practice will strictly improve adoption rates, but if the increase in rewards is not large enough the plants that stuck with the old practice will not convert fully to adoption. Driven by the differentiation effect there will be a mix of adopters and non-adopters in these plants.

Proposition 19 *In the hub-and-spoke network, two stable adoption patterns occur for a range of change in rewards:*
- $p > k$ where the plant at the centre fully adopts the new practice and the peripheral plants exhibit a mix of adopters and non-adopters at equilibrium or the peripheral plants fully adopt the new practice but the central plant has a mix of adopters and non-adopters.

- $p < k$ where the plant at the centre fully sticks with the old practice and the peripheral plants have a mix of adopters and non-adopters or the peripheral plants stick with the old practice, while the central plant exhibits a mix of adopters and non-adopters.

Proof: See in appendix

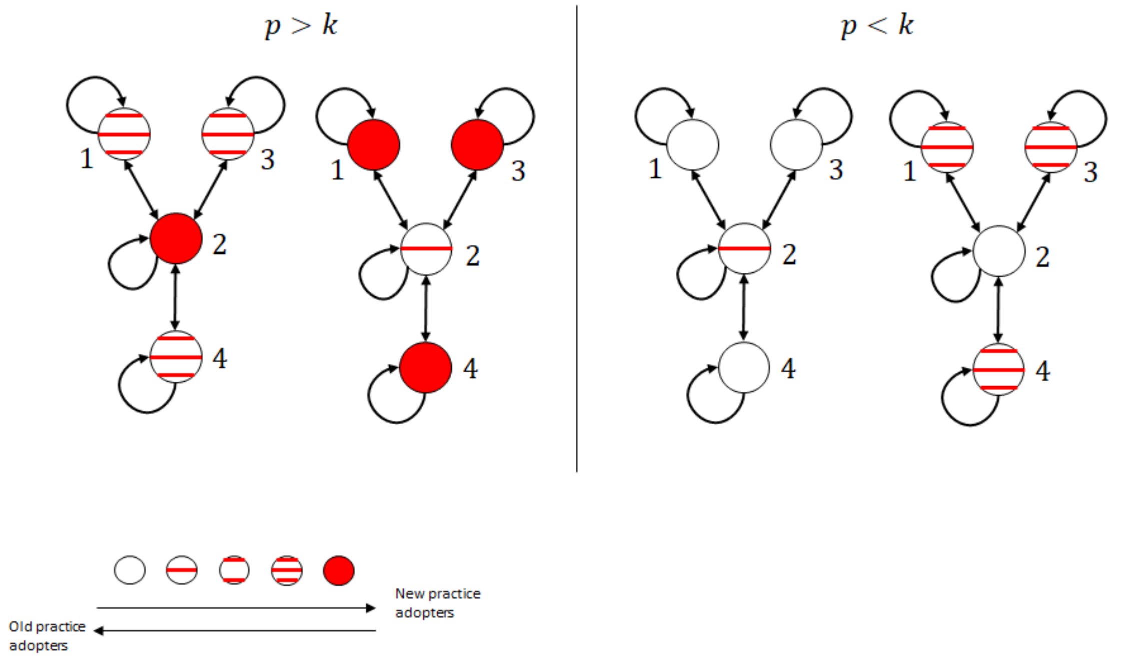

Fig. 5.7 Stable adoption patterns in the hub-and-spoke network in a ahead-seeking environment when $p \neq k$

Interestingly, in the plants that have both adopters and non-adopters, I find that the proportion of these groups is highly dependent on the connectivity.

Corollary 4 *Among the plants who have at equilibrium a mix of adopters and non-adopters:*
- When $p > k$, the plants with the highest degree of connections will have fewer adopters of the new practice than those with less connections.
- When $p < k$, the plants with the highest degree of connections will achieve a higher number of adopters of the new practice at equilibrium than the ones with less connections.

Proof: See in Appendix

This corollary is a consequence of Theorem 2. Though an increase in expected rewards reduces the impact of the social comparison effect, higher connectivity mitigates this reduction. This means that more connected plants feel the differentiation effects of the ahead-seeking environment more strongly. These plants are less sensitive to the incentives to adopt the new practice than least connected plants. The implication of this finding is that management should carefully consider the interaction between the structure and social culture of the organisation to increase the effectiveness of incentive schemes on adoption rates.

5.4.2.2 In a behind-averse environment

In a behind-averse environment employees receive a negative utility when different choices led them to under-perform compared to others. To minimise this risk, individuals are pushed to imitate others' actions. When the economic benefits of adopting the new practice are greater than those of sticking with the old practice ($p > k$) the attractiveness of undertaking the new practice increases. Only if the economic benefits of adopting the new practice are high enough to overpower the social comparisons effects, will everyone end up adopting it. However, if the economic benefits are not large enough the social comparison effects driven by behind-aversion, influence the adoption behaviour.

Proposition 20 *In the chain network, there is a range of changes in rewards, such that two additional stable adoption patterns occur where one or both of the peripheral:*
- Fully adopt the new practice ($p > k$).
- Stick with the old practice($p < k$).

Proof: See in Appendix

These results are illustrated on the left-hand side of Figure 5.8. In the two new equilibria the plant at the periphery can fully adopt the new practice while the other plants stick to the old one. In the previous section, only a central node could resist the herding behaviour provided it was connected to a peripheral node that adopted. Due to the increase in expected reward, now the peripheral nodes can also resist imitating non-adopters of other plants despite their behind-aversion, though they still conform within the plant.

Similarly, a range of rewards exists for $p < k$ such that central nodes continue to adopt the new practice despite the lower expected reward and the pressure of the peripheral nodes sticking to the old practice. A similar argument as before applies here. Though the expected utility to stick with the old practice is larger, the most connected nodes can continue to adopt as these nodes may still perceive mainly adopters in their direct network. The need to conform reduces the attractiveness of the old practice. Thus, even when the expected rewards of adopting a new practice are lower than those of sticking to the old one (e.g., due to riskiness), with the right structure an organisation can still have relatively high adoption rates.

