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INNOVATION & COMPETITION IN A MEMORY PROCESS

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ABSTRACT
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Does innovation increase or decrease with more competition when innovation follows a memory process? This thesis provides a theoretical model which analyzes the innovation and competition relationship assuming that innovation follows a memory process, i.e. the current probability of innovation success depends on previous periods' innovation successes. I find innovation increases with more product market competition, even under the Schumpeterian context where inventions are not completely appropriable. Assuming the probability to innovate increases with past innovations; a follower firm has large incentives to innovate, even in a highly competitive environment, since the memory obtained after innovating increases its probability to innovate again and become a leader. Therefore, industries will be most of the time neck-and-neck where firms innovate to escape from competition.

I test this theoretical finding using the same dataset of Aghion et al. (2005). I find ambiguous results for the innovation-competition relationship. I show that the instrumental variables used by Aghion et al. (2005) are not exogenous and the empirical model is not stable over time.

I, therefore, build a database of 220 U.S. industries to analyze the innovation-competition relationship. As in my theoretical model, I find that innovation increases with more product market competition when innovation follows a memory process. However, when the innovation process is memoryless, I find that more competition decreases the level of innovation when industries already have a high level of competition.

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Declaration of Authorship

I, Juan Luis Correa Allamand, declare that the thesis entitled "Innovation & Competition in a Memory Process" and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission.

Signed: ....

Date: ....

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Abbreviations

ABBGH	Aghion, Bloom, Blundell, Griffith and Howitt (2005)
BLS	United States Bureau of Labor Statistics
CAFC	United States Court of Appeals for the Federal Circuit
CES	United States Census Bureau's Center for Economic Studies
CUSIP	Committee on Uniform Security Identification Procedures
EU	European Union
NAICS	North American Industry Classification System
NBER	National Bureau of Economic Research
OLS	Ordinary Least Squares
SIC	Standard Industrial Classification
SMP	European Single Market Program
TFP	Total Factor Productivity
UK	United Kingdom
US	United States
USPTO	United States Patent and Trademark Office

Introduction

This thesis proposes a model regarding the relationship between innovation and competition, assuming a firm's current probability to innovate increases when this firm succeeded to innovate in the past. I theoretically find that the higher the competition's level, the more innovative an industry is, even under the Schumpeterian context where inventions are not completely appropriable. Using the same dataset of Aghion, Bloom, Blundell, Griffith and Howitt (2005), hereafter ABBGH, I find ambiguous results for the empirical relationship between innovation and competition. As the ABBGH data are not sufficiently informative to have consistent results, I build a database using US data to analyze how competition affects innovation, considering that what firms did in the past matters. I find that for memory industries there is a positive relationship between innovation and competition. However, in the case of memoryless industries, competition decreases innovation when the level of competition is high.

Jones (2002), among others, have clearly stated how important the stock of ideas is to increase economic growth. However, the economic literature does not provide a clear answer of whether the stock of ideas increase or decrease with more market competition.

An important part of the theoretical studies support the Schumpeterian idea that more competition decrease innovation as the dissipation of profits in more competitive markets discourage potential inventors to innovate. However, most of the empirical literature shows that more competitive markets boost innovation.

ABBGH reconcile these opposite lines of thought finding that changes in product market competition can both encourage and discourage innovation, depending on the level of competition. They find that at low levels of competition most of the industries are neck-and-neck (firms have similar technologies), thus an increase in competition boosts innovation since firms innovate in order to escape from competition. When the level of competition is high, most of the industries are unleveled (there is a technological leader), hence a decrease in competition encourages the follower to innovate increasing the aggregate level of innovation.

ABBGH assume, however, that the probability to innovate is independent of past innovations. Another drawback of their work is that they build their dataset using UK firms with patents in the US for the period 1973-1994. Even though there was an institutional change in the US patent system in the early 1980s, they do not test the hypothesis of a structural break in the data because of this institutional change.

I introduce a theoretical model assuming the contemporaneous probability of innovation success depends on the previous period's innovation success. In my model, as in ABBGH, there is a negative relationship between innovation and competition in unleveled industries, while this relationship is positive in neck-and-neck industries. However, since the incentive to innovate in unleveled industries is still very high at the maximum level of competition, the industries will be most of the time neck-and-neck regardless the level of competition, where the innovation-competition relationship is upward sloping; differing from the inverted-U found in ABBGH. I also find that more memory increases the level of research intensity.

I test this theoretical model using the ABBGH dataset. Across the entire sample, ABBGH find an inverted-U innovation-competition relationship. I show, however, that the instruments used by ABBGH are not valid, since they are endogenous. I also find that there is a structural break in the data in the early 1980s. Splitting the sample between 1973-1982 and 1983-1994, the empirical relationship between innovation and competition is positive for the industries which show a memory process during the period 1973-1982. However, there is no significant relationship between innovation and competition during the period 1983-1994. The inverted-U pattern does not hold for the memoryless sample either, since in fact there is no significant relationship between innovation and competition for these industries.

Hence, the data before 1983 provide some support for a memory innovation process model. I do not attempt to give a full explanation of the structural break in this paper. It is noted, however, that Jaffe and Lerner (2004) argue that the establishment of the United States Court of Appeals for the Federal Circuit (CAFC) in October 1982 decreased the difficulty of granting a patent, diminishing the quality of those which are granted. The ABBGH dataset is made up of firms listed on the London Stock Exchange that received patent grants from the United States Patent and Trademark Office. One hypothesis, then, is that this change in the US institutional environment had an effect on the innovation-competition relationship.

The last chapter of this thesis is a joint work with my supervisor Dr. Carmine Ornaghi. As when using the ABBGH dataset the results are not consistent, and there are few observations when considering the different type of industry and the structural breaks, we analyze the innovation-competition relationship using 220 US industries for the period 1991-2003. The database is constructed using Compustat firms. Using this dataset we have many more observations than when using the ABBGH dataset. At the same time, we attempt to find robust evidence of this relationship using US data, while most of the empirical studies analyzing the innovation-competition relationship use UK data.

We find that there is a positive relationship between innovation and competition for the sample of memory industries. However, this relationship differs when considering the memoryless sample. As in the ABBGH theoretical model, we find that more competition decreases innovation for high level of competition. Although the shape of the curve does not exactly look like an inverted-U, there is a part of the curve which is unambiguously negative.

We check the robustness of our finding using data of productivity provided by the United States Bureau of Labor Statistics. Although we do not find that the memory and memoryless industries differ as significantly as when using the Compustat database, the overall conclusions are similar as when using the Compustat data.

Chapter 1

Innovation & Competition: does memory matter?

In this chapter I analyze the theoretical relationship between innovation and competition, assuming innovation follows a memory process. I find innovation increases with more competition. The positive relationship between innovation and competition holds for any value of the model's parameters. I also find that when the knowledge obtained by innovating is more valuable, the level of research is also higher.

Despite the long and comprehensive literature, there is still debate about whether competition boosts or discourages innovation. Some theoretical models, such as Aghion and Howitt (1992), predict that more competition tends to decrease innovation activity. In these models, the innovation incentive is represented by the difference between the expected value of post-innovation profit and pre-innovation profit. Since a monopolist would replace her/himself whenever she/he creates a better intermediate good, incentive to innovate would be biased toward the entrant. Should the profit of being a monopoly be small, as in the case when there is high level of competition, entrants have little incentive to innovate. In contrast, Boldrin and Levine (2008) show that competition leads to more innovation. In their model it is assumed that any idea is costly to transmit, thus there are no unpriced spillovers.

Nevertheless, ABBGH find an inverted-U relationship between competition and innovation. They state when there is low competition, profits before and after innovating are not so different, hence there is not much incentive to innovate when firms are neck-and-neck. In an unleveled sector, however, if the leader innovates the follower keeps the technology distance because of spillovers, thus the leader does not have incentive to innovate. Due to that, low competition industries will be most of the time neck-and-neck where any increase in the competition level leads firms to innovate in order to escape from it (*escape-competition effect*). When there is high competition, the follower's profit after innovating is not so different to pre-innovation profit, consequently there is not much incentive to innovate in the unleveled case. On the contrary, for neck-and-neck firms any innovation would give more profit than if they remain leveled. Therefore, high competition leads industries to be unleveled most of the time, while any decrease in the level of competition boosts the follower's profit if it innovates (*Schumpeterian effect*).

Most of the these models, including the ABBGH, assume that innovation is a Poisson process, where the probability of innovating is independent over time. Although that this assumption is very useful to develop tractable theoretical models, it is unrealistic.

There is a vast literature showing that innovation is not independent over time. Among the empirical studies, Pakes and Griliches (1980), Hausman et al. (1984) and Hall et al. (1986) relate the present innovation with past investment in R&D. The basic idea is that after devoting resources to develop knowledge in some productive activities, a firm can keep this knowledge and use it as an input to create new products or processes in the future.

Hausman et al. (1984) develop a negative binomial fixed effects specification to measure the propensity to patent given present and past R&D expenditure. Hall et al. (1986), however, find difficulties to estimate R&D lag structures, since R&D expenditure usually remains constant over time or just grows slightly.

In the theoretical arena, a recent contribution in the R&D race literature is the model developed by Doraszelski (2003). He finds that knowledge accumulation has strategic implications, where a laggard firm can eventually catch up with the leader if it has a sufficiently large knowledge stock.

Although that modeling innovation and competition in a long-term knowledge accumulation environment seems to be a more plausible assumption, it also introduces more complexity to the model. Regarding this limitation, I assume that whenever a firm innovates at a certain period of time it acquires knowledge, which can be used in the next period as a research input. After that period this knowledge depreciates completely.

In my model, the knowledge obtained through the innovation process is completely appropriable and it can be used to increase the probability to innovate in the next period. Since under the Schumpeterian context the leader firm does not have incentives to innovate, the *memory prize* encourages the laggard firms to devote more efforts to research, shortening the length that the industries remain unleveled. As a result, industries will be most of the time neck-and-neck where the *competition effect* dominates.

The first section of this chapter describes the theoretical model, which assumes that firms follow a short-memory process and the leader does not innovate because of spillovers. The second section contains the steady state's solution of this model. The third section shows the results of the innovation-competition relationship. The fourth section shows the effects of the memory process over the innovation-competition relationship. The last section concludes.

1.1 The Model

Following ABBGH I assume that there are two firms, where $n_m^{k,l}$ denotes the research intensity of a firm which is m technological steps away from its competitor at time t and was k steps away from its rival at time $t - \Delta t$; and l takes the value S if the firm succeeded to innovate at time $t - \Delta t$ or F if it failed. As in ABBGH, a firm cannot be more than one step ahead of its opponent[1], since the latter can copy the leader's previous technology whenever it innovates. Therefore, the leader's research intensity is zero as it cannot obtain additional value from innovating. Consequently, a firm can be in three possible levels, one step ahead, neck-and-neck and one step behind, these states are denoted by the sub(super)scripts 1, 0 and -1 respectively.

