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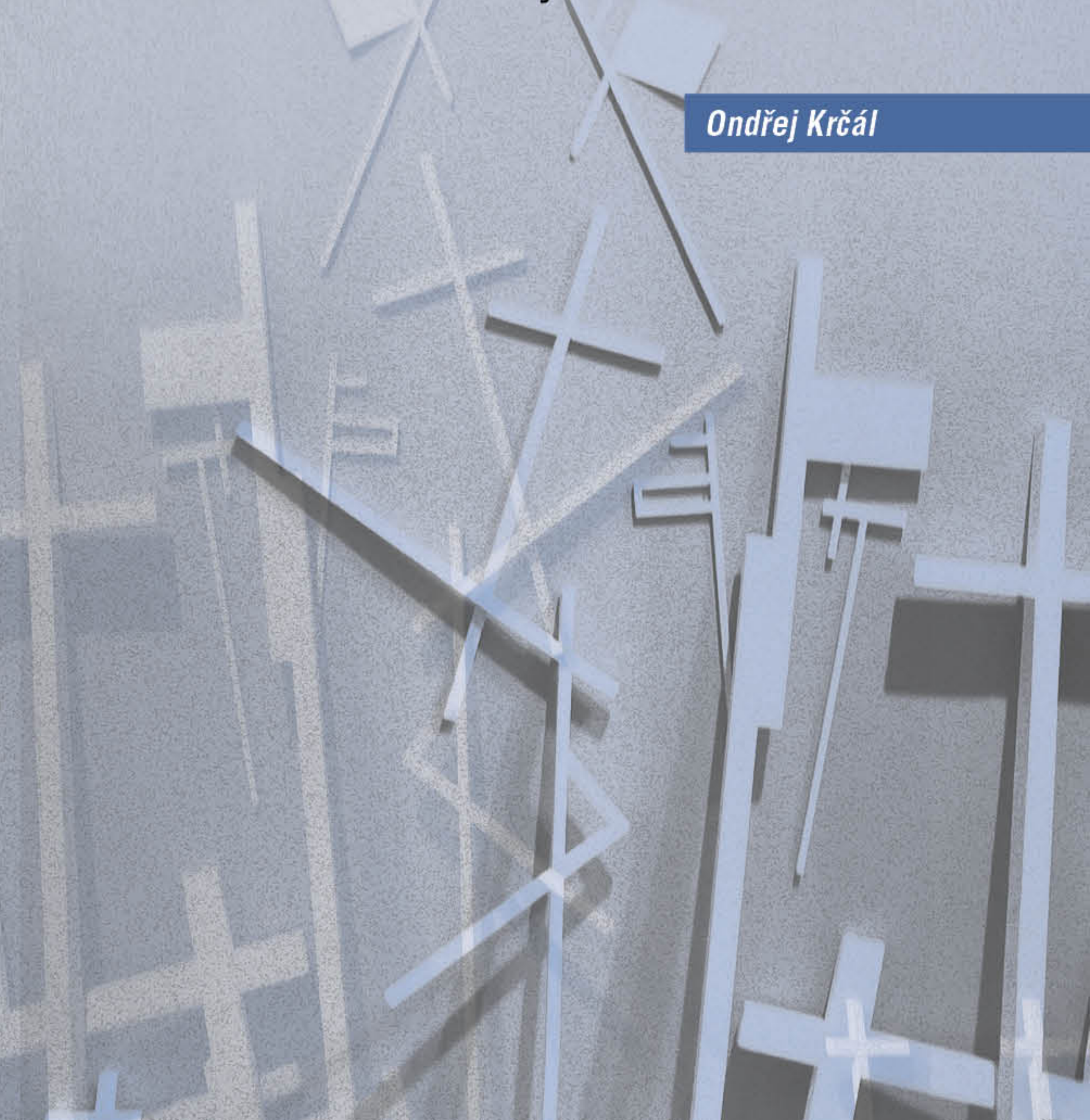
An Explanation of the Inverted-U Relationship between Profitability and Innovation

Ondřej Krčál



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MASARYK UNIVERSITY
BRNO 2014

Krčál, Ondřej
An explanation of the inverted-U relationship between profitability and innovation / Ondřej Krčál.
-- 1st ed. -- Brno : Masaryk University, 2014. -- 160 p.
ISBN 978-80-210-7423-1

330.341.1 * 339.137 * 330.13 * 519.86/.87 * 519.673:519.216.3
– innovations
– competition
– economic efficiency
– modeling and simulation
– predictive models
– monographs
– inovace
– konkurence
– ekonomická efektivnost
– modelování a simulace
– predikční modely
– monografie

330 – Economics [4]
33 – Ekonomie [4]

Citation

KRČÁL, Ondřej. *An Explanation of the Inverted-U Relationship between Profitability and Innovation*. Brno: Masaryk University, 2014, 160 p. ISBN 978-80-210-7423-1.

DOI: 10.5817/CZ.MUNI.M210-7423-2014

ISBN 978-80-210-7423-1
ISBN 978-80-210-7498-9 (online : pdf)
DOI: 10.5817/CZ.MUNI.M210-7423-2014

Acknowledgements

This book would not have been completed without the support of many people. I wish to express my sincere gratitude to my dissertation supervisor Michal Kvasnička, for his guidance, unfailing support, constructive feedback, and for his help with all aspects of academic life. My special thanks go to Rost'a Staněk with whom I had several fruitful discussions concerning the ideas developed in this work. I am grateful to my colleagues, most importantly to Rost'a Staněk, Honza Čapek, Mirek Hloušek, Pepa Menšík, Honza Jonáš, Nad'a Voráčová, Martin Slanicay and others for their willingness to help and for many thought-provoking economic discussions. I would like to thank my parents and brothers. They have always supported and encouraged me with their best wishes. Last and the most important, I would like to extend my thanks and appreciation to my wife Barča, whose understanding, encouragement, endless patience, and good humor through all my academic endeavors enabled me to complete this book.

The author gratefully acknowledges financial support from the Faculty of Economic and Administration of Masaryk University which has made the publication of this book possible.

Contents

Introduction

The literature on the relationship between competition and innovation has attracted the attention of the economic profession ever since the first publication of Schumpeter's *Capitalism, Socialism and Democracy* in 1942. In this work, Schumpeter argued that firms with market power might be more innovative than firms in competitive industries. Subsequently, many economists supported the Schumpeterian hypothesis that market power is good for innovation. Other important groups of economists argued that competition encourages innovation, or that innovation thrives at an intermediate level of competition.

The actual form of the relationship between innovation and competition, measured typically using profitability or concentration, is highly important for public policy, especially for competition policy, industrial policy and for the choice of the optimal intellectual property regime. For instance, if the Schumpeterian hypothesis is correct and competition reduces the innovative performance of firms, the goal of *competition policy* is unclear. By fostering competition, the authorities improve static efficiency because they reduce the dead-weight loss due to the market power of firms. But at the same time, they harm dynamic efficiency by reducing the innovative performance of firms. On the other hand, should market power discourage innovative activity, pro-competition policies would increase both the static and dynamic efficiency of markets. Similarly, if the goal of *industrial policy* is to create more innovative home industries, the optimal strategy also depends on the relationship between competition and innovation. Suppose that the Schumpeterian hypothesis is true and competition reduces innovation. Then it might be reasonable to use trade barriers to protect home industries from foreign competition. However, trade barriers will not be useful if competition stimulates innovation. Finally, the form of the relationship between competition and innovation is important for the choice of the optimal *intellectual property regime*. If Schumpeter's arguments are correct, a regime in which patents are assigned more easily and enforcement is stricter might be supported for two reasons. First, stronger patent protection increases the rents of the innovator and therefore the incentives to innovate. Second, stricter patent protection increases the market power of firms, which further enhances the innovative performance of the economy. On the other hand, if competition increases innovation, the possible positive effects due to stronger patent protection need to be weighed up against, among other factors, with the negative effects of less competitive environment on innovation.

Since Schumpeter's seminal discussion of the effect of market power on innovation, the relationship between competition and innovation has been widely studied in the empirical literature, mostly in the field of industrial organization, and the forces and effects behind the relationship have been discussed extensively in the theoretical literature. Unfortunately, neither the empirical nor the theoretical literature has provided clear support for the Schumpeterian hypothesis, or for the alternative hypothesis that competition encourages innovation. In the most influential recent contribution to the literature, Aghion *et al.* (2005) attempt to reconcile the opposing hypotheses. They find an inverted-U relationship between a profitability-based measure of competition and innovation and provide a natural explanation of the relationship that combines a positive and a negative effect of competition on innovation.

Following Aghion, Harris & Vickers (1997) and Aghion *et al.* (2001), Aghion *et al.* (2005) present a model of an economy consisting of a continuum of duopoly industries. Firms in these industries engage in step-by-step innovation. This means that a firm that has innovated moves exactly one technological step ahead, regardless of the technology used by the rival firm. Furthermore, the model sets the maximum possible difference between the technologies of the duopolists equal to one step. It means that firms one step ahead, called technological leaders, have no incentive to innovate. Hence the innovators are firms one technological step behind, called technological laggards, and firms at the same technological level, called neck-and-neck firms. The structure of product market competition is such that a rise in competition reduces innovation of laggard firms and increases innovation of neck-and-neck firms. The former effect of competition is called the *Schumpeterian effect* and the latter the *escape-competition effect*. The interplay of these two effects generates the inverted-U relationship between competition and innovation and two additional predictions, called Prediction B and Prediction C in this book. According to Prediction B, a rise in competition increases the share of unleveled industries with laggard and leader firms in the economy, which increases the average technological difference between the firms (called the *technology gap*). According to Prediction C, the peak of the inverted-U relationship is higher and occurs at higher levels of competition in an economy with a lower technology gap.

The predictions of the model of Aghion *et al.* (2005) have been tested in the recent empirical literature. While there is some support for the inverted-U relationship, the empirical evidence supporting the additional predictions is scarce. The lack of support for Prediction C is not so problematic because this prediction is not a necessary part of Aghion *et al.*'s explanation of the inverted-U relationship. On the other hand, Prediction B represents a necessary part of the explanation of the inverted U. According to this prediction, the proportion of neck-and-neck firms is relatively high in less competitive industries. Hence the escape-competition effect is likely to dominate the Schumpeterian effect, which means that a rise in competition increases the overall level of innovation. Conversely, the proportion of laggard and leader firms is relatively high in more competitive industries. In this case, the Schumpeterian effect is likely to dominate the escape-competition effect, which means that a rise in competition reduces innovation in the economy. The only two studies that find an inverted-U relationship between a profitability-based measure of competition and innovation and at the same time test for Prediction B are Aghion *et al.* (2005) and

Hashmi (2005). While the decreasing relationship between profitability and the technology gap found by Aghion *et al.* (2005) is consistent with their explanation, the flat and concave relationship in Hashmi (2005) is not compatible with Aghion *et al.*'s explanation of the inverted-U relationship. The empirical evidence, therefore, leaves room for an alternative explanation of the inverted-U relationship.

The goal of this book is to provide an alternative explanation of the inverted-U relationship between profitability and innovation that is able to reconcile the empirical findings of Aghion *et al.* (2005) and Hashmi (2005) related to Prediction B. More specifically, the book aims to provide realistically motivated models of the R&D decision-making of firms and test the predictions of the models using the empirical evidence of Aghion *et al.* (2005) and Hashmi (2005). The book should provide insights into possible causes of the relationship between the profitability of firms and innovation, which might prove useful for public policy.

In order to explain the empirical evidence, I introduce two models of innovation in this book: the basic model and the prospect-theory model of innovation. In the basic model, firms choose their R&D expenditures in order to maximize their expected profits within certain limitations. The aim of the model is to present a simple and general explanation of the empirical evidence. On the other hand, the prospect-theory model provides a more specific explanation, and predictions of the model correspond better to the empirical findings than predictions of the basic model. The prospect-theory model uses a behavioral theory of the decision-making process of managers. The R&D expenditures are chosen by managers of firms according to their preferences represented by the prospect-theory value function (Kahneman & Tversky 1979, Tversky & Kahneman 1992). Similarly to the model of Aghion *et al.* (2005), the size of innovation results from optimizing choices. On the other hand, the assumptions behind both models differ from Aghion *et al.*'s assumptions in several important aspects.

First, the model of Aghion *et al.* (2005) relates innovation to a theoretical measure of competition, which is shown to be increasing in the empirical profitability-based measure of competition (1−Lerner index). Thus their model is able to explain the empirical inverted-U relationship between profitability and innovation. The basic and prospect-theory models explain the empirical evidence directly by relating innovation to the profits of firms. This approach has two advantages. First, it avoids the problematic link between competition and profitability. As shown by Boone (2000, 2008), a rise in the level of competition may lead to both higher and lower industry profitability. Consequently, the predicted relationship between profitability and innovation might differ from the predicted relationship between competition and innovation. Second, it provides a more general explanation of the empirical evidence concerning the relationship between profitability and innovation because it covers all the possible factors responsible for variation in profitability, not only the intensity of competition like Aghion *et al.* (2005).

Second, the predictions of the model of Aghion *et al.* (2005) arise due to the assumption of step-by-step innovation and a specific structure of product market competition.

Thanks to these assumptions, competition has an opposite effect on innovation of laggard and neck-and-neck firms, which generates the inverted-U relationship and the related predictions. However, Aghion *et al.*'s explanation might not be valid in industries with a different mode of technological progress or different structure of product-market competition (see Subsection 1.3.2 for examples of such situations). In my explanation, all firms in an industry have the same incremental profit owing to innovation, which is either constant or decreasing in profits of firms. In this respect, my explanation is complementary to the explanation of Aghion *et al.* (2005). It is able to explain the empirical evidence even in the absence of either the Schumpeterian effect or both the Schumpeterian and escape-competition effects.

Third, there are important differences in the assumptions about the R&D process. In the model of Aghion *et al.* (2005), time is continuous. The intensity of innovative activity increases the probability that an innovation of a fixed size occurs at any moment in time. Furthermore, there are only two firms, which means that the innovative activity of one firm affects the optimal innovative effort of the other firm. On the other hand, time in my models is discrete. In each period, the R&D process generates an innovation with a certain probability. R&D expenditures influence the size of innovations. A rise in R&D expenditures increases the difference between the profits of the firm that succeeds or fails in generating an innovation. Finally, there are many firms in the industry, so that the size of R&D expenditures of one firm is assumed to have no effect on the innovative effort of other firms.

In this book, I provide several explanations of an inverted-U relationship between the profits and R&D expenditures of individual firms. The intuition behind all the explanations is similar. Starting at low levels of profits, a rise in profits tends to increase innovation because unprofitable firms, or their managers, are unable or unwilling to support high R&D expenditures. On the other hand, a rise in the profits of highly profitable firms reduces innovation because the benefits from an additional unit of R&D expenditure are decreasing in profits. The industry-level relationships between profits and R&D expenditures, called the *R&D function*, and profits and the technology gap, called the *technology-gap function*, depend on the distribution of profits in the industry. If all firms expect to earn similar profits, both R&D and technology-gap functions are likely to be inverse U- or V-shaped, which corresponds to the empirical findings of Hashmi (2005). On the other hand, if firms differ in profit earnings, the models are likely to predict an inverted-U or inverted-V R&D function and a decreasing technology-gap function, which corresponds to the findings of Aghion *et al.* (2005). In Aghion *et al.*'s model, Prediction B is a necessary component of the explanation of the inverted-U relationship. Hence the inverted-U relationship between competition and innovation emerges only if competition increases the technology gap in the industry. On the other hand, I provide a more flexible explanation of the inverted-U relationship between profits and innovation, in which the inverted-U R&D function is consistent with a concave or decreasing technology-gap function.

The rest of the book has the following structure: Chapter 1 presents a survey of literature related to the paper by Aghion *et al.* (2005). First, it presents the main assumptions and predictions of their model. Then it presents the recent empirical literature testing the predictions of their model, most importantly the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Finally, the chapter discusses the empirical evidence and some of the assumptions of the model of Aghion *et al.* and relates them to the alternative explanation presented in this book. Chapters 2 and 3 present the basic model and the prospect-theory model of innovation. Both chapters are organized in a similar way: they introduce the structure of the models first; then they present predictions of the models. More specifically: they relate firms' profits to their R&D expenditures; then they consider the relationship between profits and industry-level R&D expenditures; and finally they relate profits to the technology gap in the industry. Finally, both chapters show that for specific combinations of parameters, the predictions of the models correspond to the findings of Aghion *et al.* (2005) and Hashmi (2005). Chapter 4 discusses the robustness of the predictions to a variation in parameters. And finally, the last chapter sets down the conclusion.

Chapter 1

Survey of literature

The modern literature on the relationship between competition and innovation starts with a provocative thesis by Joseph Schumpeter. Schumpeter challenges the view that competition is beneficial for consumers. He argues that in the long run, the static inefficiency of monopolistic industries might be more than offset by their better innovative performance. He presents two arguments in favor of this thesis. First, firms with market power might have access to superior methods or better inputs because of better financial standing or uniqueness. "There are superior methods available to the monopolist which either are not available at all to a crowd of competitors or are not available to them so readily: ... for instance because monopolization may increase the sphere of influence of better, and decrease the sphere of influence of the inferior, brains, or because the monopoly enjoys a disproportionately higher financial standing." (Schumpeter, 1994 [1942], pp. 100–101) Second, he argues that monopolistic practices or a better financial standing might mitigate the negative consequences connected to uncertain innovative activities. Therefore, monopolies might be bolder innovators than competitive firms. Or as Schumpeter explains, "[t]here is no more of paradox in this than there is in saying that motorcars are traveling faster than they otherwise would because they are provided with brakes." (Schumpeter, 1994 [1942], pp. 88–89)

From the beginning of the discussion, the Schumpeterian hypothesis in favor of market power finds support among many economists. Other economists present arguments and empirical evidence in favor of a positive effect of competition on innovation. The following list of important contributions shows that the discussion continues to the present day. The notable theoretical arguments for a positive or a negative relationship between competition and innovation are put forward by Fellner (1951), Arrow (1962), Scherer (1967b), Loury (1979), Lee & Wilde (1980), Dasgupta & Stiglitz (1980), Reinganum (1982), Vickers (1986), and Aghion & Howitt (1992). For studies reporting a negative relationship between competition and innovation that are consistent with the Schumpeterian hypothesis, see e.g. Phillips (1956), Horowitz (1962), Phillips (1966), Scherer (1967a), Greer & Rhoades (1976), Kraft (1989), Tinkvall & Poldahl (2006), Artés (2009), Hashmi & Van Biesebroeck (2010), and Hashmi (2012). For studies finding a positive effect of competition on innovation, see e.g. Maclaurin (1954), Weiss (1963), Allen (1969), Adams (1970), Johannisson & Lindström (1971), Acs & Audretsch (1988), Geroski (1990), MacDonald (1994), Nickell (1996), Blundell, Griffith & Van Reenen (1999), Djankov & Murrell (2002), Okada (2005), Griffith, Harrison & Simpson (2006), Gorodnichenko, Svejnar & Terrel (2008), Bloom, Draca & Van Reenen (2011), Correa & Ornaghi (2011), Berubé, Duhamel & Ershov (2012).

A third important hypothesis is introduced to the discussion more than two decades after Schumpeter's seminal work. According to this hypothesis, the relationship between competition and innovation is first increasing and then decreasing in competition, forming an inverted-U relationship. The intriguing aspect of the inverted-U hypothesis is that it might potentially reconcile the empirical findings of positive and negative relationships between competition and innovation. Furthermore, it might explain the relationship using theoretical arguments for both a positive and a negative relationship – the positive effect of competition dominating the negative effect if competition is low, and vice-versa if competition is high. Theoretical explanations of the inverted-U relationship are presented by Scherer (1967a, 1967b), Kamien & Schwartz (1972, 1976), Nohria & Gulati (1996, 1997), Schmidt (1997), Mukuyama (2003), Aghion *et al.* (2005), Lee (2005), and Vives (2008). Some empirical support for the inverted-U hypothesis is provided by Williamson (1965), Comanor (1967), Scherer (1967a), Scott (1984), Levin, Cohen & Mowery (1985), Schaffner & Seabright (2004), Aghion *et al.* (2005), Kilponen & Santavirta (2005), Hashmi (2005), Tingvall & Poldahl (2006), Tingvall & Karpaty (2008), Askenazy, Cahn & Irac (2008), Wiel (2010), Alder (2010), Polder & Veldhuizen (2012), and Peneder & Wörter (2012).

The aim of this book is related directly to the seminal model of Aghion *et al.* (2005), which provides an explanation of the inverted-U relationship between competition and innovation and two additional testable predictions. For this reason, the discussion in this section is limited exclusively to the theoretical model of Aghion *et al.* (2005) and the related empirical literature. This limitation is justified by the fact that there are many excellent surveys of the literature on the relationship between competition and innovation (for the most important ones, see Kamien & Schwarz 1975, Cohen & Levin 1989, Scherer 1992, Cayseele 1998, Ahn 2002, Gilbert 2006, and for a specialized survey of the early literature on the inverted-U relationship, see Krčál 2010c). It is therefore not necessary to provide a comprehensive survey of the entire literature on the relationship between competition and innovation.

This chapter consists of three parts. Section 1.1 introduces the model of Aghion *et al.* (2005). It presents the main assumptions of their model and introduces three predictions relating competition, innovation and the technology gap in the industry. Section 1.2 reviews the recent studies testing predictions of the model of Aghion *et al.* (2005). The studies provide some evidence of the inverted-U relationship between competition and innovation and limited evidence supporting the additional predictions. Section 1.3 summarizes the main findings of the chapter and discusses the correspondence of the findings to predictions of the model. Furthermore, it discusses some of the assumptions of Aghion *et al.*'s model and relates them to the assumptions of my explanation presented in the subsequent chapters.

1.1 A review of Aghion *et al.*'s model

Aghion *et al.* (2005) present a general-equilibrium model that builds on the previous work of Aghion & Howitt (1992), Aghion, Harris & Vickers (1997), and Aghion *et al.* (2001). Their model economy consists of a continuum of duopoly sectors in which the duopolists have constant marginal costs. They engage in step-by-step innovation, which means that innovation on the part of each firm improves its technology by one step. This is equivalent to a reduction of marginal costs by $1/\gamma$, where the parameter $\gamma > 1$ measures the size of innovation. Furthermore, the nature of the technology is such that the difference between the levels of technological development of firms cannot exceed one step. For this reason, there are only two types of industry in the economy: *leveled industries* containing *neck-and-neck firms* that have the same marginal costs; and *unleveled industries* in which one firm (called the *leader*) is one technological step ahead of the other firm (called the *laggard*).

Because of the limitation on the technology difference between the duopolists, leaders have no incentive to innovate. Hence the potential innovators consist of the remaining neck-and-neck and laggard firms. By spending a certain amount of labor, a neck-and-neck or a laggard firm innovates with a Poisson hazard rate of n_0 or n_{-1}, respectively. Furthermore, a laggard firm may imitate the leader's technology with an exogenously determined Poisson hazard rate h (called the *imitation rate*). Hence the probability that a laggard firm moves one step ahead at any moment in time is $n_{-1} + h$. The duopolists engage in Bertrand competition with homogeneous products. Product market competition is parameterized as a level of collusion that affects only the profits of neck-and-neck firms. At the highest end of the competition range, there is no collusion and neck-and-neck firms earn zero profit. As the level of collusion increases, the profits of neck-and-neck firms increase. There is no collusion in unleveled industries. Therefore, laggard firms earn zero profits and the profits of leaders depend on the size of innovation γ.

A rise in product market competition Δ (a reduction of the level of collusion) has two effects on innovation. According to the *escape-competition effect*, competition increases innovation on the part of neck-and-neck firms. The intuition behind the effect is straightforward. A rise in competition reduces the profits of neck-and-neck firms, but has no effect on the profits of leaders. Hence competition increases the incremental profits from innovation (called the reward) of neck-and-neck firms. Consequently, competition increases the probability that a neck-and-neck firm innovates at any moment in time n_0. According to the *Schumpeterian effect*, competition reduces innovation on the part of laggard firms. This effect arises because competition lowers the profits of neck-and-neck firms, but has no effect on the profits of laggard firms. Hence a rise in competition reduces the reward of laggard firms, and therefore lowers the probability that a laggard firm innovates at any moment n_{-1}.

In steady state, the proportion of leveled and unleveled industries adjusts so that the probability that an industry becomes leveled equals the probability that an industry becomes unleveled. Hence the escape-competition and Schumpeterian effects influence the steady-state proportion of leveled and unleveled sectors in the economy, and consequently the overall innovative performance of the economy. This process generates the following three predictions:

- **Prediction A:** For certain values of parameters, the relationship between competition and the overall level of innovation in the economy has an inverted U-shape (see Proposition 2, Aghion *et al.* 2005, p. 715).

- **Prediction B:** A rise in competition increases the expected technology gap measured as the proportion of unleveled industries in the economy (see Proposition 4, Aghion *et al.* 2005, p. 717). Prediction B is also called the *composition effect*.

- **Prediction C:** The peak of the inverted-U relationship is higher and occurs at higher levels of competition in an economy with a higher proportion of leveled industries (see Proposition 5, Aghion *et al.* 2005, p. 717).

First, I explain how the escape-competition and Schumpeterian effects influence the proportion of unleveled sectors in the economy (Prediction B) and the overall innovative performance of the economy (Prediction A). Then I explain what is the relationship between the technology gap and the overall innovative performance (Prediction C).

Consider the situation of the model economy under a high, low and intermediate level of competition. If competition is high, neck-and-neck firms are highly innovative while the innovation of laggards is low. It means that while neck-and-neck firms need relatively little time to innovate and shift an industry to the unleveled state, laggards need relatively more time to innovate, so that the industry stays in the unleveled state relatively longer. Therefore, the steady-state proportion of unleveled industries among highly competitive industries is relatively high. Since innovative performance of highly competitive *unleveled* industries is low due to the Schumpeterian effect, the overall level of innovation in highly competitive industries is relatively low. On the other hand, if competition is low, laggard firms are highly innovative and neck-and-neck firms are slow to innovate. The industries need relatively less time to move from the unleveled to the leveled state, than vice-versa. Therefore, the steady-state proportion of leveled industries is relatively high. Since neck-and-neck firms under low competition are less innovative due to the escape-competition effect, the overall level of innovation will be relatively low. Finally, if the level of competition is intermediate, both laggard and neck-and-neck firms need intermediate time to innovate. The proportion of leveled and unleveled industries in the economy is also intermediate. Therefore, the level of innovation in the economy might be higher than under low or high competition.

This provides an intuitive explanation of Prediction B. More competition increases innovation of neck-and-neck firms and reduces innovation of laggard firms. Hence it increases the proportion of unleveled sectors, i.e. the expected technology gap, in the economy. The previous paragraph also explains the intuition behind Prediction A. If competition is high or low, a relatively high share of industries needs a relatively long time to innovate. If competition is intermediate, all industries need intermediate time to innovate. Therefore, the overall flow of innovation might be higher under an intermediate level of competition, so that the relationship between competition and innovation is inverse U-shaped.

Figure 1.1 presents an example of Predictions A and B for the size of innovation $\gamma = 1.1$ and the imitation rate $h = 0.13$. Panel A shows that a rise in competition increases innovation of a neck-and-neck firm n_0 (the escape-competition effect) and reduces innovation of a laggard firm n_{-1} (the Schumpeterian effect). The higher the innovation of neck-and-neck firms and the lower the innovation of laggard firms, the longer the period of time each industry persists in the unleveled state. Hence, as shown in Panel B, more competition increases the technology gap (Prediction B). Finally, Panel A shows that the interplay of the escape-competition effect, Schumpeterian effect, and Prediction B creates the inverted-U relationship between competition and innovation (Prediction A).

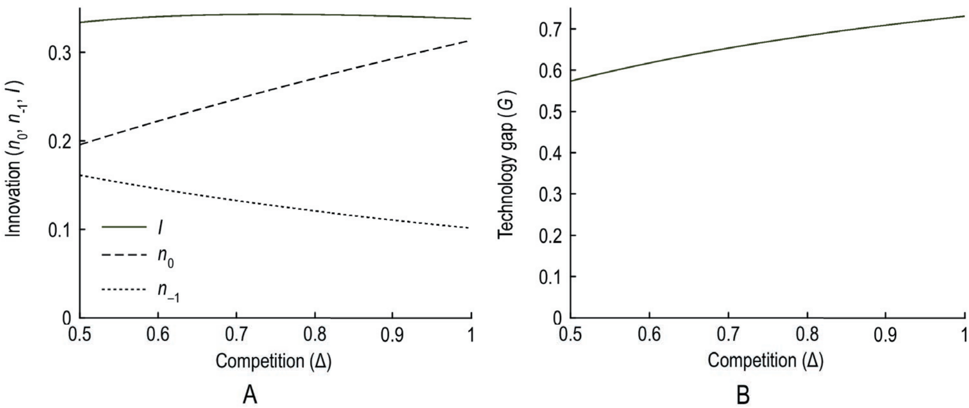


Figure 1.1: An example of Predictions A and B
In this figure, I present an example of Predictions A and B calculated for the size of innovation $\gamma = 1.1$ and the imitation rate $h = 0.13$ using Proposition 1 (p. 714) and equations (9) and (10) in Aghion *et al.* (2005). Panel A shows a relationship between competition and innovation of a neck-and-neck and laggard firm n_0 and n_{-1}, and the total flow of innovation I. Panel B shows the relationship between competition and the technology gap.

According to Prediction C, the peak of the inverted-U relationship is higher and occurs at higher levels of competition in an economy with a higher proportion of leveled industries. The intuition behind the proposition is straightforward. The economy is more leveled if the imitation rate h is higher. Because the overall flow of innovation also includes imitation, and neck-and-neck firms innovate more than laggard firms, the inverted-U relationship is higher in a more leveled economy. Moreover, the peak of the inverted-U relationship occurs at higher levels of competition because the increasing escape-competition effect is stronger in a more leveled economy. Figure 1.2 presents an example of Prediction C. Panel B shows that a rise in imitation rate h reduces the proportion of unleveled industries in the economy (equal to the technology gap G). Panel A shows that the inverted-U relationship in a more neck-and-neck economy is higher and peaks at a higher level of competition.

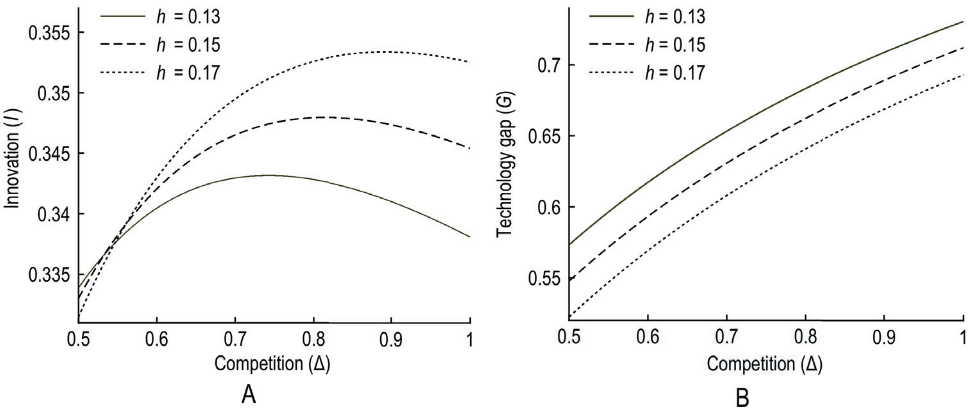


Figure 1.2: An example of Prediction C
In this figure, I present an example of Prediction C calculated using equations (9) and (10) in Aghion *et al.* (2005) for three different imitation rates h and for the size of innovation $\gamma = 1.1$. As expected, a higher imitation rate leads to a lower technology gap (Panel B). Then consistently with Prediction C, a lower technology gap leads to a higher inverted-U relationship with the peak at a higher level of competition (Panel A).

1.2 The empirical tests of Aghion *et al.*'s model

This section presents empirical tests of the predictions of Aghion *et al.* (2005). There are three main groups of measures of competition typically used in the literature:

1. profitability measures, most importantly the price-cost margin (PCM) or the Lerner index;

2. concentration or similar measures such as the Herfindahl-Hirschman index (HHI) or the number of firms in the industry;

3. new measures developed by Boone (2008) and Boone, van Ours & Wiel (2007) called relative profit differences (RPD) and profit elasticities (PE).

The most important measures of innovation used in the literature are patents, citation-weighted patents, R&D expenditures, or productivity growth. While all the innovation measures seem to be appropriate for testing the predictions of Aghion *et al.*'s model, the use of some measures of competition is problematic.

Aghion *et al.* (2005) (Proposition 3, p. 716) show that the empirical measure of competition based on the Lerner index is a monotonically increasing function of the theoretical measure used in predictions of the model. Hence the Lerner index (or the PCM) can be used for testing the predictions of Aghion *et al.* (2005). On the other hand, the number of firms or concentration measures do not seem to be appropriate for testing the predictions. For instance, a rise in the theoretical measure of competition in the model of Aghion *et al.* (2005) increases the expected concentration measured by the HHI. This is because the proportion of unleveled industries in the economy is increasing in competition (Prediction B), and the leader in an unleveled industry serves 100% of the market, whereas at the same time the neck-and-neck firms serve only 50% of the market each (the HHI of the unleveled industry is 1 and of the leveled industry is 0.5). Furthermore, the number of firms in the model of Aghion *et al.* (2005) is constant. Finally, relative profit differences (RPD) and profit elasticities (PE) are consistent with many alternative parameterizations of competition (see Boone 2008 and Boone, van Ours & Wiel 2007). The tests of the predictions provided in studies using RPD or PE are likely to be relevant. In order to provide a concise overview of the relevant empirical literature, I consider only studies using the Lerner index or the PCM and RPD or PE for measuring competition. However, if any of the studies uses not only the selected measures but also the HHI or other measures of competition, I report the full results of the study.

The organization of this section is as follows. First, I introduce the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). I present these two studies in a separate subsection because they test all three theoretical predictions using similar methodologies and they find an inverted-U relationship between profitability and innovation, which makes the tests of Predictions B and C relevant. Then, I discuss the other empirical tests of the predictions of Aghion *et al.* (2005).

1.2.1 Testing all three predictions

In this subsection, I present the empirical findings of Aghion *et al.* (2005) and Hashmi (2005) who test all three predictions introduced in the previous section. The dataset of Aghion *et al.* (2005) includes all firms listed on the London Stock Exchange whose name falls within the alphabetical range "A" to "L", and in addition all large R&D firms. From this sample, they remove firms with missing data and firms involved in large mergers and acquisitions. After eliminating the industries with a low number of firms, they derive an unbalanced panel of 354 industry-year observations across 17 industries (two-digit SIC code) over the period from 1973 to 1994. Hashmi (2005) tests all three predictions of Aghion *et al.* (2005) using a large US dataset containing 2,481 industry-year observations spanning 128 industries (four-digit SIC code) over the period 1970 to 1994. In the tests, he uses a similar methodology as Aghion *et al.* (2005). He also replicates the tests using the Aghion *el al.*'s data, which enables me to provide a direct comparison between some of the UK and US findings in this subsection.

Prediction A

First of all, I present the tests of the inverted-U relationship between competition and innovation (Prediction A). As an empirical measure of innovation, Aghion *et al.* (2005) uses the average value of citation-weighted patents in the industry taken from the NBER patent database. The empirical measure of competition is given by

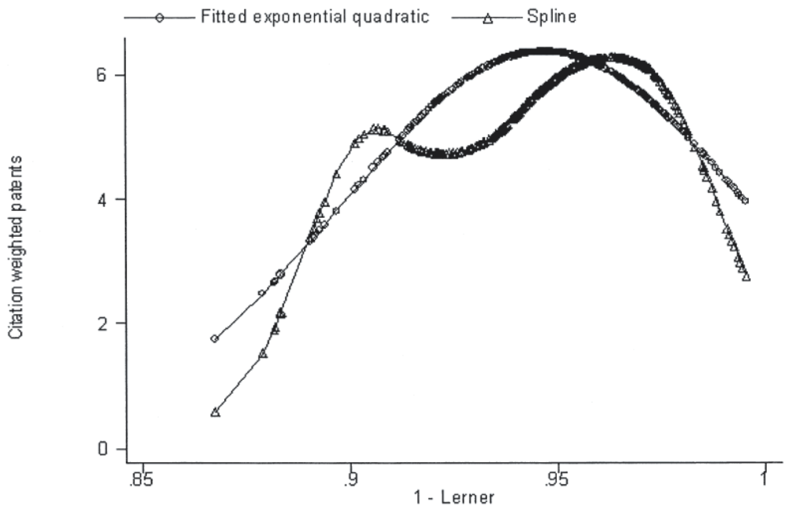
$$c_{jt} = 1 - \frac{1}{N_{jt}} \sum_{i \in j} li_{it} \tag{1.1}$$

where N_{jt} is the number of firms in industry j in year t, and li_{it} is the Lerner index of firm i in year t calculated as operating profits minus depreciation, provisions and an estimated cost of capital, divided by sales. For calculating competition, they use the complete sample of stock-market-listed firms in each industry.

The conditional citation-weighted patents are assumed to follow a Poisson regression

$$p_{jt} = e^{\{g(c_{jt}) + x'_{jt}\beta)\}},$$

where $g(c_{jt})$ is an unknown function of competition, and x_{jt} the complete set of time and industry dummy variables. Assuming that $g(c_{jt})$ has an exponential quadratic form, they find a significant inverted-U relationship between competition and innovation with the peak near the median of the distribution at 0.95 (see circles in Figure 1.3). The triangles in Figure 1.3 show that the exponential quadratic function is a reasonable approximation of the relationship in which the function $g(c_{jt})$ is estimated with a nonparametric spline.



Source: Aghion et al. *2005, Figure II*

Figure 1.3: The inverted-U relationship found in the UK data
The figure shows the exponential quadratic and semiparametric specifications with year and industry effects. The coefficients of the exponential-quadratic curve are reported in Aghion *et al.* (2005, Table I, column 2).

The exponential quadratic model is subject to three additional robustness checks. First, five-year averages are used to simulate possible innovation lags. The estimated relationship is statistically significant and inverse U-shaped. Second, R&D expenditures are substituted for citation-weighted patents. Again, the relationship is inverse U-shaped but the coefficients are not statistically significant because of a smaller sample. Third, the top four innovating industries are regressed separately and each of the estimated relationships forms an inverted-U relationship or a part of the relationship. Finally, the problem of endogeneity of competition is addressed using three sets of policy instruments: the Thatcher era privatizations; the EU Single Market Programme; and the Monopoly and Merger Commission investigations that were followed by structural or behavioral remedies. The results for the instrumented exponential quadratic model support both the competition-innovation causality and the inverted-U relationship.

Recently, the empirical findings of Aghion *et al.* (2005) related to the inverted-U relationship between competition and innovation have been questioned by Correa (2012). Correa (2012) tests whether the model is consistent over time. He identifies a structural break in the early 1980's which is related to the establishment of the United States Court of Appeals for the Federal Circuit in 1982. When he takes the structural break into account, he finds positive relationships between competition and innovation for the periods 1973-1980 and 1973-1982, and inverted-U relationships for the periods 1981-1994 and 1983-1994. Compared to the regression of the full sample, the significance of the relationships decreases substantially. However, the null hypothesis that there is no relationship between competition and innovation (competition and squared competition coefficients are equal to zero) can be rejected at 5% for the periods 1973-1980 and 1973-1982, but cannot be rejected for the periods 1981-1994 and 1983-1994.

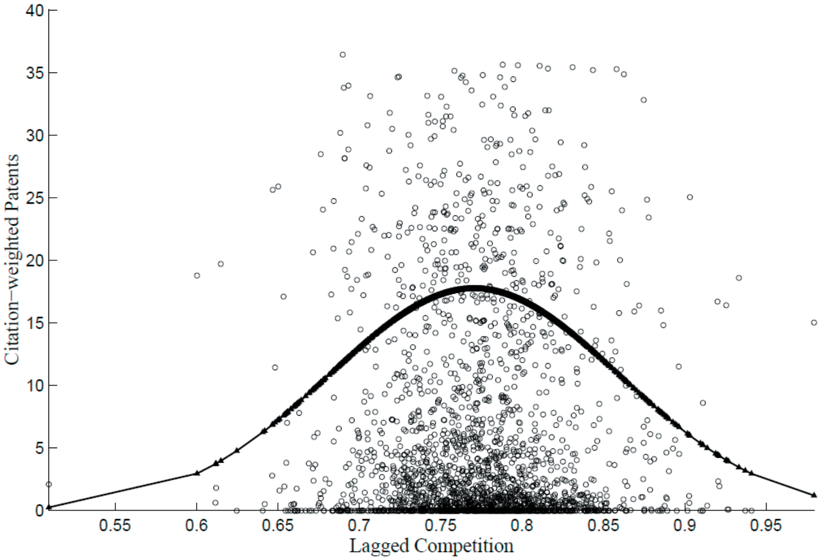
As in Aghion *et al.* (2005), Hashmi (2005) measures innovation in terms of citation-weighted patents and the source of patent data is the NBER patent database. The measure of competition is slightly different. Approximately 13% of all values of the Lerner index (li) are negative. Instead of setting all negative li equal to zero like Aghion *at al.* (2005), Hashmi (2005) sets only 3% of the lowest Lerner indices equal to zero. The third percentile of the distribution of li's is -0.1565, so he adds 0.1565 to all other Lerner indices.

Hashmi (2005) assumes that patents follow the Poisson process. However, he uses the negative binomial (NB) model instead of the Poisson model, because patents do not satisfy the Poisson assumption of equal mean and variance. He tests two specifications of the log of conditional mean of citation-weighted patents in industry j and year t:

$$\text{Model I: } \ln y_{jt} = \alpha_0 + \alpha_1 c_{jt} + \alpha_2 c_{jt}^2 + \delta \mathbf{z} + \epsilon_{jt}, \tag{1.2}$$

$$\text{Model II: } \ln y_{jt} = \alpha_0 + (\alpha_1 + \beta_1 m) c_{jt} + (\alpha_2 + \beta_1 m) c_{jt}^2 + \delta \mathbf{z} + \epsilon_{jt}, \tag{1.3}$$

where c_{jt} is competition, m_{jt} is the technology gap defined in the same way as in Aghion *et al.* (2005), and $\mathbf{z}$ is the vector of year dummies. Model I is a log-quadratic model in which competition is independent of the technology gap. In Model II, coefficients c_{jt} and c_{jt}^2 vary with the technology gap. Hashmi also controls for possible endogeneity of competition using one-year lagged values for competition. Both models fit the data well and generate similar inverted-U relationships between competition and innovation. Figure 1.4 shows the fitted model II that is preferred because of a highly significant likelihood-ratio test. Furthermore, the inverted-U relationship emerges also if firm-level citation-weighted patents and R&D expenditures are used as measures of innovation. Hence the US data presented in Hashmi (2005) provide strong support for Prediction A of Aghion *et al.* (2005).



Source: Hashmi (2005), Figure 1

Figure 1.4: The inverted-U relationship found in US data
The figure shows a scatter plot of citation-weighted patents against competition. Each point represents an industry-year observation. It includes only the data points that lie between tenth and ninetieth percentiles of the distribution of citation-weighted patents. The overlaid curve corresponds to Model II (1.3).

Prediction B

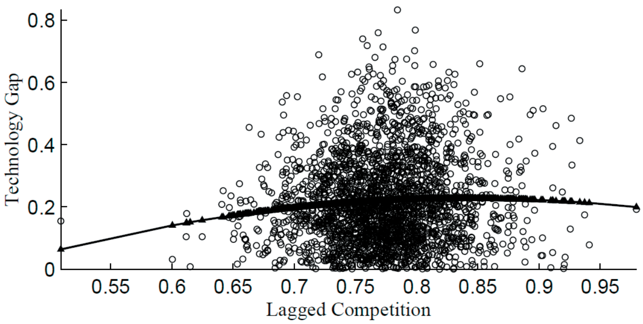
According to Prediction B, a rise in competition increases the expected technology gap. The empirical measure of the technology gap of industry j and year t in Aghion *et al.* (2005) is given by

$$m_{jt} = \frac{1}{N_{jt}} \sum_{i \in j} \frac{(TFP_{Ft} - TFP_{it})}{TFP_{Ft}}, \tag{1.4}$$

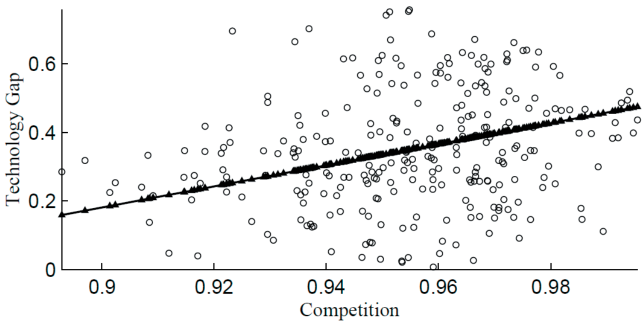
where N_{jt} is the number of firms in industry j in year t, TFP_{Ft} is the total factor productivity of the frontier firm, and TFP_{it} represents the total factor productivity of firm i. The expected technology gap m_{jt} measures the average distance of firms from the technology frontier. In this sense, industries with a high technology gap m_{jt} are more like the unleveled industries in Aghion *et al.*'s model.

Using a linear regression with a full set of year and a full set of year and industry dummies, Aghion *et al.* find a significantly positive relationship between competition and the technology gap (see Aghion *et al.* 2005, Table III, columns 1 and 2). This result supports Prediction B of their model.

Hashmi (2005) discusses the relationship between competition and the technology gap using his US data and the UK data from Aghion *et al.* (2005). I present the relationships for both datasets in order to facilitate a direct comparison of the findings. For both datasets, Hashmi uses a linear and quadratic OLS regression of competition on the technology gap. Both models show highly significant relationships between competition and the technology gap in each of the datasets. However, the linear regression better fits the UK data, while the quadratic regression better fits the US data (see Figure 1.5). Interestingly, the coefficient of the linear regression is positive and highly significant in the US and UK data. But the relationship found in the US data is very flat (the slope is more than 15 times lower than in the UK data). Hence the US dataset does not support Prediction B of the model of Aghion *et al.* (2005).



A: The US data of Hashmi (2005)
Source: Hashmi (2005), Figure 2b

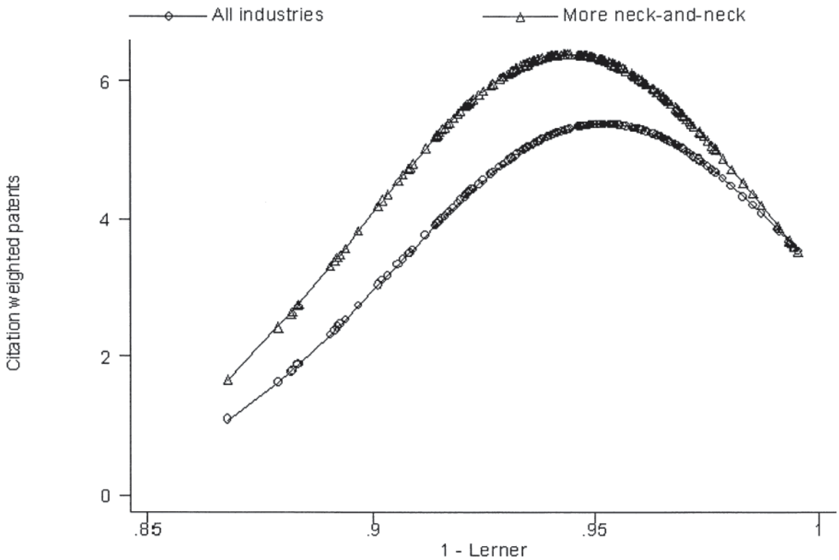


B: The UK data of Aghion *et al.* (2005)
Source: Hashmi (2005), Figure 2a

Figure 1.5: The relationships between competition and the technology gap
The figure shows scatter plots of the technology gap against competition. Panel A presents the quadratic OLS regression for the US data of Hashmi (2005) and Panel B the linear OLS regression for the UK data of Aghion *et al.* (2005).

Prediction C

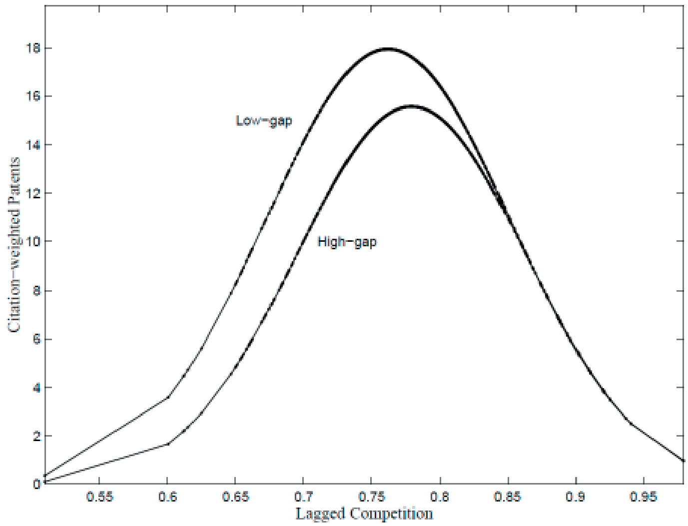
According to Prediction C, the peak of the inverted-U relationship is higher and occurs at a higher level of competition in more leveled industries. In order to test the prediction, Aghion *et al.* (2005) estimate the inverted-U relationship for a sub-sample of industries with a below-median technology gap. Figure 1.6 presents the inverted-U relationships for more neck-and-neck industries and for all industries. Consistently with Prediction C, more neck-and-neck industries show higher innovative activity for all levels of competition. Hence the peak of the inverted-U relationship is higher. On the other hand, the peak of the inverted U occurs at a lower rather than a higher level of competition. In this respect, the evidence does not support Prediction C of the model.