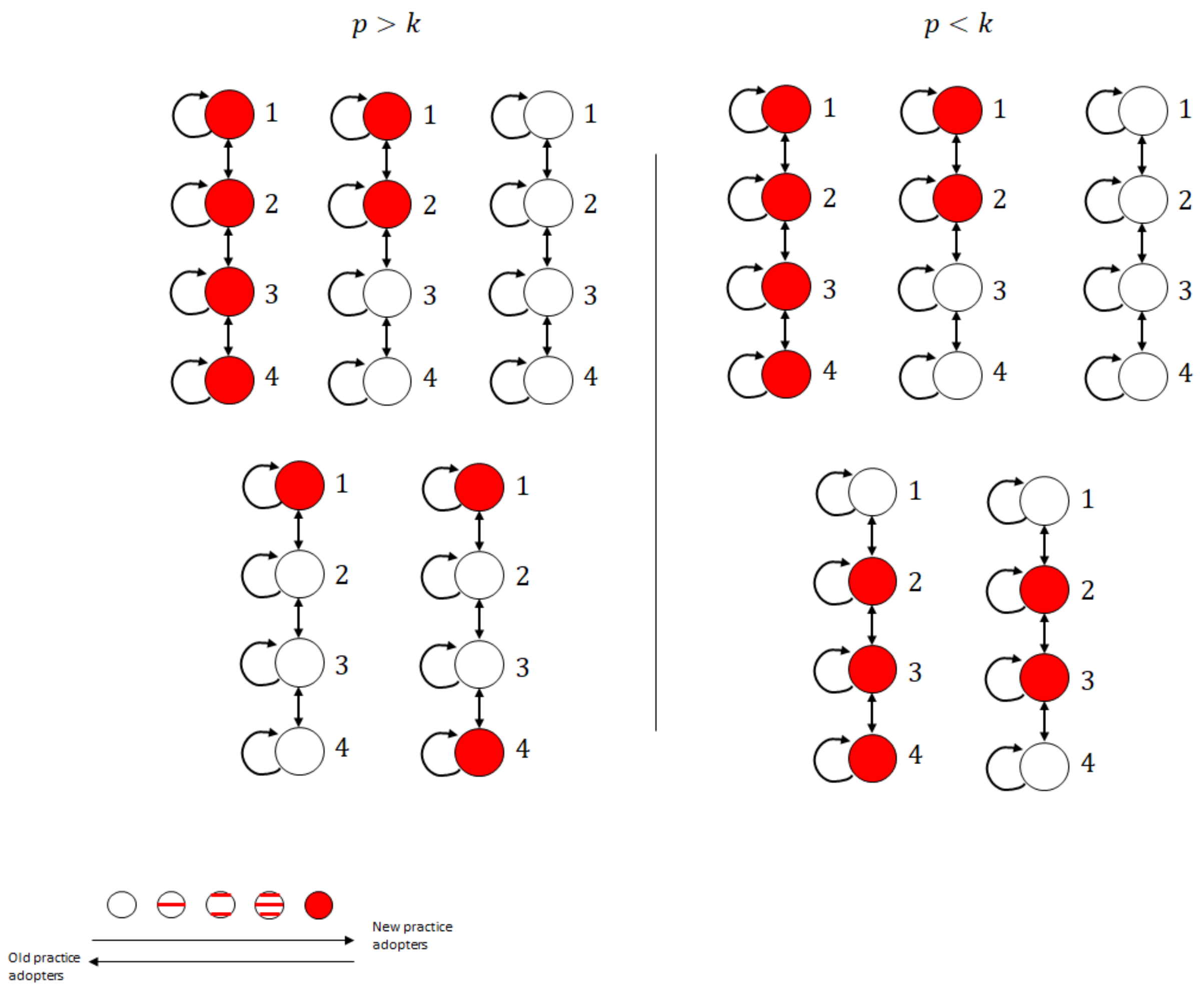

Fig. 5.8 Stable adoption patterns in the chain network in a behind-averse environment when $p \neq k$

In the previous section I showed that the hub-and-spoke network plants will end up with all their employees either adopting the new practice or sticking with the old one. When the economic benefits of adopting are higher than non-adopting ($p > k$), a stable adoption pattern emerges (in addition to those found with $p = k$) in which one of the peripheral nodes can fully adopt the new practice while the other plants of the hub-and-spoke stick with the old practice. This is illustrated on the left-hand side of Figure 5.9. The economic reward can help resist the pressure to conform with the central plant it is connected to. In turn, conformity pushes the central plant toward non-adopting despite the increase in rewards given that a higher proportion non-adopts in his network. This conformity will only drive the whole network to adopt if at least one other peripheral node would adopt.

Proposition 21 *In the hub-and-spoke network, a range of change in rewards exists, such that there is a stable adoption pattern where one of the periphery plants:*
- Fully adopts the new practice while the other plants stick with the old practice ($p > k$).
- Sticks with the old practice while the other plants fully adopt the new practice ($p < k$).