As in ABBGH and Aghion et al. (2001), h represents the copy rate or R&D spillovers. The leader obtains profit π_1 and neck-and-neck π_0, while the follower does not earn any profit. Neck-and-neck's profit π_0 can also be expressed as $\pi_1(1-\delta), \forall \delta \in [0.5, 1]$, where δ is the product market competition parameter. The higher the value of δ, the more competitive the industry is. Assuming Bertrand competition, the firms equally share the monopoly profits, π_1, with maximum level of collusion $\delta = 0.5$. On the contrary, firms receive zero profits when competition reaches its maximum level at $\delta = 1$. The research cost of a firm is given by $\frac{(n_m^{k,l})^2}{2}$. The research intensity of a rival firm is denoted as $\overline{n}_m^{k,l}$ and a symmetric Nash equilibrium turns to $n_0^{k,l} = \overline{n}_0^{k,l}$ when firms are and were neck-and-neck.

1.1.1 The memory parameters and Bellman equations

The model presented in this section is constructed assuming that changes in the relative position (leader, neck-and-neck and follower) can only occur after innovating. Hausman et al. (1984) and Hall et al. (1986) empirically find that contemporaneous R&D investment depends on previous investment. Therefore, I assume whenever a firm improves its relative position at time $t - \Delta t$, a value λ, which increases the probability of innovating at time t, will be generated under the process, where $\lambda \geq 0$.

In practice, there can also be the case that competing neck-and-neck firms innovate at the same time. Although, *ceteris paribus*, none of the firms are getting an advantage over the others, they are indeed acquiring knowledge. As knowledge is a research input in my model and the aggregate flow of innovations take into account every research input, I also consider this situation. I assume that when a firm innovates, but does not improve its relative position, it obtains a value, ϕ, which increases the probability of innovating at time t; where $\phi \geq 0$. After time t, both λ and ϕ depreciate completely, i.e. memory lasts for only one period; after that, any advantage completely disappears. The memory values of rival firms are denoted as $\overline{\lambda}$ and $\overline{\phi}$.

[1]Aghion et al. (2001) relax this assumption, assuming that there is no bounding for the distance between the leader and the follower. However, they find that there is no closed-form solution for the research equilibrium and the steady state industry structure.

The memory parameters λ and ϕ represent the knowledge obtained via the innovation process. I assume that this knowledge lasts only one period. This assumption is useful to make the model tractable. Doraszelski (2003) develops a model to study how knowledge accumulation affects the firms' behavior. In his model, knowledge has a cumulative effect over current research, therefore there is no restriction about the length of a lag. However, his model does not allow for an analytic solution. In chapter 2 I give empirical support to the short-memory assumption.

The value function of each firm is given by the current profit flow, the discounted expected value of the firm after investing in R&D and the cost of investing in R&D. The discount factor $e^{-r\Delta t}$ can be expressed as $(1 - r\Delta t)$ for Δt small. From this, we can also have that $(\Delta t)^2 \approx 0$.

For the case of unleveled industries, the leader profits flow is $\pi_1 \Delta t$, while the follower's profit is zero. Since the leader does not invest in R&D, the expected value of an unleveled firm, after the follower invests in R&D, is given by the follower's probability to innovate $(n^k_{-1} + h)\Delta t$. For the same reason only the follower incurs R&D cost. After the follower invests in R&D there are two possible outcomes: (i) both the leader and the follower continue in the same position with value functions V^1_1 and V^{-1}_{-1} respectively, or (ii) the leader is caught up by the follower with value functions V^1_0 and V^{-1}_0 respectively.

Therefore, the value function for the leader who was a leader in the previous period can be written as

$$V^1_1 = \pi_1 \Delta t + (1 - r\Delta t)\left[(\overline{n}^{-1}_{-1} + h)\Delta t V^1_0 + [1 - (\overline{n}^{-1}_{-1} + h)\Delta t]V^1_1\right];$$

for the leader who was neck-and-neck in the previous period

$$V^0_1 = \pi_1 \Delta t + (1 - r\Delta t)\left[(\overline{n}^{0}_{-1} + h)\Delta t V^1_0 + [1 - (\overline{n}^{0}_{-1} + h)\Delta t]V^1_1\right];$$

for the follower who was follower in the previous period

$$V^{-1}_{-1} = \max_{n^{-1}_{-1}}\left\{(1 - r\Delta t)\left[(n^{-1}_{-1} + h)\Delta t V^{-1}_0 + [1 - (n^{-1}_{-1} + h)\Delta t]V^{-1}_{-1}\right] - \frac{(n^{-1}_{-1})^2}{2}\Delta t\right\};$$

and for the follower who was neck-and-neck in the previous period

$$V^{0}_{-1} = \max_{n^{0}_{-1}}\left\{(1 - r\Delta t)\left[(n^{0}_{-1} + h)\Delta t V^{-1}_0 + [1 - (n^{0}_{-1} + h)\Delta t]V^{-1}_{-1}\right] - \frac{(n^{0}_{-1})^2}{2}\Delta t\right\}.$$

For neck-and-neck industries, the firm's profit flow is $\pi_0 \Delta t$. The expected value of a neck-and-neck firm, which was also neck-and-neck in the previous period and failed to innovate, is a function of its own research intensity $n^{0,F}_0$ and the rival's research intensity $\overline{n}^{0,F}_0$. In the case that the neck-and-neck firm succeeded to innovate in the previous period, the expected value is a function of the research intensities $n^{0,S}_0$ and $\overline{n}^{0,S}_0$, and the memory parameters ϕ and $\overline{\phi}$ obtained in the innovation processes.

For neck-and-neck firms which were unleveled in the previous period, the expected value of the firms is a function of the research intensities and the memory parameter λ obtained by the firm which was a follower the previous period. For any of the neck-and-neck firms there are four possible outcomes after they invest in R&D: (i) Succeeding to innovate while the rival fails with a value function V_1^0, (ii) Failing to innovate while the rival succeeds with a value function V_{-1}^0, (iii) both succeeding to innovate with a value function $V_0^{0,S}$ and (iv) both failing to innovate with a value function $V_0^{0,F}$.

Therefore, the value function for the neck-and-neck firm that was also neck-and-neck in the previous period and failed to innovate, as well as its rival, is

$$\begin{aligned} V_0^{0,F} &= \max_{n_0^{0,F}} \Big\{ \pi_0 \Delta t + (1 - r\Delta t) \Big[n_0^{0,F} \Delta t V_1^0 + \overline{n}_0^{0,F} \Delta t V_{-1}^0 + (n_0^{0,F} + \overline{n}_0^{0,F}) \Delta t V_0^{0,S} \\ &\quad + [1 - (2n_0^{0,F} + 2\overline{n}_0^{0,F}) \Delta t] V_0^{0,F} \Big] - \frac{(n_0^{0,F})^2}{2} \Delta t \Big\}; \end{aligned}$$

for the neck-and-neck firm, which was also a neck-and-neck in the previous period but succeeded to innovate, i.e. both firms innovated in the previous period,

$$\begin{aligned} V_0^{0,S} &= \max_{n_0^{0,S}} \Big\{ \pi_0 \Delta t + (1 - r\Delta t) \Big[(n_0^{0,S} + \phi) \Delta t V_1^0 + (\overline{n}_0^{0,S} + \overline{\phi}) \Delta t V_{-1}^0 \\ &\quad + (n_0^{0,S} + \phi + \overline{n}_0^{0,S} + \overline{\phi}) \Delta t V_0^{0,S} + [1 - (2n_0^{0,S} + 2\phi + 2\overline{n}_0^{0,S} + 2\overline{\phi}) \Delta t] V_0^{0,F} \Big] \\ &\quad - \frac{(n_0^{0,S})^2}{2} \Delta t \Big\}; \end{aligned}$$

for the one which was a follower in the previous period

$$\begin{aligned} V_0^{-1} &= \max_{n_0^{-1}} \Big\{ \pi_0 \Delta t + (1 - r\Delta t) \Big[(n_0^{-1} + \lambda) \Delta t V_1^0 + \overline{n}_0^1 \Delta t V_{-1}^0 + (n_0^{-1} + \lambda + \overline{n}_0^1) \Delta t V_0^{0,S} \\ &\quad + [1 - (2n_0^{-1} + 2\lambda + 2\overline{n}_0^1) \Delta t] V_0^{0,F} \Big] - \frac{(n_0^{-1})^2}{2} \Delta t \Big\}; \end{aligned}$$

and for the one which was a leader

$$\begin{aligned} V_0^1 &= \max_{n_0^1} \Big\{ \pi_0 \Delta t + (1 - r\Delta t) \Big[n_0^1 \Delta t V_1^0 + (\overline{n}_0^{-1} + \overline{\lambda}) \Delta t V_{-1}^0 + (n_0^1 + \overline{n}_0^{-1} + \overline{\lambda}) \Delta t V_0^{0,S} \\ &\quad + [1 - (2n_0^1 + 2\overline{n}_0^{-1} + 2\overline{\lambda}) \Delta t] V_0^{0,F} \Big] - \frac{(n_0^1)^2}{2} \Delta t \Big\}. \end{aligned}$$