Source: Aghion et al. *(2005), Figure III*

Figure 1.6: The effect of the technology gap found in the UK data
The figure shows the inverted-U relationship between competition and innovation for industries with a below median technology gap (for the coefficients, see Aghion *et al.* 2005, Table III, column 4) and for all industries (see Aghion *et al.* 2005, Table I, column 2).

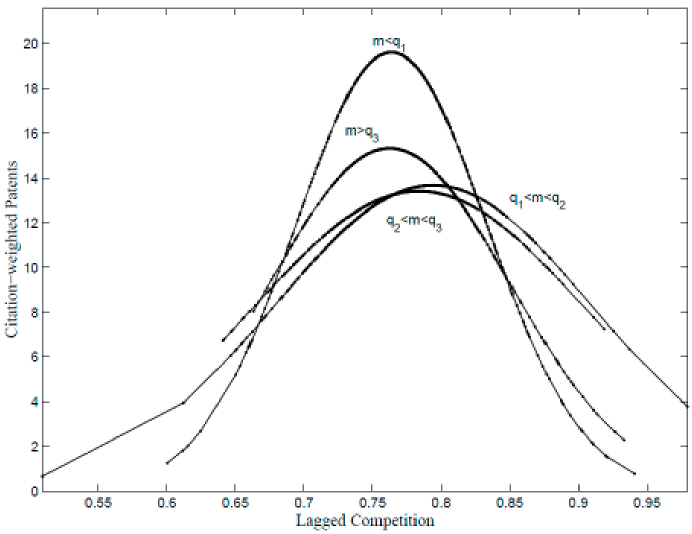
In his test of Prediction C, Hashmi (2005) estimates the inverted-U relationship for industries with both an above- and below-median technology gap. Figure 1.7 shows that the peak of the inverted-U relationship in industries with a lower technology gap is higher and occurs at a lower level of competition. So the result is very similar to the finding of Aghion *et al.* (2005) presented in Figure 1.6.



Source: Hashmi (2005), Figure 5

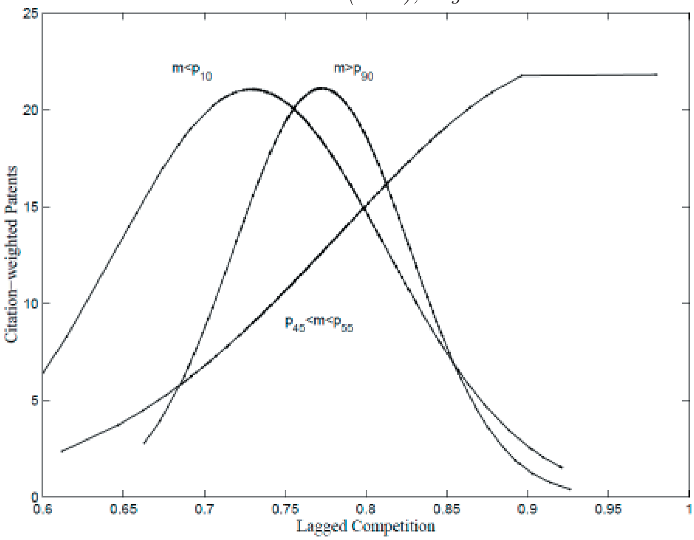
Figure 1.7: The effect of the technology gap found in the US data
The figure shows the inverted-U relationship between competition and innovation for the US industries with a below median and above median technology gap (Hashmi 2005, Table 4).

However, this pattern no longer holds if the sample is split into further sub-samples. Panel 1.8A shows the inverted-U relationships for industries with different quartiles of the technology-gap distribution. We can see that the inverted Us of industry-groups with high and low technology gaps ($m > q_3$ and $m < q_1$) are higher and occur at lower levels of competition than the inverted-U relationships of industries belonging to the second and third quartile. A similarly confusing pattern emerges if the relationships are estimated for 10% of industries with the lowest technology gap ($m < p_{10}$), 10% of industries with the highest technology gap ($m > p_{90}$), and 10% of industries around the median ($p_{45} < m < p_{55}$) (see Panel 1.8B). Here, the inverted U for the industries with $m < p_{10}$ has the lowest peak occurring at the lowest level of competition while the model predicts the opposite. Hence the evidence presented by Hashmi (2005) does not support Prediction C of Aghion *et al.* (2005).



A

Source: Hashmi (2005), Figure 6



B

Source: Hashmi (2005), Figure 7

Figure 1.8: The inverted-U relationships for sub-samples of the US industries
Panel A shows the relationships between competition and innovation for industries with the technology gap below the first quartile ($m < q_1$), between the first and second quartile ($q_1 < m < q_2$), between the second and third quartile ($q_2 < m < q_3$), and above the third quartile ($m > q_3$). Panel B shows the relationships between competition and innovation for 10% of industries with the lowest and highest technology gaps ($m < p_{10}$ and $m > p_{90}$), and 10% of industries around the median ($p_{45} < m < p_{55}$). All curves are estimated using models 1.4 or 1.3, depending on which of the models fitted the data better.

1.2.2 The remaining empirical tests

In this subsection, I present the remaining studies testing some of the predictions of the model of Aghion *et al.* (2005). First, I introduce studies based on US datasets, namely studies by Prasad (2009), Correa & Ornaghi (2011), and Hashmi (2012). Then I review the papers using data from outside the US and UK, namely Kilponen & Santavirta (2005), Tingvall & Poldahl (2006), Tingvall & Karpaty (2008), Askenazy, Cahn & Irac (2008), Wiel (2010), Polder & Veldhuizen (2012), Berubé, Duhamel & Ershov (2012), and Peroni & Ferreira (2012).

The studies using US data

Prasad (2009) reexamines the inverted-U relationship between competition and innovation predicted by Aghion *et al.* (2005). He uses a large dataset with 5,190 industry-year observations spanning 275 four-digit SIC industries over the period 1950 to 2006. Instead of the citation-weighted patents used by Aghion *et al.* (2005) and Hashmi (2005), Prasad (2009) measures innovation using R&D expenditures. R&D expenditures are regressed against four different measures of competition: the price-cost margin (PCM); relative profits differences (RPD) introduced by Boone (2008); and two types of the Herfindahl index (HHI-Sales and HHI-Assets). He carries out OLS regressions with competition, competition squared, and added controls for firm size, and free cash flow.

First, he runs the regressions for all measures of competition only with year effects and year and industry effects. He finds a significant inverted-U relationship between the PCM and R&D expenditures, a highly significant U-shaped relationship between the Herfindahl indices and R&D expenditures, and no relationship when he uses RPD. Then he investigates the effect of appropriability on the relationship between competition and R&D expenditures. For this purpose, he recodes the dataset from the four-digit SIC codes to the National Science Foundation (NSF) classification. The dataset now contains 1,112 industry-year observations for the PCM and Herfindahl indices and 1,084 observations for RPD. Using the same OLS regressions with year and industry effects, he finds similarly shaped relationships as for the dataset using the four-digit SIC codes. Moreover, he subsamples the data into four quartiles based on R&D appropriability using the Yale survey (see Cockburn & Griliches 1988) and runs the same regression for each of the subsamples. The relationship between the PCM and R&D expenditures is significant and inverse U-shaped only if the appropriability is low (quartiles 1 and 2). The relationship between Herfindahl indices and R&D expenditures is significant and U-shaped if the appropriability is very low or very high (quartiles 1 and 4).

Correa & Ornaghi (2011) provide another test of the inverted-U relationship between competition and innovation. They use the same measure of competition as Aghion *et al.* (2005), which they improve by using BLS statistics on the rental prices of capital. They also use the BLS data to construct a different PCM-based measure of competition *cn*. They investigate the relationship for four different measures of innovation: patent counts; citation-weighted patents; the total-factor-productivity (TFP) growth; and the labor productivity (LP) growth. Like Aghion *et al.* (2005) and Hashmi (2005), they obtain patent statistics from the NBER database. They have 2,788 industry-year observations spanning 220 industries (four-digit SIC) over the period 1989 to 2001. The data on productivity is from BLS statistics. It includes 1,806 industry-year observations that corresponds to 85 manufacturing industries (four-digit NAICS) over the period 1987 to 2008.

Similarly to Hashmi (2005), Correa & Ornaghi (2011) assume that patents or citation-weighted patents follow a negative binomial distribution with the specification of the log of the conditional mean of patents or citations given by

$$\ln \lambda_{jt} = \beta_1 c_{jt} + \beta_2 c_{jt}^2 + x_{jt}'\delta + \phi \hat{v}_{jt},$$

where λ_{jt} represents the expected number of patents (or citations) in industry j and year t, c_{jt} is competition, x_{jt} is the complete set time and industry dummy variables, and $\hat{v}_{jt}$ are the residuals of the control function in which competition is regressed against an instrument and time and industry dummies (the same implementation as in Aghion *et al.* 2005). The instruments used are advertising expenditures and lagged import penetration. The relationship between competition and productivity is estimated using the specification

$$\Delta Y_{jt} = \alpha_1 cn_{jt} + \alpha_2 cn_{jt}^2 + x_{jt}'\tau + \varphi \hat{\vartheta}_{jt},$$

where ΔY_{jt} is the TFP or LP growth in industry j and year t, cn_{jt} represents the alternative measure of competition, and $\hat{\vartheta}$ are the residuals of the control function with lagged import penetration as a control variable.

They estimate the above equations with and without the control functions. Without the control function, they find a significant inverted-U relationship between competition and patent citations and no significant relationship between competition and patents. However, both relationships turn positive after adding the control functions in the regressions. Similarly, the relationships between competition and productivity growth were decreasing or inverse U-shaped if the controls for endogeneity were omitted, and mostly positive with the control functions added. Additional robustness checks used in their analysis also support an increasing relationship between competition and innovation.

And finally, Hashmi (2012) tests all predictions of the model of Aghion *et al.* (2005) using a different dataset than Hashmi (2005). His sample includes 2,756 industry-year observation in 116 industries (three-digit SIC) over the period 1976 to 2006. As in Hashmi (2005), the measure of innovation is citation-weighted patents and the measure of competition is $1-$ Lerner index. For testing the inverted-U relationship between competition and innovation (Prediction A), he uses a negative binomial model similar to the model (1.4). He applies instrumental variables to address the issue of endogeneity of competition. The instrument used is the source-weighted average of industry exchange rates. He finds a significant negative relationship between competition and innovation. This relationship is robust to several alternative empirical assumptions including different definitions of innovation (patent counts and R&D expenditures) and two-digit data.

However, the relationship appears to be sensitive to changes in instruments. In an earlier version of the paper, Hashmi (2011) uses trade-weighted tariff rates and freight rates as instruments and finds a positive relationship between competition and innovation for the same dataset. In the later version of the paper, Hashmi (2012) argues that these instruments are problematic because of a likely correlation with innovation. He also claims that the same applies to import penetration used by Correa & Ornaghi (2011). Hence it is possible that the relationship between competition and innovation in Correa & Ornaghi (2011) would remain negative or inverse U-shaped, if they used different instruments.

Even though he does not find an inverted-U relationship between competition and innovation, Hashmi (2012) also tests Predictions B and C. He estimates the relationship between competition and the technology gap defined in the same way as in Aghion *et al.* (2005). He finds that the technology gap is constant in competition. Furthermore, he uses a specification similar to the model (1.3) to estimate the effect of the technology gap on the relationship between competition and innovation. He finds that the relationship for more neck-and-neck industries is very similar to the relationship for all industries. Clearly, these findings do not correspond to Predictions B and C of Aghion *et al.* (2005). However, it is not clear what should be the shapes of the relationship between competition and the technology gap and between competition and innovation in more neck-and-neck industries, if the relationship between competition and innovation for all industries is negative.

Studies using the data from other countries

In this subsection, I present the studies using data from countries other than the US or UK. Kilponen & Santavirta (2005) study the relationship between competition and innovation in a sample of Finnish firms that received grants for R&D. They use similar measures of competition and innovation as Aghion *et al.* (2005). The main difference is that Kilponen & Santavirta (2005) regress firm-level data on patents or citation-weighted patents against competition measured on the industry level (two-digit SIC). Their sample includes 3,247 firm-year observations spanning 1,517 manufacturing companies over the period 1985 to 2001. Following Aghion *et al.* (2005), they assume that patents and citation-weighted patents have a Possion distribution. The log of conditional mean of citation-weighted patents of firm i in year t is given by

$$\ln p_{it} = \alpha + \beta_1 c_{jt} + \beta_2 c_{jt}^2 + \beta_3 c_{jt}\rho_{it} + \beta_4 c_{jt}^2\rho_{it} + \beta_5\rho_{it} + x_{jt}'B,$$

where c_{jt} is competition in industry j and year t, ρ_{it} represents relative R&D subsidies defined as direct industry R&D subsidies per in-house R&D expenditures of firm i, and x_{jt} is a complete set of time and industry dummy variables. For this specification, they find a robust inverted-U relationship between competition and patent counts and citation weighted patents. Interestingly, they also find that a rise in R&D subsidies leads to a flatter and more increasing relationship between competition and innovation.

Tingvall & Poldahl (2006) test the predictions of the model of Aghion *et al.* (2005) using data on Swedish manufacturing firms over the period 1990 to 2000. They measure the effect of competition on R&D expenditures of firms using the Herfindahl index (HHI) and a firm-level PCM. They use the following baseline specification

$$\ln R\&D_{imt} = \alpha_0 + \alpha_i + \alpha_t + \beta_1 \ln \text{Competition}_{imt} + \beta_2 \ln \text{wH}_{imt} + \beta_3 \text{A-gap}_{imt-s} +$$
$$+ \beta_4 \ln r^F_{mt-s} + \beta_5 \ln \text{Size}_{imt} + \beta_6 D^{\text{private}}_{imt} + \beta_7 D^{\text{foreign}}_{imt} + \epsilon_{imt},$$

where Competition_{imt} represents the measure of competition of firm i in industry m and time t, wH_{imt} is the share of skilled workers, A-gap_{imt-s} is the distance to the technological leader, r^F_{mt-s} are technology spillovers, Size_{imt} is the relative employment to industry average, and D^{private}_{imt} and D^{foreign}_{imt} are private and foreign-ownership dummy variables. They address the endogeneity of price-cost margins using industry import penetration, capital intensity, the Herfindahl index, total-factor productivity, fixed industry effects and period dummies as instruments.

Using a PCM-based measure of competition, they find a negative relationship between competition and R&D expenditures, positive correlation between competition and the technology gap, and no positive interaction between the technology gap and innovation. Hence for the PCM-based measure of competition, the data supports only Prediction B of the model of Aghion *et al.* (2005). Using the Herfindahl index as a measure of competition, they find an inverted-U relationship between competition and R&D expenditures, and a positive correlation between competition and the technology gap. They also report a steeper inverted-U relationship between competition and R&D expenditures in more neck-and-neck industries. So for the Herfindahl index, the data supports all predictions of Aghion *et al.*'s model. However, the measure of competition based on the Herfindahl index is not consistent with Aghion *et al.*'s theoretical measure of competition.

Tingvall & Karpaty (2008) test the inverted-U prediction using the data on Swedish service-sector firms. They use a similar empirical strategy as Tingvall & Poldahl (2006). R&D expenditures measure innovation and the Herfindahl index and profit elasticities measure competition in the industry. Their results support the inverted-U relationship for both measures of competition, with the exception of non-exporting firms. They also split R&D expenditures into extramural R&D, intramural R&D, and training of employees. They find evidence of the inverted-U relationship for intramural R&D expenditures and for training of employees, but not for extramural R&D expenditures.

Askenazy, Cahn & Irac (2008) estimate the relationship between competition and innovation using French data obtained from the Fiben and Centrale des Bilans databases. Innovation of firm j is given by

$$n_j = \frac{\text{R\&D expenditures of firm } j}{\kappa_s},$$

where κ_s is the patent unit cost in industry s given by R&D expenditures divided by the number of patents in sector s. The dataset includes around 100,000 observations on 15,500 firms over the period 1990 to 2004. The empirical model that explains the innovation of firm j in year t is given by

$$n_{jt} = \lambda_{jt}(\delta_1 - \delta_2 \ln(\kappa_s) + \delta_3 \ln(WF_{jt})) + \lambda^2_{jt}(-\alpha_1 + \alpha_2 \ln(\kappa_s) - \alpha_3 \ln(WF_{jt})) + c_j + c_t + \epsilon_{jt},$$

where λ_{jt} represents the lagged firm-level Lerner index, WF_{jt} the work force, κ_s the patent unit cost in sector s, and c_j and c_t are the firm and year dummies. The results show that there is a clear inverted-U relationship for the largest firms. The curve becomes flatter in industries with higher patent unit costs at the sectoral level, and for very high patent unit cost, the inverted-U relationship disappears altogether.

Wiel (2010) studies the relationship between competition and innovation in Dutch manufacturing and service industries (three or four-digit SIC) over the period 1996 to 2006. In order to address the problem of endogeneity of competition, he estimates a model that consists of three equations (labor productivity, innovation, competition) using Generalized Methods of Moments (GMM) with lagged variables. The innovation equation is given by

$$IR_{jt} = \varphi_1 C_{jt-1} + \varphi_2 C_{jt-1}^2 + \varphi_2 W_{jt-1} + T_t + \psi_{jt},$$

where IR_{jt} denotes the innovation intensity in industry j and year t measured as total costs of contracted and intermural R&D divided by the number of employees, C_{jt-1} is competition in year $t-1$ measured using profit elasticities or the price-cost margin, W_{jt-1} is a vector of other determinants of innovation (including the distance to frontier), and T_t are time dummy variables. He finds no evidence of an inverted-U relationship between competition and innovation intensity if he omits the control variables W_{jt-1}. With these variables included in the regression, there is a significant inverted-U relationship between profit elasticities and innovation, but no significant relationship between the price-cost margin and innovation. Furthermore, he finds no evidence of a steeper inverted-U relationship in more neck-and-neck industries (Prediction C)

Polder & Veldhuizen (2012) test the predictions of the model of Aghion *et al.* (2005) using Dutch data. They gather 234 industry-year observations spanning 13 manufacturing and 21 non-manufacturing industries over the period 1999 to 2006, and approximately 14,000 firm-year observations in the period 1996 to 2006. First, they study the relationship between competition and innovation at industry level using the equation

$$\ln(R\&D_{jt}/VA_{jt}) = \beta_1 COMP_{jt} + \beta_2 COMP_{jt}^2 + \alpha_j + \lambda_t + e_{jt},$$

where $R\&D_{jt}$ are total R&D expenditures in industry j and year t, VA_{jt} is the value added, $COMP_{jt}$ is competition, and α_j and λ_t are industry and year dummy variables. They use two measures of competition, price-cost margin (PCM) and profit elasticities (PE). They find a significant inverted-U relationship between PE and innovation, but they do not find any relationship between PCM and innovation. They address the endogeneity using lagged competition measures.

Then, they use firm-level data to estimate the equation

$$\ln(R\&D_{it}/VA_{it}) = \beta_1 COMP_{jt} + \beta_2 SPREAD_{jt} \times COMP_{jt} + \beta_3 X_{it} + \alpha_i + \lambda_t + e_{it},$$

where i indexes the firm, $SPREAD_{jt}$ is a measure of the distribution of technology within industry (similar to the technology gap in Aghion *et al.* 2005), X_{it} is a vector of firm-level variables (including the distance of a firm to frontier), and α_i is a firm dummy. They find a positive parameter β_1 and a negative parameter β_2 for all measures of competition. For these parameters, a rise in product market competition increases R&D expenditures of firms with a low technology gap (SPREAD) and reduces R&D expenditures of firms with a high technology gap. This finding supports the model of Aghion *et al.* (2005). Unfortunately, Polder & Veldhuizen do not test directly for the effect of competition on technology gap (Prediction B). They also find that a rise in the distance to frontier of individual firms increases their R&D expenditures, which contradicts Prediction C of Aghion *et al.* (2005).

Berubé, Duhamel & Ershov (2012) study the relationship between competition and innovation using Canadian data. Their dataset consists of an unbalanced panel of 26,947 firm-year observations over the period 2000 to 2005. They explain the R&D expenditures of firm f in industry i and time t using the following specification of the model:

$$\ln R\&D_{fit} = \alpha_1 + \alpha_2 COMP_{(f)it} + \alpha_3 DTF_{it} + \alpha_4 COMP_{(f)it} \times DTF_{it} +$$

$$+\beta \ln L_{fit} + \gamma \ln \left(\frac{K}{LC}\right)_{fit} + \theta \left(\frac{S}{L_R}\right)_{fit} + \delta_t + \delta_i + \eta_f + \epsilon_{fit},$$

where $COMP_{(f)it}$ is competition measured as the industry or firm-level price-cost margin or profit elasticities, DTF_{it} is the industry distance to frontier measured in a similar way as the technology gap in Aghion *al.* (2005), L_{fit} is labor, $(K/LC)_{fit}$ is the tangible and intangible capital stock divided by labor cost, $(S/L_R)_{fit}$ is the proportion of skilled workforce in R&D employment, and δ_t, δ_i, and η_f represent year, industry and firm-fixed effects. They have not found appropriate instruments to deal with the endogeneity of competition. They find a positive and statistically significant relationship between all measures of competition and R&D expenditures. Unfortunately, they do not investigate the nonlinear relationship by adding a quadratic term in the regression. They also find that firms in industries with a higher distance to frontier have lower R&D expenditures (α_3). This finding supports Prediction C of Aghion *et al.* (2005). And for the firm-level price-cost margin and profit elasticities, they find negative and statistically significant coefficients α_4. This means that in industries with a high technology gap, a rise in competition has a less positive effect on R&D expenditures. Moreover, in industries with a high proportion of laggard firms the overall effect of competition on innovation might be negative.

Finally, Peroni & Ferreira (2012) test the predictions of the model using cross-section data on Luxembourgish firms from the year 2006. The innovation equation is given by

$$\ln R\&D_i = \beta_0 + \beta_1 COMP_j + \beta_2 DTF_j + \beta_3 COMP_j \times DTF_j + \beta_4 \ln L_i + \beta_k \sum_k D_i + \epsilon_i,$$

where $R\&D_i$ are R&D expenditures of firm i, $COMP_j$ denotes profit elasticities or price-cost margin in market j, DTF_j denotes the distance to frontier (similar to the measure of the technology gap of Aghion *et al.* 2005), L_i stands for employment, and D_i are dummy variables that group industries into four categories according to their technological intensity. They do not control for endogeneity of competition. They find a negative relationship between both measures of competition and R&D expenditures, that turns to a positive relationship in industries with a low distance to frontier. Adding a quadratic term for competition, they find both convex and concave relationships between profit elasticities and innovation depending on the specification of the model. Similarly, the effect of the distance to frontier on innovation (Prediction C) depends on the specification of the model and on the measure of competition used.

1.3 Summary and discussion

In this section, I provide a summary and discussion of the empirical and theoretical literature presented in this chapter. The section consists of two parts. Subsection 1.3.1 summarizes the empirical findings and relates them to the model of Aghion *et al.* (2005) and to my explanation introduced in this book. Subsection 1.3.2 discusses two important differences between the explanation of Aghion *et al.* (2005) and my explanation introduced in the subsequent chapters.

1.3.1 Summary of the empirical literature

In this chapter, I have presented only the studies that test the predictions of the model of Aghion *et al.* (2005). Furthermore, I have presented only the studies that measure competition using the price-cost margin (PCM) and relative profit differences (RPD) or profit elasticities (PE). The choice of the PCM is natural as Aghion *et al.* (2005) show that a PCM-based measure of competition (1−Lerner index) is monotonously increasing in their theoretical measure of competition. The studies using RPD and PE are included in this chapter because both measures are robust to changes in theoretical parameterization of competition. On the other hand, measures of competition based on the number of firms or industry concentration do not seem to be consistent with the theoretical parameterization of competition used by Aghion *et al.* (2005).

These studies provide some evidence in favor of the inverted-U relationship between a PCM-based measure of competition and innovation (Prediction A). Aghion *et al.* (2005) find the inverted-U relationship in the UK data (however, the existence of the inverted-U relationship in his dataset is questioned by Correa 2012), Hashmi (2005) and Prasad (2009) in the US data, Askenazy, Cahn & Irac (2008) in the French data, and Kilponen & Santavirta (2005) in the Finnish data. On the other hand, some authors fail to identify an inverted-U relationship. Instead, Correa & Ornaghi (2011) find an increasing relationship using US data, Hashmi (2012) and Tingvall & Poldahl (2006) report a decreasing relationship in the US and Swedish data respectively, and Wiel (2010) and Polder & Veldhuizen (2012) find no significant relationship between competition and innovation in the Dutch data. Using PE as a measure of competition, Tingvall & Karpaty (2008) find an inverted-U relationship in the Swedish service-sector data, and Wiel (2010) and Polder & Veldhuizen (2012) in the Dutch data. On the other hand, Prasad (2009) does not find any significant relationship between RPD and innovation in his US dataset.

Furthermore, the model of Aghion *et al.* (2005) shows that the inverted-U relationship between competition and innovation emerges only if there is an increasing relationship between competition and the technology gap (Prediction B). To my knowledge, only Aghion *et al.* (2005) and Hashmi (2005) find an inverted-U relationship and at the same time measure the relationship between competition and the technology gap (using the dispersion of total factor productivity). Consistently with Prediction B, Aghion *et al.* (2005) finds an increasing relationship between a PCM-based measure of competition and the empirical measure of the technology gap. On the other hand, Hashmi (2005) finds a flat and concave relationship between a PCM-based measure of competition and the technology gap. This finding is not consistent with Prediction B.

Finally, the model of Aghion *et al.* (2005) predicts that in more neck-and-neck sectors the inverted-U relationship is higher and peaks at a higher level of competition (Prediction C). None of the studies supports this prediction fully. Aghion *et al.* (2005) find a higher inverted-U relationship with the peak at a lower level of competition. Hashmi (2005) presents a similar finding as Aghion *et al.* (2005) when he splits his sample into high and low-gap industries. However, the prediction does not hold when the sample is divided into quartiles or deciles. Similarly, Wiel (2010) finds no evidence of a steeper inverted-U relationship between PE and innovation in more neck-and-neck industries. Furthermore, Berubé, Duhamel & Ershov (2012) find that firms in more technologically neck-and-neck industries have higher R&D expenditures, which partially supports Prediction C. However, Polder & Veldhuizen (2012) find that a rise in the distance to frontier of individual firms increases their R&D expenditures, which contradicts Prediction C.

Hence the empirical literature testing the model of Aghion *et al.* (2005) provides mixed findings. On the one hand, there are several findings of an inverted-U relationship between competition and innovation. Consistently with the logic of the model of Aghion *et al.* (2005), Polder & Veldhuizen (2012), Berubé, Duhamel & Ershov (2012), and Peroni & Ferreira (2012) find that competition increases or reduces the R&D expenditures of firms depending on the dispersion of technology in the industry. On the other hand, there is very little evidence in support of the additional Predictions B and C. While Prediction C is a consequence of different imitation rates h and the forces behind the inverted-U relationship, and is therefore not a necessary part of the explanation of the inverted-U relationship, Prediction B is directly responsible for the inverted-U relationship. Therefore, the mixed empirical findings concerning Prediction B are problematic for the explanation of Aghion *et al.* (2005).

In the following chapters, I present an alternative explanation of the inverted-U relationship and the related empirical evidence. Most importantly, my explanation is able to reconcile the inverted-U relationship with different findings on the relationship between profitability and the technology gap presented by Aghion *et al* (2005) and Hashmi (2005). Before introducing the alternative explanation, I discuss two important differences between my explanation and the explanation of Aghion *et al.* (2005) in the following subsection.

1.3.2 Discussion of Aghion *et al.*'s model

The main predictions of the model of Aghion *et al.* (2005) arise thanks to specific assumptions about technological progress and product market competition. In their model, firms engage in step-by-step innovation and the maximum feasible difference between the technological levels of firms is one step. Consequently, there are three types of firms in the model. The laggard firm is one step behind. If the laggard firm innovates, it moves one step ahead and becomes the neck-and-neck firm. Finally, the neck-and-neck firm that innovates becomes the leader. The duopolists engage in Bertrand competition with a homogeneous product. The intensity of product market competition is parameterized as the level of collusion in the market. Competition reduces profits of neck-and-neck firms, but it has no effect on profits of laggard or leader firms. Consequently, competition reduces the reward (i.e. the incremental profits from innovation) of laggard firms, and increases the reward of neck-and-neck firms. Hence the assumptions about technological progress and competition create the escape-competition and Schumpeterian effects that are responsible for the predictions of the model.

Thanks to simplifying assumptions, Aghion *et al.* (2005) are able to solve their model analytically. However, the main predictions of the model hold also under more general assumptions. For example, Hashmi (2012) presents a partial-equilibrium version of the model that also generates similar predictions if the maximum feasible technology difference is higher than one step. Similarly, the Schumpeterian and escape-competition effects also operate under different assumptions about product market competition. For example, Aghion *et al.* (2001) or Hashmi (2012) present a Bertrand duopoly model with a constant marginal cost and with the demand function

$$p(q_1, q_2) = \frac{1/q_1^{1-\alpha}}{q_1^{\alpha} + q_2^{\alpha}},$$

where $\alpha \in \langle 0, 1\rangle$ measures the degree of substitutability between the products of firms. The substitutability parameter α can be also used for measuring competition. The higher the α, the more intense is the competition. For a reasonable range of competition and reasonable size of the innovation, more competition reduces the reward of laggard firms and increases the reward of neck-and-neck firms.

On the other hand, several alternative assumptions about product market competition and technological progress in market structures with a fixed number of firms would create a situation in which the Schumpeterian effect is either non-existent or weak. For example, using the Cournot-Nash equilibrium for the same cost and demand specification as Aghion *et al.* (2001) and Hashmi (2012), the profit of a duopolist firm i is equal to

$$\pi_i(c, \alpha) = \frac{1 + (1-\alpha)c^{\alpha}}{(1 + c^{\alpha})^2},$$

where $c = c_i/c_j$ is the relative cost of both firms, and $\alpha \in \langle 0, 1\rangle$ is the parameter of competition (see Boone 2000, example 2). Like Aghion *et al.* (2005), I define the size of innovation as $\gamma > 1$. The relative cost of the leader, who is one technological step ahead, is

$c = 1/\gamma$ and the relative cost of the laggard is $c = \gamma$. If a neck-and-neck firm innovates, its profit changes by $\Delta\pi_1 = \pi_i(1/\gamma, \alpha) - \pi_i(1, \alpha)$, and the profit of the other firm changes by $\Delta\pi_{-1} = \pi_i(\gamma, \alpha) - \pi_i(1, \alpha)$. The change in profit $\Delta\pi_1$ is the reward of a neck-and-neck firm from becoming leader, and the value $-\Delta\pi_{-1}$ is the reward of a laggard firm that becomes neck-and-neck.

Figure 1.9 shows the changes in profits of neck-and-neck firms which arise from moving one step ahead or one step behind for different sizes of innovation γ. Panel A presents situations with modest sizes of innovation of γ = 1.1, 1.2, or 1.3. The panel reveals two regularities. Moving one technological step ahead or behind is rewarded or penalized by a similar change in profit. The rewards of laggard and neck-and-neck firms $-\Delta\pi_{-1}$ and $\Delta\pi_1$ increase in competition α. Hence the Schumpeterian effect will not arise if the size of innovation is relatively small. The situation may change slightly for extremely large innovations. Panel B shows situations in which innovations reduce costs to a half, fourth, or sixth. Then the size of the negative profit from becoming laggard is limited by the size of the profit earned by neck-and-neck firms. Hence the reward is clearly higher than the punishment. Consistently with the Schumpeterian effect, a rise in competition may reduce the reward of laggard firms if competition and the size of innovation are very high (see the right end of the dotted line in Panel B). But the general pattern remains similar to that shown in Panel A. A rise in competition is still likely to increase innovation of both laggard and neck-and-neck firms.

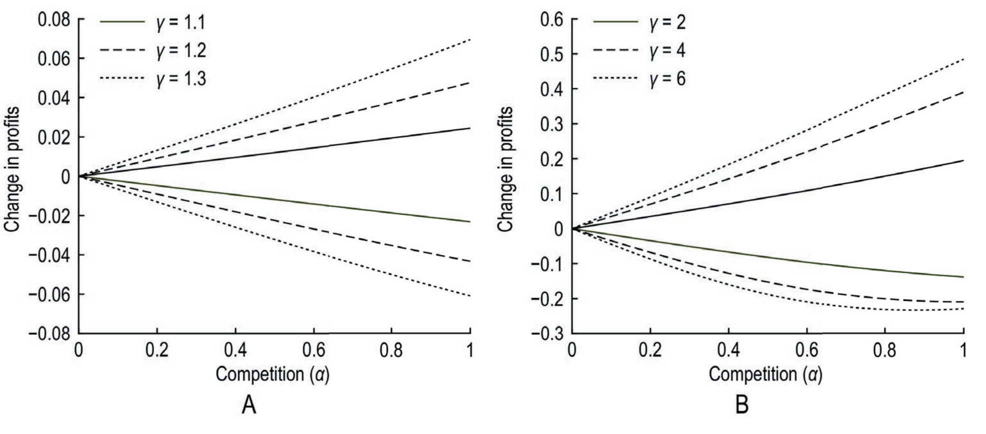


Figure 1.9: Changes in profit in a Cournot model
The figure shows the effect of the size of innovation γ on changes in the profits of neck-and-neck firms. The positive values correspond to the change in profit from becoming leader $\Delta\pi_1$. The negative values correspond to the change in profit from becoming laggard $\Delta\pi_{-1}$. The absolute value of $\Delta\pi_{-1}$ is equal to the reward of a laggard firm that becomes neck-and-neck.

The Schumpeterian effect might also become weaker or nonexistent if we change the assumptions concerning technological progress. Consider the example of a duopoly with one laggard and one leader firm. The laggard firm is not able to use the current state-of-the-art technology for production (e.g. due to patents), but it is able to use it in research and develop a superior technology, such that the laggard firm directly becomes leader. We may follow Aghion *et al.* (2005) and assume that the maximum technology gap is one step, which means that the leader does not innovate. Then the reward of the laggard firm is equal to the difference between the profit of the leader and the laggard. The effect of competition on the reward depends on the assumptions about market structure. For example, in Aghion *et al.* (2005) the reward would be equal to the profit of the leader and therefore would be constant in competition. In the differentiated Bertrand model presented by Aghion *et al.* (2001) or Hashmi (2012), the reward will tend to be increasing in competition. In the above-presented Cournot model with a differentiated product, the reward will be most likely increasing in competition. Hence this change in the nature of technological progress weakens or eliminates the Schumpeterian effect.

In the previous paragraphs, I have shown that the explanation of the inverted-U relationship based on the interplay of the Schumpeterian and escape-competition effects is not robust to some alternative assumptions. More specifically, I have shown that a different type of product market competition or different kind of technological progress may weaken or eliminate the Schumpeterian effect. In the following chapters, I introduce an explanation of the inverted-U relationship that works independently of the existence of the Schumpeterian effect. In this alternative explanation, laggard firms imitate the state-of-the art technology at the end of each period. This means that firms are technologically neck-and-neck at the moment decisions about R&D expenditures are made. Hence all industry members enjoy the same reward from innovation, which is a function constant or decreasing in profits of firms.[1] In this sense, the assumptions of my explanation are complementary to the assumptions used by Aghion *et al.* (2005). While their model provides an explanation of the inverted-U relationship only in the presence of the Schumpeterian effect, my models are able to explain the relationship in the absence of the Schumpeterian effect, or even in the absence of the Schumpeterian and escape-competition effects. I might even argue that my model provides a more general explanation of the inverted U relationship because the forces responsible for the inverted-U relationship are likely to operate even if both the Schumpeterian or escape-competition effects are present.

There is another reason why the explanation of the inverted-U relationship between profitability and innovation presented in this book might be considered as more general compared to the explanation provided by Aghion *et al* (2005). Unlike Aghion *et al.*, who relate innovation to competition, my explanation relates innovation directly to profits of firms. My explanation does not take into account the link between profits (profitability) and competition for two reasons:

- By relating profitability to competition, I would make my explanation less general because competition is only one of the factors that influence profitability of an industry. Industry profitability may be influenced also by demand factors, characteristics

[1] The result of the model would hold also if all the industry members had the same reward from innovation and if we allowed differences in technology (for the version of the model with endogenous profit difference, see Krčál 2010d or Appendix A).

of the product, government intervention, etc. In my explanation, any determinant of profits of firms may affect innovation and the distribution of technology in an industry. Therefore, my explanation is, in a sense, more general than the explanation of Aghion *et al.* (2005). While their model explains the inverted-U relationship between innovation and a specific type of competition, I explain the relationship between innovation and any determinant of profits (including competition).

- The relationship between competition and profits (or profitability) is problematic *per se* because a rise in competition may also increase profits (or profitability) if the technological differences in the industry are sufficiently large (see Boone 2000, 2008 or Krčál 2010b). That is, an explanation of the inverted-U relationship between competition and innovation might not be able to explain the observed inverted-U relationship between profitability (or profits) and innovation.

Hence my explanation provides a more general explanation of the inverted-U relationship between profitability and innovation because it does not assume that competition is the only determinant of profitability of firms, and also because it does not assume that competition is monotonous in profitability. On the other hand, the models presented in the subsequent chapters are not able to explain the inverted-U relationship between innovation and other measures of competition, such as concentration or the number of firms, found in some studies (for recent studies, see e.g. Carlin, Schaffner & Seabright 2004, Tingvall & Poldahl 2006). However, it is questionable whether these findings can be explained by the model of Aghion *et al.* (2005), as it has a constant number of firms and a rise in the theoretical measure of competition leads to a higher expected concentration in the industry (measured by the HHI).

Chapter 2

The basic model

In this chapter, I introduce a model that explains the inverted-U relationship between profitability and innovation, and the findings of Aghion *et al.* (2005) and Hashmi (2005) related to Prediction B of the model of Aghion *et al.* (2005).[1] The basic model is a highly stylized model. Its aim is to provide a simple and general explanation of the empirical evidence. A more specific model is introduced in Chapter 3.

The basic model captures the situation of an industry with a large number of firms in a discrete-time setting. At the beginning of each period, firms decide on the size of their R&D expenditures. With a given probability, the R&D process generates innovation in the same period. Successful innovators are rewarded according to a reward function, which is increasing in R&D expenditures and is identical for all firms in the industry; failed innovators receive no reward. At the end of each period, failed innovators imitate the technology of successful innovators, so that all firms have the same technology at the beginning of the next period.

The choice of R&D expenditures depends on the profits of individual firms, which are equal to the sum of the industry-specific profit, firm-specific profit and profit from R&D activities. The industry-specific profit is determined by factors that are similar for all firms in the industry, such as the intensity of competition, the institutional structure of the market, specificities of technology or product, or the regulatory framework. The firm-specific profit is determined by factors other than technology that are unique to individual firms or groups of firms within the industry, such as different market conditions in segments of the market, or ownership of specific resources. Finally, the profit from R&D activities is positive for successful innovators, and negative for firms that fail to innovate because they have to pay R&D expenditures and earn no reward from innovation.

A rise in the industry-specific profit is assumed to reduce the reward from innovation of each firm. The assumption implies a decreasing relationship between the industry-specific profit and R&D expenditures. Hence firms in low-profit industries would like to choose relatively high R&D expenditures. If the R&D process generates an innovation, the firms are able fund their R&D programs. However if the firms fail to innovate in one or several

[1] See Krčál (2014) for a simplified presentation of the basic model.

periods in a row, they are likely to have difficulties covering the costs of R&D through their profits. So they might want to maintain the size of their R&D expenditures in proportion to their profits. In this model, I assume that firms adjust their R&D expenditures so that they earn a non-negative profit even if the innovation fails. Thus a rise in the industry-specific profit might lead to higher R&D expenditures on the part of less profitable firms.

Consequently, a rise in the industry-specific profit might increase the R&D expenditures of firms in low-profit industries, and reduce the R&D expenditures of firms in high-profit industries, forming an inverted-V relationship. Furthermore, the relationships of individual firms might differ because of differences in profits due to firm-specific factors. If the differences are low, the relationships between the industry-specific profit and average R&D expenditures in the industry (called the R&D function) and between the industry-specific profit and the technology gap (called the technology-gap function) are likely to be inverse V-shaped, an outcome which resembles the findings of Hashmi (2005). On the other hand, the R&D function might be inverse V- or U-shaped and the technology-gap function decreasing, if the differences in profits are relatively high. This result corresponds to the empirical findings of Aghion *et al.* (2005).

The rest of this chapter has the following structure. Section 2.1 introduces the basic model. Section 2.2 relates the profits of firms to average R&D expenditures and the technology gap in the industry and presents the conditions for which the predictions of the model are similar to the empirical findings. Finally, Section 2.3 summarizes the main results of the model. Furthermore, Appendix B.1 presents an implementation of the basic model in `Netlogo 5.0.1`. The `Netlogo` implementation of the model is also used for generating the graphs presented in this chapter.

2.1 Structure of the model

In this subsection, I introduce the basic model of innovation. In the model, firms choose R&D expenditures to maximize their expected profits subject to the R&D-expenditure constraint. I introduce the model in the following order. First, I explain what are the determinants of firms' profits. Then I discuss the relationships between profits and the return to R&D expenditures, and introduce the R&D-expenditure constraint. Finally, I provide a summary of the basic model.

Profits

The time in the model is discrete. Suppose an industry with a continuum of firms. The profit of each firm is determined by *industry-* and *firm-specific factors*[2]. The firm-specific factors are further divided into *technology* and *other firm-specific factors*.

[2]There is a large literature that studies the effect of industry- and firm-specific factors on the performance of firms. See e.g. Rumelt (1991), McGahan & Porter (1997), Mauri & Michaels (1998), Brush, Bromiley & Hendrickx (1999), McGahan & Porter (2002), Maruyama & Odagiri (2002), Hawawini, Subramanian & Verdin (2003), Yurtoglu (2004), and Bou & Satorra (2007). These studies find that both industry- and firm-specific factors are important determinants of the profitability of firms.

Industry-specific factors are those that determine the profits of all firms in an industry in a similar way. They include factors that affect the intensity of competition in the industry, such as the substitutability of products, entry barriers, or the possibility of tacit or explicit collusion. They may include specificities of the products or their distribution, such as the level of customization of the products, or the possibility of using bundling or after-sales services for generating profits. They also include government intervention in the industry, such as a regulatory framework or government subsidies. In the model, industry-specific factors determine the *industry-specific profit* $b \in \langle \underline{b}, \bar{b} \rangle$, where $\underline{b}$ is the minimum industry-specific profit and $\bar{b} > 0$ is the maximum industry-specific profit. For simplicity, I assume that the minimum industry-specific profit is 0. The range of the industry-specific profit is therefore $b \in \langle 0, \bar{b} \rangle$. In the subsequent sections, I will investigate the effect of the industry-specific profit on properties of the model. Hence the industry-specific profit b is a variable in this model.

Technology includes all feasible combinations of inputs and outputs. It can be improved by means of innovations created in the R&D process. In this model, the R&D process is structured in the following way. At the beginning of each period, firm i chooses the size of R&D expenditures $c_i \geq 0$. The R&D process generates an innovation with the *probability of success* $p \in (0, 1)$, or it fails to generate an innovation with the probability $1 - p$. If the R&D process fails to generate an innovation, the profit of firm i changes by R&D expenditures $-c_i$. If it generates an innovation, the profit of firm i changes by the difference between the reward from innovation and R&D expenditures $r(b)c_i^\rho - c_i$, where $r(b) \geq 1$ is the *reward function*, and $\rho \in (0, 1)$ is the *scale parameter*. Furthermore, I assume that all innovations are imitated by all other firms in the industry at the end of each period. Thus all firms have the same technology at the beginning of each period when decisions about R&D expenditures for the following period are made.

Other firm-specific factors are all factors other than technology that influence the profits of individual firms in the industry in different ways. There are two important concepts that explain the intra-industry differences in profits.

- The concept of strategic groups – *Strategic groups* are groups of firms within an industry that share to varying degrees several structural characteristics such as the width of their product line, the degree of vertical integration or diversification, advertising and branding, or the geographical size of the market in which they operate. Differences in these structural characteristics may lead to differences in the profits of firms across groups. Firm-specific rents can be sustained in the long run because they may be protected from the competition of rival firms by so-called *barriers to mobility*, which may arise exactly because of differences in the structural characteristics of firms. (Caves & Porter 1977) The idea of strategic groups is especially important in the context of studies that define industries using classification systems (e.g. SIC or NAICS). These industries, especially if defined relatively broadly as in Aghion *et al.* (2005), are not homogeneous, but rather consist of several other industries or markets. Competitive or other conditions might differ in each of the sub-industries or sub-markets. This provides another reason why the long-run profits of firms in a broadly defined industry might differ.

- The resource-based view of the firm – The *resources* are defined as "those (tangible and intangible) assets which are tied semipermanently to the firm... Examples of resources are: brand names, in-house knowledge of technology, employment of skilled personnel, trade contacts, machinery, efficient procedures, capital, etc." (Wernerfelt 1984, p. 172) According to the resource-based view of the firm, firms differ in their capacities to accumulate and use resources. This may lead to differences in the profits of firms, which can be sustained in the long run thanks to *resource-position barriers*. These arise if the resources are "scarce, difficult to copy or substitute, and difficult to trade in factor markets." (Hawawini, Subramanian & Verdin 2003, p. 3)

In reality, each firm is likely to have a different firm-specific profit. For the sake of simplicity, I assume that there are only two types of firms in the industry: firms X and firms Y. The ratio of the number of firms X to all firms in the industry is $q \in (0, 1)$. The difference between the profits of firms X and Y due to other firm-specific factors is called the *firm-specific profit* $f \geq 0$. Specifically, other firm-specific factors increase the profits of all firms X by the entire firm-specific profit f while leaving the profits of firms Y unchanged.

The profits of firms are determined by industry-specific factors, technology and other firm-specific factors. The profit of firm i in any period depends not only on the size of the industry-specific profit, parameters of innovation, or on the size of the firm-specific profit, but also on whether firm i has been successful in its R&D activity in the given period, and whether it is a firm of type X or Y. The profit of firm i that fails to innovate is

$$\pi_{iF}(b, c_i) = \begin{cases} b + f - c_i & \text{if firm } i \text{ is } X, \\ b - c_i & \text{if firm } i \text{ is } Y, \end{cases} \tag{2.1}$$

where $b \in \langle 0, \bar{b} \rangle$ represents the industry-specific profit, $f \geq 0$ is the firm-specific profit, and $c_i \geq 0$ is the R&D expenditure. The profit of firm i that successfully innovates is

$$\pi_{iS}(b, c_i) = \begin{cases} b + f + r(b)c_i^{\rho} - c_i & \text{if firm } i \text{ is } X, \\ b + r(b)c_i^{\rho} - c_i & \text{if firm } i \text{ is } Y, \end{cases} \tag{2.2}$$

where $r(b) \geq 1$ is the reward function.

Decreasing return to R&D expenditures

I assume that the reward function $r(b)$ decreases in the industry-specific profit b. There are several justifications for this assumption:

- Suppose an industry with a constant number of firms, in which prices increase due to changes in the intensity of competition, the specificities of products, the specificities of the distribution process, or the form and extent of government intervention. Suppose that higher prices lead to higher profits for each firm and lower quantities of goods and services supplied to market by each firm. Now suppose that innovation does not substantially affect the total quantity supplied by each firm, but increases the profit margins of successful innovators by a specific amount. Then the return to R&D expenditures is likely to be increasing in the quantity supplied. Hence firms with higher industry-specific profits b, and lower quantity supplied, are likely to have lower returns to R&D expenditures (for a similar argument, see Arrow 1962).

Figure 2.1 presents a specific example in which this argument applies. Let's suppose two firms in Bertrand competition with a homogeneous product facing a decreasing demand function $D(p)$. Suppose that firms collude on a price $p_1 < p^M$, where p^M is the monopoly price. Each of them sells half of the market quantity $q_1/2$ and each has a constant marginal cost $c < p_1$. Now suppose that an innovation reduces the marginal cost by Δc. If both firms innovate, their prices remain at the collusive level p_1 and their profits increase by $\Delta c q_1/2$. If one firm innovates and the other does not, the innovator can either sustain collusion or compete with the other firm and sell competitive quantity q^C at the competitive price $p^C = c$. Suppose the collusive price p_1 is high enough so that $(p_1 - c + \Delta c)q_1/2 > \Delta c q^C$, which means that it is more profitable for the innovator to sustain the collusive price. Then the profit of the innovator increases by $\Delta c q_1/2$, too. Suppose now that the firms are able to collude on a price $p_2 > p_1$ such that $p_2 \leq p^M$, and each of them sells quantity $q_2/2 < q_1/2$ and earns profit $(p_2 - c)q_2/2 > (p_1 - c)q_1/2$. Then the incremental profit from innovation (reward) is $\Delta c q_2/2 < \Delta c q_1/2$. Hence firms with higher profits have lower returns to R&D expenditures.

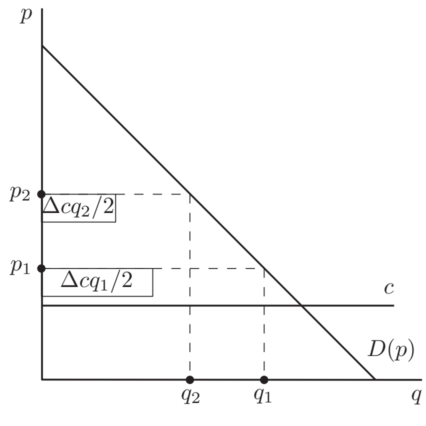


Figure 2.1: An example of decreasing return to R&D expenditures
The figure shows the effect of an increase in price on the reward in Bertrand competition with two firms. If the collusive price increases from p_1 to p_2, the quantity sold by each firm decreases from $q_1/2$ to $q_2/2$. Assuming that the innovation reduces the marginal cost by Δc, the reward falls from $\Delta c q_1/2$ to $\Delta c q_2/2$.