Proof: See in Appendix

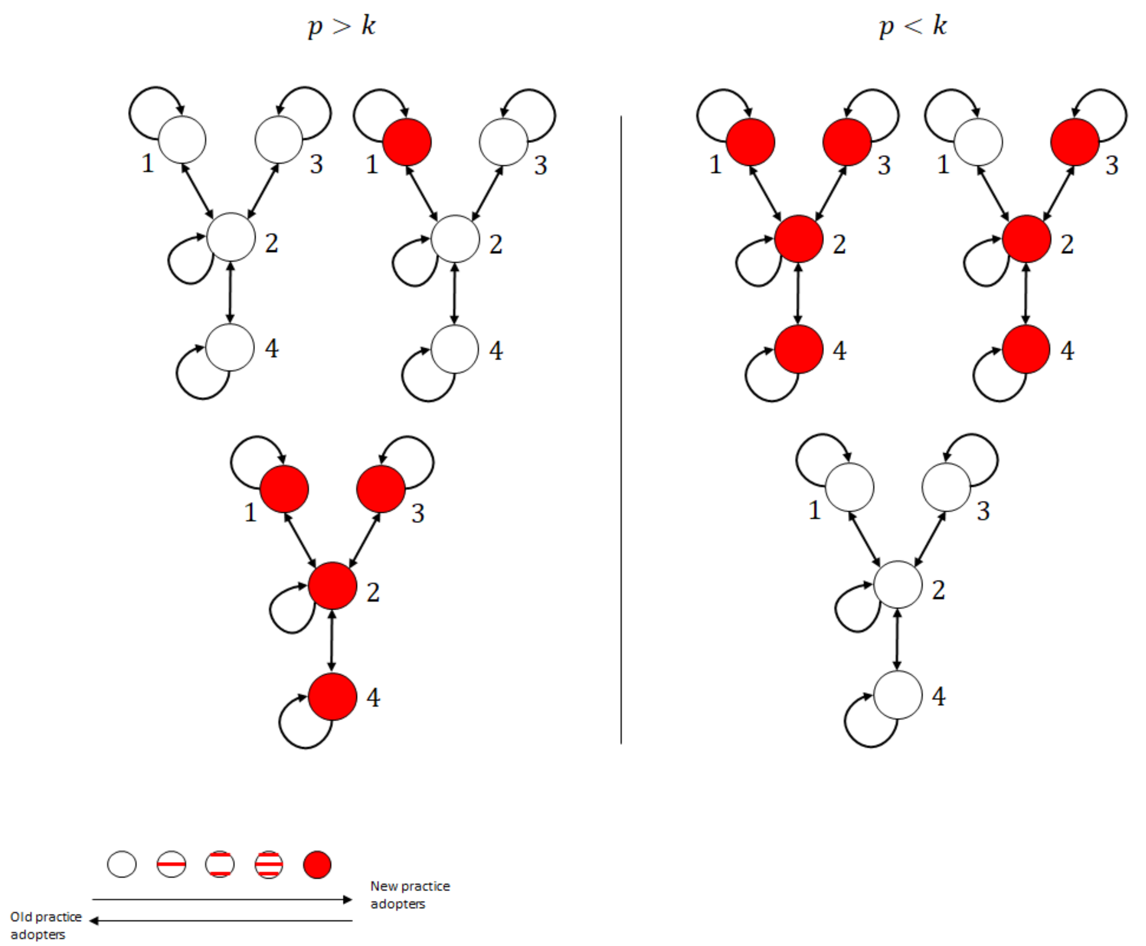

Fig. 5.9 Stable adoption patterns in the hub-and-spoke network in a behind-averse environment when $p \neq k$

Similar to the arguments above, when the economic benefits of sticking with the old practice are higher than those of adopting the new practice, one of the peripheral nodes can resist the herding effect of adopting the new practice.

Corollary 5 *The least connected plants are more sensitive to changes in rewards and hence more resistant to the herding effect of sticking with the old practice when $p < k$ or of adopting the new practice when $p > k$.*

Proof: See in Appendix

This corollary is a consequence of Theorem 2 and the above propositions. The least connected plants are the ones least sensitive to social comparisons and in the case of a behind-averse environment, to a herding behaviour of sticking with the old practice or adopting a new practice. Therefore, despite lower expected rewards of adopting, employees of central nodes can resist the herding behaviour of non-adopting from adjacent plant. Conversely, despite higher expected rewards, central nodes can continue to non-adopt driven by their fear of under-performing.

5.5 Discussion and conclusion

In this paper, I propose an evolutionary game theoretic model that analyses the adoption of new know-how practices in production networks. I study the effect and efficiency of two main operational levers a firm can use on the adoption of new management practices: the choice of production network topology (chain or hub-and-spoke) and economic rewards.

5.5.1 Managerial implications

First, I find that the topology impacts the overall adoption of new practices differently in each social comparisons environment. In a ahead-seeking environment, a chain network structure will allow half the plants to adopt the new practice while the other half will stick with the old practice. The hub-and-spoke network presents stable adoption patterns where one of the two practices is fully adopted by the centre of the plant network, while the periphery plants adopt the other. Thus, the hub-and-spoke network can facilitate higher adoption rates than the chain network only if the centre sticks with the old practice which will push the periphery plants to adopt the new practice. However, if the new practice is too risky such as in the case of new smart manufacturing practices and the firm wants to make sure that the overall adoption is at first minimal, choosing a hub-and-spoke structure can be beneficial when the plant adopting the new risky practice is centrally located or choosing a chain structure if the organisation is unable to target specific plants.

In a behind-averse environment, both the chain and the hub-and-spoke networks exhibit stable adoption patterns in which the herding effect leads all the plants either to adopt the new practice or to stick with the old practice. However, the chain network also permits an adoption pattern in which half of the plants adopt. The high connectivity of the more central nodes of the chain can break the herding effect as the downstream and upstream neighbour can pull a plant in either direction. This can result in a stable equilibrium where the more central plant does not conform to one of its neighbours. Similarly to the above discussion, if the firm wants both practices to co-exist such as in the case of new smart manufacturing practices as it is too risky to adopt it fully, a chain network may prove the best structure.

Second, the firm may use rewards (benefit of adopting the new practice or sticking with the old practice) to impact adoption. A key managerial finding in this paper is that in both social comparisons environments, the effect of changes in rewards initiated by a firm is most effective in the least connected factories.

This implies that if a firm has a specific network structure in place (chain or hub-and-spoke), it may choose to place R&D plants at the periphery to be able to influence adoption. In particular, a behind-averse environment pushes individuals of the plants to conform to either practice. So placing departments that require quick adoption rates at the periphery of such a network can avoid them conforming to old practices pursued by the rest of the organisation. In a ahead-seeking organisation, individuals differentiate and the more connected a plant is, the more its need to differentiate which will make the effect of rewards less pronounced in central nodes and more effective in periphery nodes.

5.5.2 Theoretical contributions

This paper makes several theoretical contributions in the field of adoption of practices and decision-making in social networks.

First, the role of networks in the adoption of innovative practices in organisations has been studied using simulation models (Abrahamson and Rosenkopf 1993, Lazer and Friedman 2007, Masini and Pich 2001) in organisational behaviour or using game theoretical models (Jackson 2010, Jackson and Yariv 2007) in economics. In this paper, I am extending the discussion on the topic by using a novel analytical methodology (evolutionary game theory) that enables me to incorporate bounded rationality (in contrast to hyper-rationality in economics) and behavioural features (such as social comparisons) as well as strategic interactions in the decision-making of the agents (in contrast to automata decision in previous simulation models). This paper differentiates from the organisational behaviour as it provides exact results and takes into consideration strategic interactions while keeping a dynamic and behavioural view of individual decision-making. Moreover, it differentiates greatly from the stream of research in economics of networks as we allow individuals to be bounded rational (relaxing the hyper-rationality assumption of individuals decision-making) and the practice is not inherently a complement or substitute but can act as either based on the number of adopters due to the dynamic nature of the model.