After simplifying the value functions, the annuity values can be expressed as

$$rV_1^1 = \pi_1 + (\overline{n}_{-1}^{-1} + h)(V_0^1 - V_1^1);$$

$$rV_1^0 = r\Delta t \left[\pi_1 + (\overline{n}_{-1}^{-1} + h)(V_0^1 - V_1^1) \right] + (1 - r\Delta t) rV_1^1;$$

$$rV_{-1}^{-1} = \max_{n_{-1}^{-1}} \left\{ (n_{-1}^{-1} + h)(V_0^{-1} - V_{-1}^{-1}) - \frac{(n_{-1}^{-1})^2}{2} \right\};$$

$$rV_{-1}^{0} = \max_{n_{-1}^{0}} \left\{ r\Delta t \left[(n_{-1}^{0} + h)(V_0^{-1} - V_{-1}^{-1}) - \frac{(n_{-1}^{-1})^2}{2} \right] + (1 - r\Delta t) r V_{-1}^{-1} \right\};$$

$$\begin{aligned} rV_0^{0,F} &= \max_{n_0^{0,F}} \Big\{ \pi_0 + n_0^{0,F}(V_1^0 + V_0^{0,S} - 2V_0^{0,F}) + \overline{n}_0^{0,F}(V_{-1}^0 + V_0^{0,S} - 2V_0^{0,F}) \\ &\quad - \frac{(n_0^{0,F})^2}{2} \Big\}; \end{aligned} \tag{1.1}$$

$$\begin{aligned} rV_0^{0,S} &= \max_{n_0^{0,S}} \Big\{ r\Delta t \Big[\pi_0 + (n_0^{0,S} + \phi)(V_1^0 + V_0^{0,S} - 2V_0^{0,F}) \\ &\quad + (\overline{n}_0^{0,S} + \overline{\phi})(V_{-1}^0 + V_0^{0,S} - 2V_0^{0,F}) - \frac{(n_0^{0,S})^2}{2} \Big] + (1 - r\Delta t) r V_0^{0,F} \Big\}; \end{aligned} \tag{1.2}$$

$$\begin{aligned} rV_0^{-1} &= \max_{n_0^{-1}} \Big\{ r\Delta t \Big[\pi_0 + (n_0^{-1} + \lambda)(V_1^0 + V_0^{0,S} - 2V_0^{0,F}) \\ &\quad + \overline{n}_0^{1}(V_{-1}^0 + V_0^{0,S} - 2V_0^{0,F}) - \frac{(n_0^{-1})^2}{2} \Big] + (1 - r\Delta t) r V_0^{0,F} \Big\}; \end{aligned} \tag{1.3}$$

$$\begin{aligned} rV_0^{1} &= \max_{n_0^{1}} \Big\{ r\Delta t \Big[\pi_0 + n_0^{1}(V_1^0 + V_0^{0,S} - 2V_0^{0,F}) + \\ &\quad (\overline{n}_0^{-1} + \overline{\lambda})(V_{-1}^0 + V_0^{0,S} - 2V_0^{0,F}) - \frac{(n_0^{1})^2}{2} \Big] + (1 - r\Delta t) r V_0^{0,F} \Big\}. \end{aligned} \tag{1.4}$$

First-order conditions can be formulated as

$$n_{-1}^{-1} = V_0^{-1} - V_{-1}^{-1}; \tag{1.5}$$

$$n_{-1}^{0} = V_0^{-1} - V_{-1}^{-1}; \tag{1.6}$$

$$n_0^{0,F} = V_1^0 + V_0^{0,S} - 2V_0^{0,F}; \tag{1.7}$$

$$n_0^{0,S} = V_1^0 + V_0^{0,S} - 2V_0^{0,F}; \tag{1.8}$$

$$n_0^{-1} = V_1^0 + V_0^{0,S} - 2V_0^{0,F}; \tag{1.9}$$

$$n_0^1 = V_1^0 + V_0^{0,S} - 2V_0^{0,F}. \tag{1.10}$$

From (1.5) and (1.6) we can see that the research intensity of a follower which was a follower in the previous period is the same one of the follower which was neck-and-neck. This is due to the fact that the leader does not innovate and it is not possible to be a follower after innovating, thus the value function of the leader is the same whether she/he was a leader or neck-and-neck the previous period and the value function of the follower is the same whether she/he was a follower or neck-and-neck the previous period.

From (1.7), (1.8), (1.9) and (1.10); we can also observe that each type of neck-and-neck firms has the same level of research intensity. This is because the knowledge, λ or ϕ, obtained in the previous period, is independent of the research intensity in the current time, thus it does not affect the marginal decision to research in the actual period. Therefore, notation is simplified as $n_{-1}^{-1} = n_{-1}^0 \equiv n_{-1}$ and $n_0^{0,F} = n_0^{0,S} = n_0^{-1} = n_0^1 \equiv n_0$.

After rearranging, we can see a system of two equations and two variables (the research intensities), which can be written as follows

$$0 = \frac{1-\phi\Delta t}{1-2\phi\Delta t}(V_1 - V_0^{0,F}) - \frac{\phi\Delta t}{1-2\phi\Delta t}(V_0^{0,F} - V_{-1}) - n_0;$$

$$0 = \pi_1(1-\delta)\Delta t + (1-r\Delta t)V_0^{0,F} - n_0\Delta t(V_1 - V_{-1}) + \frac{3}{2}n_0\Delta t + \lambda n_0\Delta t - \frac{r+h}{r}n_{-1} - \frac{n_{-1}^2}{2r};$$

where

$$\begin{aligned} V_0^1 \quad &= \quad \frac{r+h+n_{-1}}{r(r+h+n_{-1}) + (n_0+\lambda\Delta t)(n_{-1}+h)}\left[\pi_1(1-\delta) - \frac{\pi_1(\lambda\Delta t + n_0)}{r+h+n_{-1}}\right. \\ &\left. + \frac{3}{2}n_0^2 + \frac{\lambda n_{-1}^2\Delta t}{2r} + \lambda n_0\Delta t + n_{-1}\frac{r+h-r\lambda\Delta t}{r} + n_0(\frac{n_{-1}^2}{2r} + n_{-1}\frac{r+h}{r} - n_{-1})\right];\end{aligned}$$

$$V_0^{0,F} = \frac{1}{r}\left\{\pi_1\left[(1-\delta) - \frac{n_0}{r+h+n_{-1}}\right] + \frac{3}{2}n_0^2 + n_0(\frac{n_{-1}^2}{r} + n_{-1}\frac{r+h}{r} - n_{-1}) - \frac{n_0(n_{-1}+h)}{r+h+n_{-1}}V_0^1\right\};$$

$$V_1 = \frac{\pi_1 + (n_{-1}+h)V_0^1}{r+h+n_{-1}};$$

$$V_{-1} = \frac{n_{-1}}{r}(\frac{n_{-1}}{2} + h).$$

Notice that it is not possible to have analytical solutions for the research intensities n_{-1} and n_0. Therefore, I proceed to solve the steady state and then to have a numerical solution for both the research equations and the aggregate flow of innovations.

1.1.2 Steady state

In this model, as we can see in figure 1.1, there are four different states. The firms can be unleveled with probability μ_1; neck-and-neck, having been neck-and-neck and failed to innovate in the previous period, with probability $\mu_0^{0,F}$; neck-and-neck, having been neck-and-neck and succeeded to innovate in the previous period, with probability $\mu_0^{0,S}$; and neck-and-neck, having been unleveled in the previous period, with probability μ_0^1.

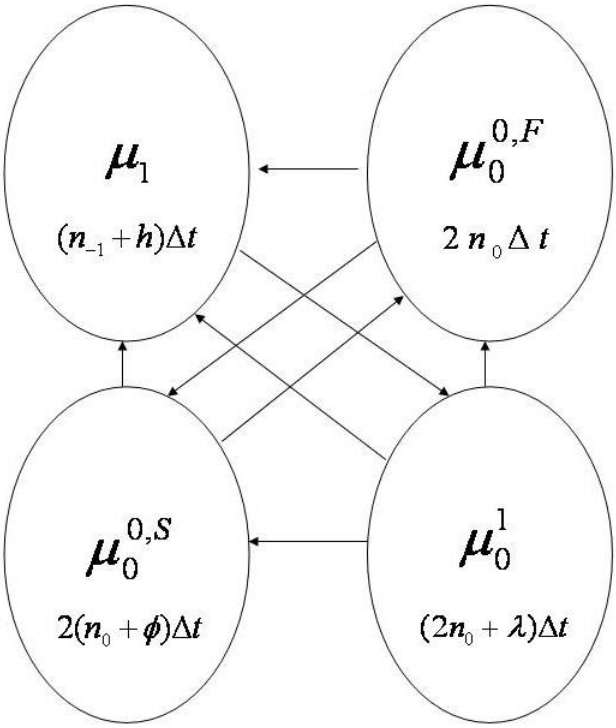


FIGURE 1.1: Steady State

An unleveled industry can become a neck-and-neck after the follower innovates, thus the outflow is equal to $(n_{-1}+h)\Delta t\mu_1$. Since the state of an unleveled industry can be originated by a neck-and-neck state which was neck-and-neck and failed to innovate in the previous period, a neck-and-neck which was neck-and-neck and succeeded to innovate in the previous period or a neck-and-neck that was unleveled in the previous period, the inflow of this case is given by $2n_0\Delta t\mu_0^{0,F} + 2(n_0+\phi)\Delta t\mu_0^{0,S} + (2n_0+\lambda)\Delta t\mu_0^1$.

A neck-and-neck industry, which was also neck-and-neck and failed to innovate in the previous period, can continue to be neck-and-neck after both firms innovate or become unleveled, thus the outflow is $4n_0\Delta t\mu_0^{0,F}$. In order to become a neck-and-neck that was neck-and-neck and failed to innovate in the past, industries must have been neck-and-neck, hence the inflow is $2(n_0+\phi)\Delta t\mu_0^{0,S} + (2n_0+\lambda)\Delta t\mu_0^1$.

A neck-and-neck industry, which was neck-and-neck and succeeded to innovate in the previous period, can continue to be neck-and-neck after both fail to innovate or become unleveled, hence the outflows are $4(n_0+\phi)\Delta t\mu_0^{0,S}$. To become a neck-and-neck that was neck-and-neck and succeeded to innovate in the previous period, industries must have been neck-and-neck, thus the inflow is $2n_0\Delta t\mu_0^{0,F} + (2n_0+\lambda)\Delta t\mu_0^1$.

Finally, a neck-and-neck industry, which was unleveled before, can switch to an unleveled or a neck-and-neck state which was neck-and-neck and either succeeded or failed to innovate in the previous period, thus the outflow of this state is $3(2n_0 + \lambda)\Delta t \mu_0^1$. Since to become a neck-and-neck having been unleveled before can only be produced by an unleveled state, the inflow is $(n_{-1} + h)\Delta t \mu_1$.