- Suppose an industry serving several markets each with a decreasing demand function (for example the pharmaceutical industry serves several markets for different types of drugs). Now suppose that innovation provides the successful innovator with a monopoly in one of the markets. Then the return to R&D expenditures is equal to the difference between the monopoly profit and the profit the innovator had earned before the innovation was implemented. If the industry-specific profit b is low, the incremental profit due to a monopolistic position in the market is high. On the other hand, if the firm earns high industry-specific profit b under competition, the reward is low. Hence the return to R&D expenditures is likely to be decreasing in industry-specific profit b in this situation (see Fellner 1951, Arrow 1962 and Aghion *et al.* 2005 for models with a similar effect).

- Suppose an industry with firms at the same technological level. The interaction in the market becomes less aggressive. A reduction in the aggressiveness of interaction can be modeled for example as a reduction in the elasticity of substitution between the goods, an increase in transport costs in the Hotelling model, or as a switch from Bertrand to Cournot (see Boone 2000 and 2008). Then firms earn higher profits but their rewards tend to be lower. This effect arises mainly because a reduction in the aggressiveness of interaction leads to a lower reallocation of market shares from less to more efficient firms. Hence a higher firm-specific profit b due to a less aggressive interaction may be related to a lower return to R&D expenditures.

In this model, the reward function is given by

$$r(b) = \frac{1}{p}\Big(1 + R - \sigma\frac{b}{\bar{b}}\Big), \tag{2.3}$$

where $p \in (0,1)$ represents the probability of success, b is the industry-specific profit, $\bar{b}$ is the maximum industry specific profit, the *slope parameter* $\sigma > 0$ determines the effect of the industry-specific profit b on the reward from innovation, and the *opportunity parameter* $R \geq \sigma > 0$ determines the attractiveness of innovation (the assumption $R \geq \sigma$ is equivalent to the assumption that $r \geq 1$).

The specific form of the reward function in (2.3) has two advantages: First, the reward function $r(b)$ varies with the probability of success p so that changes in p do not affect the return to R&D expenditures. This way, it is possible to isolate the effect of different probabilities of success from the changes in the attractiveness of innovation measured by the opportunity parameter R. Second, the opportunity parameter R has an intuitive interpretation. It is equal to the return to the first unit of R&D expenditures ($c_i = 1$) in an industry with the lowest industry-specific profit ($b = 0$).

The R&D-expenditure constraint

And finally, I assume that firm i chooses R&D expenditures c_i so that it is not in loss even if the innovation fails. It follows from (2.1) that

$$c_i \leq b + f \quad \text{for firms } X, \tag{2.4}$$

$$c_i \leq b \quad \text{for firms } Y. \tag{2.5}$$

There are several ways to justify this assumption:

- Firms might face credit constraints. If firms are not able to obtain credit, they must be able to finance their R&D activities from their current profits even if they fail to innovate. This assumption may also be justified if firms are able to obtain credit because, in that case, the banks might be reluctant to provide firms with credit that could not be fully repaid in the event that the R&D activity failed. Moreover, in a slightly modified model the main results would hold even if the maximum R&D expenditure was equal to the expected profit of the firm. This size of R&D expenditures is clearly the maximum sustainable size of the R&D budget of the firm.

- Firms might be infinitely risk averse, which means that they choose their R&D expenditures so that their profits in the worst possible outcome are non-negative (this version of infinite risk aversion is used for example by Rey & Tirole 1986). The predictions of the model are likely to be similar even if the risk aversion of firms was not infinite but if it was very high for low profits and decreasing in the profits of firms, because the shape of the utility function would resemble the prospect-theory value function (see Chapter 3).

- Firms might be infinitely risk averse, which means that they choose their R&D expenditures so that their profits in the worst possible outcome are non-negative (this version of infinite risk aversion is used for example by Rey & Tirole 1986). The predictions of the model are likely to be similar even if the risk aversion of firms was not infinite but if it was very high for low profits and decreasing in the profits of firms, because the shape of the utility function would resemble the prospect-theory value function (see Chapter 3).

- Managers of firms might be infinitely risk averse. If their compensation is linked to the performance of their firms (e.g. they earn a percentage of their profits), managers of low-profit firms would avoid high R&D expenditures. The model might also provide similar predictions if the risk aversion of managers was high for low compensation and decreasing in the size of managerial compensation, or if managers had prospect-theory preferences (see the prospect-theory model in Chapter 3).

Summary of the model

In the basic model, each firm chooses R&D expenditures that maximize its expected profit subject to the R&D-expenditure constraints (2.4) or (2.5). Firm i faces the following optimization problem:

$$\max_{c_i} \; p(b + f + r(b)c_i^{\rho} - c_i) + (1-p)(b + f - c_i) \quad \text{s.t. } c_i \leq b + f \quad \text{if firm } i \text{ is } X, \tag{2.6}$$

$$\max_{c_i} \; p(b + r(b)c_i^\rho - c_i) + (1-p)(b - c_i) \quad \text{s.t. } c_i \le b \quad \text{if firm } i \text{ is } Y, \tag{2.7}$$

where $c_i \ge 0$ represents the R&D expenditure, $p \in (0,1)$ is the probability of success, $b \in (0, \bar{b})$ is the industry-specific profit, $f \ge 0$ is the firm-specific profit, $\rho \in (0,1)$ is the scale parameter, and $r(b)$ is the reward function

$$r(b) = \frac{1}{p}\Big(1 + R - \sigma\frac{b}{\bar{\bar{b}}}\Big),$$

where $\sigma > 0$ is the slope parameter, and $R \ge \sigma > 0$ is the opportunity parameter.

2.2 Predictions of the model

In this section, I show that for some combinations of parameters the model is able to explain the empirical findings of Aghion *et al.* (2005) and Hashmi (2005) related to Predictions A and B of Aghion *et al.* (2005). The section has the following structure. In Subsection 2.2.1, I find the optimal R&D expenditures of firms X and Y. In Subsection 2.2.2, I discuss the relationship between the industry-specific profit and average R&D expenditures in the industry. In Subsection 2.2.3, I examine the relationship between the industry-specific profit and the technology gap in the industry. Finally in Subsection 2.2.4, I shortly discuss the empirical relevance of predictions of the basic model.

2.2.1 Solving the model

Using Kuhn-Tucker conditions for solving the constrained maximization problems (2.6) and (2.7), I obtain the optimal R&D expenditures of firms X and Y

$$c_i^X(b) = \min\{b + f, c_i^*(b)\} \tag{2.8}$$

and

$$c_i^Y(b) = \min\{b, c_i^*(b)\} \tag{2.9}$$

where

$$c_i^*(b) = \left(\rho + \rho R - \rho\sigma\frac{b}{\bar{\bar{b}}}\right)^{\frac{1}{1-\rho}}. \tag{2.10}$$

In the following paragraphs, I discuss the conditions under which the functions $c_i^Y(b)$ and $c_i^X(b)$ are inverse V-shaped. The function $c_i^Y(b)$ is inverse V-shaped if it peaks at $b > 0$, that is if $c_i^*(0) > 0$, and at the same time if it peaks at $b < \bar{b}$, that is if $c_i^*(\bar{b}) < \bar{b}$. Hence the function $c_i^Y(b)$ is inverse V-shaped if

$$c_i^*(\bar{b}) - \bar{b} < 0 < c_i^*(0), \text{ or}$$

$$(\rho + \rho R - \rho\sigma)^{\frac{1}{1-\rho}} - \bar{b} < 0 < (\rho + \rho R)^{\frac{1}{1-\rho}}.$$

Since $R \ge \sigma > 0$ and $\rho \in (0,1)$, the right-hand side of the inequality is always higher than zero. Hence $c_i^Y(b)$ is inverse V-shaped if

$$(\rho + \rho R - \rho\sigma)^{\frac{1}{1-\rho}} - \bar{b} < 0. \tag{2.11}$$

The function $c_i^X(b)$ is inverse V-shaped if

$$c_i^*(\bar{b}) - (\bar{b} + f) < 0 < c_i^*(0) - f, \text{ or}$$
$$(\rho + \rho R - \rho\sigma)^{\frac{1}{1-\rho}} - (\bar{b} + f) < 0 < (\rho + \rho R)^{\frac{1}{1-\rho}} - f. \tag{2.12}$$

It follows from condition (2.11) that the function $c_i^Y(b)$ is inverse V-shaped if the opportunity parameter R is relatively low, that is if $R < \bar{b}^{1-\rho}/\rho + \sigma - 1$. Furthermore, given condition (2.11) holds, the left-hand side of condition (2.12) also holds because the firm-specific profit $f \geq 0$. It means that if the function $c_i^Y(b)$ is inverse V-shaped, the function $c_i^X(b)$ is either inverse V-shaped or decreasing in the industry-specific profit b.

2.2.2 R&D expenditures

This subsection discusses the shape of the relationship between the industry-specific profit and average R&D expenditures in the industry. The R&D function is given by

$$c(b) = qc_i^X(b) + (1-q)c_i^Y(b), \tag{2.13}$$

where q is the proportion of firms X in the industry. Let b^* denote the industry-specific profit that corresponds to the maximum of the R&D function $c(b)$. If $0 < b^* < \bar{b}$, the maximum of the R&D function lies within the range of industry-specific profit $b \in \langle 0, \bar{b} \rangle$. Hence the R&D function $c(b)$ is likely to be inverse U- or V-shaped.

I assume that condition (2.11) holds which means the function $c_i^Y(b)$ is inverse V-shaped, and the function $c_i^X(b)$ is either inverse V-shaped or decreasing in the industry-specific profit b. If the firms-specific profit is relatively low, so that

$$f < (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the R&D-expenditure function of firms X $c_i^X(b)$ is inverse V-shaped (see (2.12)). Then the maximum of the R&D function $c(b)$ is at $0 < b^* < \bar{b}$. The shape of the function depends on the firm-specific profit f:

- If $f = 0$, the R&D function $c(b)$ has the same inverted-V shape as the R&D-expenditure functions of firms X and firms Y. See Panel 2.2A for an example of an inverse V-shaped $c(b)$.

- If $0 < f < (\rho+\rho R)^{\frac{1}{1-\rho}}$, the shapes of $c_i^X(b)$ and $c_i^Y(b)$ are different. Because the R&D function $c(b)$ is a weighted average of $c_i^X(b)$ and $c_i^Y(b)$, the maximum of the R&D function $c(b)$ is at $0 < b^* < \bar{b}$. See Panel 2.2B for an example of the corresponding (inverted-U) R&D function $c(b)$.

If the firms-specific profit is relatively high, so that

$$f \geq (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the R&D-expenditure function of firms X $c_i^X(b)$ is decreasing in b. Then the shape of the R&D function $c(b)$ depends on the slope of $c_i^Y(b)$:

- In the higher part of the industry-specific-profit range where $c_i^Y(b) = c_i^*(b)$, the part of the R&D function $\bar{c}(b)$ is clearly decreasing.

- In the lower part of the industry-specific-profit range where $c_i^Y(b) = b$, the slope of the part of the R&D function $\underline{c}(b)$ is given by

$$\frac{\partial \underline{c}(b)}{\partial b} = -\frac{q\rho\sigma}{\bar{b}(1-\rho)}\left(\rho + \rho R - \rho\sigma\frac{b}{\bar{b}}\right)^{\frac{\rho}{1-\rho}} + (1-q). \tag{2.14}$$

  The function $\underline{c}(b)$ is convex because

$$\frac{\partial^2 \underline{c}(b)}{\partial b^2} = \frac{q\rho^3\sigma^2}{\bar{b}^2(1-\rho)^2}\left(\rho + \rho R - \rho\sigma\frac{b}{\bar{b}}\right)^{\frac{2\rho-1}{1-\rho}} > 0.$$

  Thus the function $\underline{c}(b)$ is increasing in b, if the slope of $\underline{c}(b)$ is positive for $b = 0$. Substituting $b = 0$ into (2.14) and solving for R, I find that $\underline{c}(b)$ is increasing if

$$R < \left(\frac{\bar{b}(1-\rho)(1-q)}{q\rho^{\frac{1}{1-\rho}}\sigma}\right)^{\frac{1-\rho}{\rho}} - 1. \tag{2.15}$$

Because the part of the R&D function $\bar{c}(b)$ is always decreasing, the entire R&D function $c(b)$ is inverse V-shaped if $\underline{c}(b)$ is increasing, that is if

$$R < \left(\frac{\bar{b}(1-\rho)(1-q)}{q\rho^{\frac{1}{1-\rho}}\sigma}\right)^{\frac{1-\rho}{\rho}} - 1.$$

For an example of this outcome, see Panel 2.2C. For an example of the outcome where condition (2.15) does not hold, see Panel 2.2D.

2.2.3 The technology gap

In this subsection, I discuss the shape of the relationship between the industry-specific profit and the technology gap. The measure of the technology gap used in Aghion *et al.* (2005) and Hashmi (2005) is the industry average of firm-level technology gaps, where the technology gap of firm i is given by

$$\frac{TFP_L - TFP_i}{TFP_L}, \tag{2.16}$$

where TFP_L is total factor productivity of the technology leader, and TFP_i is total factor productivity of firm i. TFP is usually calculated as value added divided by a weighted average of input units used in production.

In the context of my model, firm i may have relatively high total factor productivity compared to other firms for two reasons:

- Firm i has better technology which means that it has a higher revenue or lower costs than other firms. The measure of the size of technology is the reward $r(b)c_i^{\rho}$.

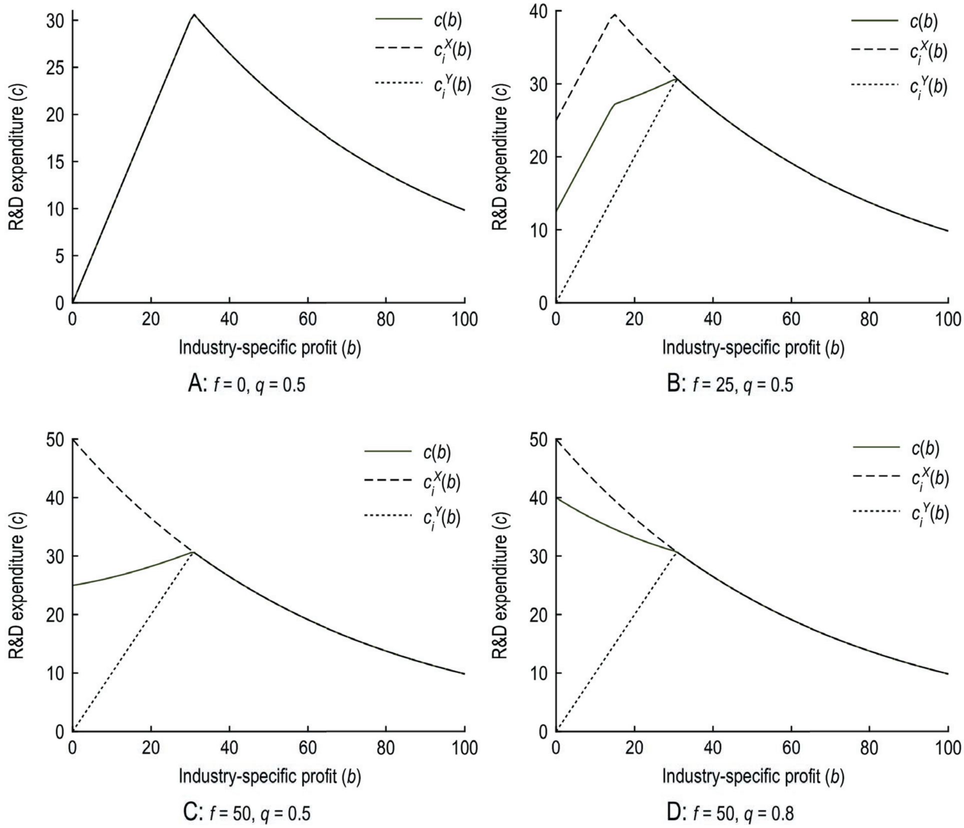


Figure 2.2: Examples of the R&D-expenditure functions
The figure shows examples of R&D-expenditure functions of firms X and Y $c_i^X(b)$ and $c_i^Y(b)$ and of the R&D functions $c(b)$. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\sigma = 0.1$, and $\bar{b} = 100$.

- If firm i has a higher profit due to other firm-specific factors, it might mean that its structural characteristics or resources enable it to have higher revenue using similar quantities of inputs. If firm i has a positive firm-specific profit f, it is likely to have higher TFP than firms with no firm-specific profit.

Consequently, I define the technology gap as an average difference between profits of leaders and other firms in the industry due to technology or other firm-specific factors. The technology gap is determined by the distribution of technology after the innovation. There are four groups of firms with different technology gaps after the innovation in a given period:

- Successful innovators X with the technology gap $G_S^X = 0$.
- Failed innovators X with the technology gap $G_F^X(b) = r(b)c_i^X(b)^{\rho}$.

- Successful innovators Y with the technology gap $G_S^Y(b) = f + r(b)c_i^X(b)^\rho - r(b)c_i^Y(b)^\rho$.
- Failed innovators Y with the technology gap $G_F^Y(b) = f + r(b)c_i^X(b)^\rho$.

Weighting the differences in profits by the share of different groups of firms in the industry, we get the technology-gap function

$$G(b) = qpG_S^X + q(1-p)G_F^X(b) + (1-q)pG_S^Y(b) + (1-q)(1-p)G_F^Y(b). \tag{2.17}$$

Let b^{G*} denote the industry-specific profit that corresponds to the maximum of the technology-gap function $G(b)$. If $0 < b^{G*} < \bar{b}$, the maximum of the technology-gap function lies within the range of industry-specific profit $b \in \langle 0, \bar{b} \rangle$. Hence the technology-gap function $G(b)$ is likely to be either inverse V- or U-shaped. On the other hand if $b^{G*} = 0$, the maximum lies at the lowest possible industry-specific profit $b = 0$, and the technology-gap function is likely to be decreasing in b.

In this subsection, I discuss the shape of the technology-gap function if the condition (2.11) holds, which implies that $c_i^Y(b)$ is inverse V-shaped and $c_i^X(b)$ is decreasing or inverse V-shaped. If the firm-specific profit is relatively high so that

$$f \geq (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the function $c_i^X(b)$ is decreasing in the industry-specific profit b. Then the technology-gap function $G(b)$ is decreasing in b because the technology-gaps of failed innovators X and Y $G_F^X(b)$ and $G_F^Y(b)$ and of successful innovators Y $G_S^Y(b)$ are decreasing in the industry-specific profit b. The technology-gaps $G_F^X(b) = r(b)c_i^X(b)^\rho$ and $G_F^Y(b) = f + r(b)c_i^X(b)^\rho$ are decreasing because both $r(b)$ and $c_i^X(b)$ are decreasing in the industry-specific profit b. $G_S^Y(b) = f + r(b)\Big(c_i^X(b)^\rho - c_i^Y(b)^\rho\Big)$ is decreasing in b because $r(b)$ is decreasing in b and

$$c_i^X(b)^\rho - c_i^Y(b)^\rho = \begin{cases} c_i^*(b)^\rho - b^\rho & \text{if } b \leq c_i^*(b) \\ 0 & \text{if } b \geq c_i^*(b) \end{cases} \tag{2.18}$$

is either decreasing in b or zero.

If the firm-specific profit is relatively low so that

$$f < (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the function $c_i^X(b)$ is inverse V-shaped. Then the shape of the technology-gap function depends on the slope of $c_i^X(b)$:

- In the higher part of the range of industry-specific profit where $c_i^X(b) = c_i^*(b)$ (the function $c_i^*(b)$ is decreasing in b), the technology-gap function $\bar{G}(b)$ is always decreasing in b for the reasons explained in the previous paragraph.
- In the lower part of the industry-specific-profit range where $c_i^X(b) = b + f$, the shape of the part of the technology-gap function $\underline{G}(b)$ depends on the size of the firm-specific profit f:

If $f = 0$, the function $\underline{G}(b)$ is increasing at low industry-specific profit b because the technology gap is zero for $b = 0$ and positive for $b > 0$.

If $0 < f < (\rho + \rho R)^{\frac{1}{1-\rho}}$, the function $\underline{G}(b)$ may be both increasing or decreasing because

$$\frac{\partial \underline{G}(b)}{\partial b} = \left(1/p - q\right)\left(\frac{\rho(1 + R - \sigma b/\bar{b})}{(b + f)^{1-\rho}} - \frac{\sigma(b + f)^{\rho}}{\bar{b}}\right) - \left(1 - q\right)\left(\frac{\rho(1 + R - \sigma b/\bar{b})}{b^{1-\rho}} - \frac{\sigma b^{\rho}}{\bar{b}}\right)$$

may be positive or negative.

What we know is that the slope of $\underline{G}(b)$ is decreasing in the firm-specific profit f because

$$\frac{\partial^2 G(b)}{\partial b \partial f} = \left(1/p - q\right)\left(- \frac{\rho(1-\rho)(1 + R - \sigma b/\bar{b})}{(b + f)^{2-\rho}} - \frac{\rho\sigma}{\bar{b}(b + f)^{1-\rho}}\right) < 0,$$

and increasing in the share of firms X q because

$$\frac{\partial^2 G(b)}{\partial b \partial q} = -\left(\frac{\rho(1 + R - \sigma b/\bar{b})}{(b + f)^{1-\rho}} - \frac{\sigma(b + f)^{\rho}}{\bar{b}}\right) + \left(\frac{\rho(1 + R - \sigma b/\bar{b})}{b^{1-\rho}} - \frac{\sigma b^{\rho}}{\bar{b}}\right) > 0.$$

To summarize, if condition (2.11) holds ($c_i^Y(b)$ is inverse V-shaped), the shape of the entire technology-gap function $G(b)$ depends primarily on the firm-specific profit f:

- If $f = 0$, then $0 < b^* < \bar{b}$ and the technology-gap function is either inverse V- or U-shaped because $\bar{G}(b)$ is decreasing in the industry-specific profit b and $\underline{G}(b)$ is increasing at low b.

- If $0 < f < (\rho + \rho R)^{\frac{1}{1-\rho}}$, then $b^{G*} < \bar{b}$ which means that the technology-gap function is likely to be either decreasing or inverse U- or V-shaped. Moreover, the slope of the part of the technology-gap function $\underline{G}(b)$ in this situation decreases with increasing firm-specific profit f and decreasing share of firms X in the industry q. It means that the entire technology-gap function $G(b)$ is more likely to have the maximum at $b = 0$ if f is high and q is low.

- If $f \geq (\rho + \rho R)^{\frac{1}{1-\rho}}$, the technology-gap function $G(b)$ is always decreasing in b.

Figure 2.3 shows examples of the R&D functions $c(b)$ and the technology-gap functions $G(b)$ for different levels of the firm-specific profit f and the share of firms X in the industry q. If f is low, the R&D function $c(b)$ and the technology-gap function $G(b)$ are inverse V-shaped. The higher the f and the lower the q, the more decreasing is the part of the technology-gap function $\underline{G}(b)$ corresponding to the low industry-specific profits b. However, for the combination of parameters used in Figure 2.3 the effect of f and q on the shape of the increasing part of $G(b)$ is relatively small.

2.2.4 Empirical relevance of the results

This section discusses whether the basic model generates predictions that correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). However, this section discusses only predictions generated for the set of parameters used in Figure 2.3. Robustness of predictions to different values of parameters is examined in Section 4.1. The structure of this section is straightforward. First, I interpret the values of the parameters used in Figure 2.3 and whenever possible, I present empirical support for the values. Then I discuss to what extent the results presented in Figure 2.3 correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005).

In Figure 2.3, I use the following values of parameters:

- the industry-specific-profit range is $b \in (0, 100)$,

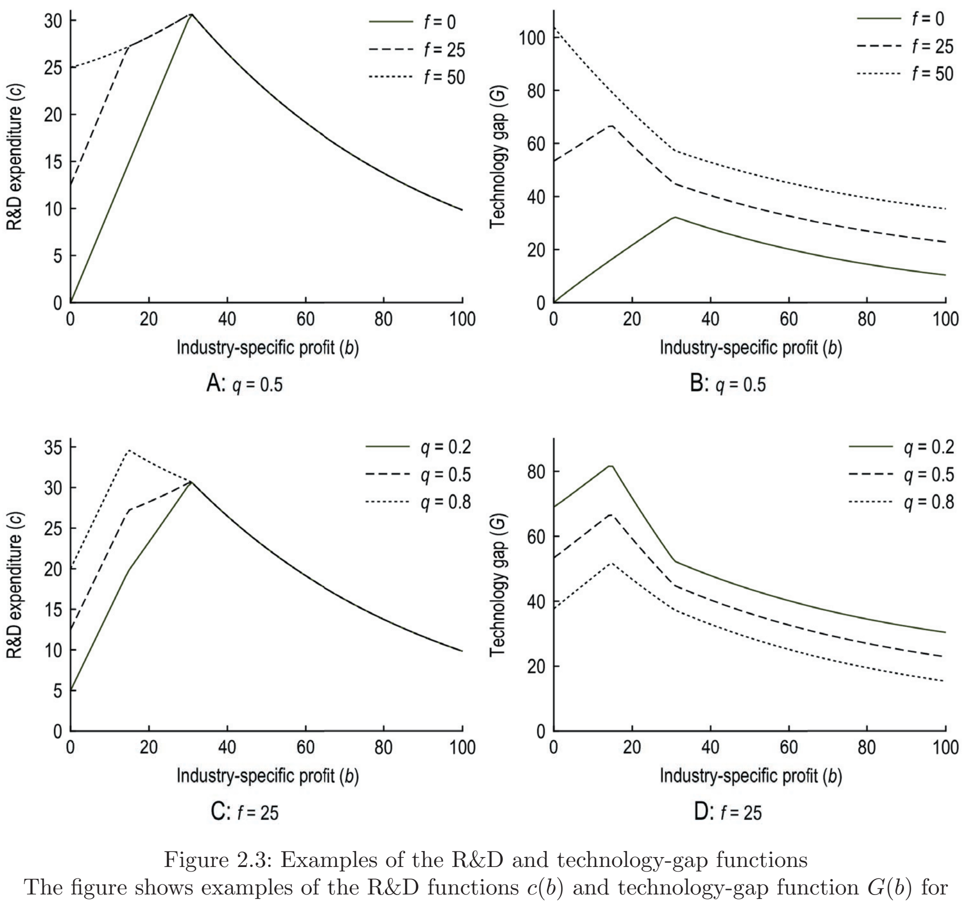


Figure 2.3: Examples of the R&D and technology-gap functions
The figure shows examples of the R&D functions $c(b)$ and technology-gap function $G(b)$ for different values of the firm-specific profit f and the share of firms X in the industry q. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\sigma = 0.1$, and $\bar{b} = 100$.

- the opportunity parameter $R = 0.28$,
- the scale parameter $\rho = 0.95$,
- the slope parameter $\sigma = 0.1$,
- the probability of success $p = 0.5$,
- the firm-specific profits $x = 0$, 25, and 50,
- the share of firms X $q = 0.2$, 0.5, and 0.8.

The industry-specific profit ranges from 0 to \$100 million. In reality, the range of the industry-specific profit can be derived from the sales of firms and from the realistic profitability range. For simplicity, I assume that all firms in the industry have the same sales which are equal to \$750 million. \$750 million (£500 million) is the approximate median sales of the firms in the dataset used by Conyon & Murphy (2000) in their study of managerial compensation. Their sample consists of the 510 largest UK firms in 1997 ranked by market capitalisation and 1,666 US firms including the firms from the S&P 500, the S&P MidCap 400, the S&P SmallCap 600 and companies in S&P supplemental indices. I set the sales of firms according to the data used by Conyon & Murphy (2000) because their study uses a similar sample of firms as Aghion *et al.* (2005) (311 firms listed on the London Stock Exchange) and Hashmi (2005) (645 manufacturing firms from S&P Compustat database), and because their study will provide us with the data on CEO compensation that will be used in the subsequent chapter. The realistic range of profitability can be determined directly using the data of Aghion *et al.* (2005) and Hashmi (2005). These authors measure profitability using the average Lerner index in the industry that is calculated as

$$LI = \frac{1}{N_{jt}} \sum_{i \in j} li_{it},$$

where N_{jt} is the number of firms in industry j in year t, and li_{it} is the Lerner index of firm i in year t calculated as operating profits minus depreciation, provisions, and an estimated cost of capital divided by sales. The average Lerner index in Aghion *et al.* (2005) ranges approximately from 0 to 0.12 and in Hashmi (2005) approximately from -0.10 to 0.20. In the basic model, I calculate profitability as the average profit of a firm in the industry divided by sales. Apart from the industry-specific profit, the most important determinant of profitability in Figure 2.3 is the firm-specific profit f and the share of firms X in the industry q. Assuming that all firms in the industry have sales of approximately \$750 million, the industry-specific profit ranges from 0 to \$100 million, profitability in Figure 2.3 ranges approx. from 0 to 0.135 if $f = 0$ and approx. from 0.035 to 0.17 if $q = 0.5$ and $f = 50$. For the realistic sales of approximately \$750 million, the range of profits earned by firms in Figure 2.3 seems realistic.

The average sales of firms in the industry determine also the realistic size of R&D expenditures. The R&D/sales ratio of top 100 R&D spenders in 1991 in all industry composite is 1.69% in the UK and 3.8% in the US.[3] Hence R&D expenditures of an average firm with sales of $750 million in 1991 would be $12.7 million in the UK and $28.5 in the US. Since the R&D/sales ratio tends to increase over time, the realistic size of R&D expenditures in the UK and in the US from the 1970s to the 1990s is below $25 to $30 millions. The size of R&D expenditures presented in Panels 2.3A and C is therefore roughly realistic.

The opportunity parameter is $R = 0.28$. It means that the return to R&D expenditures of a size $c_i = 1$ and for the industry-specific profit $b = 0$ is 28%. For $c > 1$ and $b > 0$, the return to innovation is lower because of decreasing returns to scale in innovation ($\rho < 1$), and because the reward function $r(b)$ is decreasing in the industry-specific profit b ($\sigma > 0$). If R&D expenditures of firm i equal to

$$c_i^*(b) = \left(\rho + \rho R - \rho\sigma\frac{b}{\bar{b}}\right)^{\frac{1}{1-\rho}},$$

the return to R&D expenditures is determined only by the scale parameter. In Figure 2.3, the scale parameter is $\rho = 0.95$. The return to R&D expenditures is then

$$\frac{pr(b)c_i^*(b)^\rho - c_i^*(b)}{c_i^*(b)} = \frac{1}{\rho} - 1 = 1/0.95 - 1 \approx 5.3\%.$$

For R&D expenditures between $1 < c_i < c_i^*(b)$, the return to R&D expenditures ranges from 5.3% to 28%. It is reasonable to assume that R&D expenditures include also the costs of financing (or the opportunity cost of using own funds). Then the returns to R&D expenditures are above the alternative rate of return, so that it is rational for firms to invest in R&D. But at the same time, the returns are not unreasonably high.

I set the value of the probability of success in the middle of the range at $p = 0.5$. I use different values of the firm-specific profit $f = 0$, 25, and 50. The possible range of the firm-specific profit f is limited by the importance of the resource-position and mobility barriers. However, the firm-specific profit up to a half of the maximum industry-specific profit $\bar{b} = 100$ seems realistic, especially since the empirical literature cited in Section 2.1 attributes a large share of the variation in profits to firm-specific factors. Finally, the values of the share of firms X in the industry $q = 0.2$, 0.5, and 0.8 cover a large part of the range $q \in (0, 1)$.

The shapes of the R&D and technology-gap functions in Figure 2.3 correspond approximately to the findings of Aghion *et al.* (2005) and Hashmi (2005):

- The R&D function $c(b)$ is inverse V- or U-shaped which is consistent with the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Both the range of profits and the size of R&D expenditures correspond, to a large extent, to the empirical findings.

[3] See R&D Scoreboard, http://webarchive.nationalarchives.gov.uk/20101208170217/ http://www.innovation.gov.uk/rd_scoreboard/downloads/1991_RD_Scoreboard.pdf, cited on 25.8.2012

- If the firm-specific profit f is high, the technology-gap function $G(b)$ is decreasing in b, which is consistent with the empirical findings of Aghion *et al.* (2005). On the other hand, if the firm-specific profit f is relatively low, the technology-gap function $G(b)$ is first increasing and then decreasing in the industry-specific profit b, which is approximately consistent with the findings of Hashmi (2005). We may use a higher firm-specific profit f for explaining the empirical findings of Aghion *et al.* (2005) and a lower f for explaining the findings of Hashmi (2005), because Aghion *et al.* (2005) use a broader definition of industries (two-digit SIC code) than Hashmi (2005) (four-digit SIC code). The intuition behind this reasoning is straightforward. Firms in more broadly-defined industries are likely to differ more in their structural characteristics or resources. Therefore the differences in profits due to other firm-specific factors are likely to be higher in such industries. This assumption is also supported by the difference in the technology gap found in Aghion *et al.*'s UK data and Hashmi's US data. Despite the fact that the patent citation per industry is substantially lower in the UK data than in the US data (the mean citation-weighted patents are 6.6 in the UK and 16.6 in the US data), the technology gap is higher on average in the UK data (the mean technology gap is 0.35 in the UK and 0.22 in the US data) (Hashmi 2005, p. 12). The firm-specific profit f is therefore likely to be higher in the UK than in the US data.

2.3 Summary

This chapter has introduced the basic model of innovation that explains the inverted-U relationship between profitability and innovation and the decreasing and concave relationships between profitability and the technology gap found by Aghion *et al.* (2005) and Hashmi (2005).

In the basic model, firms choose R&D expenditures in order to maximize their expected profits. The profits of firms are determined by the decisions about R&D expenditures and by exogenous industry- and firm-specific factors. At the beginning of each period, firms choose R&D expenditures that generate an innovation with a certain probability. Firms that fail to generate the innovation earn no reward from innovation and have to pay the R&D expenditures. The profits of firms that generate innovation increase by a reward from innovation minus R&D expenditures. At the end of the period, all firms imitate the technology of the most efficient firms so that all firms have the same technology at the beginning of the next period. Industry-specific factors determine the industry-specific profits of all firms in the same way. Other firm-specific factors increase the profits of a group of firms (firms X) by the firm-specific profit, while the profits of the rest of the firms (firms Y) remain constant.

The inverted-V relationship between the industry-specific profits and R&D expenditures of individual firms results from two assumptions:

- The reward from innovation is decreasing in the industry-specific profit. I present three justifications for this assumption. First, if the firms face a decreasing demand, a rise in the industry-specific profit is likely to be related to a reduction in the quantity sold. In an extreme example, firms selling a homogeneous product in a cartel have higher profit and lower quantity sold than firms in Bertrand model. If the reward from innovation is an increasing function of the quantity sold, as in the case of cost-reducing innovations, then a rise in the industry-specific profit reduces the reward from innovation. Second, suppose that the innovator earns monopoly profit. Then the reward from innovation is equal to the difference between the monopoly profit and the profit before the innovation. Then a rise in the industry-specific profit reduces the reward because it increases the profit before innovation. Third, suppose that a rise in the industry-specific profit results from a less aggressive interaction in the market. Then firms at the same technology level have a lower reward from innovation because a reduction in the price of the product of one firm would have less effect on quantities sold by its rivals.

- Firms are subject to an R&D-expenditure constraint. I assume that their R&D expenditures must be lower or equal to their profit in the case of a failed innovation. There are several possible justifications for the assumption. Firms may face credit constraints, or firms might be infinitely risk averse so that they can never choose R&D expenditures that would lead to a loss if the innovation fails. If the compensation of managers is linked to the profits of firms, the effect on R&D expenditures might be similar even if the managers are (infinitely) risk averse or if they have prospect-theory preferences over risky outcomes. (This result is shown in the subsequent chapter.)

The relationship between the industry-specific profit and average R&D expenditures in the industry (called the R&D function) depends on the shape of the relationship between the industry-specific profit and R&D expenditures of firms X and Y, and on the proportion of firms X and Y in the industry. The R&D function is certainly inverse V- or U-shaped, if the individual relationships between industry-specific profit and innovation of both types of firms are inverse V-shaped. I also show that under some conditions, the R&D function is also inverse V-shaped if the firm-specific profit is so high that R&D expenditures of firms X are decreasing in the industry-specific profit. The relationship between the industry-specific profit and the technology gap (called the technology-gap function) is influenced by the firm-specific profit and the share of firms X in the industry. A high firm-specific profit and a low share of firms X tend to generate a decreasing technology-gap function, which corresponds to the findings of Aghion *et al.* (2005). On the other hand, a low firms-specific profit and a high share of firms X in the industry tend to generate an inverse V- or U-shaped technology-gap function, which corresponds to the findings of Hashmi (2005).

Chapter 3

The prospect-theory model

In this chapter, I introduce a more specific model of innovation, called the prospect-theory model, or the PT model. The PT model differs from the basic model in several important respects. While firms in the basic model choose R&D expenditures in order to maximize expected profits, the prospect-theory model includes a behavioral theory of the decision-making process of managers. In the PT model, managers choose the size of R&D expenditures in order to maximize utility, which is an increasing function of their income. The income of managers, in turn, is positively related to the profits of firms. As in the basic model, the profits of firms are determined by exogenous firm- and industry-specific factors, and endogenous R&D expenditures. A rise in R&D expenditures leads to a higher profit if the innovation succeeds, and to a lower profit if it fails. Consequently, a rise in R&D expenditures widens the difference between the income of managers in the case of successful and failed innovation. In fact, by choosing the R&D expenditures managers select the most preferred lottery out of a set of possible lotteries given by the properties of the R&D process. Preferences over the lotteries are represented by the prospect-theory value function (Kahneman & Tversky 1979, Tversky & Kahneman 1992).

This approach has several advantages. It provides a specific explanation of the increasing part of the relationship between profits and R&D expenditures. The increasing relationship is due to specific properties of the prospect-theory value function and due to the fact that managers of less profitable firms earn lower income than managers of highly profitable firms. It also provides an additional explanation of the decreasing part of the relationship between profits and R&D expenditures, which is related to the assumption that the R&D process is a source of disutility for managers. Finally, thanks to the diminishing-sensitivity property of the value function the model generates an inverted-U relationship between profits and R&D expenditures of individual firms, instead of the inverted-V relationship in the basic model.

Furthermore, the basic model relates R&D expenditures and the technology gap to the industry-specific profit, while the average profit of a firm in the industry depends also on the size of the firms-specific profit. The PT model relates the R&D expenditures directly to the average profit of firms before the innovation takes place. The advantage of this approach is that the profitability of an industry does not depend on other firm-specific factors that influence the differences in the profits of firms. This facilitates the comparison of predictions of the PT model with the empirical findings.

The main disadvantage of the PT model is that the exponential structure of the prospect-theory value function makes it more difficult to analyze predictions of the model. For this reason, I present the results of the model under simplifying assumptions in Section 3.2. In Section 3.3, I present predictions of the full model using a numerical solution. But before I proceed to predictions I introduce the prospect-theory model and discuss its main assumptions in the following section.

3.1 Structure of the model

In this section, I introduce the prospect-theory model of innovation in which managers choose the size of R&D expenditures that maximizes their utility. The structure of the section is as follows. First, I describe how the profits of firms are determined by industry-specific factors, technology and other firms-specific factors. Then I relate the profits to managerial income and I show how the income and other factors influence the utility of managers. Finally, I present a summary of the model.

Profits

Time in the model is discrete. As in the basic model, I suppose an industry with a continuum of firms. If firm i has no R&D expenditures ($c_i = 0$), its profit is determined by industry-specific factors and other firm-specific factors. I also assume that there are two types of firms: firms Y with lower profits and firms X with higher profits, where the proportion of firms X in the industry is $q \in (0, 1)$. Differently from the basic model, I use the average profit a and the profit difference x instead of the industry-specific profit b and the firm-specific profit f. The *average profit* $a \in \langle \underline{a}, \bar{a} \rangle$ is the average profit of firms in an industry without R&D expenditures. I assume that $\underline{a} = 0$, so that the average profit $a \in \langle 0, \bar{a} \rangle$. In the following sections, I investigate the effect of a on properties of the industry. Therefore, the average profit a is a variable in the model. The *profit difference* $x \geq 0$ is the difference between the profit of firms X and Y. Firm i that has no R&D expenditures ($c_i = 0$) earns profit

$$\pi_i(a) = \begin{cases} \pi_i^X(a) = a + (1 - q)x & \text{if firm } i \text{ is } X, \\ \pi_i^Y(a) = a - qx & \text{if firm } i \text{ is } Y, \end{cases} \tag{3.1}$$

where $a \in \langle 0, \bar{a} \rangle$ represents the average profit, $q \in (0, 1)$ is the share of firms X in the market, and $x \geq 0$ is the profit difference.

The structure of the R&D process is the same as in the basic model. Firm i chooses R&D expenditures $c_i \geq 0$ at the beginning of each period. The R&D process has only two outcomes. It generates an innovation with the probability of success $p \in (0, 1)$ and fails to generate an innovation with the probability $1 - p$. At the end of each period, all firms imitate the innovation so that all firms have the same technology at the beginning of each period. If the R&D process fails to generate an innovation, the profit of firm i changes by $-c_i$. If R&D expenditures c_i generate an innovation, the profit of firm i changes by $r(a)c_i^\rho - c_i$, where $r(a)$ is the reward function and $\rho \in (0, 1)$ is the scale parameter. Hence the profit of firm i that fails to innovate is

$$\pi_{iF}(a, c_i) = \pi_i(a) - c_i \tag{3.2}$$

where $\pi_i(a)$ is the profit of firm i with no R&D expenditures (3.1), and $c_i \geq 0$ is the size of R&D expenditures. The profit of firm i that successfully innovates is

$$\pi_{iS}(a, c_i) = \pi_i(a) + r(a)c_i^\rho - c_i \tag{3.3}$$

where $\rho \in (0, 1)$ represents the scale parameter, and $r(a)$ is the reward function.

I assume that the reward function $r(a)$ may be decreasing in the average profit a for the reasons explained in Section 2.1. The reward function $r(a)$ is constructed in a similar way as in the basic model, so that the opportunity parameter R measures the return to R&D expenditures $c_i = 1$ for the average profit $a = 0$. The reward function is given by

$$r(a) = \frac{1}{p}\Big(1 + R - \sigma\frac{a}{\bar{a}}\Big), \tag{3.4}$$

where $p \in (0, 1)$ is the probability of success, $\sigma \geq 0$ is the slope parameter, and $R \geq \sigma \geq 0$ represents the opportunity parameter.

Managerial income

I assume that the income of the manager of firm i $w_i(a)$ consists of the *base salary* $\omega > 0$, and of a share of the profit of the firm i. The percentage share is called the *effective ownership* $s(a)$. As in the basic model, the units of profit are interpreted as millions of dollars. In order to obtain convenient results, units of the income are interpreted as ten thousands of dollars. This means that the effective ownership is measured in percents, that is $s(a) \in (0, 100\rangle$. Consider the following example. Suppose that the manager of firm i has a base salary $\omega = 30$ and ownership share $s(a) = 2$, and the profit of firm i is 10. Then the income of the manager of firm i is $30 + 2 \times 10 = 50$. The numbers have the following interpretation. The profit of the firm i is $10 \times$ \$1,000,000= \$10,000,000. The income of the manager of firm i is $50\times$\$10,000 = \$500,000, which is equal to the sum of the base salary of \$300,000 and 2% of the profit $0.02\times$ \$10,000,000 = \$200,000.

Furthermore, I assume that the effective ownership decreases in the profits of firms. This assumption can be justified by the common structure of managerial compensation described in Murphy (1999, pp. 9–10). According to Murphy, the size of managerial compensation depends on the size of the firm. The base salary is usually calculated as a percentage of the revenue of the firm, and other types of compensation, such as target bonuses, option grants and pension benefits, are calculated as a percentage (or a multiple) of the base salary. That is, managers of firms with the same revenue (or size) usually earn a similar base salary and performance-based compensation. Suppose now that some of the equally-sized firms earn higher profits than other firms. Then in order to pay out similar performance-based compensations, firms with higher profits need to give lower effective ownership to their managers than firms with lower profits. In this model, I assume that the effective ownership $s(a)$ decreases linearly in average profit a. However, the model would give similar predictions even if the effective ownership changed so that the income of managers remained constant in a. (For a version of the prospect-theory model with a constant income, see Krčál 2009b.)

The income of managers of firm i $w_i(a, c_i)$ is given by

$$w_i(a, c_i) = \begin{cases} w_{iF}(a, c_i) = \omega + s(a)(\pi_i(a) - c_i) & \text{if the innovation fails,} \\ w_{iS}(a, c_i) = \omega + s(a)(\pi_i(a) + r(a)c_i^{\rho} - c_i) & \text{if the innovation succeeds,} \end{cases} \tag{3.5}$$

where $\omega > 0$ is the base salary, and the effective ownership $s(a) \in (0, 100\rangle$ is given by

$$s(a) = s_0\Big(1 - \mu\frac{a}{\bar{a}}\Big), \tag{3.6}$$

where the *ownership share* $s_0 \in (0, 100\rangle$ measures the value of the effective ownership for the average profit $a = 0$, and the *decreasing-ownership parameter* $\mu > 0$ determines the effect of the average profit a on the effective ownership.

Utility of managers

The preferences of managers over the risky outcomes of the R&D process are represented by the prospect-theory value function. Prospect theory is a widely used alternative to expected utility theory. It differs from expected utility theory in several aspects. Most importantly, it assigns value to changes in wealth rather than to final states of wealth and replaces probabilities by decision weights (Kahneman & Tversky 1979; Tversky & Kahneman 1992). For simplicity, I assume that the probability weighting is linear, i.e. the decision weights are equal to probabilities. However, the model would give similar predictions also with non-linear weighting of probabilities. (For versions of the prospect-theory model with non-linear weighting of probabilities, see Krčál 2009a and 2010a.) The value of the prospect of innovation for the manager of firm i is given by

$$V_i(a, c_i) = pv(w_{iS}(a, c_i)) + (1 - p)v(w_{iF}(a, c_i)), \tag{3.7}$$

where $p \in (0, 1)$ is the probability of success of the R&D process, and v is the prospect-theory *value function.*

The value function $v(w_i(a, c_i))$ transforms the monetary outcomes into value. The form of the function reflects the principles of *diminishing sensitivity* and *loss aversion.* According to the principle of diminishing sensitivity, the impact of a change diminishes with the distance from the reference point, which is usually defined as the current wealth of the decision maker. The non-negative incomes $w_i(a, c_i) \geq 0$ are therefore perceived as gains, and the negative incomes $w_i(a, c_i) < 0$ as losses. Because of the diminishing-sensitivity principle, the value function is concave for gains and convex for losses. In both losses and gains, a change from 0 to 1 is perceived more strongly than a change from 100 to 101. According to the principle of loss aversion, losses loom larger than corresponding gains. It means that a loss of 100 is perceived more strongly than a gain of 100. (For a detailed discussion of loss aversion, see Tversky & Kahneman 1991, and Novemsky & Kahneman 2005).

The standard mathematical formulation of the value function as presented in Kahneman & Tversky (1979) is

$$v(w_i(a,c_i)) = \begin{cases} w_i(a,c_i)^\alpha & \text{if } w_i(a,c_i) \geq 0, \\ -\lambda(-w_i(a,c_i))^\alpha & \text{if } w_i(a,c_i) < 0, \end{cases} \tag{3.8}$$

where $\lambda \geq 1$ is the *loss aversion parameter*, and $\alpha \in (0,1)$ is the *diminishing-sensitivity parameter*. Figure 3.1 shows examples of the value function for $\lambda = 1$ and $\alpha = 1$ and for $\lambda = 2.25$ and $\alpha = 0.88$.

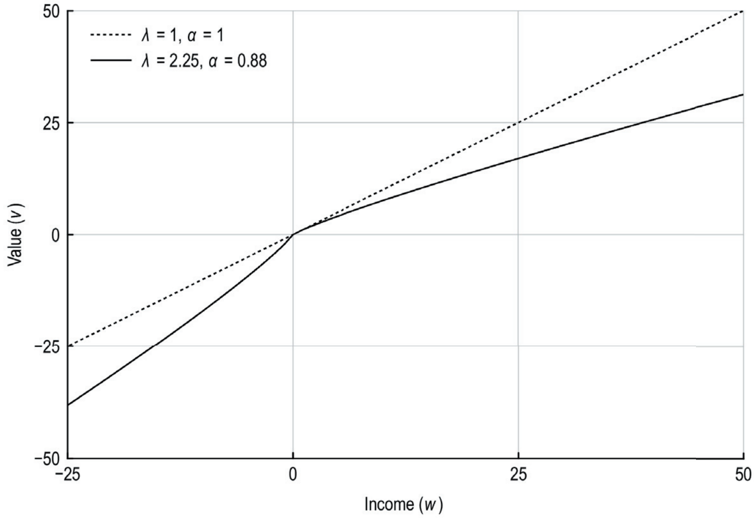


Figure 3.1: The value function
The figure presents the value function without loss aversion and diminishing sensitivity ($\lambda = 1$ and $\alpha = 1$) and for the parameters estimated by Tversky & Kahneman (1992) ($\lambda = 2.25$ and $\alpha = 0.88$).