Second, I am contributing to the research work of Chapter 3 of this dissertation on the role of the social context and relative benefits in the adoption of innovative operational practices in the following ways. I extend the work presented in Chapter 4 of this dissertation on heterogeneous interactions between individuals by including classic production network structures such as hub-and-spoke or linear seen in the manufacturing literature (Lanza et al. 2019). I also analyse the heterogeneous effect of rewards on the different plants of the network and discuss which structure may be optimal for adoption or in other cases mitigate adoption.

Lastly, the literature in manufacturing has extensively studied the impact of network structure on the diffusion of innovation (De Meyer and Vereecke 2009, Lanza et al. 2019). This stream of research usually assumes that the more connected network enables better information sharing about the new practice (Angst et al. 2010, Holweg et al. 2018) which leads to more mastery of the new practice. Therefore, the trade-off for firms is that creating links between plants is costly but helps diffusion of new practices. In this paper, I am differentiating our analysis from this stream in the following two ways. First, I am comparing structures having the same number of links but different topologies which allows to focus on the diffusion of innovation only and not the cost created by the links. Second, I incorporate strategic considerations of choosing between two practices by including social comparisons. In this context, the higher connectivity (the more information on what others are doing) does not necessarily help adoption depending on the type of social comparisons present in the organisation.

5.5.3 Limitations

A few limitations can be interesting research avenues to explore in future work. In this paper, I have assumed agents to be homogeneous in each type of network. An insightful extension would be to investigate the impact of the network structure in the presence of heterogeneous plants. Second, it would be valuable to investigate whether the results hold in other types of network structures.

5.6 Appendix

In this Appendix, I provide proofs on the stability of a series of dynamical systems studied in this chapter. These proofs are conducted with ε perturbation arguments around fixed points. Similar to Chapter 4, a more traditional approach using traces and determinants of Jacobian matrices could have been used but I believe the following type of proofs can benefit managers build a better intuition regarding the adoption of innovations in their organisation.

5.6.1 Proof of Proposition 14

In a ahead-seeking environment, when $p = k$, individuals want to differentiate from the choice of the others. In the linear network, $(1,0,1,0)$ and $(0,1,0,1)$ are stable.

In the case of $(1,0,1,0)$. Let's assume that there exists ε number of new practice adopters in plant 1 that decide to switch to stick with the old practice. Due their connectivity with plant 2 (sticking with the old practice), this pushes individuals in plant 1 to differentiate even more so they will continue adopting the new practice. This change in adopters is not enough to push employees of plant 2 to start adopting as they are connected to plant 3 that fully adopted the new practice. This network configuration is robust to ε changes of adopters in each of the plants. By argument of symmetry, $(0,1,0,1)$ is also stable.

Let's prove now *by contradiction* (in two parts) that any other configuration of adoption and non-adoption $(x_1^*, x_2^*, x_3^*, x_4^*)$ in the linear network is unstable.

a) If $x_1^* = 1$ or 0 and if $0 < x_2^* < 1$ at equilibrium. Due to plant 2 connectivity with plant 1 then $x_1^* = 1$ or 0 is unstable. By symmetry, a similar argument can be applied for the case of $x_4^* = 1$ and if $0 < x_3^* < 1$ at equilibrium.

If $x_2^* = 1$ or 0 then $x_1^* = 0$ or 1 at equilibrium. For the linear configuration to be stable, when $x_4^* = 1$ or 0, having $0 < x_3^* < 1$ is not possible due to the differentiation effect. In the case of $x_4^* = \frac{1}{2}$ the other only stable adoption pattern for plant 4 leads $x_3^* = \frac{1}{2}$ which is unstable.

Therefore, if one of the plants in the linear network fully adopts the new practice or fully sticks with the old practice, any mixed state in the other plants is unstable.

b) Let's assume now that there exists a stable equilibrium $(x_1^*, x_2^*, x_3^*, x_4^*)$ such that $0 < x_i^* < 1$ for any $i \in 1,2,3,4$.

Let's assume that there exists ε such that at instant t, there are $x_1^* + \varepsilon$ employees in plant 1 that choose to adopt the new practice. Due to the differentiation effect, plant 2 is going to differentiate and the number of adopters in plant 2 x_2 will decrease. Due to his connectivity, this decrease in adoption pushes x_1 to increase but also the number of adopters in plant 3 to increase x_3. This feedback loop will push plant 2 members to differentiate again which will lead plant 1 members to adopt. Thus, x_1 and x_3 will increase and x_2 and x_4 decrease. The equilibrium is unstable. Contradiction.

5.6.2 Proof of Proposition 15

In a ahead-seeking environment, we observe in the star network when $p = k$ two stable adoption patterns where the centre adopts the new practice and the periphery plants stick with the old practice $(0,1,0,0)$ or the centre plant sticks with the old practice, while the other plants adopt the new practice $(1,0,1,1)$.

In the case of $(1,0,1,1)$. Let's assume that there exists ε employees in plant 1 that decides to adopt the new practice. Due to the ahead-seeking social comparisons, employees will differentiate and go back to the old practice. In the plant 2, if ε employees deviate from adopting the new practice, again, due to the differentiation effect and being in the centre, the employees will adopt the new practice. By symmetry, a same argument applies to plants 3 and 4. Therefore, $(0,1,0,0)$ is asymptotically stable.

Similarly, $(1,0,1,1)$ is also asymptotically stable.

Let's prove now *by contradiction* that any other configuration of adoption and non-adoption $(x_1^*, x_2^*, x_3^*, x_4^*)$ in the star network is unstable.