In the steady state the outflows must be equal to the inflows, thus we have the following equations

$$\mu_1(n_{-1} + h) = 2n_0\mu_0^{0,F} + 2(n_0 + \phi)\mu_0^{0,S} + (2n_0 + \lambda)\mu_0^1;$$

$$4n_0\mu_0^{0,F} = 2(n_0 + \phi)\mu_0^{0,S} + (2n_0 + \lambda)\mu_0^1; \tag{1.11}$$

$$4(n_0 + \phi)\mu_0^{0,S} = 2n_0\mu_0^{0,F} + (2n_0 + \lambda)\mu_0^1; \tag{1.12}$$

$$3(2n_0 + \lambda)\mu_0^1 = (n_{-1} + h)\mu_1. \tag{1.13}$$

From (1.11) and (1.12) we have

$$\mu_0^{0,S} = \frac{2n_0 + \lambda}{2(n_0 + \phi)}\mu_0^1; \tag{1.14}$$

$$\mu_0^{0,F} = \frac{2n_0 + \lambda}{2n_0}\mu_0^1; \tag{1.15}$$

and from (1.13) we have that

$$\mu_1 = \frac{3(2n_0 + \lambda)}{n_{-1} + h}\mu_0^1. \tag{1.16}$$

From (1.14), (1.15), (1.16) and the fact that in the steady state $\mu_1 + \mu_0^{0,F} + \mu_0^{0,S} + \mu_0^1 = 1$, we have

$$\mu_1 = \frac{6n_0(n_0 + \phi)}{n_0(2n_0 + \lambda)[6(n_0 + \phi) + (n_{-1} + h)] + (n_0 + \phi)(n_{-1} + h)(4n_0 + \lambda)}; \tag{1.17}$$

$$\mu_0^{0,F} = \frac{(n_{-1} + h)(n_0 + \phi)(2n_0 + \lambda)}{n_0(2n_0 + \lambda)[6(n_0 + \phi) + (n_{-1} + h)] + (n_0 + \phi)(n_{-1} + h)(4n_0 + \lambda)}; \tag{1.18}$$

$$\mu_0^{0,S} = \frac{n_0(n_{-1} + h)(2n_0 + \lambda)}{n_0(2n_0 + \lambda)[6(n_0 + \phi) + (n_{-1} + h)] + (n_0 + \phi)(n_{-1} + h)(4n_0 + \lambda)}; \tag{1.19}$$

$$\mu_0^1 = \frac{2n_0(n_0+\phi)(n_{-1}+h)}{n_0(2n_0+\lambda)[6(n_0+\phi)+(n_{-1}+h)]+(n_0+\phi)(n_{-1}+h)(4n_0+\lambda)}. \tag{1.20}$$

Since the aggregate flow of innovations (AI) is given by the sum of the outflows, from (1.17), (1.18), (1.19) and (1.20) we have

$$AI = \frac{2(n_0+\phi)(n_{-1}+h)[3n_0+(2n_0+\lambda)(5n_0+2)]}{n_0(2n_0+\lambda)[6(n_0+\phi)+(n_{-1}+h)]+(n_0+\phi)(n_{-1}+h)(4n_0+\lambda)}.$$

Replacing the research intensities n_{-1} and n_0, we have the aggregate flow of innovations as a function of competition, memory, R&D spillovers and profit parameters. Since the research intensities do not have an analytical solution, subsection 1.2 shows the relationship between the aggregate flow of innovation and competition, using a numerical solution.

1.1.3 The memory effect

The memory parameters λ and ϕ have a direct effect over the neck-and-neck's value functions. However, the leader's value function depends on the value function of the neck-and-neck firm which was the leader in the previous period and therefore the memory parameters also have an effect over the leader's value function.

Since in this model the knowledge obtained by the innovation process does not affect the marginal research's decision, i.e. $n_0^{0,F} = n_0^{0,S} = n_0^{-1} = n_0^1 \equiv n_0$; from equations (1.1), (1.2), (1.3) and (1.4), we can notice that whenever $\lambda = \phi = 0$, the annuity value $rV_0^{0,F} = rV_0^{0,S} = rV_0^{-1} = rV_0^1$. Hence, $n_{-1} = V_0^{0,F} - V_{-1}$ and $n_0 = V_1 - V_0^{0,F}$, which is equivalent to the ABBGH model.

As the knowledge λ obtained by the neck-and-neck firm which was a follower previously gives this firm an advantage to innovate again and earn the monopoly profit, the value V_0^{-1} is larger than the value $V_0^{0,F}$ of the neck-and-neck firm which was neck-and-neck and failed to innovate. Therefore, we should expect that the research intensity of the follower n_{-1} in the memory model would be larger than in the memoryless (or ABBGH) model.

1.2 Innovation & Competition Relationship

In order to solve this model and compare the results with the memoryless model we have to follow the condition identified in ABBGH which satisfies the inverted-U relationship. First, I assume that the leader's profit π_1, the interest rate r and the time interval Δt are given. It is denoted $\phi = \alpha\pi_1$, $\lambda = \beta\pi_1$, and $h = \gamma\pi_1$.

Now, ABBGH define

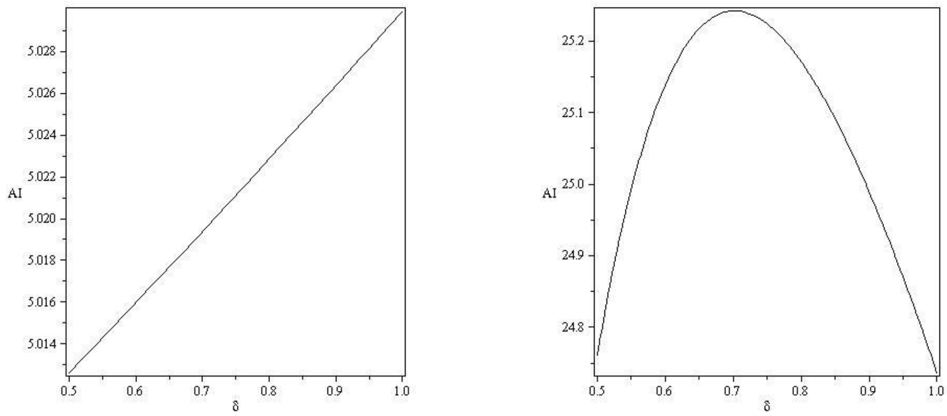
$$\widetilde{x} \equiv \sqrt{\frac{2+\gamma^2\pi_1}{3}} + \gamma\sqrt{\pi_1},$$

$$\underline{x} \equiv \sqrt{1+\gamma^2\pi_1},$$

$$\overline{x} \equiv \sqrt{2+\gamma^2\pi_1}.$$

The inverted-U pattern holds whenever $\underline{x} < \widetilde{x} < \overline{x}$. Therefore, in order to construct the benchmark model I assume that $\alpha = 0.028$, $\beta = 0.04$, $\gamma = 0.018$, $\pi_1 = 500$, $r = 0.1$ and $\Delta t = 0.001$, parameters which satisfy the inverted-U condition.

Figure 1.2 shows the relationship between the aggregate flow of innovations and the competition parameter for both the memory and the memoryless model. Subfigure 1.2a exhibits a clear positive relationship between innovation and competition. We can also notice that the aggregate flow of innovations' level is higher (at any level of competition) in the memoryless model than in the memory model.



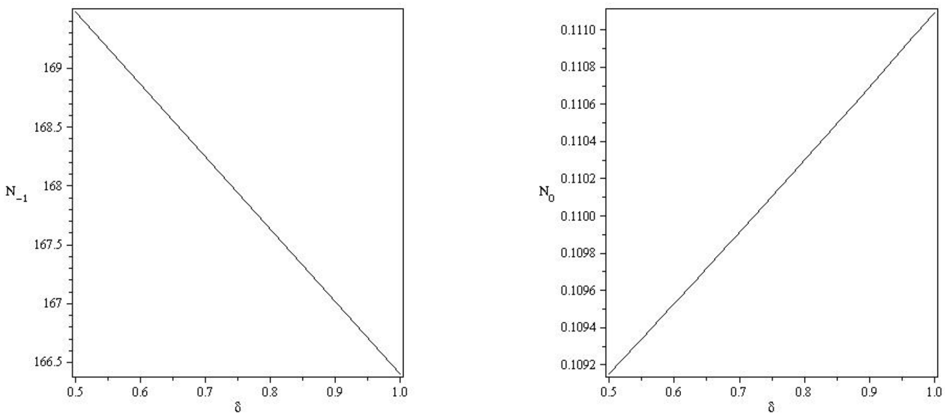
(A) Memory Model (B) Memoryless Model

FIGURE 1.2: Innovation and Competition

As we can see in figure 1.3, the memory model also shows the Schumpeterian and escape-competition effects. As displayed in subfigure 1.3a, more competition decreases the level of research intensity of the follower firm. However, even at the maximum level of competition the research intensity is still much higher than the research intensity of the neck-and-neck firm, as we can see in subfigure 1.3b.

This is because whenever the follower innovates it will be in a better position than its rival when they will be neck-and-neck, since the former follower obtained the memory value λ after innovating while its rival's probability of innovating depends just on the research intensity. Since at any level of competition the research intensity of the follower is much higher than the neck-and-neck research intensity, the follower firm quickly catches up with its rival and the firms will be most of the time neck-and-neck, where the escape-competition effect dominates over the Schumpeterian effect.

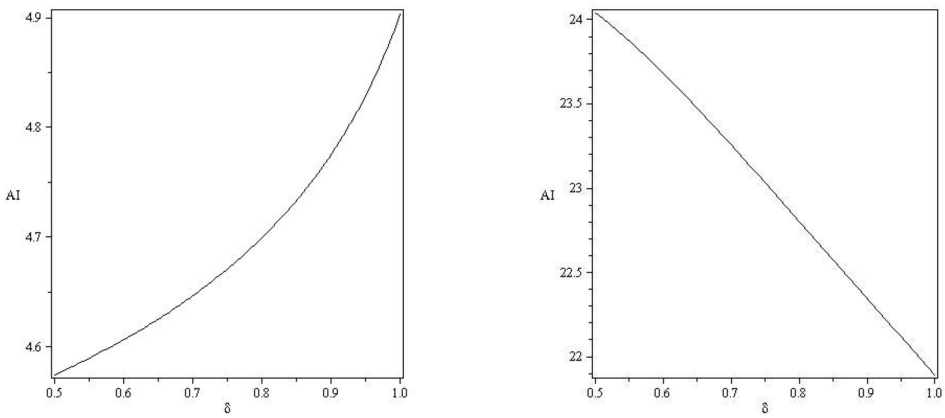
From ABBGH, the Schumpeterian effect will dominate over the whole interval when-



(A) Follower Research Intensity (B) Neck-and-Neck Research Intensity

FIGURE 1.3: Research Intensity

ever $\underline{x} \geq \widetilde{x}$. Therefore, with the same assumptions of the benchmark model but now with $\gamma = 0.002$, we can see the outcome in figure 1.4. Although in the memoryless model the Schumpeterian effect dominates in the whole interval, in the memory model the relationship between innovation and competition is still positive.