Furthermore, I assume that managers may experience disutility of innovation that is given by

$$D_i(c_i) = dc_i, \tag{3.9}$$

where $d \geq 0$ is the *disutility parameter*. There are three main reasons why managers may experience disutility of innovation that is increasing in R&D expenditures:

- Innovations that require managerial effort might reduce the utility of effort-averse managers, and larger innovations are likely to require more effort and therefore lead to a higher disutility of innovation.

- In reality, the probability distribution of the outcomes of innovation is unknown. Higher uncertainty about their income reduces the utility of ambiguity-averse managers (for a discussion of ambiguity aversion, see Ellsberg 1961, and Heath & Tversky 1991). Larger innovations are likely to lead to a wider range of uncertain outcomes.

- Innovations might hurt the interests of stakeholders of a firm, which might have negative consequences for managers. Greater innovations are likely to be more problematic for the stakeholders, and consequently for managers.

The utility of the manager of firm i is given by

$$U_i(a, c_i) = V_i(a, c_i) - D_i(c_i) = pv(w_{iS}(a, c_i)) + (1 - p)v(w_{iF}(a, c_i)) - dc_i,$$

where $V_i(a, c_i)$ represents the value of the prospect of innovation, and $D_i(c_i)$ is the disutility of innovation.

Summary of the model

In the prospect-theory model, managers choose R&D expenditures that maximize their utility. The manager of firm i faces the following optimization problem:

$$\max_{c_i} \; U_i(a, c_i) = pv(w_{iS}(a, c_i)) + (1 - p)v(w_{iF}(a, c_i)) - dc_i, \tag{3.10}$$

where $a \in \langle 0, \bar{a} \rangle$ represents the average profit, $c_i \geq 0$ is the size of R&D expenditures, $p \in (0, 1)$ is the probability of success, and $d \geq 0$ is the disutility parameter. The value function $v(w_i(a, c_i))$ is given by

$$v(w_i(a, c_i)) = \begin{cases} w_i(a, c_i)^\alpha & \text{if } w_i(a, c_i) \geq 0, \\ -\lambda(-w_i(a, c_i))^\alpha & \text{if } w_i(a, c_i) < 0, \end{cases}$$

where $\lambda \geq 1$ is the loss-aversion parameter, and $\alpha \in (0, 1\rangle$ is the diminishing-sensitivity parameter. The income of managers $w_i(a, c_i)$ is given by

$$w_i(a, c_i) = \begin{cases} w_{iF}(a, c_i) = \omega + s(a)(\pi_i(a) - c_i) & \text{if the innovation fails,} \\ w_{iS}(a, c_i) = \omega + s(a)(\pi_i(a) + r(a)c_i^\rho - c_i) & \text{if the innovation succeeds,} \end{cases}$$

where $\rho \in (0, 1)$ is the scale parameter, $\omega > 0$ is the base salary, and the effective ownership $s(a) \in (0, 100\rangle$ is given by

$$s(a) = s_0\Big(1 - \mu\frac{a}{\bar{a}}\Big),$$

where $s_0 \in (0, 100\rangle$ is the ownership share, and $\mu > 0$ is the decreasing-ownership parameter. The reward function is given by

$$r(a) = \frac{1}{p}\Big(1 + R - \sigma\frac{a}{\bar{a}}\Big),$$

where $\sigma \geq 0$ is the slope parameter, and $R \geq \sigma \geq 0$ is the opportunity parameter. Finally, the profit of firm i with no R&D expenditures ($c_i = 0$) is given by

$$\pi_i(a) = \begin{cases} \pi_i^X(a) = a + (1-q)x & \text{if firm } i \text{ is } X, \\ \pi_i^Y(a) = a - qx & \text{if firm } i \text{ is } Y, \end{cases}$$

where $q \in (0,1)$ is the share of firms X in the market, and $x \geq 0$ is the profit difference.

If the value function has diminishing sensitivity ($\alpha < 1$), it is not possible to solve the model analytically for all values of the diminishing-sensitivity parameter α. However, if the value function has constant sensitivity ($\alpha = 1$) and sufficient loss aversion (λ is sufficiently high), it is possible to analyze predictions of the model in a similar way as in the previous chapter. For this reason, I first discuss the properties of the model with constant sensitivity ($\alpha = 1$) in Section 3.2. In this model, the income of managers of firms with zero R&D expenditures has to be non-negative ($w_i(a, c_i) = w_i(a, 0) \geq 0$). Then in Section 3.3, I consider the effect of diminishing sensitivity and negative income on properties of the model.

Furthermore, I will show in the subsequent section that a rise in the average profit a may reduce R&D expenditures either because of the interaction between the disutility of innovation D_i and the decreasing effective ownership $s(a)$, or because of the decreasing reward function $r(a)$. For clarity of the presentation, I split the prospect-theory model into two models based on the cause of the decreasing relationship between the average profit a and R&D expenditures c_i:

- In **model A**, managers experience disutility of innovation $D_i(c_i)$ and the reward function $r(a)$ is constant ($d > 0$ and $\sigma = 0$).
- In **model B**, managers do not experience disutility of innovation $D_i(c_i)$ and the reward function $r(a)$ is decreasing in the average profit a ($d = 0$ and $\sigma > 0$).

The model would generate similar (and more robust) predictions if it combined the disutility of innovation with the decreasing reward function ($d > 0$ and $\sigma > 0$). But because of space limitations, a discussion of this version of the model is not included in this book.

3.2 The PT model with constant sensitivity

In this section, I discuss the properties of the model with constant sensitivity ($\alpha = 1$) and with non-negative income ($w_i(a, 0) \geq 0$). The structure of this section resembles the structure of the previous chapter. In Subsection 3.2.1, I present the conditions under which the R&D-expenditure functions of firms X and Y are inverse V-shaped. In Subsections 3.2.2 and 3.2.3, I relate the average profit to average R&D expenditures and to the technology gap in the industry. Finally in Subsection 3.2.4, I shortly discuss the empirical relevance of predictions of the PT model with constant sensitivity. Moreover, in Appendix B.2 I present an implementation of the model in `Netlogo 5.0.1`. I use the implementation of the model in `Netlogo` also for generating the graphs presented in this section.

3.2.1 Solving the model

The manager of firm i chooses R&D expenditures c_i that maximize her utility function (3.10). If the diminishing-sensitivity parameter $\alpha = 1$ and the income in the case of zero R&D expenditures $w_i(a, 0) \geq 0$, then the manager faces two different optimization problems, because the size of R&D expenditures c_i influences her income in the case of a failed innovation $w_{iF}(a) = \omega + s(a)(\pi_i(a) - c_i)$:

- If $c_i \leq \omega/s(a) + \pi_i(a)$ so that $w_{iF}(a, c_i) \geq 0$, the manager faces the optimization problem

$$\max_{c_i} U_i^P(a, c_i) = pw_{iS}(a, c_i) + (1 - p)w_{iF}(a, c_i) - dc_i,$$

$$\text{s.t.} \quad c_i \leq \frac{\omega}{s(a)} + \pi_i(a). \tag{3.11}$$

- If $c_i \geq \omega/s(a) + \pi_i(a)$, the income $w_{iF}(a, c_i) \leq 0$ is multiplied by loss-aversion parameter $\lambda > 1$. Then the manager faces the optimization problem

$$\max_{c_i} U_i^N(a, c_i) = pw_{iS}(a, c_i) + (1 - p)\lambda w_{iF}(a, c_i) - dc_i,$$

$$\text{s.t.} \quad c_i \geq \frac{\omega}{s(a)} + \pi_i(a). \tag{3.12}$$

Using Kuhn-Tucker conditions, R&D expenditures that solve the optimization problems (3.11) and (3.12) are given by

$$c_i^P(a) = \min\left\{\frac{\omega}{s(a)} + \pi_i(a), \left(\frac{\rho pr(a)s(a)}{d + s(a)}\right)^{\frac{1}{1-\rho}}\right\}, \text{ and} \tag{3.13}$$

$$c_i^N(a) = \max\left\{\frac{\omega}{s(a)} + \pi_i(a), \left(\frac{\rho pr(a)s(a)}{d + s(a)(p + \lambda(1 - p))}\right)^{\frac{1}{1-\rho}}\right\}. \tag{3.14}$$

Comparing the utility in both situations, the optimal R&D expenditures are given by

$$\max_{c_i^P, c_i^N}\{U_i^P(c_i^P(a)), U_i^N(c_i^N(a))\}. \tag{3.15}$$

The relationship between the optimal R&D expenditures and the average profit a might be inverse V-shaped if the loss-aversion parameter λ is sufficiently high so that

$$c_i^N(a) = \frac{\omega}{s(a)} + \pi_i(a).$$

Then the prospect of a negative income in the case of a failed innovation is considered to be so unpleasant, that R&D expenditures are adjusted so that the income is always non-negative. For the minimum loss-aversion parameter $\underline{\lambda}_i(a)$ that ensures this outcome it holds that

$$\frac{\omega}{s(a)} + \pi_i(a) = \left(\frac{\rho pr(a)s(a)}{d + s(a)(p + \underline{\lambda}_i(a)(1 - p))}\right)^{\frac{1}{1-\rho}}. \tag{3.16}$$

It is evident from (3.16) that $\underline{\lambda}_i(a)$ is highest for the minimum average profit $a = 0$, as the effective ownership $s(a)$ and the reward function $r(a)$ are decreasing in a, and the profit $\pi_i(a)$ is increasing in a. It is also evident that the value of $\underline{\lambda}_i(a)$ for firms Y is higher or equal to the value of $\underline{\lambda}_i(a)$ for firms X, as the profit $\pi_i^X(a) \geq \pi_i^Y(a)$ (see (3.1)). Therefore, if the loss-aversion parameter

$$\lambda \geq \underline{\lambda}_i^Y(0) = \frac{s_0\rho(1+R) - (ps_0 + d)\left(\omega/s_0 - qx\right)^{1-\rho}}{(1-p)s_0\left(\omega/s_0 - qx\right)^{1-\rho}}, \tag{3.17}$$

it will be always true that

$$U_i^P(c_i^P(a)) \geq U_i^N(c_i^N(a)).$$

Then the optimal R&D-expenditure function is

$$c_i^P(a) = \begin{cases} c_i^X(a) = \min\left\{\not{C}_i^X(a), \underline{C}_i(a)\right\} & \text{if firm } i \text{ is } X, \\ c_i^Y(a) = \min\left\{\not{C}_i^Y(a), \underline{C}_i(a)\right\} & \text{if firm } i \text{ is } Y, \end{cases} \tag{3.18}$$

where

$$\not{C}_i^X(a) = \frac{\omega}{s(a)} + a + (1-q)x \quad \text{and} \quad \not{C}_i^Y(a) = \frac{\omega}{s(a)} + a - qx, \tag{3.19}$$

and

$$\underline{C}_i(a) = \left(\frac{\rho p r(a) s(a)}{d + s(a)}\right)^{\frac{1}{1-\rho}}, \tag{3.20}$$

where $a \in \langle 0, \bar{a}\rangle$ is the average profit, $q \in (0,1)$ is the share of firms X in the industry, $x \geq 0$ is the profit difference, $\omega \geq 0$ is the base salary, $\rho \in (0,1)$ is the scale parameter, $p \in (0,1)$ is the probability of success, and $d \geq 0$ is the disutility parameter. The effective ownership is given by

$$s(a) = s_0\left(1 - \mu\frac{a}{\bar{a}}\right),$$

where $s_0 \in (0, 100\rangle$ is the ownership share, and $\mu > 0$ is the decreasing-ownership parameter. The reward function is given by

$$r(a) = \frac{1}{p}\left(1 + R - \sigma\frac{a}{\bar{a}}\right),$$

where $\sigma \geq 0$ is the slope parameter, and $R \geq \sigma \geq 0$ is the opportunity parameter.

The functions $\not{C}_i^X(a)$ and $\not{C}_i^Y(a)$ are increasing in the average profit a because the effective ownership $s(a)$ is decreasing in a. The function $\underline{C}_i(a)$ is decreasing in the average profit a for reasons that differ in model A and in model B:

- In model A ($d > 0$ and $\sigma = 0$), it is because the effective ownership $s(a)$ is decreasing in the average profit a and the disutility of innovation is positive ($d > 0$).

- In model B ($d = 0$ and $\sigma > 0$), it is because the reward function $r(a)$ is decreasing in a ($\sigma > 0$). In this respect, model B is similar to the basic model.

Since $\not{C}_i^Y(a)$ is increasing and $\underline{C}_i(a)$ is decreasing in the average profit a, the R&D-expenditure function $c_i^Y(a)$ will be inverse V-shaped with the maximum at the average profit $0 < a < \bar{a}$ if

$$\underline{C}_i(\bar{a}) - \not{C}_i^Y(\bar{a}) < 0 < \underline{C}_i(0) - \not{C}_i^Y(0). \tag{3.21}$$

Similarly, the function $c_i^X(a)$ is inverse V-shaped if

$$\underline{C}_i(\bar{a}) - \not{C}_i^X(\bar{a}) < 0 < \underline{C}_i(0) - \not{C}_i^X(0). \tag{3.22}$$

It is evident from (3.19), that

$$\underline{C}_i(\bar{a}) - \not{C}_i^Y(\bar{a}) \geq \underline{C}_i(\bar{a}) - \not{C}_i^X(\bar{a}),$$

because the profit difference $x \geq 0$. Therefore if $\underline{C}_i(\bar{a}) - \not{C}_i^Y(\bar{a}) < 0$, it is also true that $\underline{C}_i(\bar{a}) - \not{C}_i^X(\bar{a}) < 0$. Hence if the condition (3.21) holds, which means that the function $c_i^Y(a)$ is inverse V-shaped, it follows from (3.22) that the function $c_i^X(a)$ is inverse V-shaped if the profit difference is relatively low so that

$$x < \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0}, \tag{3.23}$$

and it is decreasing in the average profit a if the profit difference is relatively high so that

$$x \geq \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0}. \tag{3.24}$$

3.2.2 R&D expenditures

In this subsection, I discuss the shape of the R&D function given by

$$c(a) = qc_i^X(a) + (1-q)c_i^Y(a), \tag{3.25}$$

where q is the proportion of firms X in the industry. Let a^* denote the average profit that corresponds to the maximum of the R&D function $c(a)$. If $0 < a^* < \bar{a}$, the maximum of the R&D function lies within the average-profit range $a \in \langle 0, \bar{a} \rangle$, which means that the R&D function is likely to be inverse U- or V-shaped. In this subsection, I will assume that the condition (3.21) holds which implies that the R&D-expenditure function of firm Y $c_i^Y(a)$ is inverse V-shaped and the function $c_i^X(a)$ is either inverse V-shaped or decreasing in the average profit a.

If the profit difference is relatively low so that

$$x < \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

the R&D-expenditure function of firms X $c_i^X(a)$ is inverse V-shaped (see (3.23)). The R&D function $c(a)$ has the maximum within the average-profit range, i.e. $0 < a^* < \bar{a}$, and its shape depends on the profit difference x:

- If $x = 0$, the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ are identical. Then also the R&D function $c(a)$ has the same inverted-V shape. Panels 3.2 and 3.3A show examples of functions $c(a)$ with the profit difference $x = 0$ in model A ($d > 0$ and $\sigma = 0$) and in model B ($d = 0$ and $\sigma > 0$), respectively.

- If
$$0 < x < \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$
then $0 < a^* < \bar{a}$ because $c(a)$ is a weighted average of the functions $c_i^X(a)$ and $c_i^Y(a)$, that are both inverse V-shaped. Panels 3.2 and 3.3B show examples of the corresponding (inverted-U) R&D functions $c(a)$.

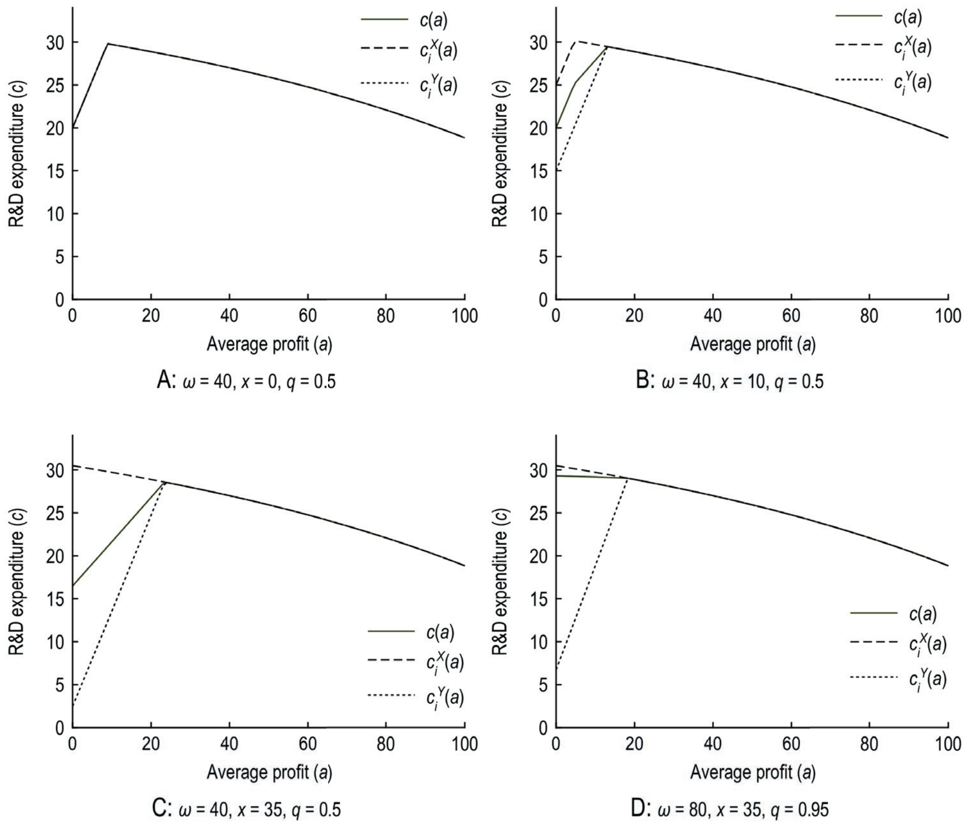


Figure 3.2: Examples of the R&D-expenditure functions in model A ($\sigma = 0$)
The figure shows examples of the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ and of the R&D functions $c(a)$. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, $d = 0.05$, $\sigma = 0$, and $\bar{a} = 100$.

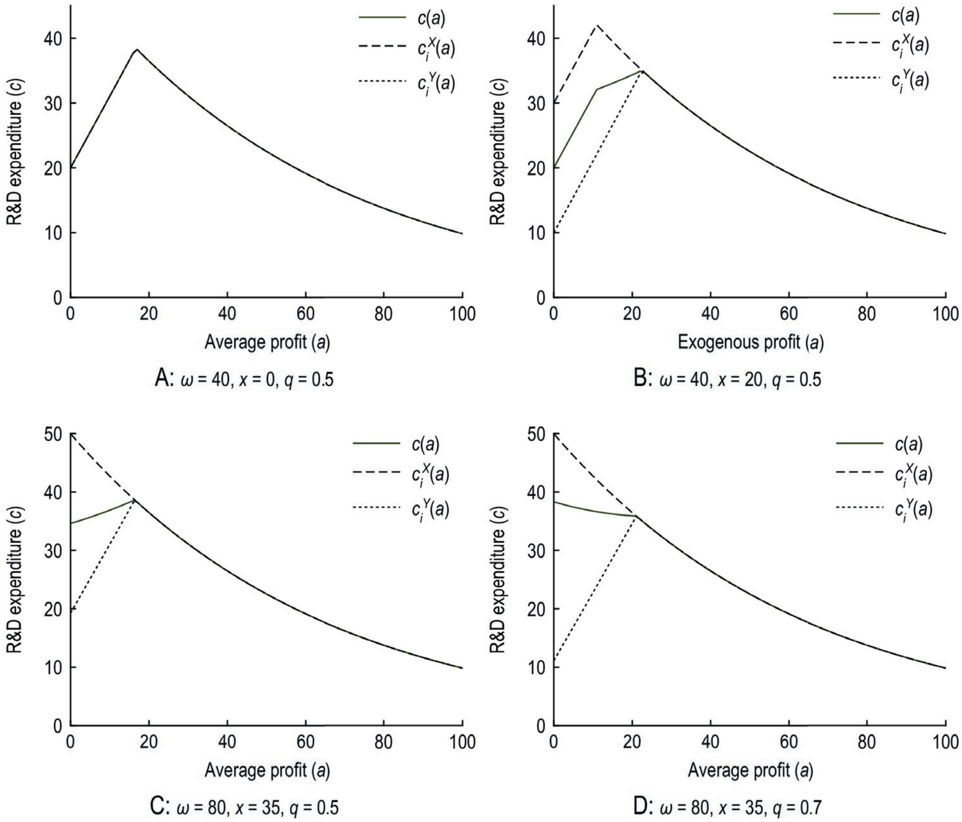


Figure 3.3: Examples of the R&D-expenditure functions in model B ($d = 0$)
The figure shows examples of the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ and of the R&D functions $c(a)$. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, $d = 0$, $\sigma = 0.1$, and $\bar{a} = 100$.

If the profit difference is relatively high so that

$$x \geq \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

the R&D-expenditure function of firms X $c_i^X(a) = \underline{C_i}(a)$ is decreasing in the average profit a (see (3.24)). The form of the R&D function $c(a)$ depends on the slope of $c_i^Y(a)$:

- In the higher part of the average-profit range where $c_i^Y(a) = \underline{C_i}(a)$ is decreasing in the average profit a, the R&D function $c(a)$ is clearly decreasing in a.

- In the lower part of the range of the average profit, where $c_i^Y(a) = \not{C}_i{}^Y(a)$ is increasing in a, the R&D function $c(a)$ might be both increasing or decreasing.

Hence if the profit difference is relatively high, the average profit $a^* < \bar{a}$. The R&D function $c(a)$ is likely to be either inverse V-shaped or decreasing. See Panels 3.2 and 3.3C for examples of inverse V-shaped R&D functions $c(a)$, and Panels 3.2 and 3.3D for examples of decreasing R&D functions $c(a)$.

3.2.3 The technology gap

In this subsection, I discuss the shape of the relationship between the average profit and the technology gap. As in the basic model, I define the technology gap as an average difference between the profits of the leaders and the other firms in the industry due to technology or other firm-specific factors. After the innovations are implemented, there are four groups of firms with different technologies:

- Successful innovators X with the technology gap $G_S^X = 0$.
- Failed innovators X with the technology gap $G_F^X(a) = r(a)c_i^X(a)^\rho$.
- Successful innovators Y with the technology gap $G_S^Y(a) = x + r(a)c_i^X(a)^\rho - r(a)c_i^Y(a)^\rho$.
- Failed innovators Y with the technology gap $G_F^Y(a) = x + r(a)c_i^X(a)^\rho$.

Weighting the differences in profits by the share of different groups of firms in the industry, we get the technology-gap function

$$G(a) = qpG_S^X + q(1-p)G_F^X(a) + (1-q)pG_S^Y(a) + (1-q)(1-p)G_F^Y(a). \qquad (3.26)$$

Let a^{G*} denote the average profit that corresponds to the maximum of the technology-gap function $G(a)$. If $0 < a^{G*} < \bar{a}$, the technology-gap function is likely to be inverse V- or U-shaped. If $a^{G*} = 0$, the technology-gap function is likely to be decreasing in the average profit a.

In the discussion of the shape of the technology-gap function $G(a)$, I assume that condition (3.21) holds, which implies that the R&D-expenditure function of firms Y $c_i^Y(a)$ is inverse V-shaped, and the R&D-expenditure function of firms X $c_i^X(a)$ is either decreasing or inverse V-shaped. If the profit difference x is relatively high so that

$$x \geq \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

the R&D-expenditure function of firms X $c_i^X(a) = \underline{C}_i(a)$ is decreasing in the average profit a. Then the technology-gap function $G(a)$ is decreasing in a if the technology gaps $G_F^X(a)$, $G_F^Y(a)$ and $G_S^Y(a)$ are non-increasing, and at least one of them is decreasing in a.

- The technology gaps $G_F^X(a) = r(a)c_i^X(a)^\rho$ and $G_F^Y(a) = x + r(a)c_i^Y(a)^\rho$ are decreasing in the average profit a because $c_i^X(a) = \underline{C}_i(a)$ is decreasing in a and the reward function $r(a)$ is constant in model A and decreasing in model B.

- The slope of the technology gap $G_S^Y(a)$ depends on the shape of the R&D-expenditure function of firms Y $c_i^Y(a)$:

  In the lower part of the average-profit range where $c_i^Y(a) = \not{C}_i{}^Y(a)$ is increasing in the average profit a, the part of the technology gap $G_S^Y(a) = x + r(a)\Big(c_i^X(a)^\rho - c_i^Y(a)^\rho\Big)$ is decreasing in models A and B. It is because $r(a)$ is decreasing in a in model B ($\sigma > 0$), and the difference

$$c_i^X(a)^\rho - c_i^Y(a)^\rho = \underline{C}_i(a)^\rho - \not{C}_i^Y(a)^\rho$$

  is decreasing in a in models A and B, because $c_i^X(a)^\rho = \underline{C}_i(a)^\rho$ is decreasing in a and $c_i^Y(a)^\rho = \not{C}_i^Y(a)^\rho$ is increasing in a.

  In the higher part of the average-profit range where $c_i^X(a)^\rho = c_i^Y(a)^\rho = \underline{C}_i(a)^\rho$, the technology gap $G_S^Y(a) = r(a)\Big(\underline{C}_i(a)^\rho - \underline{C}_i(a)^\rho\Big)$ is equal to zero.

Hence the technology-gap function $G(a)$ is decreasing in the average profit a because the technology gaps $G_F^X(a)$ and $G_F^Y(a)$ are decreasing in a, and $G_S^Y(a)$ is non-increasing in a.

If the profit difference x is relatively low so that

$$x < \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

the R&D-expenditure function of firms X $c_i^X(a)$ is inverse V-shaped. Then the shape of the technology-gap function $G(a)$ depends on the slope of $c_i^X(a)$:

- In the higher part of the average-profit range where $c_i^X(a) = \underline{C}_i(a)$ is decreasing in a, the situation is identical to that described in the previous paragraphs. Therefore, the part of the technology-gap function $\bar{G}(a)$ is always decreasing in a.

- In the lower part of the range of the average profit a where both $c_i^X(a) = \not{C}_i^X(a)$ and $c_i^Y(a) = \not{C}_i^Y(a)$ are increasing in a, the part of the technology-gap function $\underline{G}(a)$ may be both decreasing and increasing in a. It is because the slope of $\underline{G}(a)$

$$\begin{aligned}\frac{\partial \underline{G}(a)}{\partial a} &= \frac{\partial r(a)}{\partial a}\left((1-pq)\ \not{C}_i^X(a)^\rho - (p-pq)\ \not{C}_i^Y(a)^\rho\right)\\ &+ r(a)\left((1-pq)\frac{\partial\ \not{C}_i^X(a)^\rho}{\partial a} - (p-pq)\frac{\partial\ \not{C}_i^Y(a)^\rho}{\partial a}\right)\end{aligned}$$

  may be both positive and negative.

  Furthermore, the slope of $\underline{G}(a)$ decreases in the profit difference x because

$$\begin{aligned}\frac{\partial^2 \underline{G}(a)}{\partial a \partial x} &= \frac{\partial r(a)}{\partial a}\left((1-pq)\frac{\partial\ \not{C}_i^X(a)^\rho}{\partial x} - (p-pq)\frac{\not{C}_i^Y(a)^\rho}{\partial x}\right)\\ &+ r(a)\left((1-pq)\frac{\partial^2\ \not{C}_i^X(a)^\rho}{\partial a \partial x} - (p-pq)\frac{\partial^2\ \not{C}_i^Y(a)^\rho}{\partial a \partial x}\right) < 0,\end{aligned}$$

as

$$\frac{\partial r(a)}{\partial a} = 0 \text{ in model A and } \frac{\partial r(a)}{\partial a} < 0 \text{ in model B},$$

$$\frac{\partial \; \mathcal{C}_i^X(a)^\rho}{\partial x} > 0 \quad \text{and} \quad \frac{\mathcal{C}_i^Y(a)^\rho}{\partial x} < 0,$$

$$\frac{\partial^2 \; \mathcal{C}_i^X(a)^\rho}{\partial a \partial x} < 0 \quad \text{and} \quad \frac{\partial^2 \; \mathcal{C}_i^Y(a)^\rho}{\partial a \partial x} > 0.$$

And the slope of the function $\underline{G}(a)$ increases in the share of firms X in the industry q because

$$\frac{\partial^2 \underline{G}(a)}{\partial a \partial q} = -p\frac{\partial r(a)}{\partial a}\left(\mathcal{C}_i^X(a)^\rho - \mathcal{C}_i^Y(a)^\rho\right) - pr(a)\left(\frac{\partial \; \mathcal{C}_i^X(a)^\rho}{\partial a} - \frac{\mathcal{C}_i^Y(a)^\rho}{\partial a}\right)$$

$$-pq\frac{\partial r(a)}{\partial a}\left(\frac{\partial \; \mathcal{C}_i^X(a)^\rho}{\partial q} - \frac{\mathcal{C}_i^Y(a)^\rho}{\partial q}\right) - pr(a)\left(\frac{\partial^2 \; \mathcal{C}_i^X(a)^\rho}{\partial a \partial q} - \frac{\partial^2 \; \mathcal{C}_i^Y(a)^\rho}{\partial a \partial q}\right) > 0,$$

as

$$\frac{\partial r(a)}{\partial a} = 0 \text{ in model A and } \frac{\partial r(a)}{\partial a} < 0 \text{ in model B},$$

$$\mathcal{C}_i^X(a)^\rho - \mathcal{C}_i^Y(a)^\rho > 0 \quad \text{and} \quad \frac{\partial \; \mathcal{C}_i^X(a)^\rho}{\partial a} - \frac{\partial \; \mathcal{C}_i^Y(a)^\rho}{\partial a} < 0,$$

$$\frac{\partial \; \mathcal{C}_i^X(a)^\rho}{\partial q} - \frac{\partial \; \mathcal{C}_i^Y(a)^\rho}{\partial q} > 0 \quad \text{and} \quad \frac{\partial^2 \; \mathcal{C}_i^X(a)^\rho}{\partial a \partial q} - \frac{\partial^2 \; \mathcal{C}_i^Y(a)^\rho}{\partial a \partial q} < 0.$$

It means that the part of the technology-gap function $\underline{G}(a)$ is more decreasing in the average profit a if the profit difference x is high and the share of firms X q is low.

In this subsection, I assumed that the R&D-expenditure function $c_i^Y(a)$ is inverse V-shaped (condition (3.21)). Then the shape of the technology-gap function $G(a)$ depends on the profit difference x:

- If

$$x \geq \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

  the technology-gap function $G(a)$ is always decreasing in a.

- If

$$x < \frac{\left(\frac{\rho(1-R)s_0}{d+s_0}\right)^{\frac{1}{1-\rho}} s_0 - \omega}{(1-q)s_0},$$

  then $a^{G*} < \bar{a}$, which means that the technology-gap function $G(a)$ is likely to be decreasing or inverse U- or V-shaped. The higher the profit difference x and the lower the share of firms X q, the lower the slope of the part of the technology-gap function $\underline{G}(a)$.

Figures 3.4 and 3.5 present examples of the R&D functions $c(a)$ and the technology-gap functions $G(a)$ for different levels of the profit difference x and the share of firms X in the industry q in models A and B. The figure shows that the higher the x and the lower the q, the wider is the average-profit range where the technology gap function $G(a)$ is decreasing. However, as in the basic model, the effect of x and q on the slope of the increasing part of the technology-gap function $\underline{G}(a)$ is hardly visible in the figures.

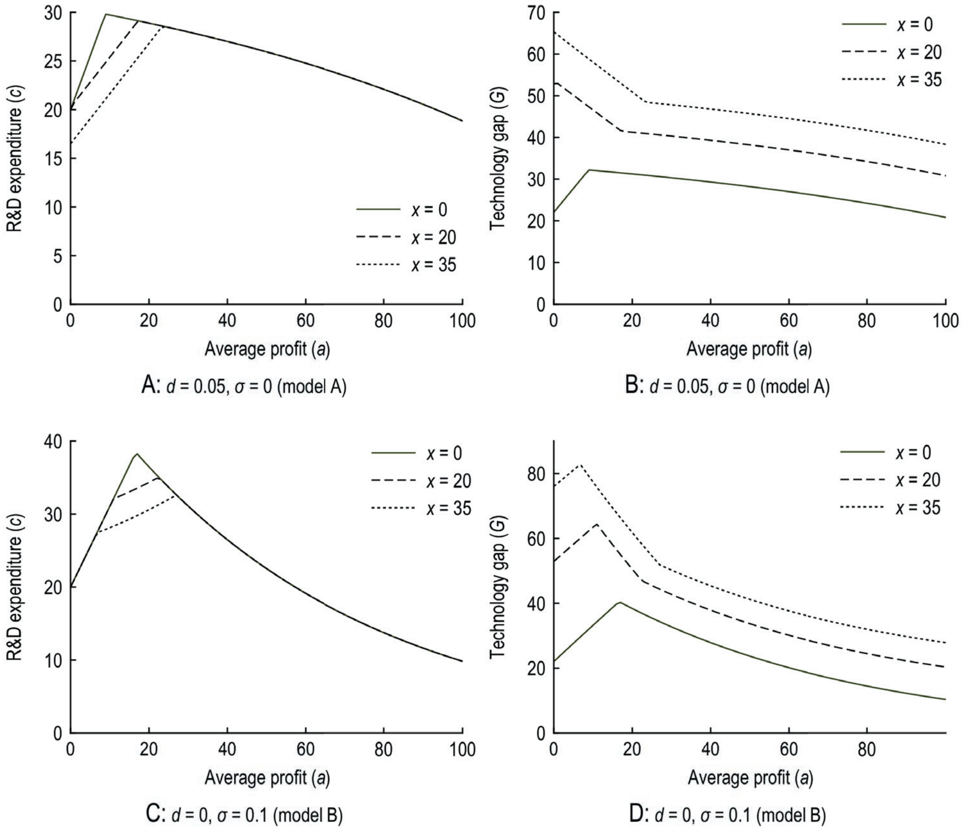


Figure 3.4: Examples of the R&D and technology-gap functions for different x
The figure shows examples of the R&D functions $c(a)$ and the technology-gap function $G(a)$ for different levels of the profit difference x. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, and $\bar{a} = 100$.

3.2.4 Empirical relevance of the results

In this subsection, I discuss whether for a set of parameters used in Figures 3.4 and 3.5 the PT model with constant sensitivity generates predictions that correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). First, I interpret the values of the parameters used in Figures 3.4 and 3.5 and I present empirical support for some of the values used. Then I compare the shapes of the functions in Figures 3.4 and 3.5 to the empirical findings.

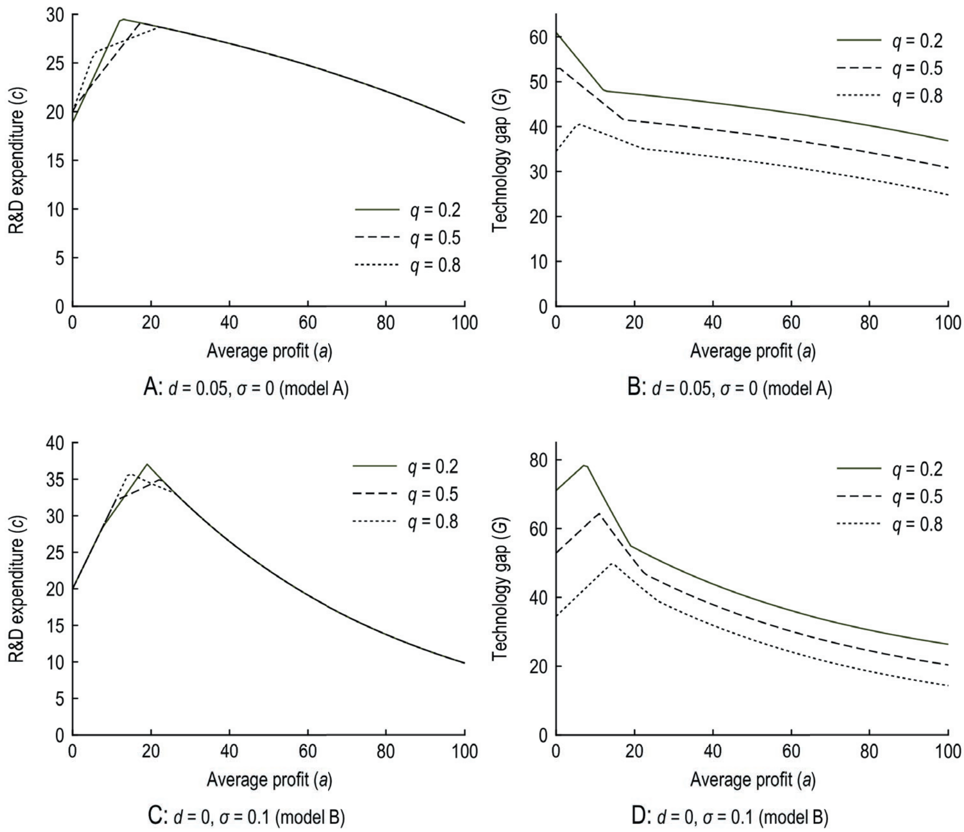


Figure 3.5: Examples of the R&D and technology-gap functions
The figure shows examples of the R&D functions $c(a)$ and the technology-gap functions $G(a)$ for different shares of firms X in the industry q. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, and $\bar{a} = 100$.

In Figures 3.4 and 3.5, I have used the following values of parameters:

- the average profit range is $a \in \langle 0, 100 \rangle$,
- the opportunity parameter $R = 0.28$,
- the scale parameter $\rho = 0.95$,
- the base salary $\omega = 40$,
- the ownership share $s_0 = 2$,

- the decreasing-ownership parameter $\mu = 0.5$,
- the loss-aversion parameter $\lambda = 2.25$,
- the probability of success $p = 0.5$,
- the disutility parameter $d = 0.05$ in model A and $d = 0$ in model B,
- the slope parameter $\sigma = 0$ in model A and $\sigma = 0.1$ in model B,
- the firm-specific profit $x = 0$, 20, and 35,
- the share of firms X in the industry $q = 0.2$, 0.5, and 0.8.

The average profit ranges from 0 to \$100 million. I use this range for the reasons explained in Subsection 2.2.4. In contrast to the basic model, the size of the profit difference x or the share of firms X in the industry q in the prospect-theory model have no direct effect on the profitability of the industry (calculated as the average profit of a firm in the industry divided by sales). For all combinations of x and q in Figures 3.4 and 3.5, the profitability ranges approximately from 0 to 0.14. This range is similar to the range found by Aghion *at al.* (2005).

The opportunity parameter R is 0.28. This means that the return to R&D expenditures of the size $c_i = 1$ and for the industry-specific profit $a = 0$ is 28%. For $c_i > 1$ and $a > 0$, the return to R&D expenditures is lower because of the scale parameter $\rho = 0.95$, and in model B also because of the slope parameter $\sigma = 0.1$. In Figures 3.4 and 3.5 in model A, the return to R&D expenditures is approximately 8% for the average profit that corresponds to the peak of the R&D function and more for lower R&D expenditures. In model B, the return to R&D expenditures equals $1/\rho - 1 \approx 5.2\%$ if the R&D-expenditure function is decreasing (the formula is derived in Subsection 2.2.4) and is higher in the increasing part of the R&D-expenditure function. As in the basic model, I assume that the R&D expenditures include costs of financing. Then the lowest return to R&D expenditures of 8% in model A or 5.2% in model B is large enough to justify positive R&D expenditures and the highest returns are not unrealistically high.

The base salary ω is 40. Because the unit of salary is \$10,000, it corresponds to \$400,000. Conyon & Murphy (2000, Table 1) report that in 1997, the average base salary of managers in the UK ranged from £245,830 (firms with sales from £200 to £500 million) to £324,540 (sales from £500 to £1,500 million). The average base salary of managers in the US ranged from £669,880 (sales from £200 to £500 million) to £850,640 (sales from £500 to £1,500 million). The base salary of \$400,000 is lower compared to the base salaries reported by Conyon & Murphy (2000). I use a relatively low value of $\omega = 40$, because base salaries have increased significantly since the 1970s (see Conyon & Murphy 2000, Fig. 1). The average base salary in the period from 1970 to 1994 is likely to be lower than in 1997.

The ownership share s_0 is 2 and the decreasing-ownership parameter μ is 0.5. So the effective ownership ranges from 2% for low average profits to 1% for high average profits. The proxy for the effective ownership $s(a)$ is the pay-performance sensitivity. The average pay-performance sensitivity for firms with sales from £200 to £500 was 2.75% in the UK and 5.2% in the US and for firms with sales from £500 to £1,500 0.91% in the UK and 3.43% in the US (Conyon & Murphy 2000, Table 5). Again, the ownership shares used in the model are somewhat lower compared to the data of Conyon & Murphy (2000). This is because Aghion *et al.* (2005) and Hashmi (2005) use data from 1970 or 1973 to 1994 while Conyon & Murply (2000) uses data from 1997. Because the pay-performance sensitivity tends to increase over time, it is reasonable to assume that the absolute value of the sensitivity was lower on average between 1970 and 1994 (for some support for this argument, see Conyon & Murphy 2000, Fig. 2).

As in the basic model, I set the value of the probability of success p at 0.5 which is exactly in the middle of the range $p \in (0, 1)$. The loss-aversion parameter is $\lambda = 2.25$ which is the value of the loss-aversion parameter estimated by Tversky & Kahneman (1992). The disutility parameter $d = 0.05$ in model A and $d = 0$ in model B. If $d = 0.05$, R&D expenditures of \$1 million lead to a reduction in the utility by 0.05, which has the same effect on the utility of managers as a reduction in the base salary of $0.05 \times \$10,000 = \$500$. The slope parameter $\sigma = 0.1$ in model B and $\sigma = 0$ in model A. This means that the reward parameter $r(a)$ is higher by σ/p if the average profit $a = 0$ than if $a = 100$. For the probability of success is $p = 0.5$ and the opportunity parameter $R = 0.28$ in model B, the reward parameter $r(0) = 2.56$ and $r(100) = 2.36$. I use the values of the profit difference x of 0, 20, and 35 that are slightly lower compared to the values of the firm-specific profit f used in the basic model. Finally, I set the values of the share of firms X q at 0.2, 0.5, and 0.8 so that they cover a large part of the range $q \in (0, 1)$.

The shapes of the R&D and technology-gap functions in Figures 3.4 and 3.5 are similar as in the basic model (see Figure 2.3).

- The inverse V-shaped R&D functions resemble the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). The size of average R&D expenditures lies below the maximum realistic R&D expenditures of \$30 million (for the discussion of the realistic R&D expenditures, see Subsection 2.2.4). Only for some values of the average profit in model B, the average R&D expenditures are somewhat higher. Compared to the basic model, shapes of the R&D functions are less affected by the profit difference x and the share of firms X in the industry q.

- If the profit difference x is high and the share of firms X in the industry q is low, the technology-gap function $G(a)$ in model A is decreasing in a which is consistent with the empirical findings of Aghion *et al.* (2005). On the other hand if x is low or q is high, the technology-gap function $G(a)$ in model A is flatter and has the maximum at $0 < a^* < 100$, which is consistent with the findings of Hashmi (2005). Subsection 2.2.4 explains why it might be reasonable to use a higher profit difference x for explaining the findings of Aghion *et al.* (2005), and a lower x for explaining the findings of Hashmi (2005). In model B, the technology-gap function is always inverse V-shaped, and the higher the x and the lower the q, the more the technology-gap function resembles the decreasing relationship found by Aghion *et al.* (2005).

3.3 The PT model with diminishing sensitivity

In this section, I discuss the shape of the R&D function $c(a)$ and the technology-gap function $G(a)$ in the model with diminishing sensitivity. I relax the assumptions I made in the previous section: The value function may have diminishing sensitivity ($\alpha \in (0, 1\rangle$) and managers of firms with zero R&D expenditures may earn negative incomes ($w_i(a, c_i) = w_i(a, 0)$ may be negative). Because it is not possible to solve the optimization problem (3.10) for all values of $\alpha < 1$, the figures in this section show the following numerical solution of the model. For each level of the average profit $a \in \{0, 1, 2, \ldots, 100\}$, I find the size of R&D expenditures $c_i \in \{0, 0.005, 0.01, \ldots, 500\}$ that maximizes the utility of the manager of firm i given by (3.10). For a detailed description of the numerical solution,see Appendix B.3.

This section is divided into three subsections. In Subsection 3.3.1, I discuss the effects of diminishing sensitivity and negative income on the shape of the R&D function $c(a)$. In Subsection 3.3.2, I relate the shapes of the R&D-expenditure functions and the technology-gap function $G(a)$. Finally in Subsection 3.3.3, I discuss the empirical relevance of predictions of the prospect-theory model with diminishing sensitivity.

3.3.1 R&D expenditures

In this subsection, I discuss the shape of the R&D function $c(a)$ in the model with diminishing sensitivity. I begin with a simple situation with zero profit difference x. Then I discuss the effect of diminishing sensitivity for the profit difference $x > 0$. As in the previous section, the R&D function is given by

$$c(a) = qc_i^X(a) + (1 - q)c_i^Y(a),$$

where $c_i^X(a)$ and $c_i^Y(a)$ are the R&D-expenditure functions of firms X and Y, and q is the share of firms X in the industry.

For the profit difference $x = 0$, the R&D-expenditure functions of firms X and Y are equal to the R&D function $c_i^X(a) = c_i^Y(a) = c(a)$. If the R&D function $c(a)$ is inverse V-shaped for $\alpha = 1$ and managers expect to earn non-negative incomes $w_i(a, c_i)$, then diminishing sensitivity (a reduction of α below 1) has a similar effect as risk aversion in the expected-utility framework. The higher the R&D expenditure c_i, the higher is the difference between the income of managers in the case of a successful and failed innovation $w_{iS}(a, c_i)$ and $w_{iF}(a, c_i)$, and the higher is the effect of diminishing sensitivity on the utility of managers. Hence diminishing sensitivity tends to reduce further relatively high R&D expenditures. Therefore, the resulting R&D function $c(a)$ is likely to have an inverted-U shape.

Figure 3.6 shows an example of the effect of diminishing sensitivity on the shape of the R&D function $c(a)$. The highest inverted-V R&D functions $c(a)$ correspond to the diminishing-sensitivity parameter $\alpha = 1$. (They are identical to the R&D functions $c(a)$ in Panels 3.4A and C for $x = 0$.) The lower the diminishing-sensitivity parameter α, the

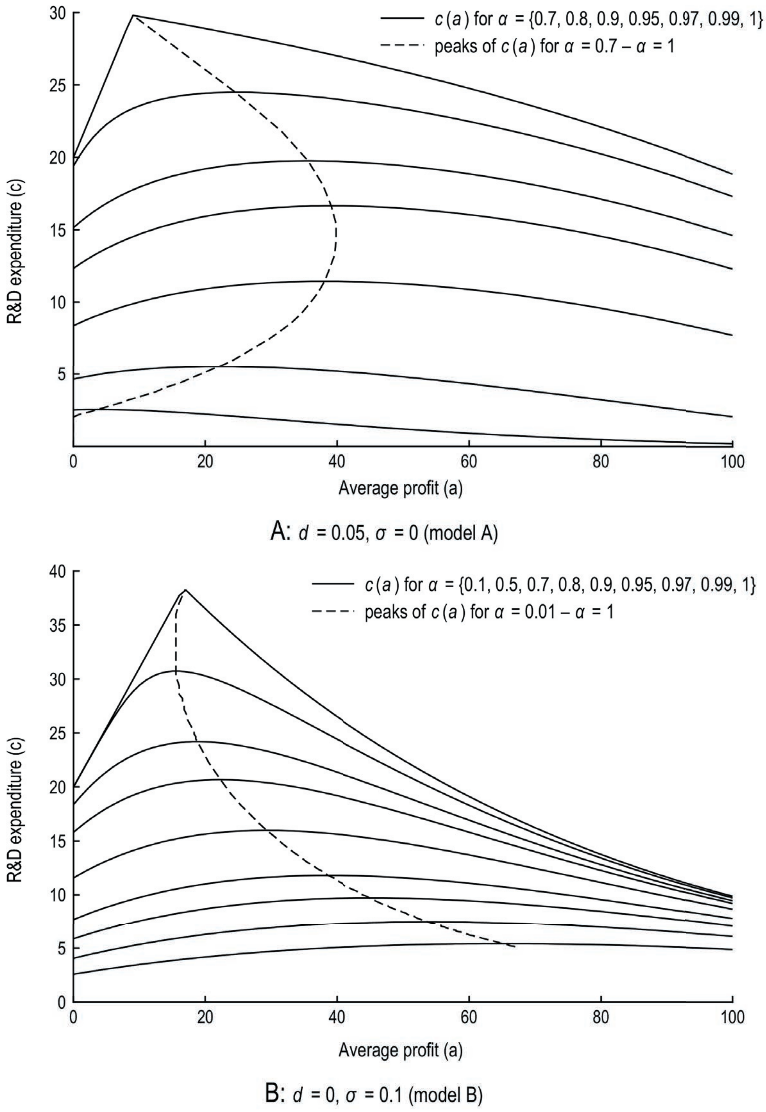


Figure 3.6: An example of the effect of diminishing-sensitivity on the R&D function $c(a)$
The figure shows examples of R&D functions $c(a)$ for the profit difference $x = 0$ and for different values of the diminishing-sensitivity parameter α. The lower the diminishing-sensitivity parameter, the lower is the R&D function. The dotted line which connects the peaks of the R&D functions was found using the procedure described in Appendix B.4. The remaining parameters are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, and $\bar{a} = 100$.

lower and flatter are the R&D functions $c(a)$. The dashed line connects the peaks of the functions $c(a)$ for different levels of the diminishing-sensitivity parameter α. (It was found using the procedure described in Appendix B.4.) Figure 3.6 suggests that for relatively high values of the diminishing-sensitivity parameter, the effect of diminishing sensitivity is rather small (see also Subsection 4.2.2 for more systematic evidence on the effect of α). This means that if $c(a)$ is inverse V-shaped with the peak not too close to the borders of the average-profit range $a \in \langle 0, \bar{a} \rangle$ in the model with constant sensitivity, it is likely to be inverse U-shaped in the model with diminishing sensitivity.