Let's assume that there exists ε such that at instant t, there are $x_1^* + \varepsilon$ in plant 1. Due to the ahead-seeking social comparisons, x_2 will decrease. Due to its position in the centre, this decrease will push employees in plants 1, 3 and 4 to adopt the new practice. This leads the number of adopters from the centre plant to decrease even more as the differentiation efefct comes from three sources, which will lead in return the number of adopters in the peripheral plants to increase. Thus, x_1, x_2 and x_3 increase and x_2 decrease leading to instability. Contradiction.

5.6.3 Proof of Proposition 16

In a behind-averse environment, employees want to imitate others' behaviour which lead that in the chain network, due to the behind-averse social comparisons, there can't exist inside a plant a mix of adopters ad non-adopters. Either everyone adopts or no-one adopts.

It is trivial to see that $(1,1,1,1)$ and $(0,0,0,0)$ are two stable adoption equilibria.

The following equilibrium $(1,1,0,0)$ and by symmetry, $(0,0,1,1)$ are also asymptotic stable. Let's assume that there exist a small ε number of employees in plants 1 or 2 that decide to stick with the old practice. Due to the interactions within the plant and their connectivity, plants 1 and 2 are still pushed by the majority of employees already adopting the new practice to adopt. However, if plant 3 and 4 stick with the old practice, they are resistant to the herding effect of adoption for any ε.

Any other configuration of adoption equilibrium in the chain network is unstable in the chain network. Let's assume that 1 of the plants in the chain network is fully adopting one of the two practices while the other 3 are choosing the other one, if a small ε number of employees in plant 1 decides to choose the same practice as the other 3 plants, the behind-averse social comparisons will push the whole plant to adopt the practice. Moreover, the equilibrium where a central node adopts a practice while the adjacent plants stick with the opposite practice $(0,1,0,1)$ or $(1,0,1,0)$ are unstable as a small change of employees in a central plant can lead to the equilibrium where all the plants adopt one of the two practices.

5.6.4 Proof of Proposition 17

Due to the behind-averse social comparisons that push individuals to imitate each other' choice, it is trivial to check that the following two equilibria $(1,1,1,1)$ and $(0,0,0,0)$ are asymptotically stable. Similar to the proof of proposition 3, no mix of adopters and non-adopters can exist within a plant.

Let's prove *by contradiction* that there does not exist other stable equilibria.

Let's assume there exist a stable equilibrium where one of the periphery nodes adopts a practice and the other plants adopt an opposite practice. If a small change occurs within the periphery plant, the herding effect will push the plant to switch practices which will lead to either $(1,1,1,1)$ or $(0,0,0,0)$ which contradicts the initial premise.

Let's assume that the centre node adopts a practice different than the periphery plants and the resulting equilibrium is stable. A small change within the plant will trigger the centre plant to be taken over by the other practice which leading to $(1,1,1,1)$ or $(0,0,0,0)$. If a small change of practices occurs within the periphery plants, the practice plant will take over the periphery plants which will lead to $(1,1,1,1)$ or $(0,0,0,0)$. Both adoption patterns contradict the initial premise.

Therefore, by contradiction $(1,1,1,1)$ and $(0,0,0,0)$ are the only stable equilibria in the star network when there are behind-averse social comparisons.

5.6.5 Proof of Theorem 2

The number of adopters grows when $U_i^N - \bar{U}_i^N > 0$. For a plant of degree n, the number of adopters grows, iff,

$C = \sum_{i=1}^{N}(\frac{1}{n}(x_i^N(U_{NN} - U_{ON}) + (1 - x_i^N)(U_{NO} - U_{OO}))) > 0$

$\Leftrightarrow \sum_{i=1}^{n}(\frac{1}{n}(U_{NO} - U_{OO} + x_i^N(U_{NN} - U_{ON} - U_{NO} + U_{OO})) > 0$

When $p \neq k$, in a ahead-seeking environment,
$C = V_N(p - k + \alpha p(1-k) - \frac{1}{N}\alpha((1-p)k + p(1-k))\sum_{i=1}^{n} x_i^N)$

When $p \neq k$, in a behind-averse environment,
$C = V_N(p - k - \gamma(1-p)k + \frac{1}{N}\gamma(p(1-k) + (1-p)k)\sum_{i=1}^{n} x_i^N)$

As N increases, a change in rewards k or p has relatively less impact on the value of C.

5.6.6 Proof of Proposition 18

In a ahead-seeking environment, when $p > k$, $U_i^N > U_i^O$ as $U_{NN} > U_{OO}$ and the differentiation effect when an adopter meets a non adopter is greater than when a non-adopter meets an adopter $\alpha p(1-k) > \alpha(1-p)k$.

In proposition 1 ($p = k$), we saw that in the chain network, plants fully adopt the new practice or stick with the old practice. When $p > k$, plants that were fully adopting still fully adopt at the equilibrium as U_N increases and it is easy to verify that there exists a range of values for p and k such that for the more central plant i in the network exhibits a mix of adopters and non-adopters x_i^N for the following conditions:

$$\begin{cases} p-k+\alpha p(1-k)-\dfrac{2+x_i^*}{3}\alpha((1-p)k+p(1-k))=0 \\ 0<x_i^*<1 \end{cases}$$

and the periphery node j exhibits a mix of adopters x_j^N such that:

$$\begin{cases} p-k+\alpha p(1-k)-\dfrac{1+x_j^*}{2}\alpha((1-p)k+p(1-k))=0 \\ 0<x_j^*<1 \end{cases}$$

Due to the differentiation effect, a small change of employees ε will not make the equilibrium deviate.

A similar reasoning applies for $p<k$ regarding the utility of the old practice instead of the utility to adopt the new practice.

5.6.7 Proof of Proposition 19

In the hub-and-spoke network, in proposition 15, due to the differentiation effect, adjacent plant adopt opposite practices at equilibrium (proved above).

When $p>k$, U_N increases and this leads the plants that adopted the new practice when $p=k$ to still adopt the new practice at equilibrium.