(A) Memory Model (B) Memoryless Model

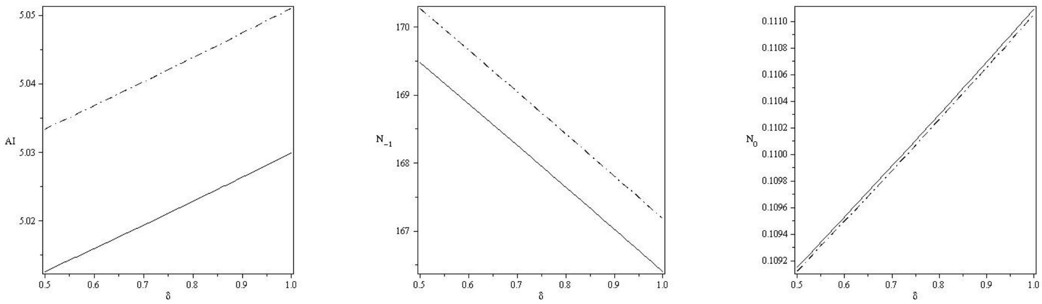
FIGURE 1.4: Schumpeterian Domination

Figure 1.5 shows the case when the knowledge parameters, λ and ϕ, increase. The solid line shows the benchmark model when $\alpha = 0.028$ and $\beta = 0.04$, while the dash-dot line displays the aggregate flow of innovation when $\alpha = \beta = 0.05$. As we can see in subfigure 1.5a, the level of the aggregate flow of innovations increases with an increase in the memory. However, there is no perceptible change in the slope of the curve.

We can also notice from subfigures 1.5b and 1.5c that an increase in the memory parameters increases the research intensity at the unleveled state, but it has almost no effect at the neck-and-neck state. As the *memory prize* increases, the follower firm invests more in R&D since if it innovates the advantage over its rival will be higher, thus the probability to innovate again and become the leader is also higher.

As we can see in the vertical axis of subfigure 1.5a, the increase in the aggregate flow of innovations with higher memory parameters is not as significant. Although the incentive for the follower to innovate is much larger after increasing the memory parameters, the fact that firms are neck-and-neck most of the time, where there is almost no effect on innovation with larger memory parameters, makes that the aggregate effect of more memory over innovation is not as significant.

As we can see in the vertical axis of subfigure 1.2b, the effect of memory over aggregate flow of innovations only holds when the memory parameters are strictly larger than zero. As soon as memory vanishes, the advantage of the neck-and-neck firm, which innovated in the previous period, drives away, dissipating the follower innovation incentive produced by the memory. Therefore, firms will be most of the time neck-and-neck with low competition and unleveled with high competition, where the usual ABBGH effect holds.



(A) Aggregate Flow of Innovations (B) Follower Research Intensity (C) Neck-and-Neck Research Intensity

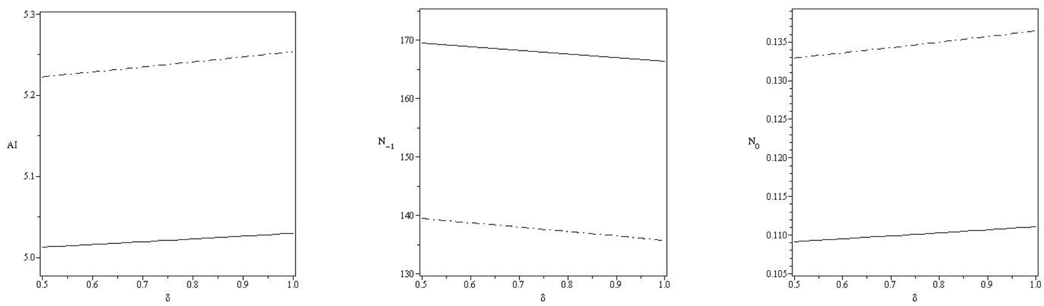
FIGURE 1.5: Increasing the Memory

1.3 Robustness of the Model

In this subsection I check whether the qualitative results of the model are affected by the other parameters. Since this chapter studies how competition affects innovation when there is memory in the process, I do not intend to analyze the effect that the other parameters have over the model.

Figure 1.6 shows how the memory model changes when increasing the interest rate. The solid line is the benchmark model ($r = 0.1$), while the dash-dot line considers an interest rate of 12%. We can see that there is no qualitative change.

Figure 1.7 shows the case when decreasing the copy rate or R&D spillovers. As the former graphic, the solid line is the benchmark model with $\gamma = 0.018$ and the dash-dot line displays a lower copy rate with $\gamma = 0.008$. We can also see that there is no qualitative change, but this time the slope of the aggregate flow of innovations is higher with a lower copy rate.

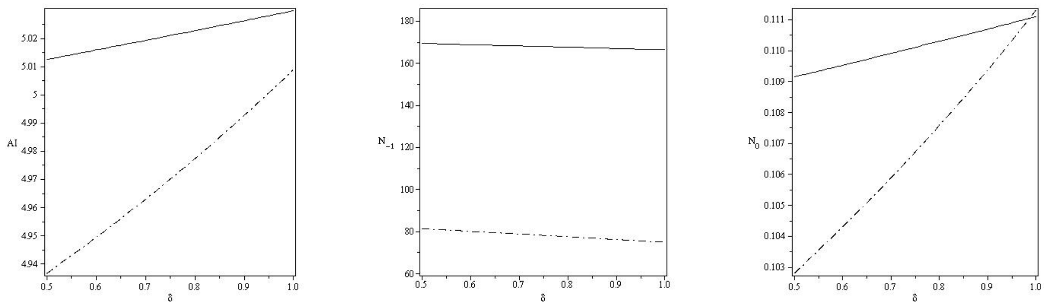


(A) Aggregate Flow of Innovations

(B) Follower Research Intensity

(C) Neck-and-Neck Research Intensity

FIGURE 1.6: Increasing the Interest Rate



(A) Aggregate Flow of Innovations

(B) Follower Research Intensity

(C) Neck-and-Neck Research Intensity

FIGURE 1.7: Decreasing R&D Spillovers

1.4 Conclusion

This chapter analyzes the theoretical relationship between innovation and competition when the research activity follows a memory process. We have seen that whenever memory is assumed, there is a positive relationship between innovation and competition. A follower firm has large incentive to innovate, even in a highly competitive environment, since the memory obtained after innovating increases its probability to innovate again and become a leader. Therefore, industries will be most of the time neck-and-neck where the escape-competition effect dominates.

Both this model and ABBGH's assume that the leader cannot stay more than one step ahead of its rival. One extension for this model is to assume that the leader can be more than one step ahead from the follower, but binding the distance to a certain level in order to have a solution for the steady state.

This model also assumes that the knowledge obtained through innovating is independent from the current period's research, thus this knowledge does not affect the marginal decision to invest in research. If this assumption is modified, the research intensities of the neck-and-neck who was leader, the neck-and-neck who was follower, the neck-and-neck who failed to innovate and the neck-and-neck who succeeded to innovate in the previous period, will be different. It would be interesting to test whether this modification changes the outcome of the model.

Another interesting extension is to relax the assumption of short-memory. Instead of assuming that the research intensity depends just on the previous period's research, it can be the result of a cumulative process model.

Chapter 2

Innovation & Competition: an inverted-U?

In this chapter I analyze the empirical relationship between innovation and competition, considering that for some industries the process of innovation is memory and for some others is memoryless. ABBGH empirical model shows an inverted-U relationship between innovation and competition. This pattern suggests that since competition increases innovation intensity is also increasing, until a threshold where it begins to decrease with more competition. Using the ABBGH dataset, I show that after taking into account structural breaks and invalid instruments, the empirical inverted-U does not hold. I find that for industries which have memory in the innovation process there is a positive relationship between innovation and competition during the period 1973-1982, however, there is no relationship between innovation and competition during the period 1983-1994. I also find that for the memoryless industries there is no relationship between innovation and competition.

The ABBGH model assume that a firm can increase its technological level with a Poisson hazard rate denoted as n, thus the arrival rate of innovation is independent of past innovation. This assumption is too restrictive, since, as stated by Hausman et al. (1984), some industries show a high degree of memory, where a firm can profit from past research increasing the probability to innovate today.

It is important to make the difference between the cumulative process produced by a firm i's application of a research tool developed by a firm j, and the one resulted by the knowledge accumulation in a particular firm. This work will be focused on the latter. When a firm is basing its inventions on other firm's past innovation, the knowledge process is not necessary appropriable, differing from the theoretical model shown in chapter 1.

Jaffe and Lerner (2004) argue that the Federal Courts Improvement Act (these rules have been in operation since October of 1982) has decreased the quality of patents granted by the United States Patent and Trademark Office (USPTO). This change in the United States institutional framework is fundamental for the analysis of the ABBGH empirical model, since their dataset is built by United Kingdom firms which have patents granted by the USPTO.

Another interesting issue in the analysis of the ABBGH empirical model is that they use 36 instruments to solve the problem of mutual causality between innovation and competition. They use as control function the residual vector of an OLS regression between competition, as the dependent variable, and the set of 36 instruments. However, some of the instruments used are also correlated with innovation, rising a problem of instrument endogeneity.

In the first section of this chapter I check the robustness of the ABBGH model. It is shown that this model exhibits instrument's endogeneity and structural breaks. Taking into account the precedent problems, the inverted-U relationship between innovation and competition does not hold. I find that using the 36 endogenous instruments there is a structural break at 1981. Considering this break, there is a positive relationship between innovation and competition for the period 1973-1980, but no relationship at all during the period 1981-1994. After cleaning the endogenous instruments and using 9 exogenous instruments, I find that there is no structural breaks and the relationship between innovation and competition is negative. However, these results must be treated carefully, since in any of the cases the instruments seem not to be relevant enough.

In the second section, I define the industries which follow a memory process. Following Hausman et al. (1984) and Hayashi (2000) I compute a negative binomial regression of citation weighted patent and its five lags. I find that there are 5 industries showing memory in the innovation process and 10 memoryless industries. There are also 2 industries whose processes are more difficult to determine. Considering the instrument endogeneity and structural break issues, I find a positive innovation-competition relationship for the memory industries before the 1982 Reform. However, I find that there is no relationship between innovation and competition for the memoryless industries. The last section concludes.

2.1 Robustness of the inverted-U

Most of the recent studies use patents as a measure of innovation. The advantage of this variable over R&D expenditure is that it takes into account inventions which are an output of some research process, while R&D expenditure is an input which is used to produce an invention. However, patents have the drawback that not all firms patent their inventions, as it is well documented by Cohen et al. (2000), therefore, whenever we use this variable we restrict the analysis to the firms which are patenting only. A broader measurement of innovation is productivity. However, productivity must be estimated, process which is not absent of difficulties. As it has been stated by Klette and Griliches (1996) and Klette (1999) among others, estimated measures of productivity may be biased in the absence of perfect competition.

In this chapter I use the ABBGH data. This database is a panel data composed of 17 SIC2 industries covering a time period between 1973 and 1994. To build this dataset, ABBGH use information of 311 firms listed in the London Stock Exchange, along with patent data obtained from the NBER patents database.[1] The sample contains all firms with names beginning with letters from "A" to "L", and all large R&D firms.

The theoretical model developed in the previous chapter assumes that an industry is composed of two firms, which face the same exogenous competition parameter. The level of innovation is the aggregate flow of innovation of the industry. As the theoretical model is built, the empirical competition variable must be at the industry level since both firms are facing the same competition index. In this framework, we can consider every SIC2 industry as the aggregation of many pairs of firms competing with each other.