Moreover, Figure 3.6 indicates that the effect of diminishing sensitivity is different in models A and B. While diminishing sensitivity has a relatively small effect on a^* in model B, a relatively large reduction in α leads to a decreasing R&D function in model A ($c(a)$ is decreasing for $\alpha < 0.7$ in Panel 3.6A). The intuition behind the decreasing R&D function in model A is straightforward. It follows from the mathematical formulation of the prospect-theory value function (3.8) that a reduction in the diminishing-sensitivity parameter α lowers the value of a change in income, and that α has a stronger effect on the value of managers with higher incomes $w_i(a, c_i)$. At the same time, managers in model A experience a disutility of innovation that is independent of α or $w_i(a, c_i)$. While a reduction in α lowers the positive value of a given size of R&D expenditures (more for managers with higher incomes), the disutility connected to the same R&D process is constant. Therefore, a relatively large reduction in α leads to a more decreasing R&D function, as managers in industries with higher average profits a (who earn higher incomes) tend to choose relatively lower R&D expenditures.

If the profit difference $x > 0$, the R&D-expenditure functions $c_i^X(a)$ and $c_i^Y(a)$ have different shapes. The R&D-expenditure functions in Figures 3.7 and 3.8 are inverse U-shaped in all situations, in which managers expect to earn non-negative incomes $w_i(a, c_i)$. On the other hand, the functions $c_i^Y(a)$ in Panels 3.7 and 3.8D are decreasing at low average profits, where the incomes of managers of firms Y in the case of a failed innovation $w_{iF}(a, c_i)$ are negative. The income $w_{iF}(a, c_i)$ is always negative, if the income of managers of firms Y for zero R&D expenditures $w_i(a, c_i) = w_i(a, 0) = \omega + s(a)(a - qx)$ is negative, as $w_{iF}(a, c_i) \leq w_i(a, 0)$. It follows from equation 3.5 that the income $w_i(a, 0)$ will be negative at least for the average profit $a = 0$ if

$$\omega - s_0 qx < 0. \tag{3.27}$$

The decreasing part of the R&D-expenditure function $c_i^Y(a)$ has the following explanation. Since a negative income $w_i(a, 0)$ corresponds to the convex part of the value function (see Figure 3.1), it is attractive for managers to increase R&D expenditures c_i as long as the income in the case of a successful innovation $w_{iS}(a, c_i)$ is negative. Once $w_{iS}(a, c_i)$ is positive, the additional benefit from increasing c_i is low because the value function is concave and relatively flat (due to the absence of loss aversion). Hence managers are likely to choose the size of R&D expenditures c_i such that $w_{iS}(a, c_i)$ is positive and close to 0. With the increasing average profit a, R&D expenditures c_i necessary to reach low positive $w_{iS}(a, c_i)$ decrease until the income $w_i(a, 0) = 0$ (see the dotted lines in Panels 3.7 and 3.8D). Because the decreasing part of $c_i^Y(a)$ is usually relatively steep, the R&D function $c(a)$ is likely to be also decreasing for low average profits a (see the solid lines in Panels 3.7 and 3.8D).

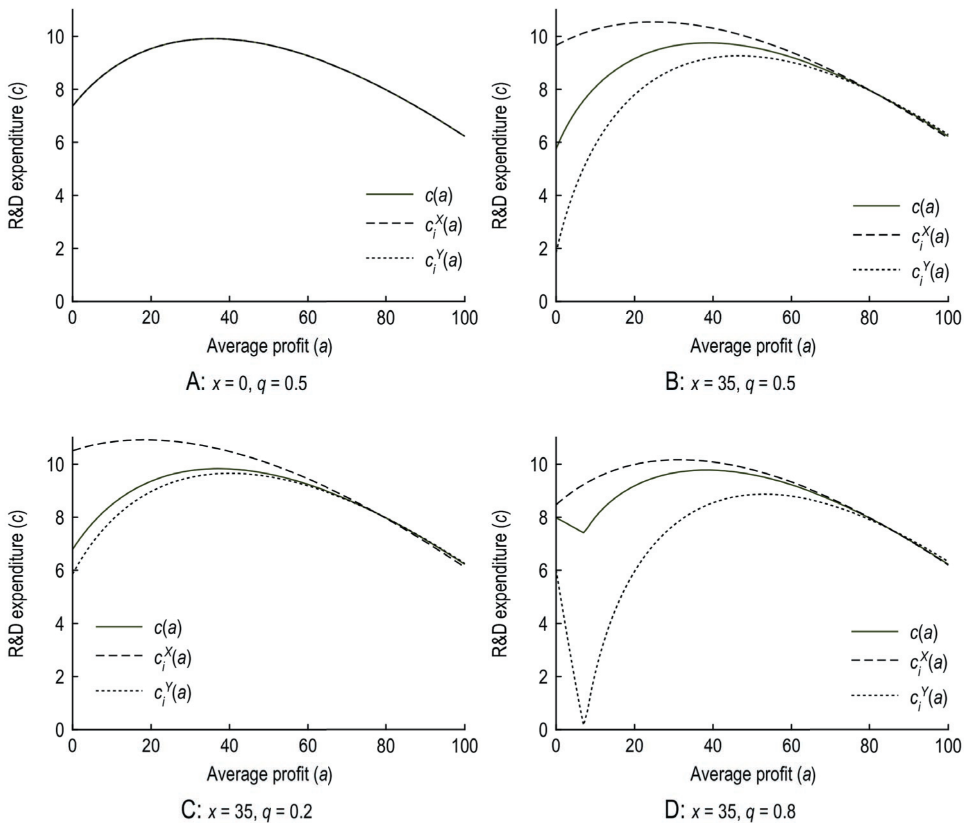


Figure 3.7: Examples of the R&D-expenditure functions in model A ($\sigma = 0$)
The figure shows examples of the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ and of the R&D functions $c(a)$. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\alpha = 0.88$, $\lambda = 2.25$, $d = 0.05$, $\sigma = 0$, and $\bar{a} = 100$.

Figures 3.7 and 3.8 present another interesting property of the model. The R&D function $c(a)$ has maximum roughly at the same average profit a^* in all panels. That is, the effect of the profit difference x and the share of firms X in the industry q on a^* seems small (see Section 4.2.3 for more systematic evidence on the effect of x and q on a^*). The intuition behind this property is as follows. If the profit difference increases by Δx in the model with constant sensitivity ($\alpha = 1$), the increasing part of the inverse V-shaped R&D-expenditure function of firms X $c_i^X(a) = \not{C}_i^X(a)$ shifts up by $(1-q)\Delta x$ and the same function of firms Y $c_i^Y(a) = \not{C}_i^Y(a)$ shifts down by $q\Delta x$ (see (3.19)). Since the decreasing $c_i^X(a) = c_i^Y(a) = \underline{C}_i(a)$ is approximately linear, the maximum of $c_i^X(a)$ shifts to the left by a distance roughly proportional to $1-q$ and the maximum of $c_i^Y(a)$ shift to the right by a distance roughly proportional to q. Because the peaks of $c_i^X(a)$ and $c_i^Y(a)$ tend to shift by distances that are roughly proportional to $1-q$ a q also under diminishing sensitivity

($\alpha < 1$), and the respective weights of $c_i^X(a)$ and $c_i^Y(a)$ in the R&D function $c(a)$ are q and $1-q$, the effect x and q on the average profit a^* is rather small.

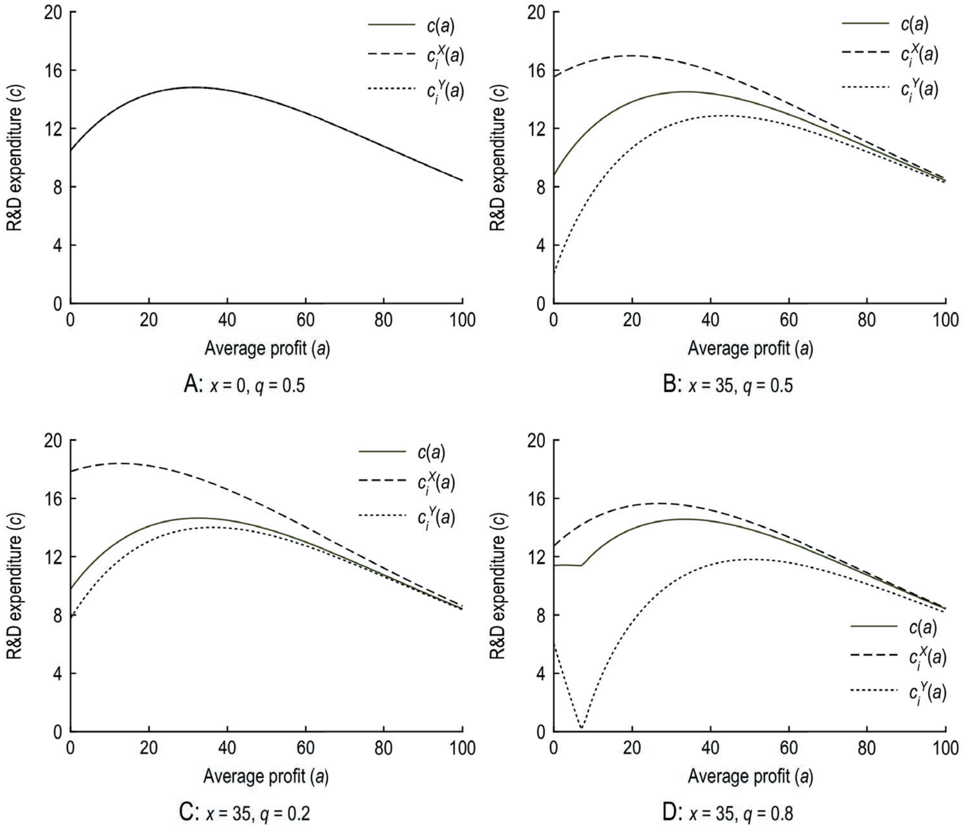


Figure 3.8: Examples of the R&D-expenditure functions in model B ($d = 0$)
The figure shows examples of the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ and of the R&D functions $c(a)$. The parameters common to all panels are $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\alpha = 0.88$, $\lambda = 2.25$, $d = 0$, $\sigma = 0.1$, and $\bar{a} = 100$.

The figures in this subsection suggest that if managers expect to earn non-negative incomes $w_i(a, c_i)$ and the R&D function $c(a)$ is inverse V-shaped in the model with constant sensitivity ($\alpha = 1$), it is likely to be inverse U-shaped in the model with diminishing sensitivity ($\alpha < 1$). If managers earn non-negative incomes, the effect of the profit difference x and the share of firms X in the industry q on the position of the maximum of $c(a)$ is likely to be small. If the income of managers of firms Y with zero R&D expenditures $w_i(a, 0)$ is negative, the R&D function $c(a)$ is likely to be decreasing at low average profits a. Finally, the R&D function in model A tends to be more decreasing because of the interaction between the disutility of innovation and diminishing sensitivity.

3.3.2 The technology gap

This subsection discusses the factors that affect the shape of the technology-gap function $G(a)$. First, it relates the shapes of the R&D and technology-gap functions for the profit difference $x = 0$. Then it discusses the effect of the profit difference x and the share of firms X in the industry q on the shape of $G(a)$.

If the profit difference $x = 0$, the technology-gap function is given by

$$G(a) = (1 - p)r(a)c(a)^{\rho},$$

where $p \in (0, 1)$ is the probability of success, $r(a)$ is the reward function, $\rho \in (0, 1\rangle$ is the scale parameter, and $c(a)$ is the R&D function (for a complete technology-gap function, see (3.26)). In model A, the shapes of $G(a)$ and $c(a)$ are similar and both functions have maximum at the same average profit a ($a^{G*} = a^*$). In model B, $G(a)$ has maximum at a lower average profit than $c(a)$ ($a^{G*} < a^*$), because the reward function $r(a)$ is decreasing in a. The solid lines in Figure 3.9 show examples of the R&D and technology-gap functions for $x = 0$.

If the profit difference $x > 0$, the R&D-expenditure functions of firms X and Y $c_i^X(a)$ and $c_i^Y(a)$ have different shapes. Then the technology gap function is given by

$$G(a) = (1 - q)x + (1 - p)r(a)c_i^X(a)^{\rho} + (1 - q)pr(a)(c_i^X(a)^{\rho} - c_i^Y(a)^{\rho}). \tag{3.28}$$

If managers earn non-negative incomes $w_i(a, c_i)$ and there is diminishing sensitivity ($\alpha < 1$), the technology-gap function $G(a)$ is likely to have maximum at a lower average profit a than the R&D function $c(a)$ ($a^{G*} < a^*$). This is because a rise in the profit difference x tends to shift the peak of $G(a)$ to a lower average profit a^{G*}. Figures 3.9 and 3.10 present the effects of x and q on the shape of the R&D function $c(a)$ and the technology-gap function $G(a)$. The left panels show that a rise in x and q have almost no effect on the position of the peak of the R&D functions a^* (see the previous subsection for the intuition behind this effect). If anything, the peak of the inverted-U relationship shifts slightly downwards and to the right. The right Panels 3.9B and D show that a rise in x shifts the peak of the technology-gap function to the right.

The explanation of the effect of x on the position of the peak of $G(a)$ follows from the fact that

$$\frac{\partial^4 v(w_i(a, c_i))}{\partial w_i(a, c_i)^4} < 0 \quad \text{if } \alpha < 1 \text{ and } w_i(a, c_i) \geq 0.$$

This means that a rise in income $w_i(a, c_i)$ reduces the concavity of the value function (3.8) at a decreasing rate for diminishing sensitivity and a non-negative income. Lower concavity is identical to a smaller effect of diminishing sensitivity, which in turn leads to higher R&D expenditures.

Because of the specific shape of the value function, a rise in the profit difference x reduces the slope of the R&D-expenditure functions of firms X $c_i^X(a)$ and increases the slope of the R&D-expenditure functions of firms Y $c_i^Y(a)$. It increases the income of managers of firms X, which reduces the effect of diminishing sensitivity more for lower average

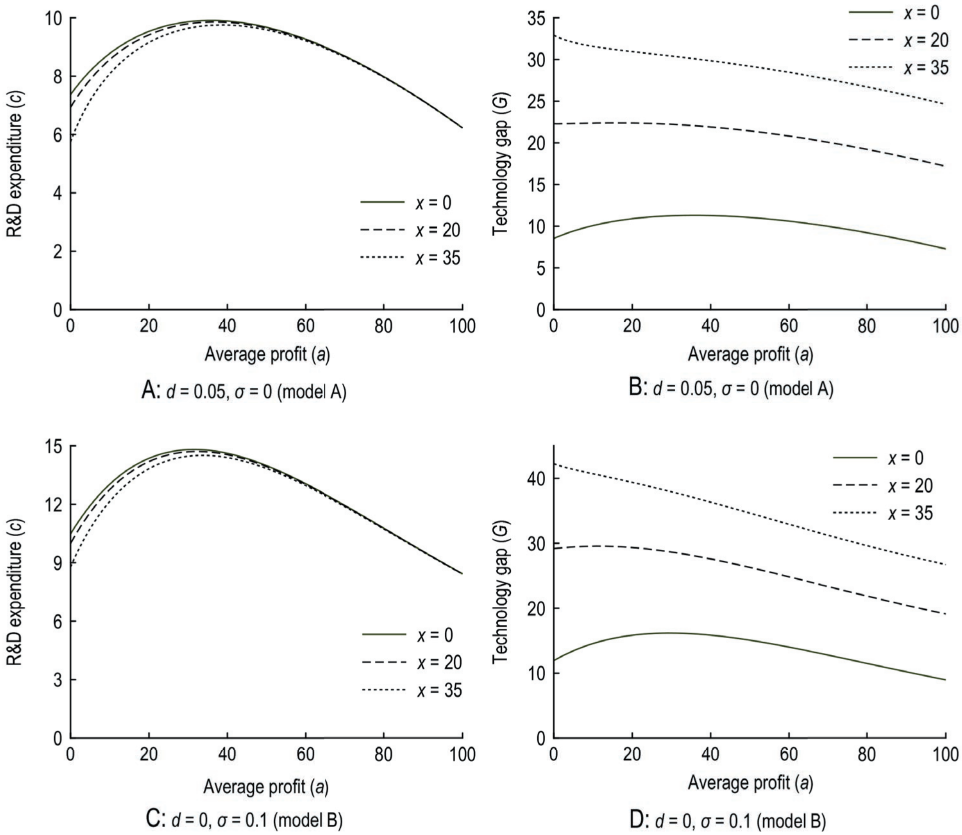


Figure 3.9: Examples of the R&D and technology-gap functions for changing x
The figure shows examples of the R&D functions $c(a)$ and the technology-gap functions $G(a)$ for different levels of the profit difference x. The parameters common to all panels are $q = 0.5$, $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\alpha = 0.88$, $\lambda = 2.25$, and $\bar{a} = 100$.

profits a. Hence a rise in x tends to increase the R&D expenditures more for lower average profits a, so that the slope of $c_i^X(a)$ is lower across the entire average-profit range $a \in \langle 0, \bar{a} \rangle$. On the other hand, a rise in the profit difference x tends to reduce the income of managers of firms Y. It increases the effect of diminishing sensitivity more for lower average profits a, so that the slope of $c_i^Y(a)$ is higher across the entire average-profit range $a \in \langle 0, \bar{a} \rangle$. (Compare the slopes of $c_i^X(a) = c_i^Y(a)$ in Panels 3.7 and 3.8A to the slopes of $c_i^X(a)$ and $c_i^Y(a)$ in Panels 3.7 and 3.8B.) Furthermore, the slope of $c_i^X(a)$ is even lower and the slope of $c_i^Y(a)$ even higher in model A because of positive disutility of innovation.

If a rise in the profit difference x reduces the slope of $c_i^X(a)$ and increases the slope of $c_i^Y(a)$, then it is likely to reduce also the average profit a^{G*}. This is because a rise in x shifts the peak of $c_i^X(a)$ to a lower average profit a, and reduces the slope of $c_i^X(a)^\rho - c_i^Y(a)^\rho$ at least in the part of the average-profit range where $c_i^Y(a)$ is increasing. The latter effect arises for the following reason. If $c_i^Y(a)$ is increasing, it is either true that $\partial c_i^X(a)/\partial a < 0$, or that $\partial c_i^Y(a)/\partial a > \partial c_i^X(a)/\partial a \geq 0$ and $c_i^X(a) > c_i^Y(a)$. In both instances, the slope of the difference $c_i^X(a)^\rho - c_i^Y(a)^\rho$, which is given by

$$\rho c_i^X(a)^{\rho-1}\frac{\partial c_i^X(a)}{\partial a} - \rho c_i^Y(a)^{\rho-1}\frac{\partial c_i^Y(a)}{\partial a} < 0.$$

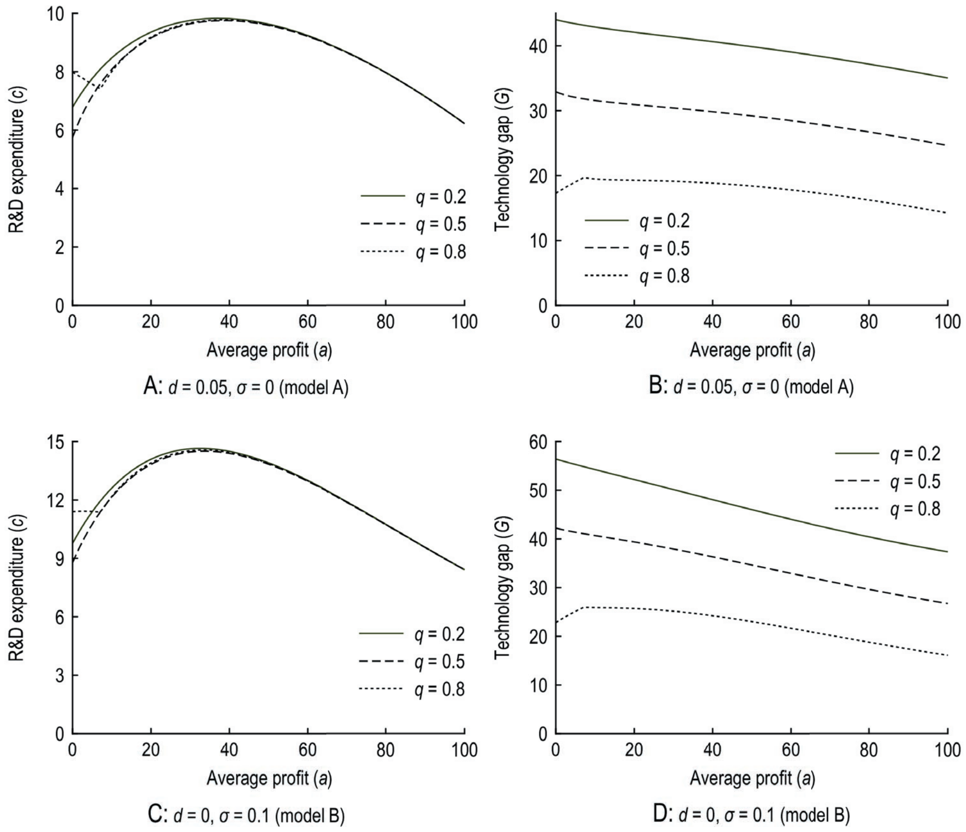


Figure 3.10: Examples of the R&D and technology-gap functions for changing q
The figure shows examples of the R&D functions $c(a)$ and the technology-gap functions $G(a)$ for different shares of firms X in the industry q. The parameters common to all panels are $x = 35$, $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\alpha = 0.88$, $\lambda = 2.25$, and $\bar{a} = 100$.

Furthermore, if managers earn non-negative incomes $w_i(a, c_i)$ and there is diminishing sensitivity ($\alpha < 1$), a reduction in the share of firms X in the industry q increases the slope of the technology-gap function $G(a)$ at least in the part of the average-profit range where $c_i^Y(a)$ is increasing. The intuition behind this effect is straightforward. It follows from 3.28 that a reduction in q increases the contribution of x and $pr(a)\left(c_i^X(a)^\rho - c_i^Y(a)^\rho\right)$ to the value of $G(a)$. This leads to a steeper technology-gap function $G(a)$ at least in the part of the average-profit range where $c_i^Y(a)$ is increasing, because x is a constant and $pr(a)\left(c_i^X(a)^\rho - c_i^Y(a)^\rho\right)$ is decreasing in a if $\partial c_i^Y(a)/\partial a > 0$. Therefore, a reduction in q tends to shift the maximum of an inverted-U technology-gap function $G(a)$ to a lower average profit a^{G*}

The shape of the technology-gap function $G(a)$ might change if the income of managers of firms Y $w_{iF}(a, c_i)$ is negative for low average profits a (because $\omega - s_0 qx < 0$). Then the R&D function of firms Y $c_i^Y(a)$ is likely to be decreasing in a. If the slope of the R&D function of firms X $c_i^X(a)$ is positive, the difference $c_i^X(a)^\rho - c_i^Y(a)^\rho$ is increasing in a. Consequently, the technology-gap function $G(a)$ is likely to be increasing at low average profits a (see the dotted lines in Panels 3.10B and D).

This subsection shows that if the profit difference $x = 0$, the technology-gap function $G(a)$ has maximum at the same average profit as the R&D function $c(a)$ in model A ($a^{G*} = a^*$) and at a lower average profit in model B ($a^{G*} < a^*$). Furthermore, if managers earn non-negative incomes $w_i(a, c_i) \geq 0$ and the diminishing-sensitivity parameter $\alpha < 1$, a rise in the profit difference x and a reduction in the share of firms X in the industry q tend to shift the maximum of the inverted-U technology-gap function $G(a)$ to a lower average profit a^{G*}. Finally, if the income of managers of firms Y with zero R&D expenditures is negative, the technology-gap function is likely to be increasing at low average profits a.

3.3.3 Empirical relevance of the results

In this subsection, I discuss whether the R&D and technology-gap functions in Figures 3.9 and 3.10 correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). In Figures 3.9 and 3.10, I use the same parameter values as in Figures 3.4 and 3.5 except for the value of the diminishing-sensitivity parameter α.

The diminishing-sensitivity parameter α is 0.88, which is the value estimated by Tversky & Kahneman (1992). However, the size of the effect is reduced by the fact that one unit of the income is interpreted as \$10,000. The average profit $a \in \langle 0, 100 \rangle$ generates a range of profitability from 0 to 0.14, which is similar to the range reported by Aghion *et al.* (2005). The opportunity parameter $R = 0.28$ generates a higher return to R&D expenditures compared to the model with constant sensitivity. Because the R&D expenditures in Figures 3.9 and 3.10 are lower than in Figures 3.4 and 3.5, the lowest returns to R&D expenditures in Figures 3.9 and 3.10 are 14% in model A and 6% in model B.

Compared to predictions of the basic model and the PT model with constant sensitivity (see Figures 2.3, 3.4 and 3.5), the shapes of the R&D and technology-gap functions shown in Figures 3.9 and 3.10 are more similar to the relationships found by Aghion *et al.* (2005) and Hashmi (2005).

- The inverted-U shape of the R&D functions is consistent with the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). The R&D expenditures are around \$10 millions in both models, which is below the maximum realistic R&D expenditures of \$30 millions (for the discussion of the realistic R&D expenditures, see Subsection 2.2.4).

- The technology-gap function is decreasing if the profit difference x is high and the share of firms X in the industry q is low. This result is consistent with the empirical findings of Aghion *et al.* (2005). On the other hand, the technology-gap function $G(a)$ is flat and inverse U-shaped if x is low and q is high, which is consistent with the findings of Hashmi (2005). (In Subsection 2.2.3, I explain why we might use higher x for explaining the empirical findings of Aghion *et al.* 2005, than for the findings of Hashmi 2005.)

3.4 Summary

This chapter has introduced the prospect-theory model of innovation that explains the inverted-U relationship between profitability and innovation, and the relationships between profitability and the technology gap found by Aghion *et al.* (2005) and Hashmi (2005). The model is presented in two versions. First, I analyze predictions of the prospect-theory model with constant sensitivity. Then I add diminishing sensitivity to the model and discuss predictions of the complete model.

In the model, managers expect to earn a share of the profits of their firms. The profits depend on industry-specific factors and other firm-specific factors, which determine the average profit in the industry, and on the outcome of the R&D process and on the size of R&D expenditures chosen by the managers. The higher the R&D expenditures, the higher the cost that must be paid if the innovation fails, and the larger is the reward if the innovation succeeds. In fact, by choosing the R&D expenditures, the managers create a lottery in which they earn higher incomes if the innovation succeeds, and lower incomes if it fails. The managers choose R&D expenditures in order to maximize their utility. The utility of the lottery is determined using the prospect-theory value function. Furthermore, a rise in R&D expenditures reduces the utility of managers in model A (disutility of innovation).

The explanation of the inverted-U or inverted-V relationship between the average profit and R&D expenditures of individual firms has two parts. First, a rise in the average profit increases R&D expenditures of low-profit firms because of the loss-aversion and diminishing-sensitivity principles of the prospect-theory value function. Managers expecting low incomes choose relatively small R&D expenditures in order to avoid negative incomes (loss aversion) or very low positive incomes (diminishing sensitivity), if their firms fail to innovate. Hence managers of less profitable firms prefer relatively low R&D expenditures because of the properties of the value function. Second, a rise in the average profit reduces R&D expenditures of high-profit firms either because of a combination of the decreasing effective ownership, disutility of innovation and diminishing sensitivity in model A, or because of decreasing return to R&D expenditures in model B. In model A, the disutility of an innovation of a certain size is constant, but the value of the same innovation decreases in the average profit because of the decreasing effective ownership and diminishing sensitivity. At relatively high average profits, the disutility of innovation may outweigh the positive value of the R&D process, so that managers prefer smaller R&D expenditures.

The forms of the relationships between the average profit and average R&D expenditures in the industry (R&D function) and the average profit and the technology gap in the industry (technology-gap function) depend on the differences in profits of firms in the industry due to other firm-specific factors. If the differences in profits of firms are small, the R&D and technology-gap functions tend to be inverse U- or V-shaped. The R&D function will have a similar form as the individual relationships, because it is an average of the individual inverted-U or inverted-V relationships. The technology-gap function is likely to be inverse U- or V-shaped because higher R&D expenditures lead to more important differences between technologies of successful and failed innovators, and therefore to higher technology gaps.

On the other hand, if the differences in profits of firms are relatively large, the R&D function may be inverse U- or V-shaped and the technology-gap may be decreasing in profits. A decreasing technology-gap function may result from two effects. First, in an industry with low average profits, managers of relatively more profitable firms are less affected by loss aversion or diminishing sensitivity and therefore choose higher R&D expenditures than managers of relatively less profitable firms. With an increasing average profit in the industry, the difference between R&D expenditures of these firms decreases, which contributes to a decreasing technology-gap function. Second, the size of the technology gap depends more on R&D expenditures of relatively more profitable firms. Since their relationship between the average profit and R&D expenditures is decreasing over a wider average-profit range compared to the R&D function, also the technology-gap tends to be more decreasing than the R&D function.

Using a specific set of parameters, the predicted inverted-U or inverted-V relationships between the average profit and R&D expenditures correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Also the relationships between the average profits and the technology gap correspond well to the empirical evidence. The predicted relationship is decreasing in profits (as in Aghion *et al.* 2005), if the differences in the profits of firms are large. On the other hand, it is inverse U- or V-shaped (as in Hashmi 2005), if the differences in profits are relatively small. The question is why should the differences in profits be smaller in the US than in the UK. One possible answer is that Aghion *et al.* (2005) uses a broader definition of industries (2-digit SIC codes) than Hashmi (2005) (4-digit SIC codes). In more broadly defined industries, other firm-specific factors are likely to lead to higher differences in profits of firms.

The problem of the approach presented in this chapter is that predictions are generated only for specific combinations of parameters. It is therefore not clear whether the results hold for other combinations of parameters. The robustness of the results to variation in parameters is investigated in the following chapter.

Chapter 4

Sensitivity analysis

In the previous chapters, I have shown that for some combinations of parameters the basic and PT models generate predictions that explain the inverted-U relationship between profitability and innovation and the empirical findings related to Prediction B of Aghion *et al.* (2005). In this chapter, I investigate whether the predictions also hold for different values of parameters. It is important to state here that the aim of the chapter is *not* to show that the models generate the required predictions for all realistic parameter combinations. As shown in Chapter 1, there are many studies finding increasing or decreasing relationships between competition and innovation. Therefore, it would be incorrect to conclude that the models are empirically irrelevant only because they provide other than inverted-V or inverted-U relationships for realistic parts of the parameter space. Instead the aim of the chapter is to show that the basic and prospect-theory models are able to explain the empirical evidence related to the inverted-U relationship between profitability and innovation. In line with this aim, the chapter discusses whether the models generate predictions consistent with the empirical evidence for a wider range of parameters around the parameter combinations used in the previous chapters.

This chapter consists of two sections. In Section 4.1, I discuss the robustness of predictions of the basic model. First, I review the conditions under which the model gives the required predictions. Then I discuss the determinants of robustness of the predictions and present parts of the parameter space specified by the conditions. In Section 4.2, I discuss the sensitivity of the results of the prospect-theory model to variation in parameters. I introduce simulations that produce predictions for a large number of parameter combinations and present the predictions graphically.

4.1 The basic model

This section discusses the robustness of predictions of the basic model. In order to simplify the discussion, I assume a fixed range of industry-specific profit equal to $b \in \langle 0, 100 \rangle$ (for a justification of the range, see Subsection 2.2.4). The section proceeds as follows. In Subsection 4.1.1, I discuss the properties of the parameter space for which the R&D function $c(b)$ has maximum at the industry-specific profit $0 < b^* < 100$, forming an inverted-V or inverted-U relationship. Moreover, I show parts of the parameter space graphically. In Subsection 4.1.2, I present the conditions for which the technology-gap function $G(b)$ has maximum at $b^{G*} = 0$ or $0 < b^{G*} < 100$. Finally in Subsection 4.1.3, I summarize the main findings of the section.

4.1.1 R&D expenditures

For clarity of presentation, I split the parameter space into two parts depending on the relative size of the firm-specific profit f. I have shown in Section 2.2.2 that if the firm-specific profit is low enough so that

$$f < (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the R&D function $c(b)$ is inverse U- or V-shaped if the opportunity parameter

$$R \geq \sigma = LB \quad \text{and} \quad R < \frac{100^{1-\rho}}{\rho} + \sigma - 1 = UB_1, \tag{4.1}$$

where $\sigma > 0$ is the slope parameter, and $\rho \in (0, 1)$ is the scale parameter. The difference between the lower boundary LB and upper boundary UB_1 in (4.1) is decreasing in the scale parameter ρ (as $\partial UB_1/\partial\rho < 0$) and constant in all other parameters.

Panels 4.1A, C and E present three parts of the parameter space described by condition (4.1) for the scale parameters $\rho = 0.925, 0.95$, and 0.975. The R&D function is inverse V- or U-shaped for all combinations of the opportunity parameters R and the slope parameters σ corresponding to the points between the upper and lower boundaries. The panels show clearly that a reduction in the scale parameter ρ increases the distance between the boundaries and that the distance remains constant for different values of the slope parameter σ.

I have also shown in Section 2.2.2 that if the firm-specific profit is high enough so that

$$f \geq (\rho + \rho R)^{\frac{1}{1-\rho}},$$

the R&D function is inverse V-shaped if the opportunity parameter

$$R \geq LB \quad \text{and} \quad R < UB_1 \quad \text{and} \quad R < \left(\frac{100(1-\rho)(1-q)}{q\rho^{\frac{1}{1-\rho}}\sigma}\right)^{\frac{1-\rho}{\rho}} - 1 = UB_2, \tag{4.2}$$

where $q \in (0, 1)$ is the share of firms X in the industry. There is one lower boundary LB and two upper boundaries UB_1 and UB_2. If $UB_1 \leq UB_2$, we have the same situation as in (4.1) – the difference between the boundaries is decreasing in the scale parameter ρ and constant in all other parameters. If $UB_1 > UB_2$, the difference between the boundaries is decreasing in the share of firms X in the industry q, slope parameter σ, and scale parameter ρ (as $\partial UB_2/\partial q < 0$, $\partial UB_2/\partial\sigma < 0$, and $\partial UB_2/\partial\rho < 0$) and constant in all other parameters.

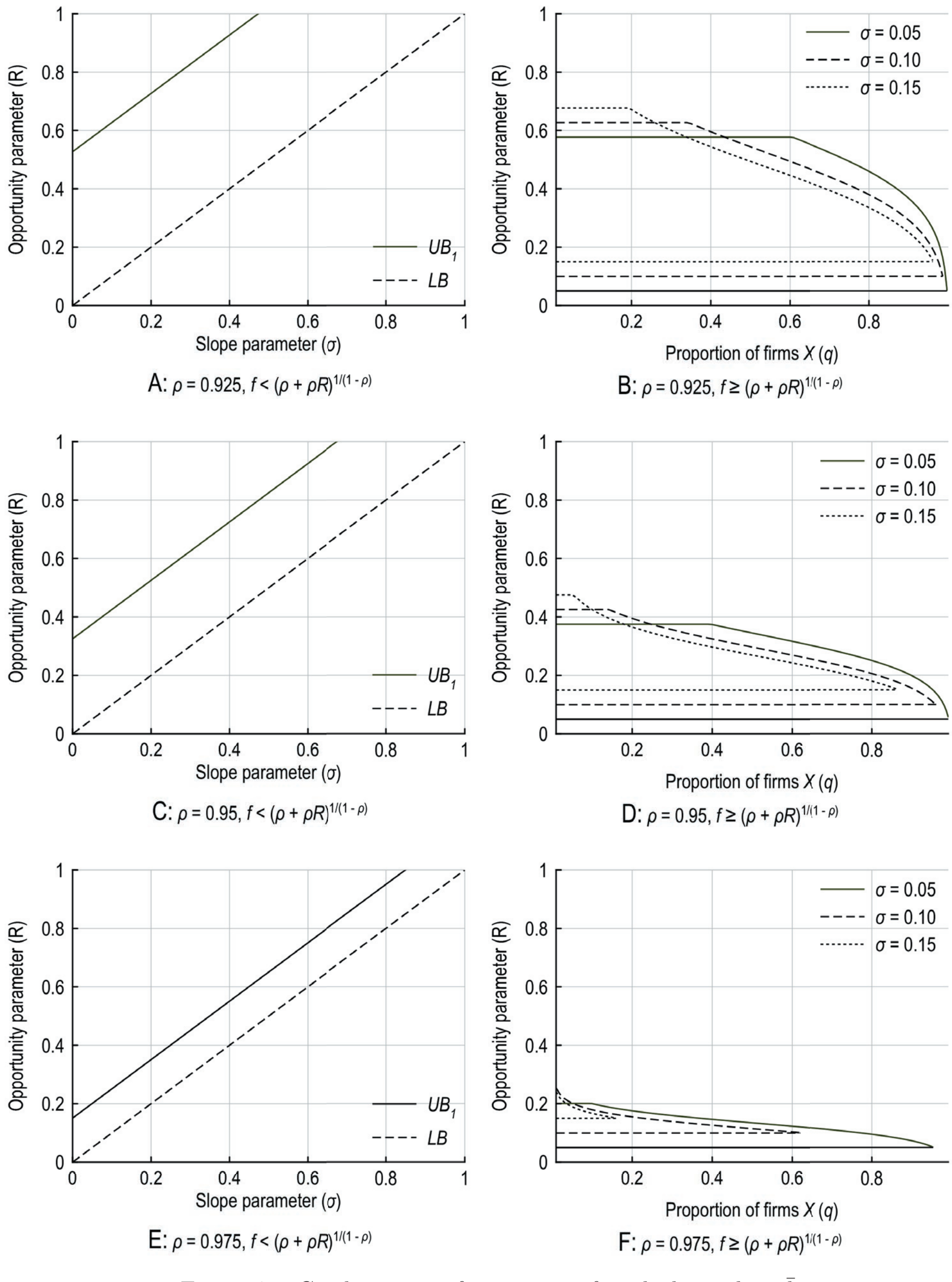


Figure 4.1: Combinations of parameters for which $0 < b^* < \bar{b}$
The figure shows the combinations of parameters for which $0 < b^* < \bar{b}$ for the range of the industry-specific profit $b \in \langle 0, 100 \rangle$. The parameter combinations lie between the lines LB and UB_1 in Panels A, C, and E, and in the area to the left of the lines in Panels B, D, and F.

Panels 4.1B, D and F present nine parts of the parameter space determined by conditions (4.2) for the slope parameters $\sigma = 0.05$, 0.1, and 0.15 and the scale parameters $\rho = 0.925$, 0.95, and 0.975. The R&D function $c(b)$ is inverse V-shaped for all combinations of the opportunity parameter R and the share of firms X in the industry q that correspond to points within the areas to the left of the lines (the lower horizontal line is LB, the upper horizontal line UB_1, the decreasing line UB_2). The panels show that a reduction in the scale parameter ρ and the slope parameter σ increases the parameter space for which the R&D function $c(b)$ inverse V-shaped.

4.1.2 The technology gap

In Section 2.2.3, I have shown that if condition (2.11) holds, that is if

$$R < \frac{\bar{b}^{1-\rho}}{\rho} + \sigma - 1,$$

the shape of the technology-gap function $G(b)$ depends on the firm-specific profit f:

- If $f = 0$, the maximum of $G(b)$ corresponds to the industry-specific profit $0 < b^{G*} < \bar{b}$ and the technology-gap function $G(b)$ is inverse V-shaped.
- If $f \geq (\rho + \rho R)^{\frac{1}{1-\rho}}$, the industry-specific profit $b^{G*} = 0$ and the technology-gap function $G(b)$ is decreasing.
- If $0 < f < (\rho + \rho R)^{\frac{1}{1-\rho}}$, the maximum of the technology-gap function $G(b)$ corresponds to the industry-specific profit $0 < b^{G*} < \bar{b}$ or $b^{G*} = 0$ depending on the values of parameters. Moreover, the higher the firm-specific profit f and the lower the share of firms X in the industry q, the lower is the slope of the part of the technology-gap function $\underline{G}(b)$. That is, the entire technology-gap function $G(b)$ is more likely to have the maximum at $b^{G*} = 0$, if f is high and q is low.

Figure 4.2 presents the parameter space that determines the shape of the technology-gap function $G(b)$ for three values of scale parameter $\rho = 0.925$, 0.95, and 0.975 given condition (2.11) holds. The lines are given by $f = (\rho + \rho R)^{\frac{1}{1-\rho}}$, or inversely by

$$R = \frac{f^{1-\rho}}{\rho} - 1.$$

A rise in the scale parameter ρ shifts the lines up if $f > e^{-\frac{1}{\rho}}$. (Since $\rho < 1$, a rise in ρ shifts the lines up always if $f \geq 1/e \approx 0.37$.) The technology-gap function $G(b)$ is inverse V-shaped for all parameters along the vertical axis ($f = 0$). It is decreasing for all combinations of parameters corresponding to the points to the right of the lines. For the remaining combinations of parameters, the technology-gap function $G(b)$ has the maximum either at $0 < b^{G*} < \bar{b}$ or at $b^{G*} = 0$.

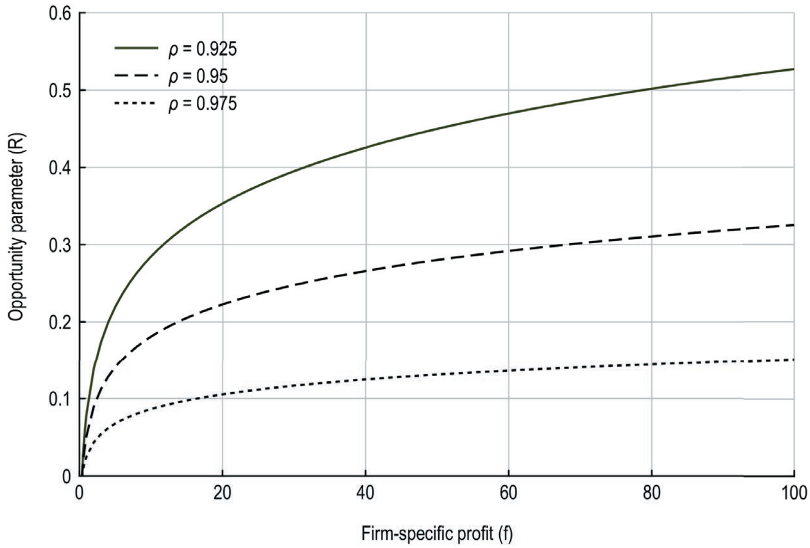


Figure 4.2: Combinations of parameters that determine the shape of $G(b)$
The figure shows the combinations of parameters for which the technology-gap function $G(b)$ is decreasing or inverse V- or U-shaped for different values of the scale parameter $\rho = 0.925$, 0.95, and 0.975, and the maximum industry-specific profit $\bar{b} = 100$.

4.1.3 Summary

In this section, I discussed shortly the size of the parameter space for which the basic model produces realistic predictions for the range of the industry-specific profit of $b \in \langle 0, 100 \rangle$. It follows from the above analysis that the model generates predictions that are in line with the empirical evidence for a wider range of parameters around the parameter combinations used in Chapter 2. More specifically, a reduction in the scale parameter ρ increases the parameter space consisting of all remaining parameters for which the basic model generates the required predictions. Furthermore, I find that the lower the scale parameter ρ, the share of firms X in the industry q and the slope parameter σ, the wider is the range of the opportunity parameter R and the firm-specific profit f for which $0 < b^* < \bar{b}$ and $b^{G*} = 0$. This result is consistent with the empirical findings and predictions of the model of Aghion *et al.* (2005). Similarly, the lower the scale parameter ρ and the firm-specific profit f, the larger is the parameter space consisting of all remaining parameters for which $0 < b^* < \bar{b}$ and $0 < b^{G*} < \bar{b}$. These predictions are consistent with the empirical findings of Hashmi (2005).

4.2 The prospect-theory model

In this section, I discuss the effect of a variation in parameters on predictions of the prospect-theory model. I propose simulations that measure the position of the peak of the R&D and technology-gap functions for different combinations of parameters. The results of the simulations are presented in a convenient graphical form.

Furthermore, this section discusses mainly the robustness of the prospect-theory model with diminishing sensitivity. The sensitivity analysis of the model with constant sensitivity is limited to the discussion of the value of the minimum loss-aversion parameter $\underline{\lambda}$ (3.17). This approach was chosen mainly due to space limitations. There are, however, two other reasons for concentrating more on the prospect-theory model with diminishing sensitivity.

- It is possible to analyze predictions of the model with constant sensitivity only thanks to the additional assumptions of constant sensitivity and non-negative income, that are not present in the model with diminishing sensitivity. It means that the model with constant sensitivity is a special case of the model with diminishing sensitivity.

- The solution of the model with constant sensitivity in Section 3.2 reveals great similarity to the solution of the basic model. For this reason, we might expect that the PT model with constant sensitivity generates the required predictions for a wider range of parameters around the parameters used in Section 3.2, as in the case of the basic model. However, due to a higher number of parameters in the PT model with constant sensitivity it is difficult to analyze the model in a similar way as in the previous section.

The section is divided in three parts. In Subsection 4.2.1, I start with a simplified situation. I test the robustness of the R&D and technology-gap functions if firms X and Y earn the same profits ($x = 0$). Then in Subsection 4.2.2, I discuss the effect of the individual parameters on the relationship between profits and innovation. Finally in Subsection 4.2.3, I test the robustness of predictions of the model to variation in parameters for different combinations of the profit difference x and the share of firms X in the industry q.

4.2.1 Zero profit difference

This subsection explores the effect of a variation in parameters on predictions of the prospect-theory model for the profit difference $x = 0$. I start with the zero-profit-difference situation for the following reasons. If $x = 0$, the technology-gap function $G(a)$ has a similar shape to the R&D function $c(a)$. Also, the shapes of both functions are not influenced by the share of firms X in the industry q. This simplifies the presentation of the results of sensitivity analysis in this section, and facilitates the discussion of the effects of variation in individual parameters in Subsection 4.2.2.

Furthermore, if the income of managers of firms Y is non-negative and the R&D function $c(a)$ and technology-gap function $G(a)$ are inverse U-shaped for $x = 0$, $c(a)$ is likely to be inverse U-shaped and $G(a)$ is likely to be either decreasing or inverse U-shaped also for $x > 0$ (see Section 3.3 for a detailed discussion). Hence the results of the robustness test for zero profit difference provide relevant information about the robustness of the model for positive profit differences.

Description of simulations

The simulations measure the effect of variation of parameters on the shape of the R&D and technology-gap functions $c(a)$ and $G(a)$ for a given average-profit range $a \in \langle 0, 100 \rangle$. In the simulation, I change the values of all parameters that may affect the shape of $c(a)$ or $G(a)$ for zero profit difference with one exception. The loss-aversion parameter is set at the value directly estimated by Tversky & Kahneman (1992), which is equal to $\lambda = 2.25$. This way, I reduce the computational burden of the simulation without significantly affecting the results, because the loss-aversion parameter has very limited or no effect on the shapes of $c(a)$ or $G(a)$. This is because diminishing-sensitivity ($\alpha < 1$) reduces the size of R&D expenditures of firms so that the income in the case of a failed innovation $w_{iF}(a, c_i)$ is usually higher than zero. Hence loss aversion in the model with diminishing sensitivity usually does not directly restrict the size of R&D expenditures as in the model with constant sensitivity.

In the simulations, I change the values of the following nine parameters: the opportunity parameter R, scale parameter ρ, disutility parameter d in model A, slope parameter σ in model B, probability of success p, base salary ω, ownership share s_0, decreasing-ownership parameter μ, and diminishing-sensitivity parameter α. Simulations in models A and B use different parameters, as the slope parameter σ in model A and the disutility parameter d in model B are equal to zero by definition. So I change the values of eight parameters in each simulation. Furthermore, there are two types of simulation depending on the magnitude of the variation of parameters: a 25% variation and a 50% variation. Hence we have the following four simulations: the 25% and 50% variation in model A, and the 25% and 50% variation in model B.

In each simulation, I use three different values of parameters (see Table 4.1):

- *Medium value* is equal to the value of the parameters presented in Subsections 3.2.4 and 3.3.3. The parameters that have different values in models A and B are the disutility parameter d (model A: $d = 0.05$, model B: $d = 0$) and slope parameter σ (model A: $\sigma = 0$, model B: $\sigma = 0.1$).

- *Low value* is equal to the medium value minus 25% of the medium value (25% variation), or minus 50 % of the medium value (50% variation).

- *High value* is equal to the medium value plus 25% of the medium value (25% variation), or 50 % of the medium value (50% variation). The only exception is the value of the slope parameter σ in the 50% variation that is increased only to $\sigma = 0.14$, so that it does not exceed the low value of the opportunity parameter R in the 50% variation.

Furthermore, high and low values of the scale parameter ρ and the diminishing-sensitivity parameter α are calculated from $1-\rho$ and $1-\alpha$. For example, the 50% variation of $\alpha = 0.88$ is $\alpha = \{0.82, 0.88, 0.94\}$. It is because $1-\rho$ measures the size of decreasing returns to scale, and $1-\alpha$ measures the size of diminishing sensitivity.