In the case when the centre adopted the new practice, it is easy to verify that the periphery node x_i^* admits a mix of adopters and non-adopters for a range of p and k such that:

$$\begin{cases} p-k+\alpha p(1-k)-\dfrac{1+x_i^*}{2}\alpha((1-p)k+p(1-k))=0 \\ 0<x_i^*<1 \end{cases}$$

In the case when the periphery plants adopted the new practice, it is also easy to verify that the centre node x_j^* admits a mix of adopters and non-adopters for a range of p and k such that:

$$\begin{cases} p-k+\alpha p(1-k)-\dfrac{3+x_j^*}{4}\alpha((1-p)k+p(1-k))=0 \\ 0<x_j^*<1 \end{cases}$$

Due to the differentiation effect, a small change of employees ε will not make the equilibrium deviate.

When $p<k$, a similar reasoning by considering the old practice instead of the new practice and conditions in a similar fashion as above can be easily derived.

5.6.8 Proof of Corollary 3

Propositions 18 and 19 show the existence of a mix of adopters in some plants. Theorem 1 shows the effect of changes in p and k is most sensitive in the least connected plants. Therefore, when $p>k$, the plants having a mix of adopters and non-adopters have more adopters as the more connected they are. When $p<k$, the plants with a mix of both practices have more employees choosing the old practice the less connections they have.

5.6.9 Proof of Proposition 20

When $p>k$, the utility to adopt the new practice increases.

Let's prove that there exists a range of values for p and k such that the following two additional adoption patterns are stable: $(1,0,0,0)$ and $(1,0,0,1)$. By a symmetry argument, $(1,0,0,0)$ is equivalent to $(0,0,0,1)$.

$(1,0,0,0)$ is stable, iff, for a range of $p>k$ and small changes of adopters in each of the plant, respectively, ε_1, ε_2, ε_3 and ε_4, we have:

$$\begin{cases} p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2}{2}\gamma(p(1-k)+(1-p)k)>0 \\ p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2+\varepsilon_3}{3}\gamma(p(1-k)+(1-p)k)<0 \\ (1-p)k+\dfrac{\varepsilon_2+\varepsilon_3+\varepsilon_4}{3}\gamma(p(1-k)+(1-p)k)<0 \\ (1-p)k+\dfrac{\varepsilon_3+\varepsilon_4}{2}\gamma(p(1-k)+(1-p)k)<0 \end{cases}$$

This condition is easily verified.

$(1,0,0,1)$ is stable, iff, for a range of $p > k$, and small changes in each of the plant, ε_1, ε_2, ε_3 and ε_4, we have:

$$\begin{cases} p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2}{2}\gamma(p(1-k)+(1-p)k)>0 \\ p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2+\varepsilon_3}{3}\gamma(p(1-k)+(1-p)k)<0 \\ (1-p)k+\dfrac{\varepsilon_2+\varepsilon_3+1-\varepsilon_4}{3}\gamma(p(1-k)+(1-p)k)<0 \\ p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_4+\varepsilon_3}{2}\gamma(p(1-k)+(1-p)k)>0 \end{cases}$$

This condition is easily verified.

A similar reasoning can be drawn in the case of $p < k$ with the new practice and the old practice having symmetric roles in the proof.

5.6.10 Proof of Proposition 21

$(1,0,0,0)$ is stable, iff, for a range of $p > k$, and small changes in each of the plant, ε_1, ε_2, ε_3 and ε_4, we have:

$$\begin{cases} p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2}{2}\gamma(p(1-k)+(1-p)k)>0 \\ p-k-\gamma(1-p)k+\dfrac{1-\varepsilon_1+\varepsilon_2+\varepsilon_3+\varepsilon_4}{4}\gamma(p(1-k)+(1-p)k)<0 \\ p-k-\gamma(1-p)k+\dfrac{\varepsilon_2+\varepsilon_3}{2}\gamma(p(1-k)+(1-p)k)<0 \\ p-k-\gamma(1-p)k+\dfrac{\varepsilon_2+\varepsilon_4}{2}\gamma(p(1-k)+(1-p)k)<0 \end{cases}$$

This condition is easily verified.

By a symmetry argument, this is the case for $(0,0,1,0)$ and $(0,0,0,1)$.

Let's prove by contradiction that any other adoption pattern where 2 or 3 plants adopted the new practice, while the others did not adopt is unstable.

a) Any adoption pattern such that the centre adopted the new practice, while the old practice is chosen in one of the periphery plants is unstable.

If only one periphery node stuck with the old practice at equilibrium then, $p - k - \gamma(1 - p)k + \frac{1-\varepsilon}{2}\gamma(p(1-k) + (1-p)k) < 0$ which is impossible when $p > k$. Contradiction.

b) Any adoption pattern with $n = 2$ or 3 plants adopting the new practice at the periphery and the centre sticking with the old practice is unstable.

Such adoption pattern is stable for any ε iff, $p - k - \gamma(1-p)k + \frac{n+\varepsilon}{4}\gamma(p(1-k) + (1-p)k) < 0$ when $p > k$ which is impossible. Contradiction.

A similar proof can be drawn when $p < k$ by exchanging the role of the new practice with the old practice in the proof.

5.6.11 Proof of Corollary 4

This corollary is a direct consequence of Theorem 2 and Propositions 20 and 21.

Chapter 6

Conclusion

Failing to adopt new operational practices frequently undermines innovation in companies and communities. It is important to understand how this failure can be avoided, due to the strong relationship between economic growth and the adoption of new operational practices. In this dissertation, I study a critical phenomenon influencing adoption but not yet explored by the operations management literature: relative benefits of adoption triggered by two key behavioural effects, ahead-seeking and behind-averse social comparisons. I then examine how the type of rewards put in place in organisations (individual vs collective), the level of collaboration between teams (wide vs narrow bridges) and the network structure of an organisation (centralised vs decentralised) influence these relative benefits and provide guidelines for organisations.

6.1 Theoretical and managerial contributions

In Chapter 2, I review the research conducted in the last decades on the topic of practice adoption. While many reviews have been written for specific disciplines, in marketing (Libai et al. 2017) and economics (Foster and Rosenzweig 2010) for example, or for specific methodologies (Kiesling et al. 2012), I provide an original review gathering the main findings, similarities and differences across these disciplines to identify the key determinants of adoption. New lines of inquiry and gaps are identified.