The innovation variable is citation weighted patents. Some firms patent as strategic behavior to block the entrance of potential competitors. These patents sometimes lack of innovativeness and they should not have been considered as an innovation. To deal with this problem it is useful to consider a measure of quality. Whenever a patent is cited we can expect that the patent is worthy as other firms are using this patent to build their own inventions. Weighting the patents by citations permits to control for quality of patents.

As a measure of competition ABBGH use a Competition Index which is constructed as 1 minus the unweighted industry Lerner index. To build the unweighted industry Lerner index, ABBGH measure the firm Lerner index, which is as follows

$$L_{it} = \frac{OP_{it} - FC_{it}}{R_{it}},$$

where OP_{it} is the firm i operating profit net of depreciation and provisions at time t, FC_{it} is a financial cost calculated using a constant capital cost rate of 8.5% and the capital stock measured with the perpetual inventory method, and R_{it} is the sales.

The mean of the variable citations weighted patents is 6.65, with 13% of the observations being zero, a maximum of 45 and a standard deviation of 8.43. The mean of the Competition Index is 0.95, with a minimum of 0.87, a maximum of 0.99 and a standard deviation of 0.023.

ABBGH model shows an inverted-U relationship between innovation and competition. The ABBGH outcome suggests that more competition increases the research intensity when the level of competition is relatively low, but decreases it when the competition level is relatively high.

ABBGH state that the conditional citation weighted patents p_{jt} follow a Poisson re-

[1] See Hall et al. (2001).

gression

$$p_{jt} = \exp\{\beta_0 + \beta_1 c_{jt} + \beta_2 c_{jt}^2 + \phi \hat{v}_{jt} + \sum_{j=22}^{49} \alpha_j D_j + \sum_{t=1973}^{1994} \gamma_t D_t + u_{jt}\}, \tag{2.1}$$

where c_{jt} is 1 minus the Lerner index (Competition Index) in industry j at time t, $\hat{v}$ denotes the vector of residuals from the regression of Competition Index on instruments[2], and the sums represent industry and time effects respectively.[3] Figure 2.1 shows clearly the ABBGH inverted-U relationship given by $\hat{p}_{jt} = \exp\{\hat{\beta}_0 + \hat{\beta}_1 c_{jt} + \hat{\beta}_2 c_{jt}^2\}$ and c_{jt}.

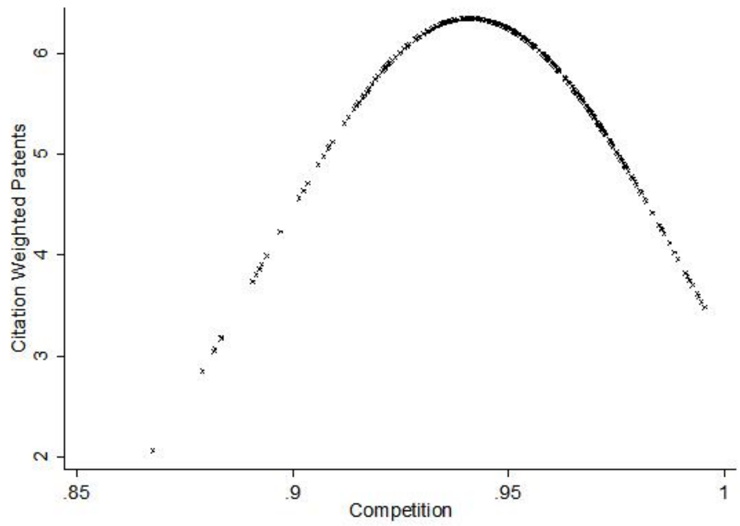


FIGURE 2.1: Inverted-U

Even though this empirical finding apparently follows the predicted model, it is necessary to check that the inverted-U is not explained by just particular features of the dataset. In order to achieve this, I analyze the validity of instruments used in the ABBGH model. Then, I use different approaches to identify structural breaks in the data. Finally, I show the empirical relationship between innovation and competition, considering these particularities of the ABBGH dataset.

2.1.1 Instrumental variables

The main question is whether more or less innovation results from an increase in the level of competition. However, after an invention is materialized the level of competition in an industry can also change. To face this simultaneity problem ABBGH use 36 instruments; a set of policy instruments, including major privatizations, the EU Single Market Programme and Monopoly and Merger Commission investigations; and foreign-industry instruments.[4]

[2]The following subsection explains further the instruments used.

[3]Industries considered can be seen in appendix A.3

[4]Foreign-industry and policy instruments were used to address the problem of simultaneous causality bias. More details about this problem are given in appendix A.1. The list of instruments used in the ABBGH model is provided in table A.5 of appendix A.3.

The EU Single Market Programme (SMP) was established to promote competition among European Union's industries. The ABBGH instruments include a dummy variable with value zero before the SMP and 1 if the the SMP had a significant impact in the respective industry[5], and another dummy variable with value zero before the SMP and 1 if the SMP had an intermediate impact in the respective industry[6] Among the policy instruments, there is also an industry dummy taking a value of 1 if there was an order by the Monopoly and Merger Commision or a major privatization.[7]

Foreign-industry instruments include the relative R&D, productivity, imports, exports and output in the US and France. They also include the mark-up in the US and France.

The inclusion of these 36 instruments can drive instrument endogeneity.[8] For instance, major privatizations can be correlated with innovation, since one of the aims of privatizing is indeed decreasing costs. Therefore, I apply a J test.[9] After having predicted values $\hat{p}_{jt}$ for patents, using actual values c_{jt} and c_{jt}^2 for both competition and competition squared in (2.1), residuals are computed as $\hat{u}_{jt} = p_{jt} - \hat{p}_{jt}$, defining Z as the complete set of instruments and then regressing

$$\hat{u}_{jt} = \eta + Z\xi + \sum_{j=22}^{49} \omega_j D_j + \sum_{t=1973}^{1994} \vartheta_t D_t + \epsilon_{jt}. \tag{2.2}$$

Now, I test

$$\begin{aligned} H_0 &: \xi = 0, \\ H_1 &: \text{otherwise}. \end{aligned} \tag{2.3}$$

Since the F^{obs} is equal to 4.58 and the J-statistic is $J = mF^{obs}$, for m the number of instruments, the null hypothesis of instrument exogeneity is rejected at the 5% significance level. Consequently, the application of endogenous instruments leads to that estimators do not converge in probability to the population coefficients.

I repeat the test but with 9 instruments[10], which present the least t-statistic values in regression (2.2), and fail to reject the null hypothesis of instrument exogeneity at 5% significance level, since the F^{obs} is equal to 0.77 and the J-statistic[11] to 6.93.

In the case of foreign-industry instruments, only do relative exports seem to be exogenous. This result is expected as exports in a particular year from the US and

[5]Industries with high barriers decreased their Lerner index by 10%.

[6]Industries with intermediate barriers decreased their Lerner index by 5%.

[7]Takes the value 1 in the investigation or privatization year onwards.

[8]If any instrument is correlated with the error term, the predicted values of competition will be also correlated with the error, thus the two stage regression is inconsistent.

[9]The methodology of this test is shown in appendix A.2. See Sargan (1958) and Hansen (1982) for further information.

[10]The instruments used for this test are the numbers 14, 15, 16, 17, 26, 27, 29, 30 and 34 in table A.5 of appendix A.3. Concerning about instrument relevance, there is not much difference between using the 36 instruments and the 9 ones. The F-statistic for the coefficient vector of instruments in the first stage regression is 4.81 in the case of 36 instruments and 3.49 for 9 instruments.

[11]The J-statistic is asymptotically distributed with a chi-square distribution with $(m - k)$ degrees of freedom.

France might not affect patent applications in the UK for that particular year. Regarding relative R&D, it can be the case that firms in the US, France and the UK are competing in a patent race, which can drive correlation between R&D expenditures in the US and France, and patent applications in the UK. A similar explanation might hold for productivity, as significant inventions can be accompanied by increase in productivity.

Considering the policy instruments, the exogenous instruments are the SMP, and the periodical and brewing dummies. The SMP directly affected the Lerner index and most of the initiatives were to establish common rules on regulation and takeovers, which could hardly affect patent applications. In the periodical, brewery and razor industry, the Monopoly and Merger Commission orders pointed to prohibit anti-competitive behavior. As expected, all industries including privatizations are endogenous.

Table 2.1 shows the coefficients of the regression (2.1), comparing the 36 endogenous and the 9 non-endogenous instruments. Testing

$$\begin{aligned} H_0 &: \beta_1 = \beta_2 = 0, \\ H_1 &: \text{otherwise}; \end{aligned} \tag{2.4}$$

we reject the null hypothesis at 5% significance level when using non-endogenous instruments, since the χ^2-statistic is 43.59.

TABLE 2.1: Alternative Instruments

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
36 Instruments	386.59 (67.61)**	-205.32 (36.11)**	-180.13 (31.66)**	0.66	354
9 Instruments	310.95 (68.84)**	-176.65 (36.31)**	-134.25 (32.78)**	0.66	354

Standard errors in parentheses. ** significant at 1% level.

Figure 2.2 shows the relationship between innovation and competition, given by $\hat{p}_{jt} = \exp\{\hat{\beta}_0 + \hat{\beta}_1 c_{jt} + \hat{\beta}_2 c_{jt}^2\}$ and c_{jt}, comparing the use of the 36 endogenous and the 9 non-endogenous instruments.

We can clearly see that using the 9 non-endogenous instruments, instead of the 36 instruments used by ABBGH, the inverted-U does not hold. Moreover, there is a negative relationship between innovation and competition, as predicted by traditional Schumpeterian models, such as Aghion and Howitt (1992). Another interesting outcome is that the peak of the innovation level using the 9 instruments is much higher than the peak innovation level using the 36 instruments.