Parameters	**25% variation**	**50% variation**
opportunity parameter R	0.21, 0.28, 0.35	0.14, 0.28, 0.42
scale parameter ρ	0.9375, 0.95, 0.9625	0.925, 0.95, 0.975
disutility parameter d (model A)	0.0375, 0.05, 0.0625	0.025, 0.05, 0.075
disutility parameter d (model B)	0	0
slope parameter σ (model A)	0	0
slope parameter σ (model B)	0.075, 0.1, 0.125	0.05, 0.1, 0.14
probability of success p	0.375, 0.5, 0.625	0.25, 0.5, 0.75
base salary ω	30, 40, 50	20, 40, 60
ownership share s_0	1.5, 2, 2.5	1, 2, 3
decreasing-ownership parameter μ	0.375, 0.5, 0.625	0.25, 0.5, 0.75
diminishing-sensitivity parameter α	0.85, 0.88, 0.91	0.82, 0.88, 0.94
loss-aversion parameter λ	2.25	2.25

Table 4.1: The values of parameters used in the proposed simulations.

For each combination of parameters in Table 4.1, I obtain one R&D function $c(a)$ and one technology-gap function $G(a)$. Using three values of each of the eight parameter, I obtain a set of 6 561 pairs of the R&D and technology-gap functions $c(a)$ and $G(a)$ from each simulation. The information that characterizes well the shape of the functions $c(a)$ and $G(a)$ is the position of the maximum. As in the previous chapter, a^* represents the average profit that corresponds to the maximum of $c(a)$, and a^{G*} denotes the average profit that corresponds to the maximum of $G(a)$. (I derive the data on a^* and a^{G*} using the procedure described in Appendix B.4.) Therefore, each simulation generates a set of $6,561$ values of the average profits a^* and a^{G*}.

In model A, the R&D and technology-gap functions $c(a)$ and $G(a)$ have the highest values at the same average profit, i.e. $a^* = a^{G*}$. This is because for $x = 0$, the R&D function $c(a) = c_i^X(a) = c_i^Y(a)$ and the technology gap function is

$$G(a) = (1-p)r(a)c_i^X(a)^\rho,$$

where the reward function $r(a)$ is a constant. In model B, the R&D function peaks at a higher average profit than the technology-gap function ($a^* > a^{G*}$) because $r(a)$ is decreasing in the average profit a.

Results of simulations

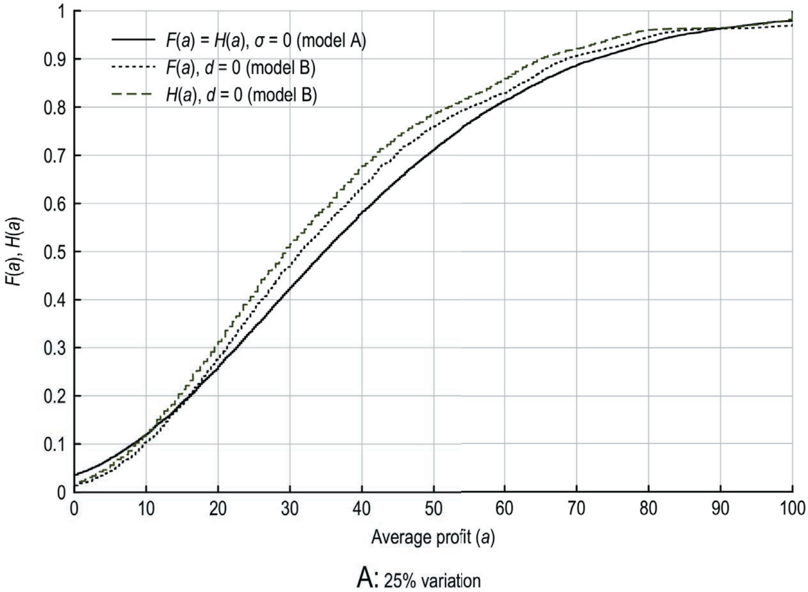
I present the data generated in the simulations using two functions:

- The function $F(a)$ measures the share of the R&D functions $c(a)$ with the average profit $a^* \leq a$. E.g. $F(0) = 0.1$ means that the maximum of 10% of the functions generated in the simulation corresponds to $a = 0$.
- The function $H(a)$ measures the share of the technology-gap functions $G(a)$ with the average profit $a^{G*} \leq a$. E.g. $H(30) = 0.2$ means that 20% of the set of the technology-gap functions have the maximum at $a \leq 30$.

The functions $F(a)$ and $H(a)$ are identical in model A, since the functions $c(a)$ and $G(a)$ have maximum at the same average profit. In model B, $c(a)$ peaks at a higher average profit than $G(a)$, therefore $F(a) < H(a)$ for any average profit $a \in \langle 0, 100 \rangle$.

Figure 4.3 presents functions $F(a)$ and $H(a)$ for all four simulations. Panel A presents functions $F(a)$ and $H(a)$ for the 25% variation in model A and B. Panel B presents functions $F(a)$ and $H(a)$ for the 50% variation in model A and B. The interpretation of the figure is straightforward. The values of $F(0)$ and $H(0)$ measure the share of R&D and technology-gap functions $c(a)$ and $G(a)$ in a given set of 6,561 functions that have the maximum at the average profit $a = 0$. In the PT model with diminishing sensitivity, these functions are likely to be decreasing in the average profit a. On the other hand, the values of $1 - F(99.\bar{9})$ and $1 - H(99.\bar{9})$ show the share of the functions with the maximum at $a = 100$. These functions are likely to be increasing in the average profit a. Finally, the values of $F(99.\bar{9}) - F(0)$ and $H(99.\bar{9}) - H(0)$ measure the share of functions with the peak at $0 < a < 100$. There functions are likely to have an inverted-U form.

For example, the solid line in Panel B shows that approximately 20% of the R&D and technology-gap functions generated by the 50% variation in model A are decreasing in the average profit a ($F(0) \approx 0.2$), 16% of the functions are increasing in a ($F(100) - F(99.9) \approx 0.16$) and approximately 64% of the functions are inverse U-shaped ($F(99.9) - F(0) \approx 0.64$). Furthermore, the figure provides information about the share of the functions with the maximum at any range of the average profit. For example, the solid line in Panel A also shows that the share of functions generated by the 50% variation in model A with $20 < a^* < 60$ is approximately 30%. The figure also shows that the functions $F(a)$ are below the functions $H(a)$ in model B. However, the difference between the functions is rather small. Hence the shift of the technology-gap function $G(a)$ due to a decreasing reward function $r(a)$ is relatively unimportant.



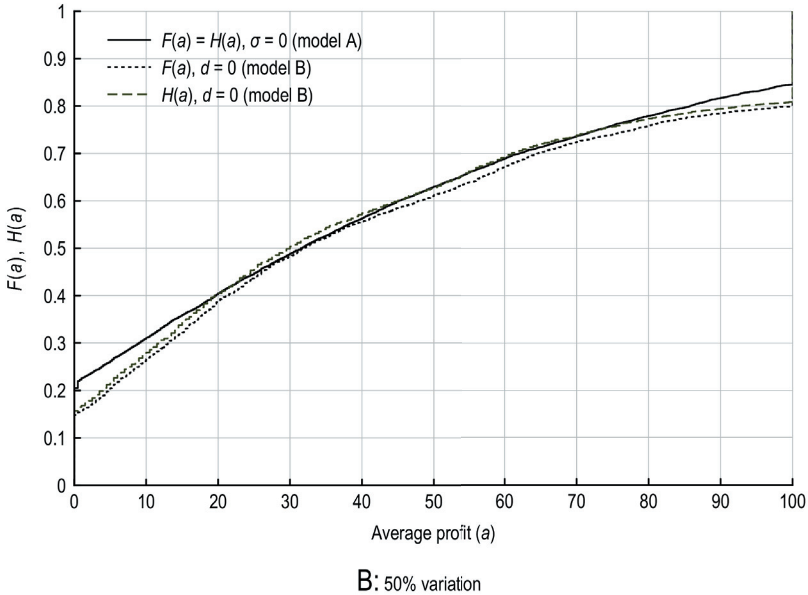


Figure 4.3: The effect of variations in parameters on predictions of the model
The lines present the functions $F(a)$ and $H(a)$ that measure the share of the functions $c(a)$ and $G(a)$ with a^* and a^{G*} lower or equal to $a \in \langle 0, 100 \rangle$ in a set of 6,561 functions $c(a)$ and $G(a)$ generated for the parameter values from Table 4.1.

Table 4.2 summarizes the main findings presented in Figure 4.3. The second column (denoted by $a^* = a^{G*} = 0$) presents the shares of the decreasing R&D and technology-gap functions $c(a)$ and $G(a)$ in the datasets generated by the four simulations. While the shares are the same in model A, the share of the decreasing R&D functions $c(a)$ is lower than the share of the decreasing technology-gap functions $G(a)$ in model B. The third column displays the share of the increasing $c(a)$ and $G(a)$. Most importantly, the fourth column shows what share of the R&D and technology-gap functions is inverse U-shaped. We see that the results are similar in both models A and B and that the share of inverse U-shaped R&D and technology-gap functions is lower for the 50% variation than for the 25% variation.

Sets of $c(a)$ and $G(a)$	$a^* = a^{G*} = 0$	$a^* = a^{G*} = 100$	$0 < a^* = a^{G*} < 100$
25% variation, model A	0.04	0.02	0.94
50% variation, model A	0.20	0.16	0.64
Sets of $c(a)$	$a^* = 0$	$a^* = 100$	$0 < a^* < 100$
25% variation, model B	0.01	0.03	0.96
50% variation, model B	0.15	0.2	0.65
Sets of $G(a)$	$a^{G*} = 0$	$a^{G*} = 100$	$0 < a^{G*} < 100$
25% variation, model B	0.02	0.02	0.96
50% variation, model B	0.16	0.19	0.65

Table 4.2: A summary of the main findings presented in Figure 4.3
The table shows shares of the R&D functions $c(a)$ with $a^* = 0$, $a^* = 100$ and $0 < a^* < 100$ and the shares of the technology-gap functions $G(a)$ with $a^{G*} = 0$, $a^{G*} = 100$, and $0 < a^{G*} < 100$ in different sets of $c(a)$ and $G(a)$.

The interpretation of the results is straightforward. If the profit difference is $x = 0$, approximately 95% of all R&D and technology-gap functions $c(a)$ and $G(a)$ created in the 25% variation are inverse U-shaped, and 64 or 65% of $c(a)$ and $G(a)$ functions created in the 50% variation are inverse U-shaped. Furthermore, if the R&D function is inverse U-shaped, also all technology gap functions in model A and a large majority of the technology gap functions in model B are inverse U-shaped. This pattern is consistent with the empirical findings of Hashmi (2005).

Moreover, the previous chapter shows that if the functions $c(a)$ and $G(a)$ are inverse U-shaped for the profit difference $x = 0$, $c(a)$ tends to be inverse U-shaped and $G(a)$ either decreasing or inverse U-shaped for positive profit differences. Therefore, a similar proportion of the functions that are consistent with the empirical findings of Hashmi (2005) are likely to be consistent either with the findings of Hashmi (2005) or Aghion *et al.* (2005) if the profit difference is positive. But before I consider predictions of the model for positive profit differences, I explore the effect of individual parameters on the robustness of predictions for the profit difference $x = 0$.

4.2.2 The effect of individual parameters

In this subsection, I keep one of the parameters constant and vary all other parameters of the simulation. This way, I decompose each of the functions $F(a)$ presented in the previous subsection into 24 different functions, one for each value of the parameters. That is, each of the four datasets (the 25% and 50% variations in model A and the 25% and 50% variations in model B) containing 6,561 values of a^* is divided into 24 subsets each containing 2,187 values of a^*. The functions $F(a)$ for the data of each of the subsets are presented in Figures 4.4–4.10. Each function $F(a)$ corresponds to one value of the parameters that are varied in Table 4.1. For example, the solid line in Panel 4.4A presents the functions $F(a)$ using the dataset generated by the 25% variation in model A for the opportunity parameter $R = 0.21$.

The aim of this exercise is to see what is the effect of variation in individual parameters on the distribution of the shapes of the R&D functions $c(a)$. In particular, we will consider two related questions:

1. What is the direction and size of a shift in the function $F(a)$ due to a rise in individual parameters. Both the direction and size of the effect are apparent from the following figures. We may capture the effect also using the measure A^*, that is calculated as the average of 2,187 values of a^* in a given dataset (for the values of A^* for each of the datasets, see Table 4.4). This discussion provides us with information about the results of the model for different values of the individual parameters. Moreover, we find out what parameters contribute more to the variation in the average profit a^*.

2. What is the effect of variation in individual parameters on the robustness of the inverted-U result between the average profit and R&D expenditures. The measure of robustness of the inverted-U result we used already in the previous subsection is the share of the R&D functions with $0 < a^* < 100$, which will be denoted by I (for the values of I for each of the datasets, see Table 4.4). We will see whether a change in the value of a parameter in both directions reduces the robustness of the inverted-U result to variation in all other parameters, or whether a change in some direction increases the robustness of the prediction. If a change in both directions reduces the robustness of the inverted-U result, high and low values of the parameter are clearly responsible for a relatively larger share of the increasing or decreasing R&D functions. Then variation of the parameter reduces the robustness of the inverted-U result for the entire dataset.

		Datasets							
		model A				model B			
		25% variation		50% variation		25% variation		50% variation	
		I	A^*	I	A^*	I	A^*	I	A^*
R	low	0.9	20.4	0.59	14.8	0.96	17.2	0.64	11.2
	medium	0.98	38	0.7	42.3	1	34.7	0.79	44.1
	high	0.95	55.6	0.63	64.4	0.91	56.6	0.52	73.2
ρ	low	0.93	25.4	0.67	23.4	0.96	21.7	0.71	20
	medium	0.96	36.4	0.67	38.1	1	33.7	0.72	40
	high	0.94	52.2	0.57	60	0.91	53.1	0.53	67.8
d or σ	low	0.95	48.3	0.65	56	0.9	45.7	0.55	56.2
	medium	0.95	40.1	0.66	38.2	0.99	35	0.70	40.6
	high	0.93	28.6	0.61	27.3	0.98	27.8	0.70	31.7
p	low	0.96	43.6	0.7	48	0.97	40	0.7	48.8
	medium	0.95	37.9	0.66	40	0.97	35.6	0.66	42
	high	0.92	32.6	0.56	34	0.95	32.6	0.59	37.7
ω	low	0.97	41.2	0.72	44.9	0.96	39.4	0.75	47.7
	medium	0.95	37.9	0.63	40.1	0.96	36.1	0.65	42.4
	high	0.92	34.9	0.57	36.6	0.94	33	0.56	38.4
s_0	low	0.89	25.5	0.59	21.3	0.94	32.7	0.54	37.3
	medium	0.98	39.2	0.71	43.9	0.96	36.7	0.68	44.1
	high	0.96	49.3	0.73	56.3	0.96	39.2	0.73	47.1
μ	low	0.92	45.9	0.7	48	0.96	35.8	0.66	41.9
	medium	0.96	37.2	0.66	39.4	0.95	36.1	0.66	42.5
	high	0.96	31	0.74	30.1	0.95	36.6	0.63	44.1
α	low	0.95	33.7	0.64	34.2	0.96	39.1	0.67	47.1
	medium	0.95	38.4	0.65	41.6	0.96	36.3	0.66	43.3
	high	0.94	41.9	0.61	45.7	0.95	33.1	0.62	38.2

Table 4.3: The effect of individual parameters
The columns labeled by I present the values of the share of the R&D functions with $0 < a^* < 100$ for 96 different subsets of 2,187 values of the average profit a^*. The columns labeled by A^* present the average value of a^* calculated for 24 different subsets of 2,187 values of a^*.

The opportunity parameter R

A rise in the opportunity parameter R shifts the functions $F(a)$ in Figure 4.4 to the right. It means that on average, the maximum of the R&D function $c(a)$ shifts to a higher average profit a. The shift of the function $F(a)$ due to a rise in the opportunity parameter R from low to high values is larger in model B than in model A. In model A, a rise in R from low to high values increases A^* approximately by 35 (25% variation) or 49 (50% variation). In model B, a rise in the average profit a from low to high values increases A^* approximately by 39 (25% variation) or 62 (50% variation).

It is evident from Figure 4.4 that a rise or a reduction in R reduces robustness of the inverted-U result, as the functions $F(a)$ for high and low R indicate a higher share of increasing or decreasing R&D functions than the functions $F(a)$ for the medium value $R = 0.28$. This effect is more evident in model B. Consistently with this observation, the value of I for the medium value of $R = 0.28$ in Table 4.4 is higher than for high and low values of the opportunity parameter R.

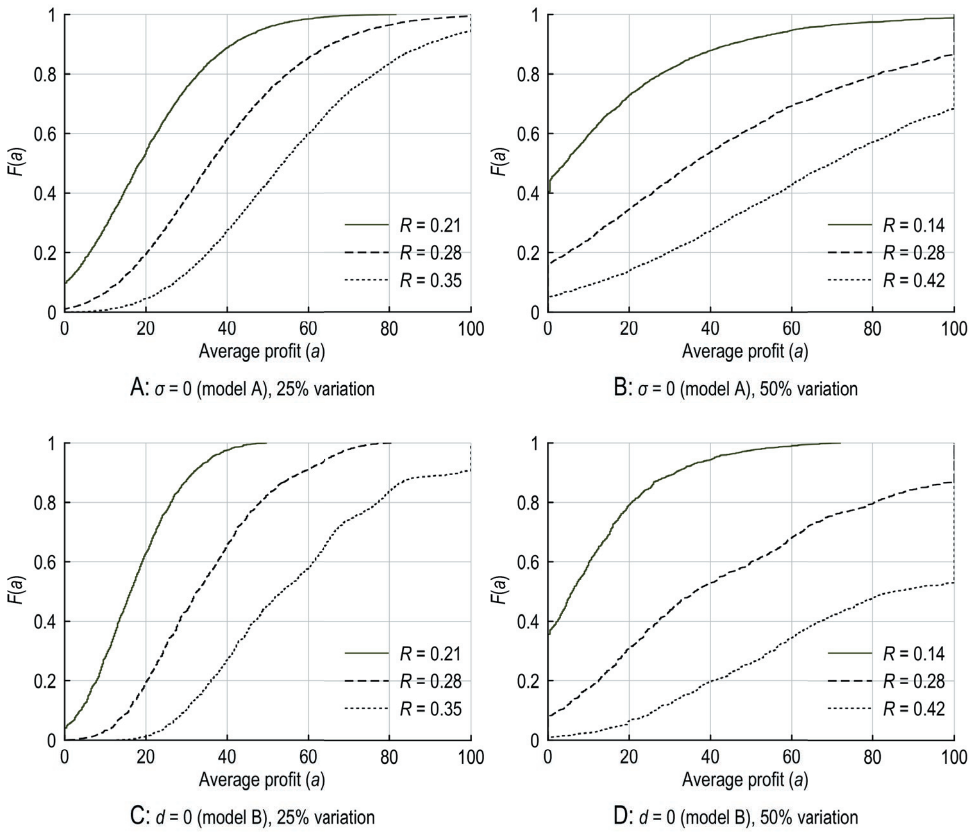


Figure 4.4: The effect of the opportunity parameter R
The figure presents the effect of the opportunity parameter R on functions $F(a)$. Each line corresponds to a dataset of 2,187 observations generated using the process described in Appendix B.4 for given values of R, the profit difference $x = 0$ and the parameter values from Table 4.1.

The scale parameter ρ

Variation in the scale parameter ρ has similar effects as variation in the opportunity parameter R. A rise in ρ leads to a rightward shift of the functions $F(a)$ (see Figure 4.5). That is, the peak of $c(a)$ moves on average to a higher average profit a. The shift of $F(a)$ is somewhat smaller compared to the shift due to a rise in the opportunity parameter R. Table 4.4 shows that a rise in ρ from low to high values increases A^* by approximately 27

(25% variation) or 37 (50% variation) in model A and by 31 (25% variation) or 48 (50% variation) in model B.

As in Figure 4.4, the shapes of the functions $F(a)$ for high and low ρ in Figure 4.5 indicate a higher share of increasing or decreasing functions $c(a)$ than the functions $F(a)$ for the medium value of $R = 0.28$. As in the case of variation in R, a rise or a reduction in ρ reduces the robustness of the inverted-U result. Consistently with this observation, Table 4.4 shows that the value of I for $\rho = 0.95$ is higher than the value of I for high and low values of ρ.

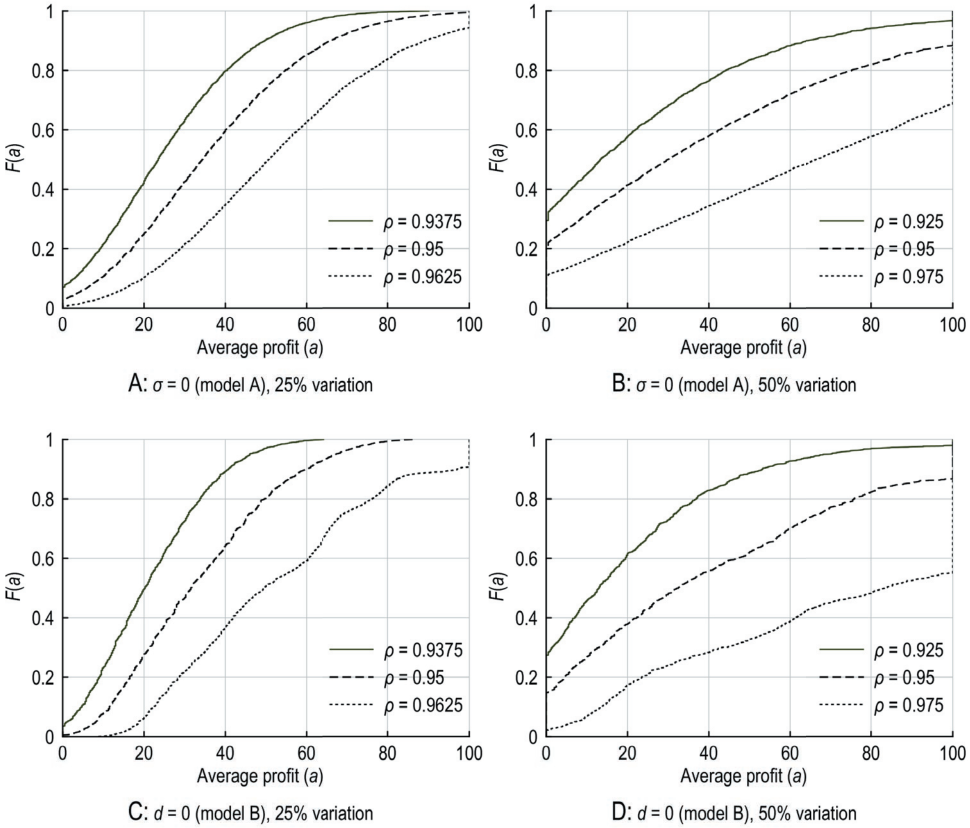


Figure 4.5: The effect of the scale parameter ρ

The figure presents the effect of the scale parameter ρ on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of the scale parameter ρ, the profit difference $x = 0$ and the parameter values from Table 4.1.

The disutility parameter d and slope parameter σ

In contrast to the previous figures, a rise in the disutility parameter d and the slope parameter σ in Figure 4.6 shifts the functions $F(a)$ to the left, which means that a rise in d and σ tends to move the peaks of the R&D functions $c(a)$ to the left. The shift of $F(a)$ due to a rise in d or σ is smaller compared to Figures 4.4 and 4.5. A rise in d from low to high values reduces A^* by approximately 20 (25% variation) or 29 (50% variation), while a rise in σ reduces A^* by approximately 18 (25% variation) or 25 (50% variation).

The effect of the parameters d and σ on the robustness of the inverted-U result is somewhat smaller compared to the effect of R or ρ. However, as for R or ρ a rise or a reduction of d and σ still seems to reduce slightly the robustness of the inverted-U result. This effect is larger in the case of a reduction in σ.

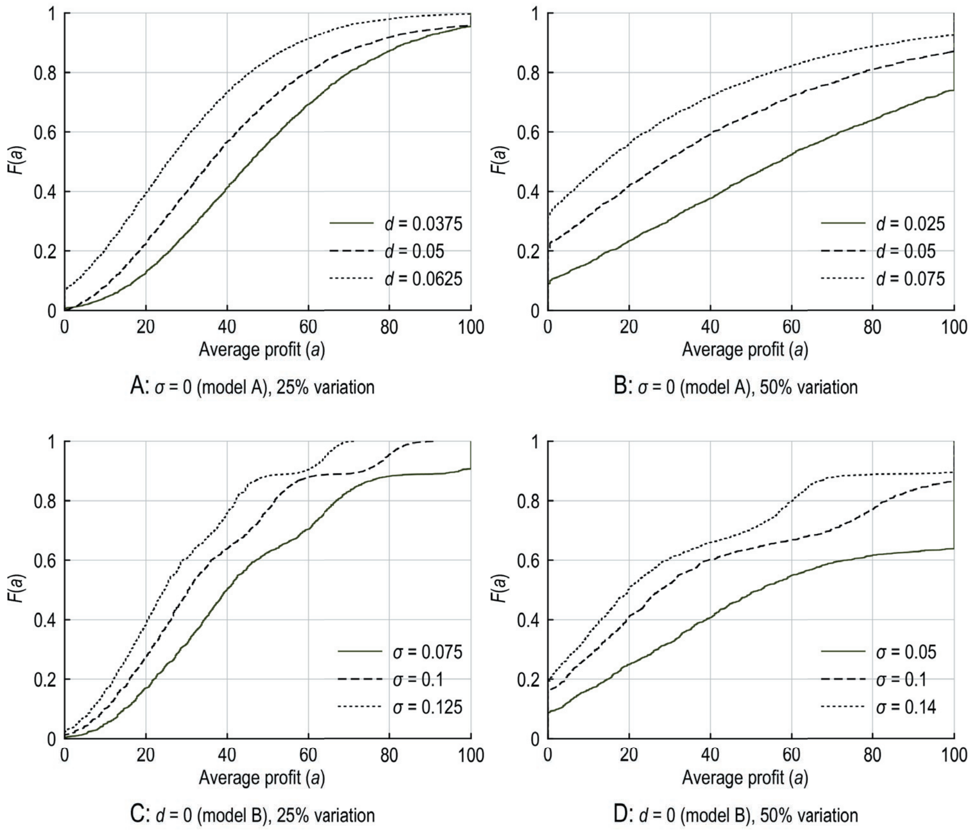


Figure 4.6: The effect of the disutility parameter d and the slope parameter σ
The figure presents the effect of d and σ on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for the given values of d or σ, the profit difference $x = 0$ and the parameter values from Table 4.1.

The probability of success p

Similarly to Figure 4.6, a rise in the probability of success p shifts the functions $F(a)$ in Figure 4.7 to the left which means that, on average, the peaks of the R&D functions $c(a)$ move to the left. However, the size of the effect is relatively small. Table 4.4 shows that a rise in the probability of success p from low to high values reduces A^* by values between 5 and 15.

The effect of variation in the probability of success p on the robustness of the inverted-U result shown in Figure 4.7 is different from the effects in the previous graphs. The functions $F(a)$ in Figure 4.7 converge with increasing average profit a. A rise in p increases the share of decreasing functions $c(a)$ in each subset of $c(a)$, while leaving the share of increasing $c(a)$ constant. It means that while a rise in p reduces robustness of the inverted-U result, a reduction in p leads to higher robustness of the prediction.

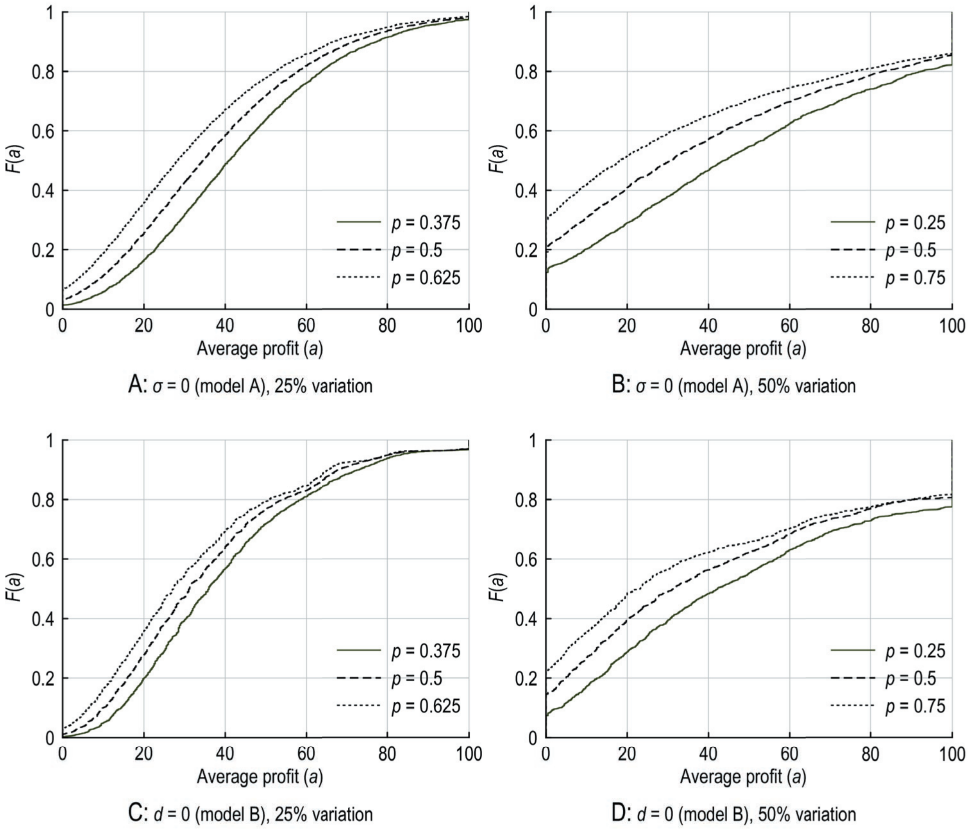


Figure 4.7: The effect of the probability of success p
The figure presents the effect of the probability of success p on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of p, the profit difference $x = 0$ and the parameter values from Table 4.1.

The base salary ω

Variation in the base salary ω has similar effects as variation in the probability of success p. A rise in ω shifts the functions $F(a)$ to the left (see Figure 4.8). On average, the R&D functions $c(a)$ peak at lower average profits a. The shift of $F(a)$ due to a rise in ω is slightly smaller than the shift due to a rise in the probability of success p. A rise in ω from low to high values reduces A^* by values between 5 and 10.

Also the effect of the base salary ω on the robustness of the inverted-U result is similar to the effect of the probability of success p. The functions $F(a)$ in Figure 4.8 clearly converge with an increasing average profit a. Therefore, a rise in ω reduces I, while a reduction in ω tends to increase I.

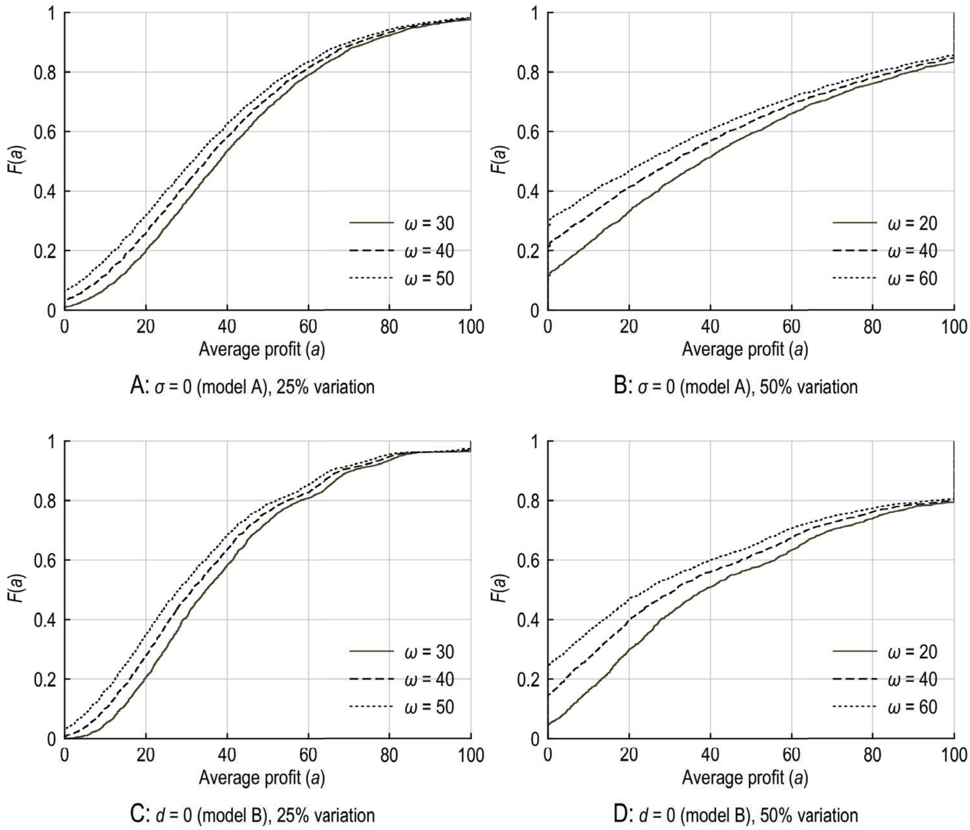


Figure 4.8: The effect of the base salary ω
The figure presents the effect of the base salary ω on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of ω, the profit difference $x = 0$ and the parameter values from Table 4.1.

The ownership share s_0

Figure 4.9 shows that a rise in the ownership share s_0 shifts functions $F(a)$ to the right. The size of the shift is different in models A and B. While in model A a rise in s_0 from low to high values increases A^* by 24.4 (25% variation) or 35 (50% variation), it increases A^* only by 6.5 (25% variation) or 9.8 (50% variation) in model B. This difference is due to the fact that the decisions of managers in model A depend on the size of their income relative to the disutility of innovation, while the disutility of innovation in model B is zero.

Also the effect of the ownership share s_0 on the robustness of the inverted-U result is different in models A and B. While the effect is not clear in model A, the functions $F(a)$ clearly converge in model B. A rise in s_0 in model B increases the robustness of the inverted-U prediction to variation in all other parameters.

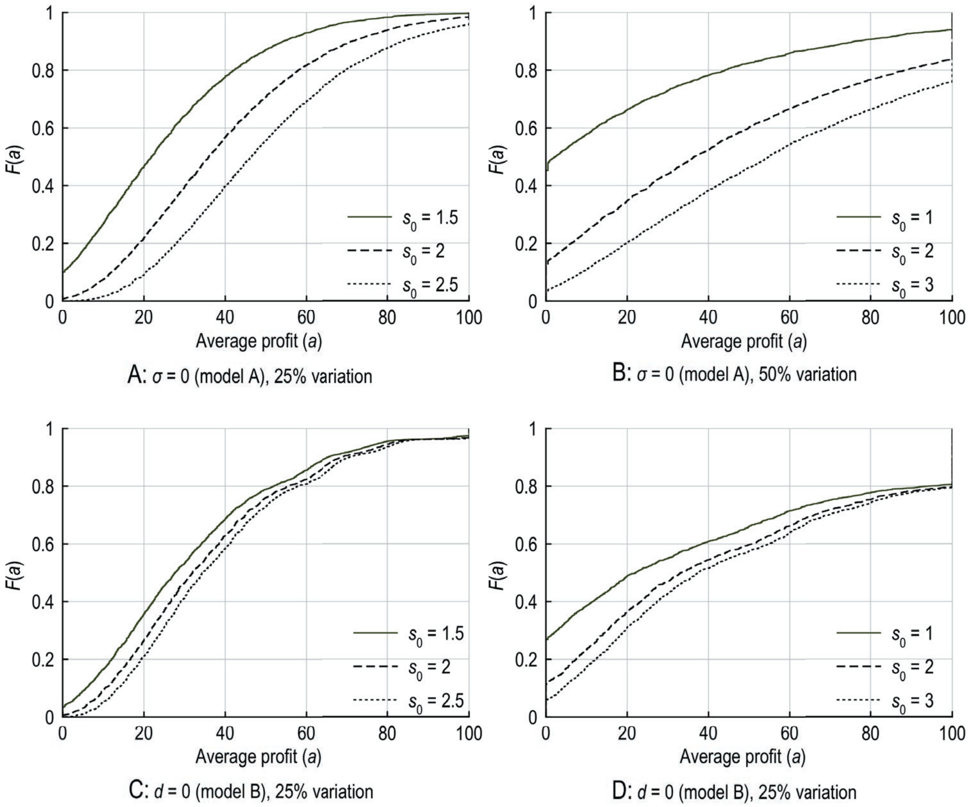


Figure 4.9: The effect of the ownership share s_0
The figure presents the effect of the ownership share s_0 on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of s_0, the profit difference $x = 0$ and the parameter values from Table 4.1.

The decreasing-ownership parameter μ

A rise in the decreasing-ownership parameter μ leads to a leftward shift of the functions $F(a)$ in model A, which means that the peaks of the R&D functions move, on average, to lower average profits a. On the other hand, a rise in μ has almost no effect on functions $F(a)$ in model B (see Figure 4.10). A rise in μ from low to high values reduces A^* by 14.9 (25% variation) or 17.9 (50% variation) in model A and increases A^* by 0.8 (25% variation) or 2.2 (50% variation) in model B. As in the case of the ownership share, this difference is due to the absence of the disutility of innovation in model B.

Variation in μ does not have a clear effect on the robustness of the inverted-U result in model A, as a rise and a reduction in μ seem to reduce I for the 25% variation (see Panel 4.10A) and increase the I for the 50% variation (see Panel 4.10B). The effect of μ on the robustness of the inverted-U result in model B is negligible.

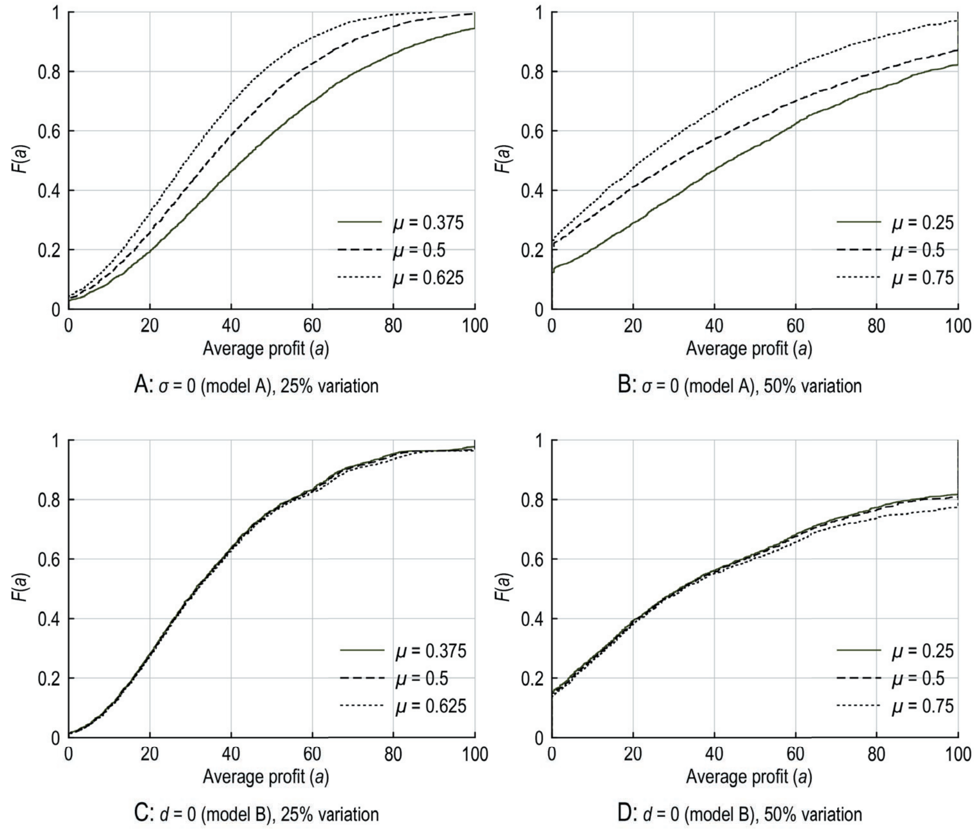


Figure 4.10: The effect of the decreasing-ownership parameter μ
The figure presents the effect of the decreasing-ownership parameter μ on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of μ, the profit difference $x = 0$ and the parameter values from Table 4.1.

The diminishing-sensitivity parameter α

Figure 4.11 shows that a rise in the diminishing-sensitivity parameter α shifts the functions $F(a)$ in the opposite directions: to the right in model A and to the left in model B. This is due to the effects of disutility of innovation and diminishing sensitivity on the shape of the R&D function in model A described in Subsection 3.3.1 (see also Figure 3.6). The size of the shift is relatively small. A rise in the diminishing-sensitivity parameter α from low to high values increases A^* by 8.2 (25% variation) or 11.5 (50% variation) in model A and reduces A^* by 6 (25% variation) or 8.9 (50% variation) in model B.

Similarly, the effect of the diminishing-sensitivity parameter α on the robustness of the inverted-U result presented in Figure 4.11 and in Table 4.4 is relatively small and the direction of the effect is difficult to determine.

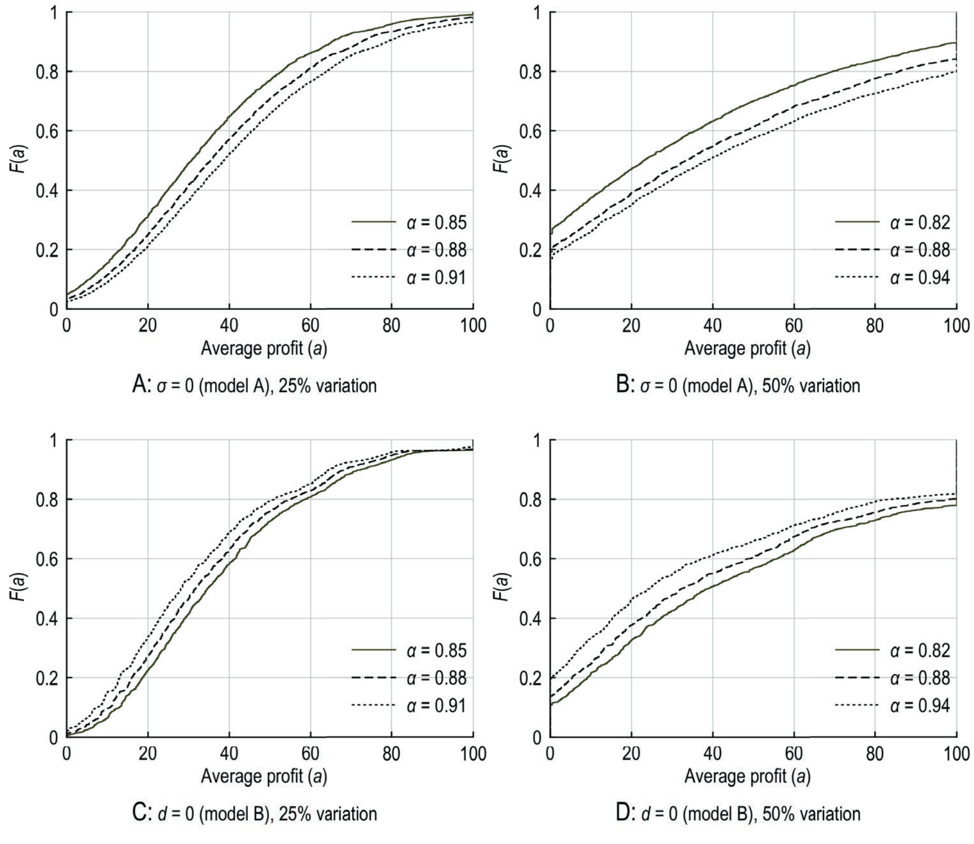


Figure 4.11: The effect of the diminishing-sensitivity parameter α
The figure presents the effect of the diminishing-sensitivity parameter α on functions $F(a)$. Each line corresponds to 2,187 observations generated using the process described in Appendix B.4 for given values of α, the profit difference $x = 0$ and the parameter values from Table 4.1.

After discussing the effect of three different values of the diminishing-sensitivity parameter $\alpha < 1$ on the shape of the R&D function $c(a)$, I will add a short discussion of the effect of constant sensitivity $\alpha = 1$ for the profit difference $x = 0$. It follows from the equation (3.17) that the R&D function $c(a)$ will be either inverse V-shaped or increasing in the average profit a if the loss-aversion parameter

$$\lambda \geq \underline{\lambda} = \frac{s_0\rho(1+R) - (ps_0 + d)\,(\omega/s_0)]^{1-\rho}}{(1-p)s_0\,(\omega/s_0)^{1-\rho}}.$$

I present the distribution of the values of the minimum loss-aversion parameters $\underline{\lambda}$ generated for the diminishing-sensitivity parameter $\alpha = 1$, the profit difference $x = 0$ and for the parameter values from Table 4.1. Using all possible combinations of parameters, I generate four different sets of 2,187 values of $\underline{\lambda}$ for the 25% variation in models A and B, and the 50% variation in models A and B. I present the data using a function $L(\lambda)$ that measures the share of the values of the minimum loss-aversion parameters $\underline{\lambda}$ in different datasets with $\underline{\lambda} \leq \lambda$.

Figure 4.12 presents the functions $L(\lambda)$. It shows that for almost all combinations of parameters, the minimum loss-aversion λ is lower than 2.25, which is the value estimated by Tversky & Kahneman (1992). For all combinations of parameters in the 25% variation and more than 90% of the combinations of parameters in the 50% variation, the minimum loss-aversion λ is lower than 1.625 (which would be the *low value* of λ in the case of the 50% variation). Hence the inverse-V result in the model with constant sensitivity and with the profit difference $x = 0$ is robust to variation in parameters even for the low value of loss-aversion parameter $\lambda = 1.625$.

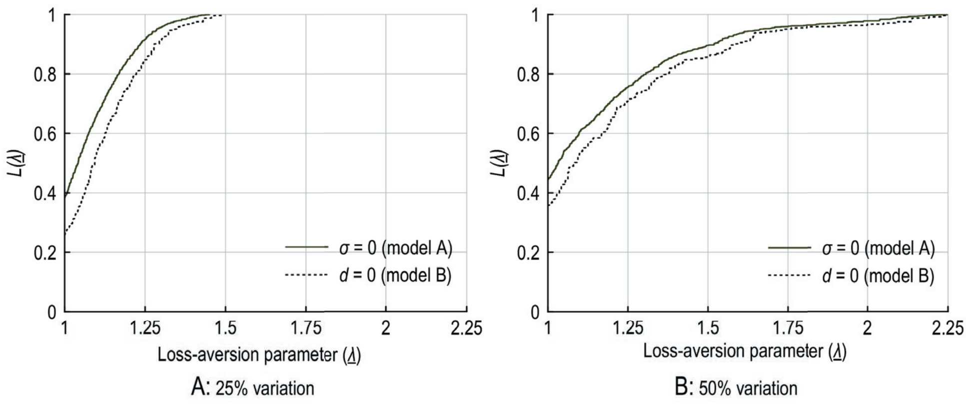


Figure 4.12: The values of the minimum loss-aversion parameter $\underline{\lambda}$
The figure presents the function $L(\lambda)$ that measures the share of the minimum loss-aversion parameters $\underline{\lambda}$ that are lower or equal to $\lambda \in \langle 1, 2.25 \rangle$ in four sets of 2,187 values of the minimum loss-aversion parameter generated using the parameter values from Table 4.1, $\alpha = 1$, and $x = 0$.

Summary

This subsection has discussed the effect of individual parameters on the shape of the R&D function $c(a)$. It addressed two questions:

1. What is the direction and the size of the shift of the function $F(a)$ due to a change in the value of individual parameters. The shift in the function $F(a)$ measures the average effect of variation in parameters on the position of the peak of the R&D functions $c(a)$.

2. What is the effect of a change in the value of individual parameters on the robustness of the inverted-U result.

The effect of individual parameters on the direction of the shift of $F(a)$ is as follows. A rise in the opportunity parameter R, scale parameter ρ, ownership share s_0, decreasing-ownership parameter μ in model B and diminishing-sensitivity parameter α in model A shifts the function $F(a)$ to the right, which means that functions $c(a)$ peak on average at higher values of the average profit a. On the other hand, a rise in the disutility parameter d, slope parameter σ, probability of success p, base salary ω, decreasing-ownership parameter μ in model B and diminishing-sensitivity parameter α in model B shifts the function $F(a)$ to the left, so that the function $c(a)$ peaks at lower average profits a.

Furthermore, the effect of individual parameters on the size of the shift of $F(a)$ is as follows. A rise from low to high values of the opportunity parameter R, scale parameter ρ, disutility parameter d, slope parameter σ, and ownership share s_0 in model A changes the value of A^* by more than 20 at least in one of the versions of the simulation. On the other hand, a rise from low to high values of the base salary ω and diminishing-sensitivity parameter α changes the value of A^* by less than 10 in all versions of the simulation, and a rise in the value of the ownership share s_0 and decreasing-ownership parameter μ changes the value of A^* by less than 10 in model B. Hence while changes in R, ρ, d, σ and s_0 have relatively large effects on the position of the peak of the R&D functions, changes in ω, α in both models and s_0 and μ in model B have relatively low effects on a^*.

The effect of individual parameters on the robustness of the inverted-U result can be summarized as follows. The effect of variation of μ and α on the robustness of the inverted-U prediction is not clear. A change in both directions in the value of the opportunity parameter R, scale parameter ρ, disutility parameter d and slope parameter σ reduces the robustness of the inverted-U result. On the other hand, the robustness of the inverted-U prediction increases with a rise in the probability of success p and ownership share s_0 and with a reduction in the base salary ω. Consequently, if the profit difference $x = 0$, the inverted-U shape of the R&D function $c(a)$ is likely to be more robust to variation in parameters for a high probability of success p and ownership share s_0 and for a low base salary ω.