In particular, one of the key contributions of this dissertation has been to identify and provide answers to a conceptual gap in the adoption literature: the role of relative benefits compared to others' choices due to strategic considerations. I propose a series of evolutionary game theoretical models exploring the role of behavioural biases and population dependent strategic interactions in the adoption of new operational practices. Chapters 3, 4 and 5 of this dissertation build on this original idea, starting a new pipeline of research for the field.

In Chapter 3, I explore the role of relative benefits between individuals in the adoption of new practices in organisations triggered by social comparisons. Past research works have not recognised the critical role that social interactions play in evaluating whether to adopt or not based on others' decisions. I build an evolutionary game theoretic model encompassing two new phenomena concerning the adoption of new practices. First, individual utilities depend on each others' choices within the organisation, hence the threshold of adoption is calculated in relative terms, rather than absolute terms. Secondly, I introduce the behavioural micro-foundations that give rise to this social imitation mechanism. These are supported by recent findings in neuroscience and decision science literatures showing the importance of ahead-seeking and behind-averse social comparisons.

I find that the same practice introduced in two organisations with similar reward systems but different social comparison environments may exhibit different patterns of adoption. I find that behind-averse social comparisons create a bandwagon phenomenon where a critical mass is needed to encourage the whole organisation to adopt the new practice. But an organisation with ahead-seeking social comparisons creates an adoption pattern that leads both practices to co-exist in the organisation. I then investigate the effects of introducing economic rewards to influence the adoption decision such as collective levies (winner takes all schemes) and bonuses. In particular, I highlight that social comparisons can act against a collective bonus put in place by management, inhibiting adoption. Interestingly, I find that in a behind-averse organisation, collective levies can be more effective than collective bonuses to drive adoption, while collective levies will only inhibit adoption in a ahead-seeking organisation. Lastly, I find that "learning" to master the new practice over time (as uncertainty around the successful adoption diminishes) does not always lead to full adoption in the organisation.

These findings have important managerial implications (see Table 6.1). In an organisation where the culture is more behind-averse, managers can drive full adoption by hiring or training individuals to adopt the new practice and if a critical mass is reached, the whole organisation can end up adopting it, while such initiative will have no impact in a ahead-seeking organisation. In the latter case, managers can only influence adoption through economics rewards. Another important managerial finding is that the organisation can influence the level of social comparisons felt by their employees and certain cultures may better fit certain types of practices. For example, an organisation may want to avoid the whole organisation to adopt a practice if this practice is unethical such as prescribing unnecessary medical procedures or medicine. Unfortunately, a behind-averse environment can drive the whole organisation to adopt such practice if a critical mass is reached. Top management can avoid this outcome by making sure this critical mass is not reached by using collective levies to make the critical mass needed higher. An ahead-seeking culture can also give rise to the use of unethical practices such as sabotage and cheating (Charness et al. 2013) but this practice will not take over the whole organisation as both unethical and ethical practices will coexist. In this scenario, an organisation can moderate the intake of such practices through collective levies. For other types of practices, such as a lean process or a best practice in hospitals (Song et al. 2017), a behind-averse environment can be very beneficial as the whole organisation will adopt the new practice. However, organisations may wish to always sustain a mix of adopters and non-adopters. For example, practices that bear a significant risk of failing but when successful bring high value to the organisation (risky investment practices in financial organisations). If the whole organisation adopts such practice, it could hurt the organisation in the long term. Thus, a ahead-seeking environment can always ensure that a portion of their organisation is adopting this risky practice but the rest still sticks to a safer practice. The ratio of adopters and non-adopters can then be moderated through collective bonuses to increase it or collective levies to diminish it.

Table 6.1 Chapter 3 key managerial insights

Type of practice	Ahead-seeking organisation	Behind-averse organisation
Best Practice (e.g. lean or kaizen)	**No training Collective bonus**	**Training Collective bonus**
Unethical or overly risky practices	**Collective levy**	**Collective levy**

In Chapter 4, I challenge a recent research discussion suggesting that wide bridges between different parts of an organisation enhance adoption of new operational practices (Centola 2019) and I refine the conditions for which this outcome occurs (see Table 6.2). Collaboration between teams has always been considered beneficial for knowledge sharing but when heterogeneous groups in an organisation interact, they may experience strategic interactions differently. I find that, contrary to past literature, unforeseen consequences of adopting competing operational practices can arise from the conflict between either two different social comparisons environments when individuals have similar adoption capabilities, or when individuals exhibit different adoption capabilities in a behind-averse or a ahead-seeking organisation.

I reveal that in an organisational setting where collaboration occurs between teams with different social comparisons, allowing wide bridges can only lead to a unique asymptotic stable state if the team with ahead-seeking social comparisons is relatively more sensitive to social comparisons than the team with behind-averse social comparisons. This brings an interesting managerial insight as it creates a mix adoption of practices within the behind-averse group which was not possible without this bridge (as seen in Chapter 3). Thus, top management can create in both groups a mix of adoption which is beneficial for innovative but risky practices and it avoids full or non-adoption of this practice in the behind-averse group. However, if the team with behind-averse social comparisons is relatively more sensitive to social comparisons than the team with ahead-seeking social comparisons, the organisation will not reach any stable equilibrium over time which is a situation an organisation would want to avoid as the outcome is unpredictable.

Moreover, many organisations separate employees with different capabilities by creating isolated units gathering the top performers, for example GoogleX and Google, UberX and Uber. I find that, in a ahead-seeking organisation, allowing wide bridges between teams (mixing teams) with different capabilities can be beneficial for high capability individuals to adopt an innovative practice rather than isolating the high capable individuals only if the organisation is willing to make a sufficiently upfront investment in training in the high capability team. If not, the low capable team can end up adopting fully the new practice and the high capable team sticks with the old practice. On the other hand, in a behind-averse organisation, top management should consider implementing wide bridges as it drives adoption of the new practice in both teams with less initial investment in training compared to narrow bridges.

In Chapter 5, I investigate how the structure of a production network can help or inhibit the adoption of new operational practices (see Table 6.3). I explore the adoption of new practices on two classic production networks: a chain and a hub-and-spoke structures (Lanza et al. 2019). The structure of the network plays an important role on how employees interact with each other and how they react to social comparisons when deciding whether to adopt.