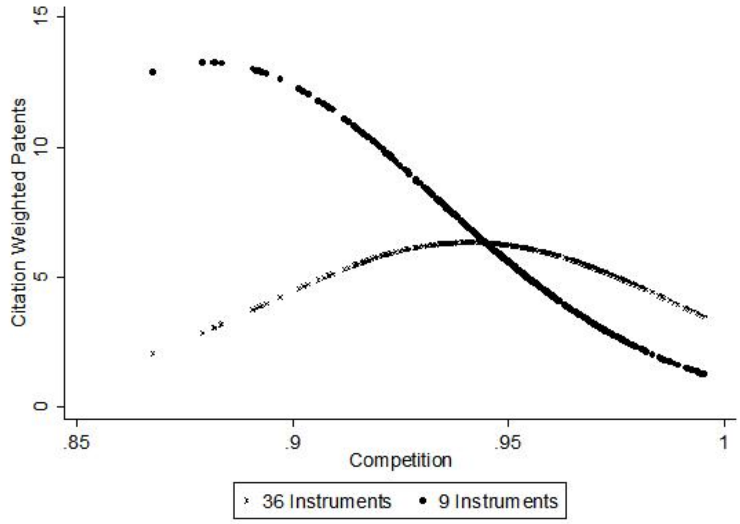


FIGURE 2.2: Instruments Comparison

2.1.2 Structural breaks

Before 1982, appeals of patent cases were heard by the regional courts in the United States. However, after that year all patent appeals have been analyzed by the Court of Appeals for the Federal Circuit (CAFC). Jaffe and Lerner (2004) state that after the establishment of the CAFC there has been a significant increase in the number of patent applications as well as in the fraction of patent grants. They also state that the CAFC has produced a decrease in the level of quality of patents granted. Moser (2005) has found that the level of patent protection influences the direction of innovation activity. This suggests that the Reform of 1982 might change the incentives to patent, inducing industries which are more dependent of patent protection to be relatively more active than in the past.

A first approach to checking stability of competition measure parameters can be done by regressing (2.1) using a group of years. Table A.1 in appendix A.3 reports the outcome of four periods of four years each and one of six. Testing (2.4), that the competition and competition squared coefficients are not significantly different from zero, we fail to reject the null hypothesis at 5% significance level for all periods with the exception of 1973-1976. As we can see in figure 2.3 the relationship between innovation and competition is an inverted-U.

Now, I proceed to analyze structural breaks which can be produced by the establishment of the CAFC. Performing a Chow test for

$$p_{jt} = \exp\{\beta_0+\beta_1 c_{jt}+\beta_2 c_{jt}^2+\phi\hat{v}_{jt}+\delta_1 D_\tau c_{jt}+\delta_2 D_\tau c_{jt}^2+\sum_{j=22}^{49}\alpha_j D_j+\sum_{t=1973}^{1994}\gamma_t D_t+u_{jt}\}, \quad (2.5)$$

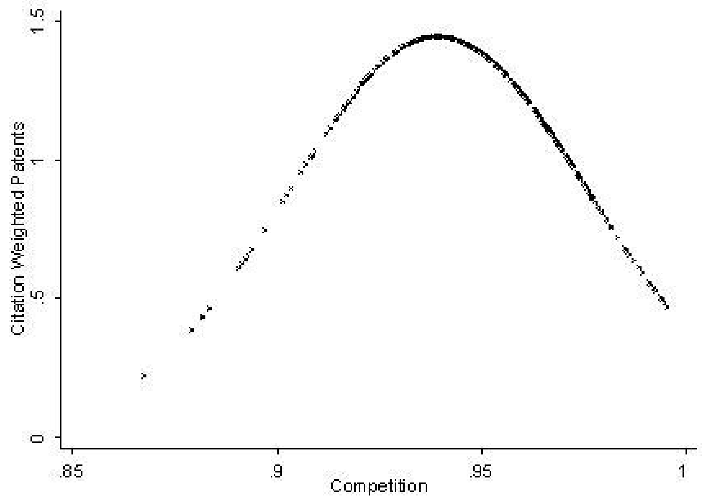


FIGURE 2.3: Period 1973-1976

where

$$D_\tau = \begin{cases} 1 & \forall t \geq \pi \\ 0 & \forall t < \pi \end{cases}$$

and testing

$$\begin{aligned} H_0 &: \delta_1 = \delta_2 = 0, \\ H_1 &: \text{otherwise}; \end{aligned} \tag{2.6}$$

we reject the null hypothesis of time stability for $\pi = 1983$ in competition and competition squared coefficients, at 5% of significance, for both the 36 instruments and the 9 non-endogenous instruments, since the χ^2-statistics are 13.04 and 9.38 respectively. The coefficients of the regression (2.1), but considering the break at 1983, can be seen in table 2.2. We can notice that in the case of the endogenous instruments, there are 9 instruments[12] that are not available for the period 1973-1982 and 1 instrument[13] which is not available for the period 1983-1994. When considering the exogenous insruments, there are 5 instruments[14] which are not available for the period 1973-1982 and all of them are available for the period 1983-1994.

Testing (2.4), whether both competition and competition squared coefficients are equal to zero, we reject the null hypothesis at 5% significance level for the period 1973-1982 using the 36 ABBGH instruments, since the χ^2-statistic is 14.66. We fail to reject the null at 5% significance level for the period 1983-1994 using the 36 instruments and the periods 1973-1982 and 1983-1994 using the 9 non-endogenous

[12]These instruments are the numbers 26, 27, 28, 29, 30, 33, 34, 35 and 36 in table A.5 of appendix A.3.

[13]This instrument is the number 9 in table A.5 of appendix A.3.

[14]These instruments are the numbers 26, 27, 29, 30 and 34 in table A.5 of appendix A.3.

TABLE 2.2: Structural Break at 1983

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
1973-1982	229.18	-114.90	-114.91	0.72	160
27 Instruments	(122.68)	(66.49)	(56.62)		
1983-1994	113.43	-60.85	-49.81	0.69	194
35 Instruments	(100.74)	(53.38)	(47.64)		
1973-1982	247.01	-131.19	-117.39	0.72	160
4 Instruments	(122.85)	(67.72)	(56.33)		
1983-1994	104.37	-59.94	-41.97	0.69	194
9 Instruments	(100.52)	(53.36)	(47.66)		

Standard errors in parentheses.

instruments, since the χ^2-statistics are 1.38, 4.36 and 2.3 respectively.

Figure 2.4 shows the relationship between innovation and competition for the period 1973-1982 using all instruments. We can see that instead of the inverted-U there is a positive relationship between these two variables.

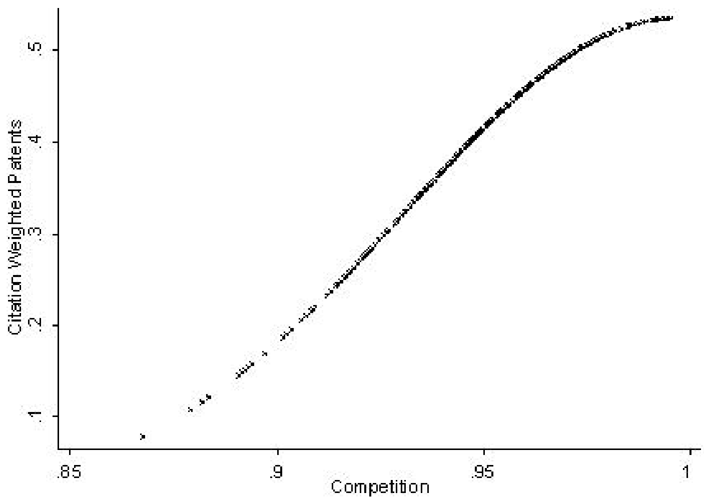


FIGURE 2.4: 1973-1982 using 27 Instruments

The Chow test considers only one structural break without certainty in its location, although either the break could be in another year or there could be more than one break. Because of that, I regress (2.5) and follow Andrews (1993) to test

$$\begin{aligned} H_0 &: \delta_1 = \delta_2 = 0, \\ H_{1T}(\pi) &: \delta_{jt} = \begin{cases} \delta_{j1}(\pi) & \forall t = 1,..,T\pi \\ \delta_{j2}(\pi) & \forall t = T\pi + 1,.. \end{cases}; \end{aligned} \tag{2.7}$$

for constants $\delta_{j1}(\pi)$ and $\delta_{j2}(\pi)$, and break point $\pi \in (0,1)$, where

$$\sup_{\pi \in \Pi} W_T(\pi) = \arg\max[W(\pi_{\underline{\Pi}}), W(\pi_{\underline{\Pi}}) + 1, .., W(\pi_{\overline{\Pi}})],$$

for $\Pi = [0.04, 0.05]$. Since sup $W_T(\pi)$ in the first iteration when using all instruments[15] is larger than critical value at 5% significance level provided by Andrews (2003), but lower than it in the second iteration, we conclude that there is one structural break at year 1981. Repeating the test but using non-endogenous instruments, there is also a structural break at 1981.[16]

An interesting point is that the ABBGH dataset includes patents considering their year of application and not the year where they were granted. Bloom and Van Reenen (2002) state that there is a lag between applying for and granting a patent of about two years. Therefore, it is likely that the Reform of October 1982 would affect patents which applied after 1981.

Table 2.3 shows the outcome of regression (2.1) considering the break at 1981 and the 36 ABBGH instruments. Testing (2.4), both competition and competition squared coefficients are equal to zero, for the period 1973-1980 we reject the null hypothesis at 5% significance level, but we fail to reject it for the period 1981-1994, since the χ^2-statistics are 6.35 and 1.51 respectively. As we can see in figure 2.5 there is also a positive relationship between innovation and competition, however the level of innovation is much lower than the one that we can see in figure 2.4.

TABLE 2.3: Structural Break at 1981

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
1973-1980 27 Instruments	207.76 (157.74)	-105.46 (85.97)	-116.40 (663.01)	0.75	128
1981-1994 35 Instruments	118.78 (97.56)	-62.40 (51.63)	-53.59 (46.16)	0.67	226

Standard errors in parentheses.

2.2 Innovation regarding memory and memoryless processes

In the previous section I show that the inverted-U relationship between competition and innovation does not hold after considering instrument endogeneity and structural breaks. We also have to consider that different technologies among industries may affect the strategy of competition. Therefore, dominance between escape-competition and Schumpeterian effects could be unequal, considering that an industry can have a memory process or a memoryless one. This section attempts to undo the different processes in order to analyze innovation and competition relationship in each context. The first subsection defines whether an industry has memory or does not. Then, ABBGH empirical model is tested in each group in order to have the innovation and competition relationship. Finally, tests used in the previous section are

[15] The sup $W_T(\pi)$ is equal to 14.11 at year 1981.
[16] The sup $W_T(\pi)$ is equal to 12.71.

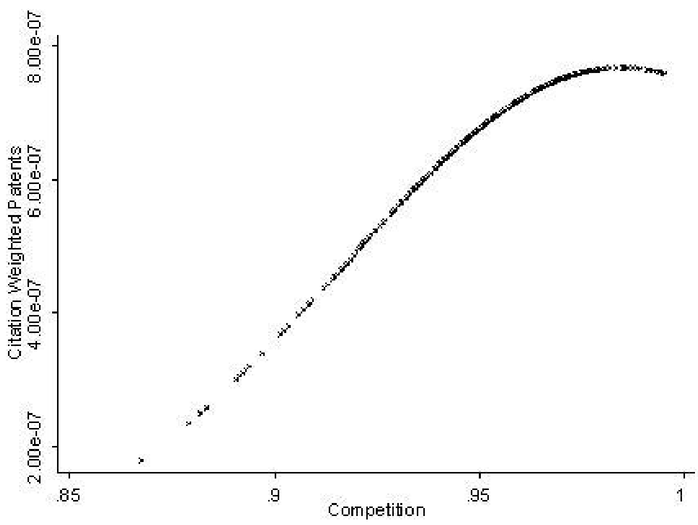


FIGURE 2.5: 1973-1980 using 27 Instruments

repeated in order to analyze the robustness of the outcome of this section.