4.2.3 Positive profit difference

In previous subsections, I discussed the robustness of predictions of the PT model for zero profit difference ($x = 0$). In this subsection, I show what are the effects of positive profit difference on predictions of the model. I run 6 additional simulations using different combinations of the profit difference x and the share of firms X in the industry q for each simulation. The values of x and q are chosen to cover important parts of the realistic ranges of these parameters. The values of the profit difference are $x = \{20, 35\}$, and the values of the share of firms X in the industry are $q = \{0.2, 0.5, 0.8\}$. Together with the four simulations for $x = 0$, this subsection presents datasets from 28 simulations. Each simulation generates 6,561 R&D and technology-gap functions using combinations of parameters presented in Table 4.1. For each function $c(a)$ and $G(a)$, I find the average profits a^* and a^{G*} (for the procedure used, see Appendix B.4). Hence each of the 28 datasets presented in this subsection consists of 6,561 values of a^* and a^{G*}.

Figures 4.13–4.16 use functions $F(a)$ and $H(a)$ to present the data graphically. The function $F(a)$ measures the share of the R&D functions $c(a)$ with the maximum at $a^* < a$ and the function $H(a)$ measures the share of the technology-gap functions $G(a)$ with the maximum at $a^{G*} < a$ in a given set of 6,561 functions $c(a)$ and $G(a)$ generated in each simulation. The solid lines are the functions $F(a)$ and $H(a)$ for the profit difference $x = 0$. These functions are identical to the curves presented in Figure 4.3. The dashed and dotted lines correspond to the profit differences $x = 20$ and $x = 35$, respectively. The rows present $F(a)$ and $H(a)$ for the shares of firms X in the industry $q = 0.2$, 0.5, and 0.8.

The shapes of the functions $F(a)$ and $H(a)$ in Figures 4.13–4.16 are consistent with the following two findings explained in Section 3.3:

- Finding 1: If managers earn non-negative income $w_i(a, c_i)$, the effect of the profit difference x and the share of the firms X in the industry q on the shape of the R&D function $c(a)$ is likely to be small.

- Finding 2: If managers earn non-negative incomes $w_i(a, c_i) \geq 0$, the diminishing-sensitivity parameter $\alpha < 1$ and the technology-gap function is inverse-U shaped, a rise in the profit difference x and a reduction in the share of firms X in the industry q are likely to reduce the average profit a^{G*}.

The managers will earn negative incomes $w_i(a, c_i)$ if they expect to earn negative income in the case of zero R&D expenditures $w_i(a, 0)$, that is if $\omega - s_0 qx < 0$ (see (3.27)). If the profit difference $x = 0$, it is always true that $\omega - s_0 qx \geq 0$ as the base salary $\omega \geq 0$. If $x > 0$, the income of managers of firms Y $w_i(a, c_i) = w_i(a, 0)$ might be negative. Let S denote the share of parameter combinations in a given simulation for which $\omega - s_0 qx < 0$. Table 4.4 presents the values of S for different combinations of x and q in the 25% and 50% variations. The table shows that the share S is non-decreasing in the parameters x and q. (Note that the values of S in models A and B are the same, because $\omega - s_0 qx$ depends neither on the disutility parameter d nor on the slope parameter σ.)

Sets of $c(a)$ and $G(a)$		S
25% variation model A and B	$x = 0$	0
	$x = 20,\ q = 0.2$	0
	$x = 35,\ q = 0.2$	0
	$x = 20,\ q = 0.5$	0
	$x = 35,\ q = 0.5$	1/3
	$x = 20,\ q = 0.8$	2/9
	$x = 35,\ q = 0.8$	8/9
50% variation model A and B	$x = 0$	0
	$x = 20,\ q = 0.2$	0
	$x = 35,\ q = 0.2$	1/9
	$x = 20,\ q = 0.5$	1/9
	$x = 35,\ q = 0.5$	1/3
	$x = 20,\ q = 0.8$	1/3
	$x = 35,\ q = 0.8$	2/3

Table 4.4: The share of combinations of parameters with $\omega - s_0qx < 0$
The table shows the share of combinations of parameters S for which $\omega - s_0qx < 0$ in different sets of the functions $c(a)$ and $G(a)$.

Consistently with Finding 1, Figures 4.13–4.16 show that the profit difference x and the share of firms X q have almost no effect on $F(a)$ if S is relatively low (the income of managers of firms Y is relatively high). In fact, the functions $F(a)$ for the profit difference $x > 0$ are slightly below the functions $F(a)$ for $x = 0$. It means that on average, a rise in x shifts the peak of the inverse U-shaped R&D function $c(a)$ to the right. However if x and q are high, the functions $F(a)$ tend to be higher for a lower part of the average-profit range (for example, see the dotted lines in Panels 4.13–4.16E).

The irregular shapes of the functions $F(a)$ have the following explanation. Suppose that the profit difference x and the share of firms X in the industry q are high enough, so that for some combinations of parameters $\omega - s_0qx < 0$. Then the R&D function $c(a)$ is likely to be decreasing for low average profits (for the explanation of this effect, see Subsection 3.3.1). If for the same parameters and $x = 0$ the R&D function peaked at a low average profit a, then for high x the entire R&D function may be decreasing in a because of the effect of negative income ($a^* = 0$). On the other hand, if the R&D function for $x = 0$ peaked at a high average profit a, then the position of the peak of the R&D function a^* is not likely to change for high x (for examples of such R&D functions, see Panels 3.7 and 3.8D).

Consider the following example. Suppose the R&D function $c(a)$ for a given combination of parameters and for the profit difference $x = 0$ is inverse U-shaped $c(a)$ with the peak at the average profit $a^* = 10$. Now due to a rise in x, the R&D function $c(a)$ is decreasing for $a < 20$ and has a similar shape as for $x = 0$ for $a \geq 20$. Then the R&D function $c(a)$ is decreasing in a, i.e. the maximum of the function corresponds to $a^* = 0$. However, if the R&D function peaks at $a^* = 90$ for $x = 0$, then the maximum is likely to remain at a^* close to 90 even if $c(a)$ is decreasing for $a < 20$. This explains why some of the dotted or dashed $F(a)$ lines are above the solid lines for low average profits a but slightly below the solid lines for high average profits a.

Consistently with Finding 2, Figures 4.13–4.16 show that a rise in the profit difference x and a reduction in the share of firms X in the industry q leads to a higher function $H(a)$ if the share $S = 0$ (see e.g. the lines in Panels 4.13 and 4.14B and the solid and dashed lines in Panels 4.13 and 4.14D). However, the functions $H(a)$ have an irregular steeply increasing shape at low average profits a if $S > 0$. In this case, the dotted $H(a)$ lines might lie below the corresponding dashed or solid lines.

The explanation of the dented shape of the functions $H(a)$ is as follows. If $S > 0$, a part of the parameter combinations gives $\omega - s_0qx < 0$. For these parameter combinations, the technology-gap functions $G(a)$ are likely to be increasing at low average profits a (see Subsection 3.3.2 for the explanation). The higher the x or q, the higher is the share of parameter combinations S producing an increasing $G(a)$ at low a. It means that the maximum of higher proportion of functions $G(a)$ cannot correspond to very low average profits, at which $G(a)$ is increasing. Furthermore, the higher the x or q, the lower is the value of $\omega - s_0qx$ for some of these combinations. A lower $\omega - s_0qx$ implies a higher range of average profits a for which the technology-gap function $G(a)$ is increasing. Hence the irregular steeply increasing parts of functions $H(a)$ are likely to stretch over a wider range of the average profits a. Consistently with the explanation, the functions $H(a)$ for high x and q in Figures 4.13–4.16 have lower values of $H(0)$ and their dented parts correspond to a larger part of the average-profit range. On the other hand, S seems to have no effect on $H(a)$ if the average profit a is relatively high. Figures 4.13–4.16 clearly show that higher x and lower q increase the function $H(a)$ for high values of a.

Furthermore, the figures show that a rise in the average profit a reduces the effect of any change in the profit difference x or in the share of firms X in the industry q on the function $H(a)$. For example, the same change in x or q affects the values of $H(40)$ more than the values of $H(100)$. The effect arises because the concavity of the prospect-theory value function $v(w(a, c_i))$ is decreasing in income $w_i(a, c_i) > 0$ at a decreasing rate (see Subsection 3.3.2 for a more detailed explanation). The lower the average profit a, the higher the effect of a change in x or q on managerial incentives. Larger changes in incentives lead to higher differences in technology-gap functions, and consequently to larger shifts in a^{G*}.

To summarize, a rise in the profit difference x or a reduction in the share of firms X in the industry q have almost no effect on $F(a)$ but increase $H(0)$ if $S = 0$. Hence the proportion of parameter combinations producing an inverse U-shaped R&D function ($0 < a^* < 100$) and a decreasing technology-gap function ($a^{G*} = 0$) is likely to be higher than zero. The same result is likely to emerge also if $S > 0$. However, the share of parameter combinations producing this result will be lower because the negative income $w_i(a, 0)$ reduces the shares of the R&D functions $c(a)$ with $0 < a^* < 100$ and of the technology-gap functions $G(a)$ with $a^{G*} = 0$.

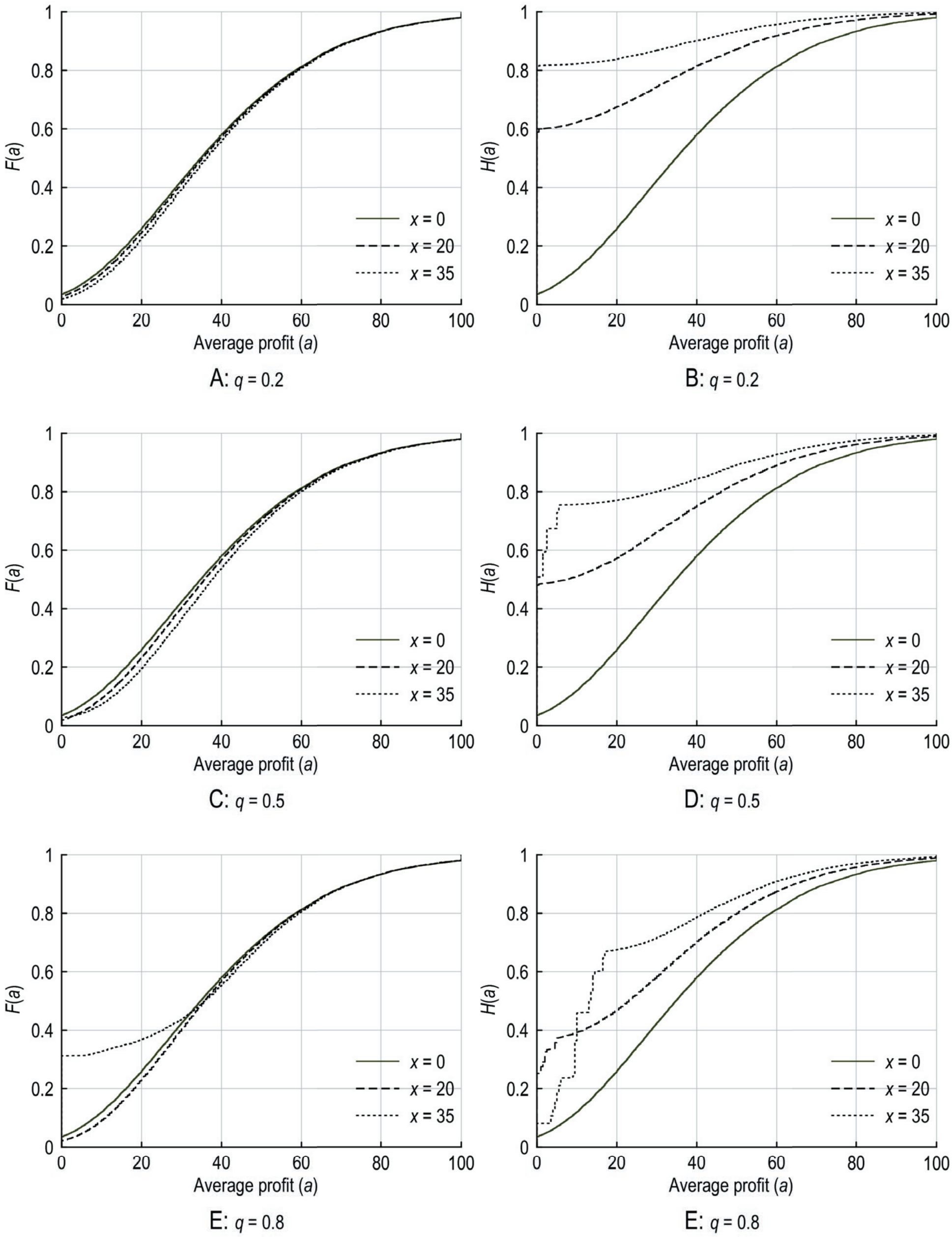


Figure 4.13: The effect of x and q in the 25% variation in model A
Each line in panels A, C and E presents the share of the R&D functions $c(a)$ with $a^* \leq a \in \langle 0, 100\rangle$ and each line in panels B, D and F presents the share of the technology-gap functions $G(a)$ with $a^{G*} \leq a \in \langle 0, 100\rangle$ in a set of 6,561 functions $c(a)$ and $G(a)$ generated for given values x and q and for the parameter values from Table 4.1 (25% variation in model A).

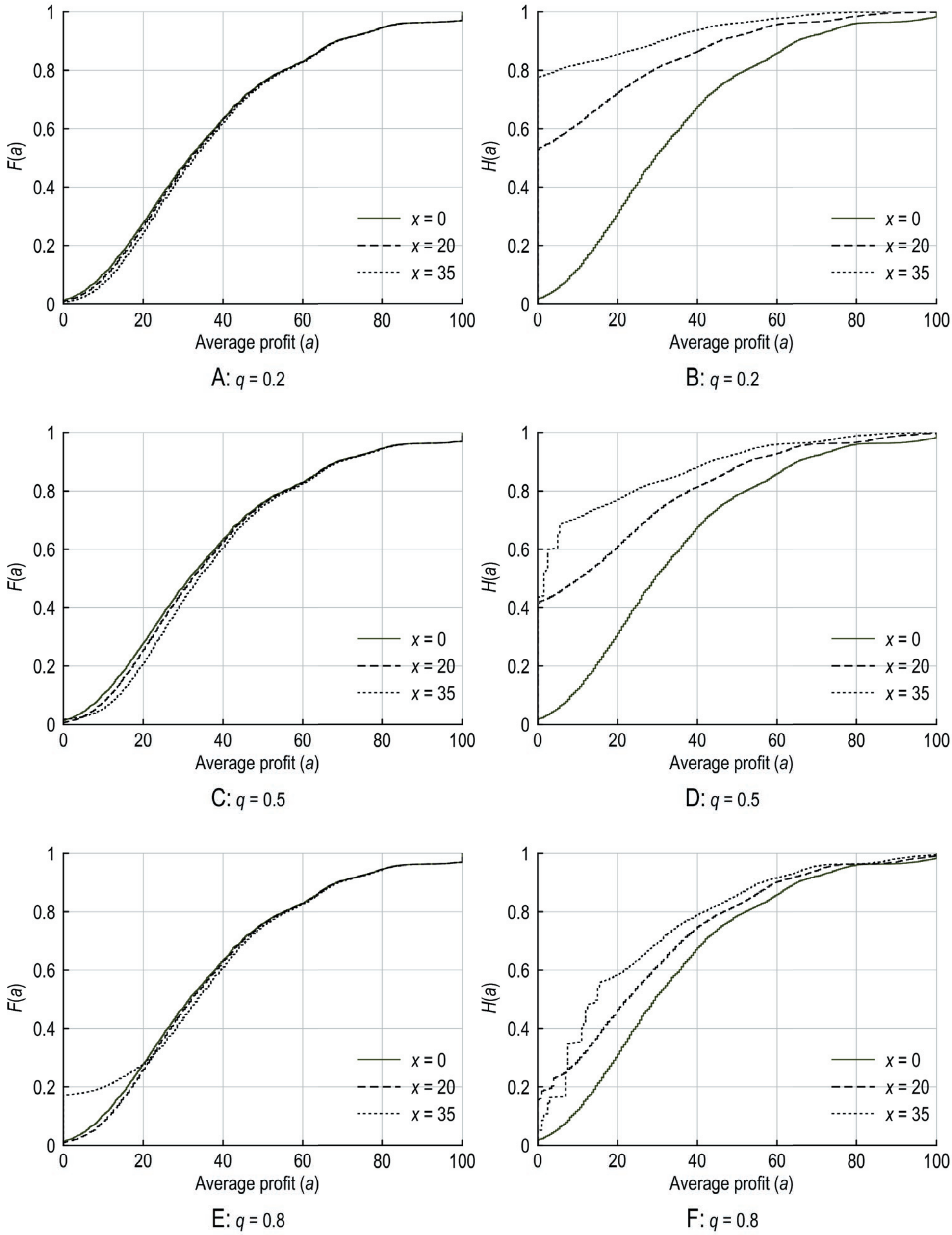


Figure 4.14: The effect of x and q in the 25% variation in model B
Each line in panels A, C and E presents the share of the R&D functions $c(a)$ with $a^* \leq a \in \langle 0, 100 \rangle$ and each line in panels B, D and F presents the share of the technology-gap functions $G(a)$ with $a^{G*} \leq a \in \langle 0, 100 \rangle$ in a set of 6,561 functions $c(a)$ and $G(a)$ generated for given values x and q and for the parameter values from Table 4.1 (25% variation in model B).

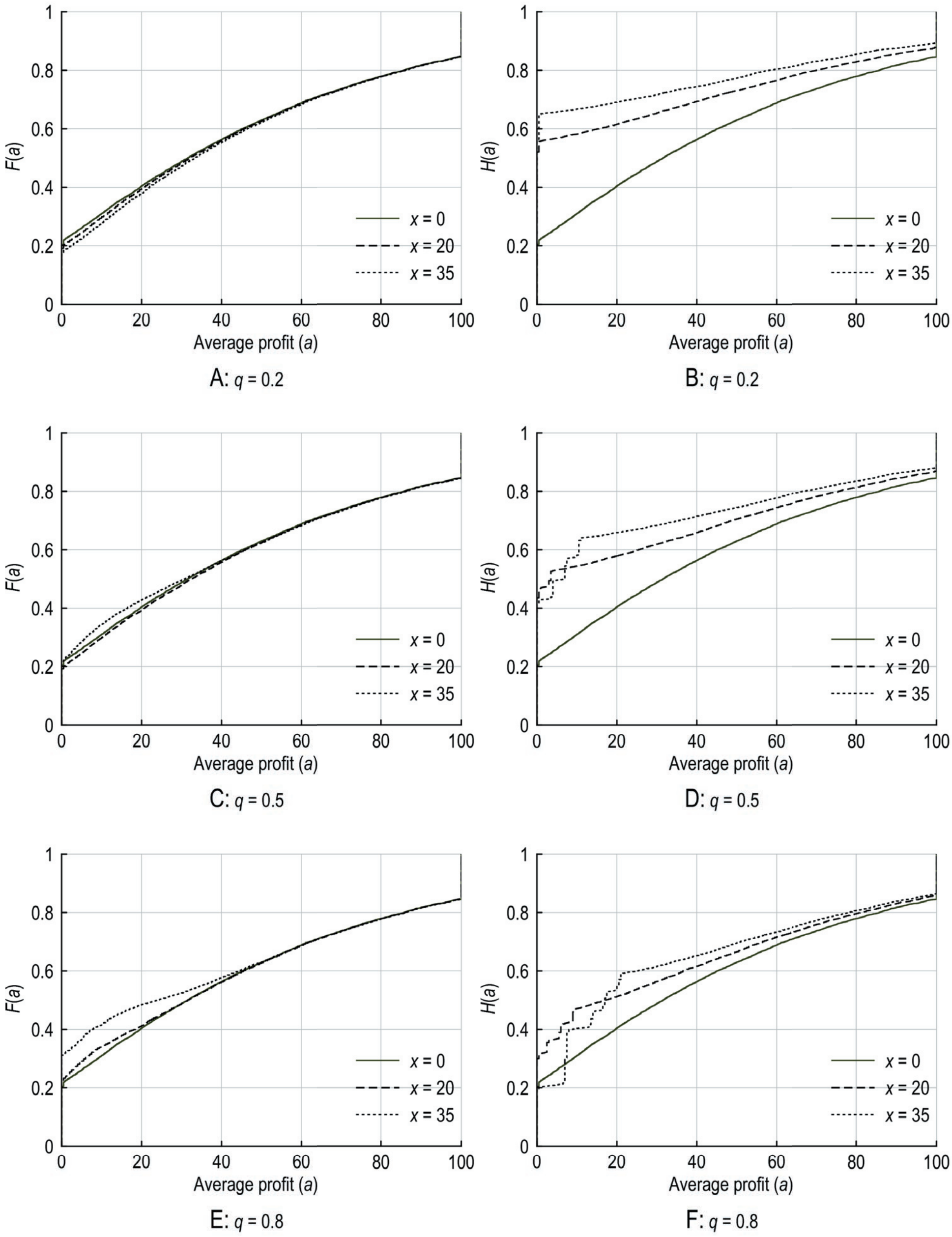


Figure 4.15: The effect of x and q in the 50% variation in model A
Each line in panels A, C and E presents the share of the R&D functions $c(a)$ with $a^* \leq a \in \langle 0, 100\rangle$ and each line in panels B, D and F presents the share of the technology-gap functions $G(a)$ with $a^{G*} \leq a \in \langle 0, 100\rangle$ in a set of 6,561 functions $c(a)$ and $G(a)$ generated for given values x and q and for the parameter values from Table 4.1 (50% variation in model A).

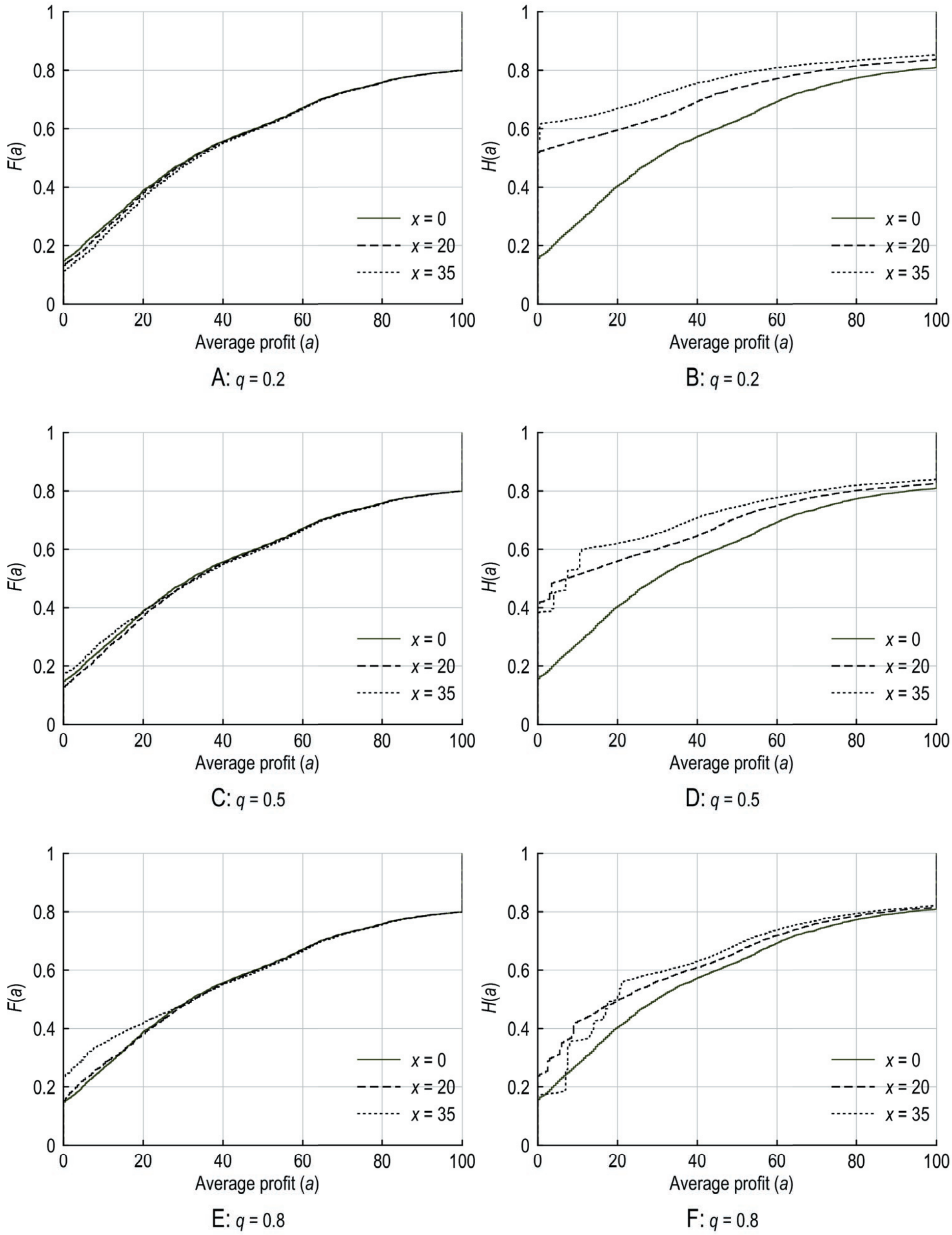


Figure 4.16: The effect of x and q in the 50% variation in model B
Each line in panels A, C and E presents the share of the R&D functions $c(a)$ with $a^* \leq a \in \langle 0, 100\rangle$ and each line in panels B, D and F presents the share of the technology-gap functions $G(a)$ with $a^{G*} \leq a \in \langle 0, 100\rangle$ in a set of 6,561 functions $c(a)$ and $G(a)$ generated for given values x and q and for the parameter values from Table 4.1 (50% variation in model B).

Table 4.5 summarizes the main findings of this subsection. Column I. presents the share of the R&D functions $c(a)$ with $0 < a^* < 100$ in the sets of $c(a)$ generated by the 28 simulations. For most of the sets, the share of $c(a)$ with $0 < a^* < 100$ is approximately 95% in the 25% variation and 65% in the 50% variation. The shares are substantially lower only for $x = 35$ and $q = 0.8$. Column II. presents the shares of parameter combinations for which $0 < a^* < 100$ and $a^{G*} = 0$. These values of a^* and a^{G*} are consistent with the

Sets of $c(a)$ and $G(a)$		I. $0 < a^* < 100$	II. $0 < a^* < 100$ and $a^{G*} = 0$	III. $0 < a^* < 100$ and $0 < a^{G*} < 100$
25% variation model A	$x = 0$	0.94	0	0.94
	$x = 20$, $q = 0.2$	0.95	0.56	0.39
	$x = 35$, $q = 0.2$	0.96	0.79	0.17
	$x = 20$, $q = 0.5$	0.96	0.46	0.5
	$x = 35$, $q = 0.5$	0.95	0.50	0.45
	$x = 20$, $q = 0.8$	0.96	0.21	0.75
	$x = 35$, $q = 0.8$	0.75	0.07	0.68
25% variation model B	$x = 0$	0.96	0	0.96
	$x = 20$, $q = 0.2$	0.96	0.52	0.44
	$x = 35$, $q = 0.2$	0.96	0.77	0.19
	$x = 20$, $q = 0.5$	0.96	0.41	0.55
	$x = 35$, $q = 0.5$	0.95	0.43	0.52
	$x = 20$, $q = 0.8$	0.96	0.15	0.81
	$x = 35$, $q = 0.8$	0.8	0.05	0.75
50% variation model A	$x = 0$	0.64	0	0.64
	$x = 20$, $q = 0.2$	0.66	0.36	0.30
	$x = 35$, $q = 0.2$	0.67	0.42	0.25
	$x = 20$, $q = 0.5$	0.65	0.28	0.37
	$x = 35$, $q = 0.5$	0.63	0.31	0.32
	$x = 20$, $q = 0.8$	0.63	0.15	0.48
	$x = 35$, $q = 0.8$	0.53	0.10	0.43
50% variation model B	$x = 0$	0.65	0	0.65
	$x = 20$, $q = 0.2$	0.67	0.39	0.28
	$x = 35$, $q = 0.2$	0.68	0.44	0.24
	$x = 20$, $q = 0.5$	0.67	0.30	0.37
	$x = 35$, $q = 0.5$	0.62	0.30	0.32
	$x = 20$, $q = 0.8$	0.65	0.14	0.51
	$x = 35$, $q = 0.8$	0.56	0.1	0.46

Table 4.5: Robustness of predictions of the PT model to variation in parameters
This table summarizes the main results of the robustness test. Column I. shows the share of parameter combinations generating the R&D functions $c(a)$ with $0 < a^* < 100$. Column II. presents the share of parameter combinations producing $c(a)$ and $G(a)$ with $0 < a^* < 100$ and $a^{G*} = 0$. Column III. shows the share of parameter combinations generating $c(a)$ and $G(a)$ with $0 < a^* < 100$ and $0 < a^{G*} = 100$.

empirical findings of Aghion *et al.* (2005). The shares giving this prediction range from more than 70% (for the 25% variation and $x = 35$ and $q = 0.2$) to 0% (for $x = 0$). Finally, Column III. presents the shares of parameter combinations for which $0 < a^* < 100$ and $0 < a^{G*} < 100$. These values of a^* and a^{G*} are consistent with the empirical findings of Hashmi (2005).

4.2.4 Summary

In this section, I discuss the effect of variation in parameters on predictions of the PT model with diminishing sensitivity. I introduce a simulation that increases and decreases the parameter values used in the previous chapters by 25% or 50%. Then I measure the position of the maximum of the R&D and technology-gap functions for all combinations of parameters and present the distribution of the positions graphically. The sensitivity analysis is conducted in two steps.

First, I discuss the sensitivity of the model to variation in parameters for zero profit difference x. I show that more than 90% of all parameter combinations generated in the 25% variation and more than 60% of all parameter combinations generated in the 50% variation predict inverse U-shaped R&D and technology-gap functions (which is consistent with the findings of Hashmi 2005). I also consider the effect of individual parameters on predictions of the model with zero profit difference. I find that on average, a rise in some parameters (R, ρ, s_0, and α in model A) generates more increasing R&D functions, and a rise in other parameters (d, σ, p, ω, μ in model A, and α in model B) generates more decreasing R&D functions. Furthermore, I find that only variation in the opportunity parameter R, scale parameter ρ, disutility parameter d and in the ownership share s_0 in model A have a significant effect on the position of the maximum of the R&D functions. Hence these parameters are most responsible for the variability of predictions. Finally, while a rise or a reduction in the value of most of the parameters reduces the robustness of the inverted-U result, a rise in the probability of success p, ownership share s_0, and a reduction in the base salary ω increases the robustness of the inverted U to variation in all other parameters.

Second, I discuss the effect of the profit difference x and the share of firms X in the industry q on predictions of the model. I find that if managers earn non-negative income for R&D expenditures $c_i = 0$, then x and q have a very small effect on the shape of the R&D function. Hence the robustness of the inverted-U result remains similar to the situation with zero profit difference. That is, more than 90% or 60% of all parameter combinations generate the inverted-U relationship in the 25% or 50% variation, respectively. Furthermore, if managers earn non-negative incomes, a rise in x and a reduction in q shift the maximum of the technology-gap function to lower average profit a^{G*}. It means that the share of parameter combinations that generate a decreasing technology-gap function increases in x and decreases in q. In 25% variation for $x = 35$ and $q = 0.2$, more than 70% of all parameter combinations generate an inverse U-shaped R&D function and a decreasing technology-gap function (which is consistent with the findings of Aghion *et al.*

2005). On the other hand, if x and q are so high that managers of firms with low average profit a expect to earn negative incomes for R&D expenditures $c_i = 0$, the percentage of parameter combinations generating the inverse U-shaped R&D function and the decreasing technology-gap function is lower.

The main findings of this section are as follows. If the profit difference x is low and the share of firms X in the industry q is large, the predictions consistent with the findings of Hashmi (2005) are generated for a relatively wide range of other parameters around the parameter combinations used in the previous chapter. On the other hand, if x is high and q is low, the predictions corresponding to the empirical findings of Aghion *et al.* (2005) form an important share of all predictions generated in the simulations. Moreover, I show that changes in some parameters have little effect on predictions of the model. So the predictions of the model are likely to be consistent with the empirical findings even for a larger variation in these parameters.

Conclusion

The relationship between competition and innovation represents one of the long-studied but as yet unresolved economic problems. In their seminal paper, Aghion *et al.* (2005) present an elegant explanation of the inverted-U relationship between competition and innovation. Their model generates two additional predictions: Prediction B stating that a rise in competition increases the expected technology gap, and Prediction C according to which the inverted-U relationship in more technologically leveled industries is higher and peaks at a higher level of competition. The tests of the predictions provide mixed results. Several studies support the inverted-U relationship, but there is little support for the additional predictions. Especially troubling are the mixed findings related to Prediction B (presented in Aghion *et al.* 2005 and Hashmi 2005), since this prediction represents a necessary part of Aghion *et al.*'s explanation of the inverted-U relationship. Consequently, there is scope for an alternative explanation of the inverted-U relationship that would be able to reconcile the inverted-U relationship with the empirical evidence on Prediction B.

In this book, I have introduced two models that explain the inverted-U relationship between profitability and innovation, and the empirical evidence related to Prediction B. The basic model presents a simple and general explanation of the empirical findings. In this model, firms choose R&D expenditures in order to maximize their expected profits subject to the R&D-expenditure constraint. The prospect-theory model offers a more specific explanation of the empirical evidence. It contains a theory about the decision-making process of managers. In this model, managers choose the size of R&D expenditures according to their preferences represented by the prospect-theory value function.

Both models predict an inverse U- or V-shaped relationship between the profits and R&D expenditures of individual firms. The models offer several explanations of the relationship. A rise in profits may lead to higher R&D expenditures of low-profit firms for several reasons. First, the size of R&D expenditures of firms might be limited by the profits they expect to earn, because they face credit constraints or because they wish to avoid low or negative profits, if they fail to innovate. Second, the size of R&D expenditures might be limited by the preferences of managers. Managers with incomes linked to the profits of their firms might be reluctant to choose high R&D expenditures, if their firms expect to earn low profits. In the prospect-theory model, I show that this effect may arise because of the loss-aversion or diminishing-sensitivity principles of the prospect-theory value function. On the other hand, a rise in profits may reduce R&D expenditures of high-profit firms for three different reasons. First, because the return to R&D expenditures is decreasing in the profits of firms. Second, because of the disutility of innovation and the decreasing effective ownership. Third, because of the disutility of innovation and the diminishing-sensitivity principle of the prospect-theory value function.

The shapes of the relationships between profits and R&D expenditures of individual firms determine the relationships between profits and average R&D expenditures in the industry (the R&D function) and between profits and the technology gap (the technology-gap function). In both models, the industry consists of two types of firms, firms X expecting to earn higher profits than firms Y. If the individual firms differ in their expected profits, the relationships between profits and R&D expenditures of firms X and firms Y have different shapes. Especially in low-profit industries, firms X will innovate more because their R&D programs are less constrained by the lack of profits. If the differences in profits are low, the firm-level relationships between profits and R&D expenditures have similar shapes and the industry-level R&D and technology-gap functions are likely to be inverse U- or V-shaped. This prediction corresponds to the empirical evidence presented by Hashmi (2005). However, if the differences in profits within the industry are relatively large, the model may generate an inverse U- or V-shaped R&D function and a decreasing technology-gap function, which corresponds to the evidence of Aghion *et al.* (2005).

The models presented in this book provide a more flexible explanation of the inverted-U relationship than the model of Aghion *et al.* (2005). In Aghion *et al.*'s model, the inverted-U relationship arises because competition increases innovation on the part of neck-and-neck firms (the escape-competition effect), reduces innovation on the part of laggard firms (the Schumpeterian effect), and increases the steady-state proportion of laggard firms in the economy (Prediction B). It means that Prediction B is a necessary part of the explanation of the inverted-U relationship. In my model, the industry-level inverse U-shaped R&D function follows from the shapes of the firm-level relationships between profits and R&D expenditures. In addition to that, the firm-level relationships may lead to an inverted-U or a decreasing technology-gap function. Hence the technology-gap function consistent with Prediction B is not a necessary part of the explanation of the inverted-U relationship.

Furthermore, the basic and prospect-theory models provide, in a sense, a more general explanation of the inverted-U relationship between profitability and innovation than the model of Aghion *et al.* (2005). The explanation is more general in two respects. First, they relate innovation to profits instead of competition. Therefore, they include all possible factors affecting profitability of firms, not only competition as does Aghion *et al.* (2005). Moreover, they avoid the problematic connection between competition and profitability. A rise in competition may increase profitability in the industry, if the differences in the costs of firms are relatively large (see Boone 2000, 2008). Hence in a setting with endogenous cost differences, the predicted relationships between competition and innovation and between profitability and innovation might be different (however, this problem does not occur in the paper of Aghion *et al.* 2005). Second, Aghion *et al.*'s explanation of the inverted-U relationship depends on specific assumptions about the nature of technological progress and product market competition. Subsection 1.3.2 presents examples of alternative assumptions for which the Schumpeterian effect is either very weak or nonexistent. My explanation assumes that all firms in the industry have the same reward from innovation which is either constant or decreasing in the profits of firms. Hence my models provide an explanation of the inverted-U relationship in the absence of the Schumpeterian effect or both the Schumpeterian and escape-competition effects. In this sense, my explanation works under a wider range of assumptions about the technological process and product market competition than the explanation of Aghion *et al.* (2005).

Using specific combinations of parameter values, I show that the models are able to explain the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Both models predict an inverse U- or V-shaped R&D function with a realistic range of profitability and R&D expenditures. They also predict either an inverse U- or V-shaped or a decreasing technology-gap function. The technology-gap function tends to be inverse U- or V-shaped in industries in which firms earn similar profits and decreasing in industries with higher differences in profits. Hence this explanation assumes that the differences in profits in the sample of industries used by Aghion *et al.* (2005) are higher than in the sample used by Hashmi (2005). This assumption seems to be consistent with the fact that Aghion *et al.* (2005) use a broader definition of industry (two-digit SIC code) than Hashmi (2005) (four-digit SIC code). The intuition is that firms in two-digit industries are likely to differ more in terms of profits than firms in four-digit industries.

Finally, I show that the models provide the required predictions for a wider range of parameters around the combinations of parameters used for presenting predictions of the models. For both models, I find that if firms earn similar profits, the predictions of the models tend to be similar to the empirical findings of Hashmi (2005) for a relatively wide range of parameter combinations. On the other hand, the higher the difference between profits of firms X and Y and the lower the share of firms X in the industry, the wider tends to be the range of parameter combinations for which the predictions of the model correspond to the empirical findings of Aghion *et al.* (2005).

In sum, this book provides an alternative explanation of the inverted-U relationship between profitability and innovation that reconciles the empirical findings of Aghion *et al.* (2005) and Hashmi (2005) related to Prediction B of Aghion *et al.* (2005). In some sense, the models provide a more general explanation than the model of Aghion *et al.* (2005). The predictions of the models generated for specific sets of parameter values correspond well to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Finally, the book shows that the models generate the required predictions for a wider range of parameter combinations around the specific sets of parameter values.

The models presented in this book could be used for deriving alternative testable predictions. For instance, it would be interesting to test whether there is an inverted-U relationship between profitability and innovation on the part of individual firms, or whether the shape of the relationship between profitability and the technology gap depends on the average differences in profitability in the industry. Should the models receive sufficient empirical support, the explanations presented in this book might have policy implications. For example, it might be preferable to consider the effect of specific policy measures on the profitability or profits of firms instead of other measures of competition, such as market share or concentration, which dominate especially in the context of competition policy. Furthermore, policy measures might be designed in a way that would avoid or mitigate the reduction in R&D expenditures due to low profitability or profits of firms. Our models suggest that the potentially important determinants of innovative performance in less profitable industries are the average costs and riskiness of an R&D project, the average number R&D projects with independent risks performed within firms in given industries, the availability of credit or other debt instruments for financing innovations. The prospect-theory model also emphasizes the importance of the structure of managerial contracts and the ownership structures prevalent in given industries.

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Appendix A

Endogenous profit difference

The prospect-theory (PT) model with endogenous profit difference relaxes two important assumptions of the models presented in Chapters 2 and 3. First, the differences in profits of firms do not arise because of exogenous firms-specific factors, but because of the differences in the technologies of firms. Technological levels of individual firms may differ because imitation eliminates only a part of the technology gaps between laggard firms and the leader. Second, innovation by one firm has a negative effect on profits of the other firms in the industry. This implies that the choice of R&D expenditures of one firm depends on the expected change in technologies of other industry members. This chapter provides a simplified version of the model. For a more complex version, see Krčál (2010d).

The PT model with endogenous profit difference is presented in two sections. Section A.1 introduces the assumptions of the model. Section A.2 presents predictions of the model. Most importantly, it shows that for some combinations of parameters the model is able to explain the empirical findings of Hashmi (2005) and Aghion *et al.* (2005).

A.1 Structure of the model

The PT model with endogenous profit difference has a similar structure as the PT model with diminishing sensitivity (see Section 3.3). In particular, managers in both models choose the size of R&D expenditures according to their preferences represented by the prospect-theory value function. This section has the following structure. First, it presents the determinants of profits of firms. Then it explains how the expected profits of firms are affected by innovative performance on the part of other firms in the industry. Finally, it explores the effect of innovation on the income and utility of managers.

Profits

Suppose an industry with n firms in a discrete-time setting. The profit of firm i in period t depends on industry-specific factors, the technology difference of firm i in period t, and on the R&D expenditures of firm i in period t. Industry-specific factors influence the average profit a, which ranges from 0 to the maximum average profit $\bar{a}$ (see Section 2.1 for a discussion of industry-specific factors). The technology difference of firm i in period t is given by

$$\delta_{it} = \tau_{it} - \frac{1}{n-1} \sum_{j \neq i} \tau_{jt}, \tag{A.1}$$

where $\tau_{it} \geq 0$ represents the technology of firm i, and $\tau_{jt} \geq 0$ are technologies of other firms in the industry. The technology difference of firm i is determined by innovation and imitation on the part of firms in the industry. Innovation and imitation of firm i in period t has the following timing. At the beginning of period t, firm i imitates. This means that its technology increases by

$$(1-h)(\tau_{Lt} - \tau_{it}), \tag{A.2}$$

where $h \in \langle 0, 1 \rangle$ is the appropriability parameter, and $\tau_{Lt} \geq 0$ is the technology level of the leader. Hence the technology difference of firm i at the beginning of the period t is given by $\delta^I_{it} = h\delta_{it-1}$, where δ_{it-1} is the technology difference of firm i in period $t-1$. Then the manager of firm i chooses R&D expenditures c_{it} that generate innovation with a probability of success $p \in (0, 1)$. If firm i innovates successfully in period t, its technology τ_{it} increases by $r(a)c^{\rho}_{it}$, where $\rho \in (0, 1)$ is the scale parameter, and $r(a) > 1$ denotes the reward function given by (3.4). If firm i fails to innovate, its technology remains the same.

The profits of firm i that fails or succeeds to generate an innovation in period t are

$$\pi_{itF}(a, c_{it}) = a - c_{it} + \delta_{itF},$$

$$\pi_{itS}(a, c_{it}) = a - c_{it} + \delta_{itS},$$

where $a \in \langle 0, \bar{a} \rangle$ is the average profit, and δ_{itF} is the technology difference of firm i in period t if the firm fails to innovate, and δ_{itS} is the technology difference if the firm innovates successfully. Because a successful innovation increases technology difference of firm i by $r(a)c^{\rho}_{it}$, the technology difference in the case of successful innovation is $\delta_{itS} = \delta_{itF} + r(a)c^{\rho}_{it}$. Hence the profit of a successful innovator i can be written as

$$\pi_{itS}(a, c_{it}) = a - c_{it} + r(a)c^{\rho}_{it} + \delta_{itF}.$$

Expectations

The manager of firm i has no precise knowledge about the technology difference δ_{it} when she decides about the R&D expenditures for period t. Hence the decision about the size of R&D expenditures c_{it} is based on the knowledge of the technology gap at the beginning of period t δ^I_{it} and on expectations about the technology change of other firms in period t. The expected technology difference of firm i that fails to innovate is given by

$$\delta^e_{itF} = \delta^I_{it} - T^e_{it},$$

where T^e_{it} represents the expectations of firm i about the average change in technology of all other firms. The expectations are formed in the following autoregressive process

$$T^e_{it} = \phi T^e_{it-1} + (1-\phi)T_{it-1}, \tag{A.3}$$

where $\phi \in (0,1)$ is the expectations parameter, T^e_{it-1} is the expected change in technology in period $t-1$, and T_{it-1} is the average change in technology of other firms in period $t-1$ given by

$$T_{it-1} = \frac{1}{n-1} \sum_{j \neq i} (\tau_{jt-1} - \tau_{jt-2}). \tag{A.4}$$

Hence the expected profits of firm i in the case of failure and success are given by

$$\pi^e_{itF}(a, c_{it}) = a - c_{it} + \delta^I_{it} - T^e_{it},$$

$$\pi^e_{itS}(a, c_{it}) = a - c_{it} + \delta^I_{it} + r(a)c^\rho_{it} - T^e_{it}.$$

Income and utility

As in the prospect-theory model presented in Chapter 3, the income of managers consists of the base salary and of a share of the current profit. The expected income of the manager of firm i in the case of failure or success is given by

$$w_{itF}(a, c_{it}) = \omega + s(a)\pi^e_{itF}(a, c_{it}) = \omega + s(a)(a - c_{it} + \delta^I_{it} - T^e_{it}), \tag{A.5}$$

$$w_{itS}(a, c_{it}) = \omega + s(a)\pi^e_{itS}(a, c_{it}) = \omega + s(a)(a - c_{it} + \delta^I_{it} + r(a)c^\rho_{it} - T^e_{it}), \tag{A.6}$$

where $\omega \geq 0$ is the base salary, $s(a) \in \langle 0, 100 \rangle$ is the effective ownership given by (3.6), $a \in \langle 0, \bar{a} \rangle$ is the average profit, c_{it} are R&D expenditures of firm i in period t, δ^I_{it} is the technology difference at the beginning the period t, and T^e_{it} is the expected change in the average technology of the other firms in the industry.

Managers have prospect-theory preferences above the risky outcomes of innovation. The value of the prospect of innovation for the manager of firm i in period t is given by

$$V_{it}(a, c_i) = pv(w_{itS}(a, c_{it})) + (1-p)v(w_{itF}(a, c_{it})),$$

where $p \in (0,1)$ is the probability of success, and $v(w_i(a, c_i))$ is the prospect-theory value function is given by

$$v(w_{it}(a, c_{it})) = \begin{cases} w_{it}(a, c_{it})^\alpha & \text{if } w_{it}(a, c_{it}) \geq 0, \\ -\lambda(-w_{it}(a, c_{it}))^\alpha & \text{if } w_{it}(a, c_{it}) < 0, \end{cases}$$

where $\lambda \geq 1$ is the loss-aversion parameter, and $\alpha \in (0, 1\rangle$ is the diminishing-sensitivity parameter.

The utility of manager of firm i in period t is equal to

$$U_{it}(a, c_{it}) = V_{it}(a, c_{it}) - dc_{it}, \tag{A.7}$$

where $V_{it}(a, c_{it})$ represents the value of the prospect of innovation, and $d \geq 0$ is the disutility parameter.

A.2 Predictions of the model

This section presents the main predictions of the prospect-theory model with endogenous profit difference. The predictions are generated in a simulation implemented in `Netlogo 5.0.1`. For the code of the simulation , see Appendix B.5.

The following procedure is repeated for each value of average profit $a = \{0, 1, 2, \ldots, 100\}$. Before the beginning of the first period, the model creates n firms with the technology $\tau_{i1} = 0$ and with expected change in technology of other firms $T_{it}^e = 0$. Then the simulation runs for t_E periods. Each period consists of the following five steps.

1. Each firm imitates part of the leader's technology according to the process (A.2).

2. Each firm measures its technology difference (A.1) and adjusts the expectation about the average change in technology of other firms using (A.3) (except for the first period, in which $T_{it}^e = 0$).

3. Each manager chooses R&D expenditures that maximize her utility $U_{it}(a, c_{it})$ given by (A.7).

4. Each firm innovates with probability of success p and increases its technology by $r(a)c_{it}^{\rho}$ if the innovation is successful.

5. Each firm observes the actual change in technology of all other firms T_{it} (A.4) and the average R&D expenditures in the industry and the technology gaps are recorded.

R&D expenditures reported in Panels A.1A and C are average R&D expenditures across all firms and all periods $t_A < t \leq tE$

$$c = \frac{1}{(t_E - t_A)} \sum_{t=t_A+1}^{t_E} \frac{1}{n} \sum_{i=1}^{n} c_{it},$$

where t_A and t_E represent the numbers of periods, n is the number of firms, and c_{it} are R&D expenditures of firm i in period t. The technology gap reported in Panels A.1B and D is given by

$$G = \frac{1}{(t_E - t_A)} \sum_{t=t_A+1}^{t_E} \left(\tau_{Lt} - \frac{1}{n} \sum_{i=1}^{n} \tau_{it}\right),$$

where τ_{Lt} is the technology of the leader, and τ_{it} is technology of firm i in period t. R&D expenditures and technology gaps are recorded only for periods $t_A{+}1$ to t_E. This is because firms form their expectations about future change in other firms' technology in the first t_A periods. The number of periods t_A necessary for the expectations to adjust depends on the expectation parameter $\phi \in (0, 1)$. The higher the ϕ, the more persistent are the expectations, and the higher number of periods t_A is necessary.