I find that, in a ahead-seeking environment, adoption and non-adoption happen alternatively due to the differentiation effect in the network. However, if top management wishes to obtain a maximum adoption of the innovative practice, it may prefer a hub-and-spoke structure

Table 6.2 Chapter 4 key managerial insights

Type of practice	Ahead-seeking organisation with heterogeneous capabilities' teams	Behind-averse organisation with heterogeneous capabilities' teams	Organisations with heterogeneous social comparisons' cultures
Best Practice (e.g. lean or kaizen)	**Mix if initial training made** **Separate if no initial training made**	**Mix for less initial training**	**Mix if no initial training made and ahead-seeking $>$ behind-averse** **Separate if initial training made and/or ahead-seeking $<$ behind-averse**
Unethical or overly risky practices	**Separate**	**Separate**	**Separate**

where the central plant is not trained to adopt the new practice thus may stick with the old practice which will create adoption in the peripheral plants. On the other hand, if adoption of the innovative practice occurs in the central plant, a chain network will be preferable as it will always enable half the plants to adopt the new practice. In a behind-averse environment, there is a herding effect to imitate the plants' members. This leads to two stable scenarios in the hub-and-spoke network, where all or none of the plants adopt. Interestingly, an other stable scenario can occur in a chain network where the herding effect stops when half of the factories have adopted. In such environment, top management can push for adoption of the innovative practice by training the central plant. However, as discussed in chapter 5, an organisation may not wish the whole organisation to adopt some practices at first, such as smart manufacturing practices and this network configuration bears the risk of the whole network to adopt it while the chain network can stop its diffusion. For such practices, the chain network should be preferred.

Another important lever for top management is to promote the new practice to be adopted through reward schemes. As a general result, I find that in both social settings and for both types of networks, the effect of changes in rewards initiated by a firm is most effective in the least connected plants. This result leads to the following conclusions. In a behind-averse setting, I show that peripheral plants in the chain and hub-and-spoke networks can better resist potential herding behaviour of sticking with the old practice. Therefore top management should place R&D units at the peripheral. In the presence of ahead-seeking social comparisons, if a more central plant adopted the new practice, a change in reward initiated by top management, could have a high impact on the adoption behaviour of the peripheral plants. However, if peripheral plants adopted the new practice, a change in rewards may not have the desired effect on the more central plant due to the high level of differentiation present because of the high connectivity of this plant.

Table 6.3 Chapter 5 key managerial insights

Type of practice	Ahead-seeking organisation	Behind-averse organisation
Best Practice (e.g. lean or kaizen)	**Hub-and-spoke if periphery plants targeted** **Incentives high effect on periphery plants**	**Hub-and-spoke if central plant targeted** **Incentives high effect on periphery plants**
Overly risky practices	**Hub-and-spoke if central plant targeted** **Disincentives high effect on periphery plants**	**Chain** **Disincentives high effect on periphery plants**

6.2 Future research perspectives

In this dissertation I have developed a new approach to the field of new practice and technology adoption and there are numerous opportunities to extend it.

The first concerns method. Most analytical works that have been proposed so far on strategic interactions to adopt have been static methods. I propose a novel methodology to this field - evolutionary game theory - that combines the aggregate behaviour models of epidemiology with the strategic interactions of game theory. This thesis offers a series of such evolutionary models tackling diverse research questions. I encourage the community to use this kind of methodology and build other novel models as it incorporates population effects and long term adoption behaviour, while still encompassing the trade-offs that occur during strategic interactions. Moreover, a common assumption in classic models has been that individuals are hyper-rational and able to optimise their decisions by looking forward. However, evidence in a wide range of disciplines in strategy, organisational behaviour and psychology show that individuals are bounded rational and make decisions based on the current state of the system. In evolutionary models, individuals are assumed to be bounded rational and I encourage the community to suggest models that take this assumption into consideration.

Secondly, in Chapter 3, I highlight the role of behavioural biases such as social comparisons and population effects in affecting the relative benefits of adoption. Combined with notions of risk-return, social comparisons have been deemed as key components in the decision about whether or not to adopt new practices or technologies. The findings of this thesis allow managers to take this key factor into consideration. Other factors could affect these relative benefits. I believe that researching these factors either by exploring other literatures' empirical findings for inclusion in analytical models, or finding experimental evidence would both be worthwhile.

Thirdly, Chapter 4 highlights the role of collaboration (wide vs narrow bridges) in the adoption of new practices between heterogeneous teams (in social comparisons or capabilities). Chapter 5 highlights the role of network topology in the adoption patterns of a new practice. To do this, I modelled homogeneous individuals in social comparisons and capabilities but plants did not have the same level of interactions with others based on their position in the network. A promising research avenue would be to combine Chapters 4 and 5 by exploring how to place heterogeneous plants in social comparisons and capabilities along the network to help or mitigate adoption.

Fourthly, even though, these analytical models are built on assumptions and evidence found in the literature, it would be interesting to verify the validity of the results of the dynamic aspect of the models with data. While measuring the effect of social comparisons on individuals' behaviour over time and choices of adoption in an uncontrolled environment such as an organisation could prove challenging, it might be possible to approximate the scenarios through laboratory-based experiments.

Lastly, the models suggested in this thesis have been descriptive. Their purpose is to measure the impact on adoption of a new practice of certain types of characteristics among individuals (social comparison behaviours, riskiness of practices) and of organisations (type of network of plants, or level of interactions between units). It could be an interesting research avenue to allow the organisation to optimise the adoption pattern along an optimal control formulation by influencing decisions, either through training or by changing initial conditions of the population of adopters, structuring incentives by finding the optimal reward schemes for each practice, or changing other characteristics of the system (links in the network, or intensity of interactions between teams and plants). Due to the complexity of the existing models, close form solutions by incorporating optimization mechanisms may prove challenging to find. Computational approaches to find numerical solutions may be more effective in doing so.

6.3 Closing remark

In the current globalised world, competition is rife and rapid adoption of new and better practices or technologies become vital for the survival of organisations but also communities. This dissertation gives guidance on how strategies intended to increase adoption rates can be more effective by accounting for strategic interactions, behavioural phenomenon within the organisation. This will enable firms to utilize available resources more efficiently as well as foresee unintended consequences of their social culture, structure, and reward schemes.

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