As in the PT model in Chapter 3, I split the model into two models. In model A, managers experience disutility of innovation but the reward function is constant in the average profit a ($d > 0$ and $\sigma = 0$). In model B, managers do not experience disutility of innovation but the reward function is decreasing in the average profit a ($d = 0$ and $\sigma > 0$).

Figure A.1 shows the effect of the appropriability parameters $h = 0.4$, 0.6, and 0.8 on predictions of the model. There are $n = 30$ firms in the industry and the expectations parameter $\phi = 0.95$. In this case, $t_A = 100$ periods are enough for the firms to form correct expectations. The simulation ends after $t_E = 600$ periods. Therefore the values presented in Figure A.1 are averages of 500 periods. The values of the remaining parameters are the same as those used in Chapter 3 (see Subsections 3.2.4 and 3.3.3 for the discussion of the parameter values).

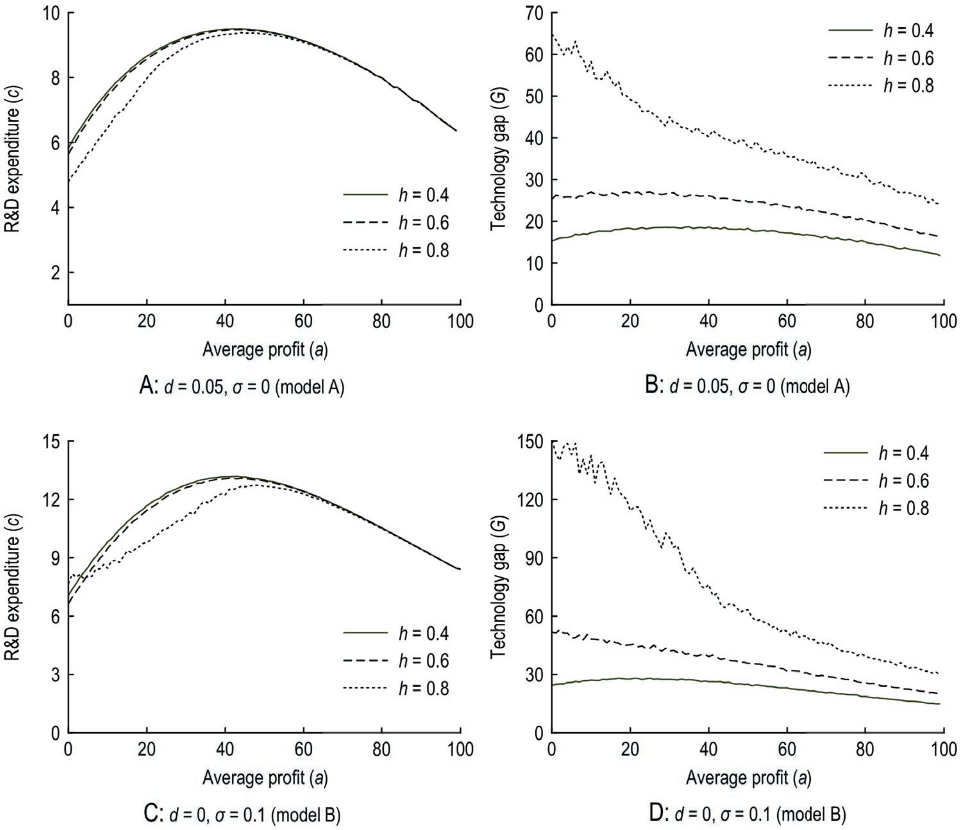

Figure A.1: The PT model with endogenous profit difference
The figure shows examples of predictions A and B for different levels of the appropriability parameters h. The parameters common to all panels are $n = 30$, $\phi = 0.95$, $R = 0.28$, $\rho = 0.95$, $p = 0.5$, $\omega = 40$, $s_0 = 2$, $\mu = 0.5$, $\lambda = 2.25$, $\alpha = 0.88$, $\bar{a} = 100$, $t_A = 100$, and $t_E = 600$.

Panels A.1A and C display inverted-U relationships between the average profit and R&D expenditures. The effect of the appropriability parameter on R&D expenditures is limited. Panels A.1B and D present relationships between the average profit and the technology gap. If the appropriability parameter is relatively low ($h = 0.4$), the relationship is flat and concave. This result corresponds to the empirical findings of Hashmi (2005). On the other hand, for the appropriability parameter $h = 0.8$, the relationship is high and decreasing, which resembles the empirical evidence of Aghion *et al.* (2005).

The intuition behind the inverted-U relationship between the average profit and R&D expenditures is the same as in the PT model with diminishing sensitivity. The increasing part of the relationship is due to loss aversion or diminishing sensitivity of the prospect-theory value function. The decreasing part is due to the decreasing reward function in model B, or due to the disutility of innovation, diminishing sensitivity and decreasing effective ownership in model A. The flat and concave relationships between average profits and technology gap for low levels of appropriability mirror the size of corresponding R&D expenditures. The decreasing relationships between the average profit and the technology gap for high levels of appropriability arise because of the following dynamics. If the average profit a is low, the technological leader has higher R&D expenditures than laggard firms. Therefore, the differences in technologies of firms in the industry tend to increase. However, they increase only to a level where, thanks to imitation, the technology levels of laggard firms grows at a similar pace as the technology of the leader firm. With increasing average profit a, the R&D expenditures of the leader and followers converge. Hence the technology gap in the industry tends to fall in the average profit a.

Appendix B

Netlogo codes

This chapter presents codes of all the models implemented in `Netlogo 5.0.1`. I use the software `Netlogo` for three reasons. First, `Netlogo` provides an interactive interface, in which it is easy to generate predictions of the model for different combinations of parameters. Additionally, the interactive interface runs on the web without the need for installing `Netlogo` itself. Second, `Netlogo` includes a tool called `Behavior space` designed for performing sensitivity analysis for different combinations of parameters. It is therefore appropriate for performing the simulations presented in Section 4.2. Third, `Netlogo` represents a suitable tool for the implementation of the agent-based PT model with endogenous profit difference.

The rest of the chapter is organized as follows. In Sections B.1–B.3, I present the interfaces and the codes of the basic model, the prospect-theory model with constant sensitivity, and the prospect-theory model with diminishing sensitivity. Section B.4 presents the procedure used for finding the position of the maximum of the R&D and technology-gap functions used in Section 4.2. Finally, Section B.5 presents the interface and the code of the prospect-theory model with endogenous profit difference presented in Appendix A.

B.1 The basic model

In this section, I present the interactive version of the basic model implemented in `Netlogo 5.0.1`. The model uses the solution of the model presented in Chapter 2 for plotting R&D expenditures and the technology gap for industry-specific profits $b = \{0, 1, 2, \ldots, \bar{b}\}$, where $\bar{b}$ is the maximum industry-specific profit.

Figure B.1 presents the graphical interface of the basic model. It contains two buttons, seven sliders, one chooser, and two plots. The button setup clears the graphs and the button go generates new predictions. The sliders correspond to the following parameters of the model: R is the opportunity parameter R, rho is the scale parameter ρ, p is the probability of success p, sigma is the slope parameter σ, max-b is the maximum industry-specific profit $\bar{b}$, f is the firm-specific profit f, and q is the share of firms X in the industry q. The scenario none enables choosing parameter values freely and other scenarios recreate predictions corresponding to Figure 2.2. The plot R&D function presents the R&D-expenditure function of firms X $c_i^X(b)$ (the red line cX), the R&D-expenditure function of firms Y $c_i^Y(b)$ (the green line cY), and the R&D function $c(b)$ (the black line c) for the values of parameters in the sliders. The plot technology-gap function shows the technology-gap function $G(b)$ for the same values of parameters.

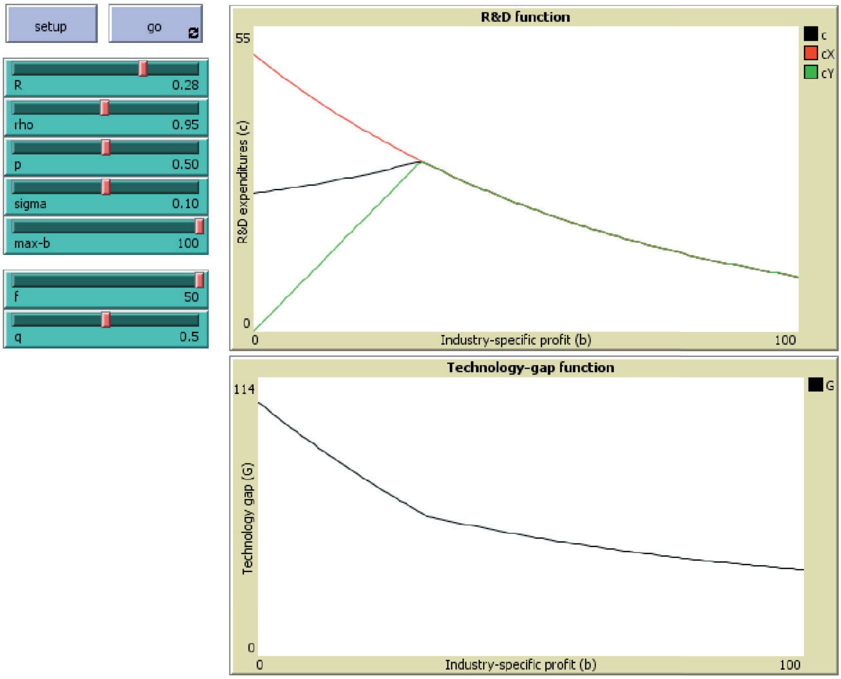

Figure B.1: Interface of the basic model in `Netlogo 5.0.1`

Figure B.2 presents important parts of the code of the basic model. Section globals lists all remaining variables of the model that are not defined as sliders: b represents the industry-specific profit b, reward is the reward parameter r, c* is the decreasing part of the R&D-expenditure function of firms X or Y c_i^*, cX and cY are R&D expenditures of firms X and Y c_i^X and c_i^Y, c represents average R&D expenditures in the industry c, and G is technology gap G. The procedure setup resets the model. The procedure go generates the plots for the values of the industry-specific profit $b = \{0, 1, 2, \ldots, \bar{b}\}$. It includes procedures innovation and do-plot. The procedure innovation generates the average R&D expenditures c and technology gap G for a given value of industry-specific profit b. The procedure uses the equations presented in Chapter 2 (the numbers of equations are in comments). The procedure do-plots draws values of R&D expenditures c_i^X, c_i^Y, and c, and of the technology gap G for each value of the industry-specific profit b.

```
globals [
  b
  reward
  c*
  cX
  cY
  c
  G
]

to setup
  __clear-all-and-reset-ticks
end

to go
  innovation
  do-plots
  tick
  if b = max-b
    [stop]
  set b b + 1
end

  to innovation
    set reward (1 + R - sigma * b / max-b) / p ;(2.3)

    set c* (rho + rho * R - rho * sigma * b / max-b)^(1 / (1 - rho)) ;(2.10)
    ifelse c* < b + f ;(2.8)
      [ set cX c* ]
      [ set cX b + f  ]
    ifelse c* < b ;(2.9)
      [ set cY c* ]
      [ set cY b]

    set c (q * cX + (1 - q) * cY) ;(2.13)
    set G  q * (1 - p) * (reward * cX ^ rho)
      + (1 - q) *(p * (f + reward * cX  ^ rho - reward * cY  ^ rho)
      + (1 - p)*(f + reward * cX  ^ rho)) ;(2.17)
  end

  to do-plots
    set-current-plot "R&D function"
    set-current-plot-pen "cX"
    plot cX
    set-current-plot-pen "cY"
    plot cY
    set-current-plot-pen "c"
    plot c

    set-current-plot "Technology-gap function"
    set-current-plot-pen "G"
    plot G
  end
```

Figure B.2: The `Netlogo` code of the basic model

B.2 The PT model with constant sensitivity

This section presents the interactive version of the prospect-theory model with constant sensitivity implemented in `Netlogo 5.0.1`. Using the solution of the model presented in Section 3.2, the model plots R&D expenditures and the technology gap for average profits $a = \{0, 1, 2, \ldots, \bar{a}\}$, where $\bar{a}$ is the maximum average profit.

Figure B.3 presents the graphical interface of the PT model with constant sensitivity. It contains two buttons, twelve sliders, one chooser, one monitor, and two plots. The button setup clears the plots, and the button go generates new predictions. The sliders correspond to the following parameters of the model: R represents the opportunity parameter R, rho is the scale parameter ρ, p is the probability of success p, omega is the base salary ω, s0 is the ownership share s_0, mu is the decreasing-ownership parameter μ, lambda is the loss-aversion parameter λ, d the disutility parameter d, sigma is the slope parameter σ, max-a is the maximum average profit $\bar{a}$, x is the profit difference x, q is the share of firms X in the industry q. The scenario none enables choosing parameter values freely and other scenarios correspond to Figures 3.2 and 3.3. The monitor displays the value of the minimum loss-aversion parameter $\underline{\lambda}_i^Y(0)$ (3.17).

The plot R&D function presents the R&D-expenditure function of firms X $c_i^X(a)$ (the red line cX), the R&D expenditures of firms Y $c_i^Y(a)$ (the green line cY), and the R&D function $c(a)$ (the black line c) for the values of parameters in the sliders. Similarly, the plot technology-gap function depicts the technology-gap function $G(a)$ for the same parameter values.

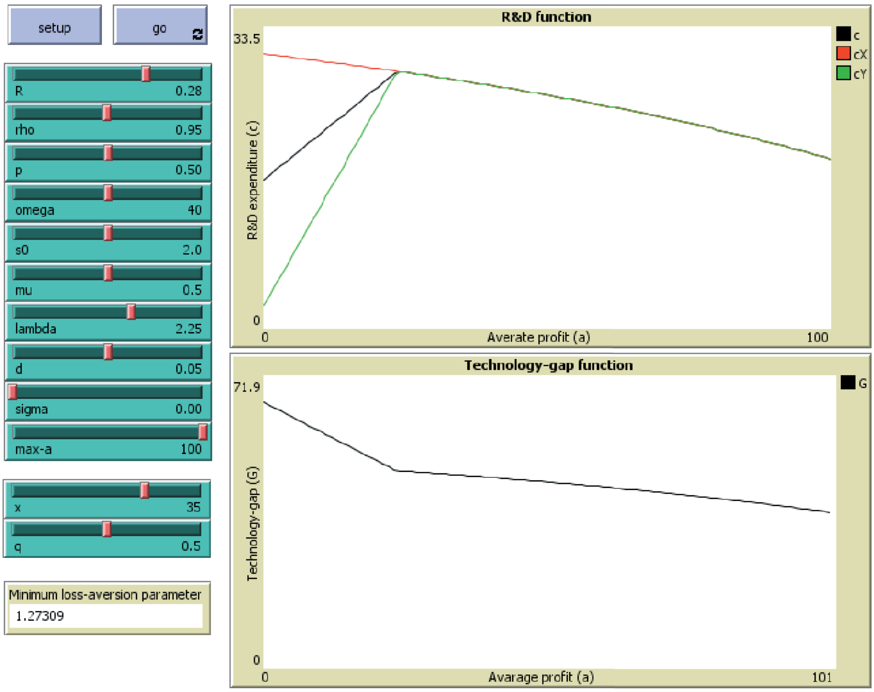

Figure B.3: The interface of the PT model with constant sensitivity in `Netlogo 5.0.1`

Figure B.4 presents important parts of the code of the model. Section globals contains all remaining variables of the model that are not defined as sliders: a is the average profit a, min-lambda is the minimum loss-aversion parameter $\underline{\lambda}_i^Y(0)$, reward is the reward parameter r, s is the effective ownership parameter s, _c is the decreasing part of the R&D-expenditure function $\underline{C}_i$, /cX and /cY are the increasing parts of the R&D-expenditure functions of firm X and Y $/C_i^X$ and $/C_i^Y$, cX and cY are R&D expenditures of firms X and Y c_i^X and c_i^Y, c represents average R&D expenditures in the industry c, and G is the technology gap G.

The procedure setup resets the model and calculates the minimum loss-aversion parameter. The procedure go generates the plots for the average profits $a = \{0, 1, 2, \ldots, \bar{a}\}$.

```
globals [
  a
  min-lambda
  reward
  s
  _c
  /cX
  /cY
  cX
  cY
  c
  G
]

to setup
  __clear-all-and-reset-ticks
  set min-lambda ((s0 * rho * (1 + R) - (p * s0 + d)*(omega / s0 - q * x)^(1 - rho))/
    ((1 - p)* s0 * (omega / s0 - q * x))^(1 - rho)) ;(3.17)
end

to go
  innovation
  do-plots
  tick
  if a = max-a
    [stop]
  set a a + 1
end

  to innovation
    set reward ((1 + R - (a / max-a) * sigma)) / p ;(3.4)
    set s s0 - s0 * mu * (a / max-a) ;(3.6)

    set /cX (omega + s * (a + (1 - q) * x ))/ s ;(3.19)
    set /cY (omega + s * (a - q * x))/ s ;(3.19)
    set _c ((rho * p * reward * s)/(d + s))^ (1 /(1 - rho)) ;(3.20)

    ifelse _c < /cX ;(3.18)
      [ set cX _c ]
      [ set cX /cX ]
    ifelse _c < /cY ;(3.18)
      [ set cY _c ]
      [ set cY /cY ]

    set c (q * cX + (1 - q) * cY) ;(3.25)
    set G q * (1 - p) * (reward * cX ^ rho) + (1 - q) * p * (x + reward * cX ^ rho  - reward * cY ^ rho)
      + (1 - q) * (1 - p)*(x + reward * cX ^ rho) ;(3.26)
  end


  to do-plots

    set-current-plot "R&D function"
    set-current-plot-pen "cX"
    plot cX
    set-current-plot-pen "cY"
    plot cY
    set-current-plot-pen "c"
    plot c

    set-current-plot "Technology-gap function"
    set-current-plot-pen "G"
    plot G
  end
```

Figure B.4: The Netlogo code of the PT model with constant sensitivity

It includes procedures innovation and do-plot. The procedure innovation generates average R&D expenditures c and the technology gap G for a given value of average profit a. The procedure consists of the equations presented in Section 3.2 (the numbers of equations are shown in gray color). Finally, the procedure do-plots depicts the values of R&D expenditures c_i^X, c_i^Y, and c and the technology gap G for each value of a.

B.3 The PT model with diminishing sensitivity

In this section, I present an interactive version of the prospect-theory model with diminishing sensitivity implemented in `Netlogo 5.0.1`. The code provides a numerical solution that finds R&D expenditures and the technology gap for the average profits $a = \{0, 1, 2, \ldots, \bar{a}\}$, where $\bar{a}$ is the maximum average profit.

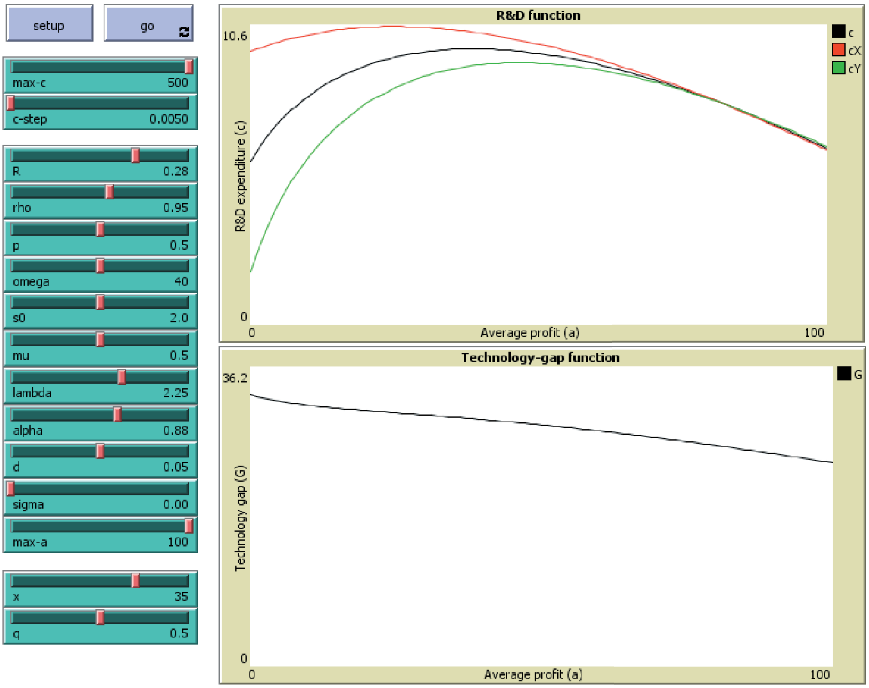

Figure B.5: The interface of the PT model with diminishing sensitivity in `Netlogo 5.0.1`

In Figure B.5, I present the graphical interface of the prospect-theory model with diminishing sensitivity. It contains two buttons, fifteen sliders, one chooser, and two plots. The button `setup` clears the graphs and the button `go` restarts the simulation. The sliders correspond to the following variables of the model: `max-c` and `c-step` determine the values from which managers of firms X and Y choose the optimum sizes of R&D expenditures, `R` is the opportunity parameter R, `rho` is the scale parameter ρ, `p` is the probability of success p, `omega` is the base salary ω, `s0` is the ownership share s_0, `mu` is the decreasing-ownership parameter μ, `lambda` is the loss-aversion parameter λ, `alpha` is the diminishing-sensitivity parameter α, `d` is the disutility parameter d, `sigma` is the slope parameter σ, `max-a` is the maximum average profit $\bar{a}$, `x` is the profit difference x, `q` is the share of firms X in the industry q. The plot `R&D function` presents the R&D-expenditure function of firms X $c_i^X(a)$ (the red line `cX`), the R&D-expenditure function of firms Y $c_i^Y(a)$ (the green line `cY`), and the R&D function $c(a)$ (the black line `c`) for the values of parameters in the sliders. The scenario none enables the free choice of parameter values and other scenarios recreate predictions corresponding to Figures 3.7 and 3.8. Only the lines are a little bit dented since max-c is set at 200 and c-step at 0.1 in order to increase the speed of the solution. The plot technology-gap function shows the technology-gap function $G(a)$ for the same values of parameters.

Figure B.6 presents important parts of the code of the model. Section globals lists the remaining variables of the model that are not defined as sliders: a denotes the average profit a, reward is the reward parameter r, s is the effective ownership parameter s, U is the utility of the manager of firm i U_i, U* is the optimum utility of the manager, wS or wF is the income of the manager of firm i that innovates successfully w_{iS} or fails to innovate w_{iF}, cF is a help parameter used for finding the optimum R&D expenditures, cX and cY are R&D expenditures of firms X and Y c_i^X and c_i^Y, c are average R&D expenditures c, and G is the technology gap G.

The procedure setup clears all plots and resets all global variables of the model. The procedure go generates the plots for the average profits $a = \{0, 1, 2, \ldots, \bar{a}\}$. It includes procedures innovation and do-plot. The procedure Innovation finds average R&D expenditures c and the technology gap G for a given value of the average profit a (comments link the code to equations in Chapter 3). The procedure finds R&D expenditures that maximize the utility of managers of firms X or Y out of the values of R&D expenditures cF = {0, c-step, 2c-step, ..., max-c}. All figures in Section 3.3 use values c-step = 0.005 and max-c = 500, which seem to be sufficient as the value of max-c = 500 is five times as high as the maximum average profit $\bar{a} = 100$ (the average R&D expenditures of firms in reality are below 30, see Subsection 2.2.4), and c-step = 0.005 provides the total number of 100,000 steps. Finally, the procedure do-plots plots the values of R&D expenditures c_i^X, c_i^Y, and c, and the technology gap G for each value of the average profit a.

```
globals [
  a
  reward
  s
  U
  U*
  wS
  wF
  cF
  cX
  cY
  c
  G
]

to setup
  __clear-all-and-reset-ticks
end

to go
  innovation
  do-plots
  tick
  if a = max-a
    [stop]
  set a a + 1
end
```

```
to innovation
  set reward ((1 + R - (a / max-a) * sigma)) / p ;(3.4)
  set s s0 - s0 * mu * (a / max-a) ;(3.6)

  ;; Finding R&D expenditure of firms X "cX" by maximizing utility U (3.10) of manaagers of firms X
  ;; for all sizes of R&D expenditures "cF = {0, c-step, 2c-step, ..., max-c}"
  set cF 0
  set cX 0
  set U* -1000
  set U 0
  repeat (max-c / c-step + 1)
    [ set wS omega + s * (a + (1 - q) * x  + reward * cF ^ rho - cF) ;(3.5)
      set wF omega + s * (a + (1 - q) * x - cF) ;(3.5)
      if (wS < 0)
          [ set U ((- p) * lambda  * (abs wS) ^ alpha
            - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wS >= 0 and wF < 0)
          [ set U (p * wS ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wF >= 0)
        [ set U (p * wS ^ alpha + (1 - p) * wF ^ alpha - d * cF) ]
      ifelse U > U*
        [ set U* U
          set cX cF ]
        [ set U 0]
        set cF cF + c-step ]

  ;; Finding R&D expenditure of firms Y "cY" by maximizing utility U (3.10) of managers of firms Y
  ;; for all sizes of R&D expenditures "cF = {0, c-step, 2c-step, ..., max-c}"
  set cF 0
  set cY 0
  set U* -1000
  set U 0
  repeat (max-c / c-step + 1)
    [ set wS omega + s * (a - q * x  + reward * cF ^ rho - cF) ;(3.5)
      set wF omega + s * (a - q * x  - cF) ;(3.5)
      if (wS < 0)
        [ set U ((- p) * lambda  * (abs wS) ^ alpha
          - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ] ;(3.7) and (3.8)
      if (wS >= 0 and wF < 0)
        [ set U (p * wS ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ] ;(3.7) and (3.8)
      if (wF >= 0)
        [ set U (p * wS ^ alpha + (1 - p) * wF ^ alpha - d * cF) ] ;(3.7) and (3.8)
      ifelse U > U*
        [ set U* U
          set cY cF ]
        [ set U 0]
          set cF cF + c-step ]

    set c q * cX + (1 - q) * cY ;(3.25)
    set G q * (1 - p) * (reward * cX ^ rho) + (1 - q) *(p * (x + reward * cX ^ rho - reward * cY ^ rho)
      + (1 - p)*(x + reward * cX ^ rho)) ;(3.26)
end

to do-plots
  set-current-plot "R&D function"
  set-current-plot-pen "c"
  plot c
  set-current-plot-pen "cX"
  plot cX
  set-current-plot-pen "cY"
  plot cY

  set-current-plot "Technology-gap function"
  set-current-plot-pen "G"
  plot G
end
```

Figure B.6: The `Netlogo` code of the PT model with diminishing sensitivity

B.4 Sensitivity analysis

This section presents a procedure that finds the average profit that corresponds to the maximum of the R&D and technology-gap functions in the PT model with diminishing sensitivity implemented in `Netlogo 5.0.1`.

Figure B.7 presents the graphical interface that contains two buttons, fourteen sliders, two plots, and two monitors. The button setup clears the graphs, and the button go starts the simulation. The sliders correspond to the following variables of the model: a-step is the minimum difference between the values of the average profit used in the simulation a = {0, a-step, 2a-step, ..., max-a}, R is the opportunity parameter R, rho is the scale parameter ρ, p is the probability of success p, omega is the base salary ω, s0 is the ownership share s_0, mu is the decreasing-ownership parameter μ, lambda is the loss-aversion parameter λ, alpha is the diminishing-sensitivity parameter α, d is the disutility parameter d, sigma is the slope parameter σ, max-a is the maximum average profit $\bar{a}$, x is the profit difference x, q is the share of firms X in the industry q. The plots R&D function and technology-gap function present the R&D function $c(a)$ and the technology-gap function $G(a)$ for the values of parameters in the sliders. Finally, the monitors a* and aG* show the average profits that corresponds to the maximum of the R&D and technology-gap functions, respectively.

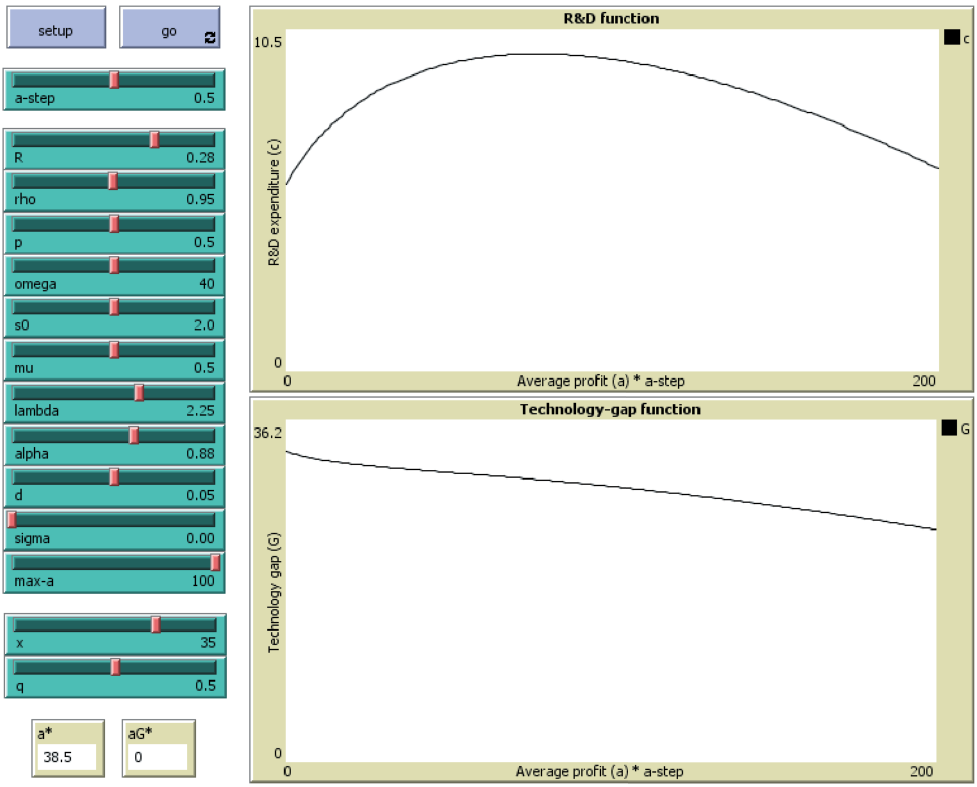

Figure B.7: The interface of the application for finding position of the maximum of the R&D function $c(a)$ and the technology-gap function $G(a)$ in `Netlogo 5.0.1`

Figure B.8 presents the code of the model. Section globals lists the remaining variables that are not defined as sliders: a represents the average profit a, the variables a*, a*-, a*+ describe the position of the maximum of the R&D function, aG*, aG*-, aG*+ describe the position of the maximum of the technology gap function, reward is the reward parameter r, s is the effective ownership parameter s, U is the utility of managers, U* is the optimum utility of managers, wS or wF is the income of the manager of firm i that innovates successfully w_{iS} or fails to innovate w_{iF}, cF is a help parameter used for finding the optimum R&D expenditures, cX and cY are R&D expenditures of firms X and Y c_i^X and c_i^Y, c represents average R&D expenditures in the industry c, c*-, c*+ are help parameters describing the maximum of the R&D function, G is technology gap G, G*-, G*+ are help parameters describing the maximum of the technology-gap function, and max-X-c, max-Y-c, c-X-step, c-Y-step determine the values from which managers of firms X and Y select the optimum size of R&D expenditures.

The procedure setup resets the model and sets the initial values of the help parameters max-X-c, max-Y-c, c-X-step, c-Y-step. The procedure go generates the plots for the average profits a = {0, a-step, 2a-step, . . . , max-a}. In the simulations in Section 4.2, I use the value of a-step = 0.5. The procedure go includes the following four procedures (comments link the code to equations in Chapter PT-model):

1. The procedure innovation finds R&D expenditures c* that maximize the utility of managers of firms X and Y for a given average profit a. The managers of firms X choose one of the values cF = {0, c-X-step, 2c-X-step, . . . , max-X-c} and the managers of firms Y one of the values cF = {0, c-Y-step, 2c-Y-step, . . . , max-Y-c}.

2. The procedure find-maximum reports the average profits a* and aG* that correspond to the highest values of the R&D and technology-gap functions. If the given function is flat, more values of average profits a = {0, a-step, 2a-step, . . . , max-a} might correspond to the maximum of the function. Then the average profits a* and aG* are equal to (a*- + a*+)/2 and (aG*- + aG*+)/2, where a*- and aG*- record the average profits at which the functions stop increasing, and a*+ and aG*+ show the average profits at which the functions start decreasing. If at the end of the simulation a*- = 0 and a*+ > 0 (or aG*- = 0 and aG*+ > 0), the procedure go sets a* (or aG*) equal to 0, which means that the function is reported as decreasing instead of inverse U-shaped. Subsequently, if a*+ = 100 and 0 < a*- < 100 (or aG*+ = 100 and 0 < aG*- < 100), the procedure go sets a* (or aG*) equal to 100, so that the function is reported as increasing.

3. The procedure adjust-grid changes the values of max-X-c, max-Y-c, c-X-step, c-Y-step in order to measure R&D expenditures in the procedure innovation more precisely and in order to reduce the computational burden of the procedure.

4. And finally, the procedure do-plots depicts the values of R&D expenditures c and the technology gap G for each value of the average profit a.

```
globals [
  a
  a*
  a*-
  a*+
  aG*
  aG*-
  aG*+
  reward
  s
  U
  U*
  wS
  wF
  cF
  cX
  cY
  c
  c*-
  c*+
  G
  G*-
  G*+
  max-X-c
  max-Y-c
  c-X-step
  c-Y-step
]

to setup
  __clear-all-and-reset-ticks
  set a 0
  set max-X-c 1000
  set max-Y-c 1000
  set c-X-step 0.005
  set c-Y-step 0.005
end

to go
  innovation
  find-maximum
  adjust-griding
  do-plots
  tick
  ifelse a < max-a
    [ set a a + a-step ]
    [ if a*- = 0 [set a*+ 0]
      if a*+ = 100 [set a*- 100]
      stop ]
end

to innovation
  set reward ((1 + R - (a / max-a) * sigma)) / p ;(3.4)
  set s s0 - s0 * mu * (a / max-a) ;(3.6)

  ;; Finding R&D expenditure of firms X "cX" by maximizing utility U (3.10) of managers of firms X
  ;; for all sizes of R&D expenditures "cF = (0, c-step, 2c-step, ..., max-c)"
  set cF 0
  set cX 0
  set U* -1000
  set U 0
  repeat (max-X-c / c-X-step + 1)
    [ set wS omega + s * (a + (1 - q) * x  + reward * cF ^ rho - cF)
      set wF omega + s * (a + (1 - q) * x - cF)
      if (wS < 0)
          [ set U ((- p) * lambda  * (abs wS) ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wS >= 0 and wF < 0)
          [ set U (p * wS ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wF >= 0)
        [ set U (p * wS ^ alpha + (1 - p) * wF ^ alpha - d * cF) ]
      ifelse U > U*
        [ set U* U
          set cX cF ]
        [ set U -1000]
        set cF cF +  c-X-step ]
```

```
  ;; Finding R&D expenditure of firms Y "cY" by maximizing utility U (3.10) of managers of firms Y
  ;; for all sizes of R&D expenditures "cF = (0, c-step, 2c-step, ..., max-c)"
  set cF 0
  set cY 0
  set U* -1000
  set U 0
  repeat (max-Y-c / c-Y-step + 1)
    [ set wS omega + s * (a - q * x  + reward * cF ^ rho - cF)
      set wF omega + s * (a - q * x  - cF)
      if (wS < 0)
        [ set U ((- p) * lambda  * (abs wS) ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wS >= 0 and wF < 0)
        [ set U (p * wS ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF) ]
      if (wF >= 0)
        [ set U (p * wS ^ alpha + (1 - p) * wF ^ alpha - d * cF) ]
      ifelse U > U*
        [ set U* U
          set cY cF ]
        [ set U -1000]
          set cF cF + c-Y-step ]

   set c q * cX + (1 - q) * cY ;(3.25)
   set G q * (1 - p) * (reward * cX ^ rho) + (1 - q) *(p * (x + reward * cX ^ rho - reward * cY ^ rho)
     + (1 - p)*(x + reward * cX ^ rho)) ;(3.26)
end

to find-maximum
   ;;The maximum of R&D function corresponds to average profit between "a*-" and "a*+"
   if c > c*-
     [ set c*- c
       set a*- a ]
   if c >= c*-
     [ set c*+ c
       set a*+ a ]
   set a* (a*- + a*+)/ 2
   ;;The maximum of Technology-gap function corresponds to average profit between "aG*-" and "aG*+"
   if G > G*-
     [ set G*- G
       set aG*- a ]
   if G >= G*-
     [ set G*+ G
       set aG*+ a ]
   set aG* (aG*- + aG*+)/ 2
end

to adjust-griding
   ;;Adjusting the gridding according to the size of R&D expenditures "cX"
   if cX > 0
   [ set max-X-c 4
     set c-X-step 0.0005]
   if cX > 3
   [ set max-X-c 10
     set c-X-step 0.001]
   if cX > 8
   [ set max-X-c 25
     set c-X-step 0.002]
   if cX > 15
   [ set max-X-c 60
     set c-X-step 0.005]
   if cX > 50
   [ set max-X-c 150
     set c-X-step 0.01]
   if cX > 120
   [ set max-X-c 300
     set c-X-step 0.02]
   if cX > 250
   [ set max-X-c 500
     set c-X-step 0.04]
   if cX > 300
   [ set max-X-c 800
     set c-X-step 0.06]
   if cX > 600
   [ set max-X-c 2000
     set c-X-step 0.1]
```

```
    ;;Adjusting the gridding according to the size of R&D expenditures "cX"
    if cY > 0
    [ set max-Y-c 4
      set c-Y-step 0.0005]
    if cY > 3
    [ set max-Y-c 10
      set c-Y-step 0.001]
    if cY > 8
    [ set max-Y-c 25
      set c-Y-step 0.002]
    if cY > 15
    [ set max-Y-c 60
      set c-Y-step 0.005]
    if cY > 50
    [ set max-Y-c 150
      set c-Y-step 0.01]
    if cY > 120
    [ set max-Y-c 300
      set c-Y-step 0.02]
    if cY > 250
    [ set max-Y-c 500
      set c-Y-step 0.04]
    if cY > 300
    [ set max-Y-c 800
      set c-Y-step 0.06]
    if cY > 600
    [ set max-Y-c 2000
      set c-Y-step 0.1]
end

to do-plots
  set-current-plot "R&D function"
  set-current-plot-pen "c"
  plot c

  set-current-plot "Technology-gap function"
  set-current-plot-pen "G"
  plot G
end
```

Figure B.8: The `Netlogo` code of the application for finding the position of the maximum of the R&D function $c(a)$ and the technology-gap function $G(a)$

B.5 The PT model with endogenous profit difference

This section presents an interactive version of the prospect-theory model with endogenous profit difference implemented in `Netlogo 5.0.1`. The code offers a numerical solution that finds the R&D expenditures and the technology gap for the values of the average profit $a = \{0, 1, 2, \ldots, \bar{a}\}$, where $\bar{a}$ is the maximum average profit.

Figure B.9 presents the graphical interface of the model. It contains two buttons, nineteen sliders, one chooser, and two plots. The button setup clears the plots and the button go restarts the simulation. The sliders correspond to the following variables of the model: n is the number of firms in the industry n, max-c and c-step determine the values from which managers of firms X and Y choose the optimum size of R&D expenditures, phi is the expectations parameter ϕ, R is the opportunity parameter R, rho is the scale parameter ρ, p is the probability of success p, omega is the base salary ω, s0 is the ownership share s_0, mu is the decreasing-ownership parameter μ, lambda is the loss-aversion parameter λ, alpha is the diminishing-sensitivity parameter α, d is the disutility parameter d, sigma is the slope parameter σ, max-a is the maximum average profit $\bar{a}$, h is appropriability parameter h, tA denotes the number of periods for which R&D expenditures and the technology gaps are not measured, and tE is the total number of periods. The scenario none enables choosing parameter values freely and other scenarios correspond to Figure A.1. The plots R&D expenditures and technology gap depict the R&D function $c(a)$ and the technology-gap function $G(a)$ for the values of parameters shown in the sliders.

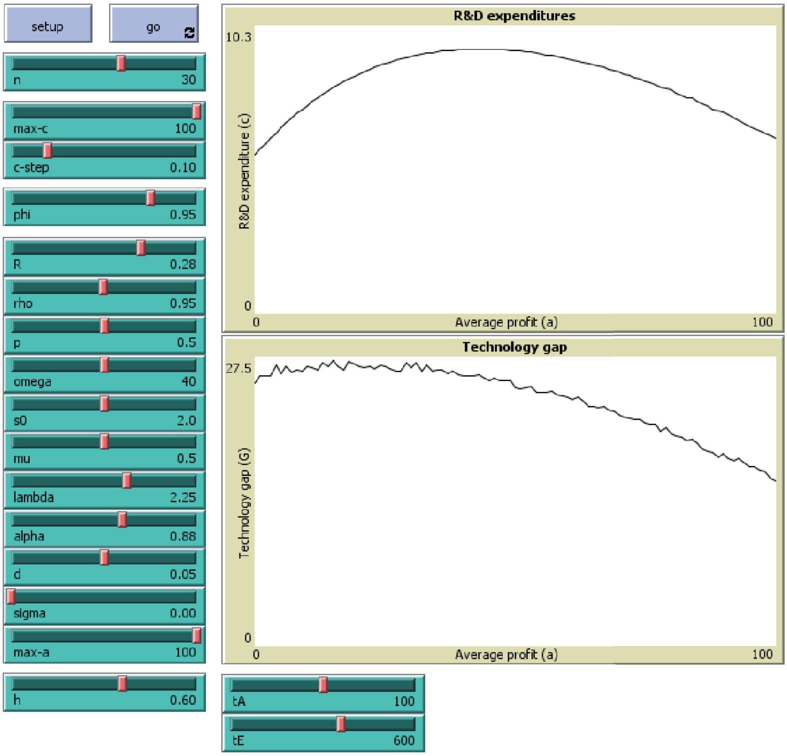

Figure B.9: The interface of the PT model with endogenous profit difference in `Netlogo 5.0.1`

Figure B.10 presents important parts of the code. Sections globals and turtle-own include the variables that are not defined as sliders. Section globals lists the variables that are identical for all the firms: a denotes the average profit a, reward is the reward parameter r, s is the effective-ownership parameter s, Sc is the sum of average R&D expenditures of firms in periods $t_A < t \geq t_E$, Gt is the technology gap G in time t, SG the sum of the technology gaps in periods $t_A < t \geq t_E$, and x the measure of periods. Section turtle-own contains the firm-specific variables: U is the utility of managers, U* is the optimum utility of managers, wS or wF is the income of the manager of firm i in the case of success and failure w_{iS} and w_{iF}, tau and tau-1 are technology levels of firm i in periods t and $t-1$ τ_{it} and τ_{it-1}, Tei and Tei-1 are expected changes in the average technology of the other firms in periods t and $t-1$ T^e_{it} and T^e_{it-1}, delta is the technology difference at the beginning of period t δit^I, cF is a help parameter used for finding the optimum size of R&D expenditures, cit denotes R&D expenditures of firms i in time t c_{it}, Ti-1 is the change in technology of all other firms in the industry in period $t-1$ T_{it-1}, and tau_j and tau_j-1 are average technology levels of the other firms in the industry in periods t and $t-1$ τ_{jt} and τ_{jt-1}.

The procedure setup resets the model and creates n firms. The procedure go generates R&D expenditures and the technology gaps for the average profits $a = \{0, 1, 2, \ldots, \bar{a}\}$. It includes procedures simulation and do-plot. The procedure simulation finds average R&D expenditures c and the technology gap G for a given value of average profit a (comments link the code to equations in Appendix A). At the beginning of the procedure, the expectations of firm i regarding the change in technology of other firms Tei and the other variables are set equal to zero. Then the simulation runs for tE periods. Each period consists of the following five steps: First, the laggard firms imitate a part of the state-of-the-art technology and all firms calculate the technology difference at the beginning of the period delta. Second, each firm forms expectations about the technology of other firms Tei. Third, each manager chooses the value of R&D expenditures that maximizes her utility out of the values cF = {0, c-step, 2c-step, . . . , max-c}. Fourth, successful innovators increase their technology by $r(a)c_{it}^{\rho}$ and calculate the change of the other firms' technology Ti-1. Fifth, the model calculates sums of average R&D expenditures and the technology gaps in the industry for all periods with the number x > tA, where tA is the number of periods firms have for adjusting their expectations about the change in technology of other firms. Finally, the procedure do-plots reports average R&D expenditures and the technology gap Sc/(tE - tA) and SG/(tE - tA).

```
globals [
  a
  reward
  s
  Sc
  Gt
  SG
  x
]

turtles-own [
  U
  U*
  wS
  wF
  tau
  tau-1
  Tei
  Tei-1
  delta
  cF
  cit
  Ti-1
  tau_j
  tau_j-1
]

to setup
  __clear-all-and-reset-ticks
  crt n
end

to go
  simulation
  do-plots
  tick
  if a = max-a
    [stop]
  set a a + 1
end
```

```
to simulation
  ;; setup before the start of simulation
  ask turtles [ set Tei 0 ] ;each firm expects zero growth of other firms in period -1
  set Sc 0
  set SG 0
  set x 0

  ;; runs
  repeat tE
    [ set x x + 1
  ;; imitation
      ask turtles
        [ set tau tau + ([tau] of max-one-of turtles [tau] - tau)* (1 - h) ] ;(A.2)
      ask turtles
        [ set tau_j ((sum [tau] of turtles - tau) / (n - 1)) ;(A.1)
          set delta tau - tau_j
          set tau-1 tau]

  ;; forming expectations about innovation of all other firms
      ask turtles
        [ set Tei-1 Tei
          set Tei (phi * Tei-1 + (1 - phi)* Ti-1) ;(A.3)

  ;; Finding R&D expenditure of firms "cit" by maximizing utility U (A.7) of managers
  ;; for all sizes of R&D expenditures "cF = (0, c-step, 2c-step, ..., max-c)"
          set reward ((1 + R - (a / max-a) * sigma)) / p ;(3.4)
          set s s0 - s0 * mu * (a / max-a) ;(3.6)
          set cF 0
          set cit 0
          set U* -1000
          repeat (max-c / c-step + 1)
            [ set wF omega + s * (a - cF + delta - Tei) ;(A.5)
              set wS omega + s * (a - cF + delta + reward * cF ^ rho - Tei) ;(A.6)
              if (wS < 0)
                [ set U ((- p) * lambda  * (abs wS) ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF)]
              if (wS >= 0 and wF < 0)
                [ set U (p * wS ^ alpha - (1 - p) * lambda * (abs wF) ^ alpha - d * cF)]
              if (wF >= 0)
                [ set U (p * wS ^ alpha + (1 - p) * wF ^ alpha - d * cF)]
              if U > U*
                [ set U* U
                  set cit cF ]
          set cF cF + c-step ]]

  ;; adjusting technological level and measuring growth in technology of other firms
      ask turtles
        [ if random-float 1 > p
           [ set tau tau + reward * cit ^ rho ]]
      ask turtles
        [ set tau_j-1 tau_j  ;(A.4)
          set tau_j ((sum [tau] of turtles - tau) / (n - 1))
          set Ti-1 tau_j - tau_j-1 ]

  ;; measuring technology gap and R&D expenditures
      set Gt ([tau] of max-one-of turtles [tau] - (sum [tau] of turtles / n))
      if x > tA [set Sc Sc + mean [cit] of turtles]
      if x > tA [set SG SG + Gt]]
end

to do-plots
  set-current-plot "R&D expenditures"
  set-current-plot-pen "c"
  plot Sc / (tE - tA)

  set-current-plot "Technology gap"
  set-current-plot-pen "G"
  plot SG / (tE - tA)
end
```

Figure B.10: The Netlogo code of the PT model with endogenous profit difference

Abstract

In this book I introduce two models of innovation that explain the inverted-U relationship between profitability and innovation, and the findings of Aghion *et al.* (2005) and Hashmi (2005) related to the relationship between profitability and the dispersion of productivity in the industry. The basic model provides a simple and general explanation of the empirical findings. In the basic model firms choose R&D expenditures that maximize their expected profits under the assumption that R&D expenditures of firms might be constrained by the size of their profits.

The prospect-theory model provides a more specific explanation of the empirical findings, which includes a behavioral model of managerial decision-making. Managers in the model choose R&D expenditures according to the preferences represented by the prospect-theory value function. For specific sets of parameter values, both models generate predictions that correspond to the empirical findings of Aghion *et al.* (2005) and Hashmi (2005). Finally, I show that both models generate realistic predictions for a wider range of parameter combinations around the specific parameter values.

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An Explanation of the Inverted-U Relationship between Profitability and Innovation

Editorial Board of Faculty of Economics and Administration: Petr Pirožek, Petr Suchánek, Milan Viturka, Vladimír Hyánek, Eva Hýblová, Daniel Němec, Markéta Matulová

Cover by Jarmila Marvanová
Printed by Reprocentrum, a. s., Blansko
Published by Masaryk University, 2014
First edition

ISBN 978-80-210-7423-1
ISBN 978-80-210-7498-9 (online : pdf)
DOI: 10.5817/CZ.MUNI.M210-7423-2014

This book studies the determinants of innovative activity of firms. It presents a new theory that explains the empirically observed relationship between profitability, innovation and technological differences among firms in an industry.
The book is based on the doctoral thesis which won the Masaryk University Rector's award for an outstanding doctoral thesis in 2014.

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