2.2.1 Defining memory and memoryless innovation processes

Some industries show that technology improvements can be independent over time, while in others this improvements are based in each other. Hausman et al. (1984) and Hall et al. (1986) estimate the relationship between R&D expenditure and innovation using contemporaneous and past R&D investment as regressors. Doraszelski (2003) develops a model of knowledge accumulation in an R&D race. Both works are focused in the effect of R&D over innovation. My methodology differs in the procedure of measuring memory, since I define this as the link between present and past innovation.

In the Poisson distribution the mean is equal to the variance. However, Cameron and Trivedi (1998) state that when there is dynamic dependence, i.e. the occurrence of an event changes the subsequent probability of occurrence of a similar event, the mean and variance equality may not hold. Moreover, they state that serial dependence leads to over-dispersion and the Poisson specification is not correct.

Since Hausman et al. (1984) have found that the negative binomial specification allows for over-dispersion when using memory specifications, I employ an autoregressive model with drift and year trend, running the negative binomial regression

$$p_t^{(j)} = \exp\left\{\varsigma_0^{(j)} + \lambda^{(j)} t^{(j)} + \sum_{s=1}^{k} \varsigma_s^{(j)} p_{t-s}^{(j)} + \varepsilon_t^{(i)}\right\}.$$

Following Hayashi (2000) to determine the memory in each industry, the sequential rule is used to test

$$H_0 \;:\; \varsigma_k^{(j)} = 0,$$
$$H_1 \;:\; \text{otherwise.}$$

The test begins with a five-lags model. After testing significance of the last lag, the latter is dropped when not significant and the test is repeated recursively until $k = 1$. The outcome can be seen in table A.2 of appendix A.3. We can notice that Extraction of other minerals (23), Chemicals (25), Office and computing machinery (33), Motor vehicles (35), Food manufacture (41), and Other manufacture (49) industries show memory in the process of innovation.

Even though Rubber and plastic products (48) industry does not show any significant coefficient for its lags, and Other manufacturing (49) industry shows memory, they must be seen more carefully since more than 3/4 of the citation weighted patents in industry 48 are equal to zero and industry 49 has just 12 observations where half of them are equal to zero.

2.2.2 Innovation and competition relationship

Considering that over-dispersion may cause problems with the memory group but not with the memoryless one, I first define the industries 23, 25, 33, 35, 41 and 49 as the memory group, and all the other industries as the memoryless group; then, equation (2.1) is regressed with a negative binomial regression for the memory group and a Poisson regression for the memoryless sample. The outcome is displayed in table 2.4. After testing (2.4), both competition and competition squared coefficients are equal to zero, we reject the null hypothesis at 5% significance level for the memory group for both including and excluding industry 49, since the χ^2-statistics are 16.23 and 19.14 respectively. In the case of the memoryless group we fail to reject the null hypothesis for both including and and excluding industry 49, since χ^2-statistics are 4.04 and 4.46 respectively.

TABLE 2.4: Memory and Memoryless Groups

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
Memory Including 49	427.10 (151.54)**	-222.34 (81.64)**	-202.85 (70.32)**	0.15	116
Memoryless Including 48	239.36 (158.23)	-130.01 (83.55)	-110.05 (74.93)	0.67	238
Memory Excluding 49	364.60 (103.71)**	-191.26 (55.74)**	-170.78 (48.15)**	0.22	104
Memoryless Excluding 48	258.39 (160.41)	-140.15 (84.69)	-120.46 (76.04)	0.66	216

Standard errors in parentheses. ** significant at 1% level.

As we can see in figure 2.6 the memory group shows an inverted-U relationship between the predicted values of innovation and the competition index. However, we can also see that the innovation intensity is relatively higher when dropping industry 49.

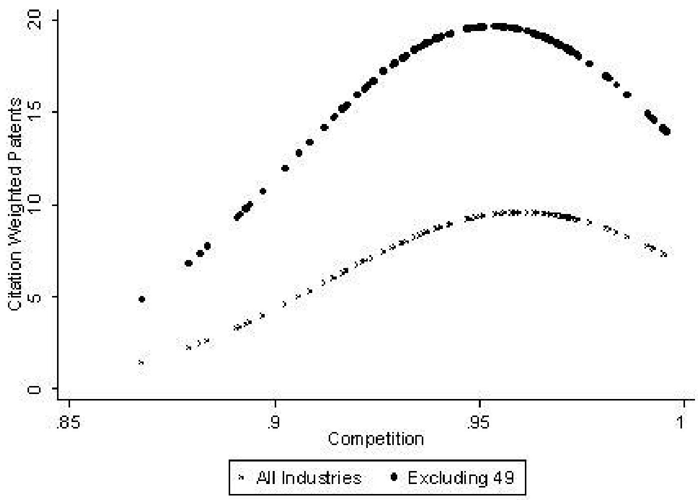


FIGURE 2.6: Memory Group

Although it is found an inverted-U relationship in the case of a memory process and no correlation in the case of the memoryless group, it is necessary to repeat the tests of the previous section to see how instrument endogeneity and structural breaks affect these results.

2.2.2.1 Instrumental variables

Repeating J test of (2.3), the F^{obs} are equal to 3.35 and 3.63 for both memory and memoryless, respectively. Since the number of instruments[17] used for the memory group is 28 and for the memoryless group 33, we reject the null hypothesis of instrument exogeneity at 5% significance level for both memory and memoryless group.[18]

Now, I reduce the number of instruments as in section 2.1 in order to find non-endogenous instruments. I test (2.3) with six instruments in the case of the memory group and 9 instruments for the memoryless sample.[19] We fail to reject the null hypothesis of instrument exogeneity at 5% significance level for both memory and memoryless groups, since the F^{obs} are equal to 1.08 and 1.34 respectively.[20]

[17]The instruments dropped in the case of the memory group are numbers 9, 29, 30, 31, 33, 34, 35 and 36 of table A.5 in appendix A.3. For the memoryless group the dropped instruments are numbers 9, 28 and 32.

[18]Testing without 49 and 48 industries, the F^{obs} are equal to 2.54 and 3.54 for both memory and memoryless, respectively. Thus, there is still endogeneity in both cases.

[19]The memory group instruments are the numbers 14, 15, 16 ,17, 26 and 27 of table A.5 in appendix A.3; while the memoryless instruments are the same used in section 2.1.

[20]After dropping industries 49 and 48 F^{obs} of memory and memoryless groups are 0.29 and 1.43 respectively, thus we also fail to reject the null hypothesis in these cases.

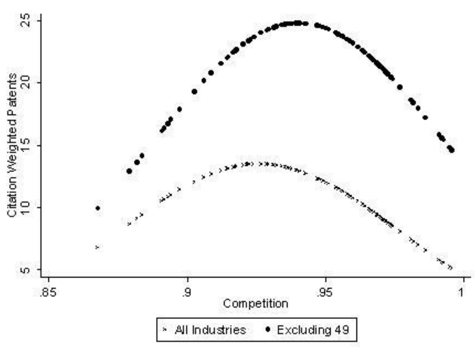
Using the non-endogenous instruments we regress equation 2.1 with a negative binomial regression for the memory group and a Poisson regression for the memoryless one. The outcome can be seen in table 2.5. After testing (2.4), that the competition and competition squared coefficients are not significantly different from zero, we reject the null hypothesis at 5% significance level for the memory group for both including and excluding industry 49, since the χ^2-statistics are 6.99 and 10.34 respectively. In the case of the memoryless group we also reject the null hypothesis for both including and excluding industry 49, since the χ^2-statistics are 9.21 and 9.10 respectively.

TABLE 2.5: Memory and Memoryless Groups with Non-endogenous Instruments

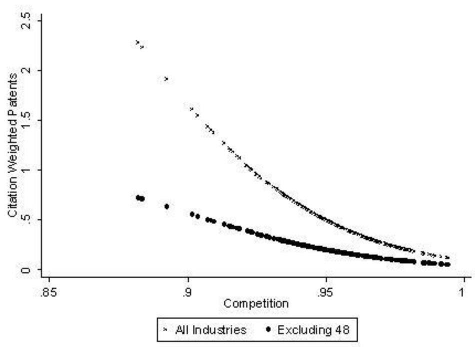
Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
Memory All Industries	374.96 (144.69)*	-202.42 (77.55)**	-171.03 (67.54)*	0.16	116
Memoryless All Industries	146.31 (159.40)	-92.03 (83.19)	-56.63 (76.52)	0.67	238
Memory Excluding 49	325.80 (102.14)**	-173.24 (54.60)**	-149.97 (47.73)**	0.22	104
Memoryless Excluding 48	172.81 (161.05)	-104.66 (84.19)	-71.33 (77.28)	0.66	216

Standard errors in parentheses. ** significant at 1% level; * significant at 5% level.

Figure 2.7a shows that there is an inverted-U relationship between innovation and competition for the memory sample when using non-endogenous instruments. The outcome does not differ too much from the result displayed by figure 2.6. Figure 2.7b shows that for the memoryless case, using non-endogenous instruments, the inverted-U relationship between innovation and competition does not hold, moreover, it shows that more competition decreases innovation.



(A) Memory Group



(B) Memoryless Group

FIGURE 2.7: Memory and Memoryless with Non-endogenous Instruments

2.2.2.2 Structural breaks

Testing (2.6), the Chow test, for the memory group including industry 49 we fail to reject the null hypothesis of time stability, at 5% of significance, for both all instruments and non-endogenous instruments, since the χ^2-statistics are 3.70 and 2.50 respectively. However, after dropping industry 49 we reject the null hypothesis for both all instruments and non-endogenous instruments, since the χ^2-statistics are 8.67 and 7.19.

After performing the negative binomial regression (2.1) for the period 1973-1982 of the memory sample using the endogenous instruments and excluding industry 49, I test (2.4) that the competition and competition squared coefficients are not significantly different from zero, rejecting the null hypothesis at 5% significance level, since the χ^2-statistic is 20.83. Now, repeating the same but for the period 1983-1994, we fail to reject the null that the competition and competition squared coefficients are equal to zero, since the χ^2-statistic is 1.05.

Repeating the same exercise but using the non-endogenous instruments (excluding industry 49), we reject the null hypothesis that the competition and competition squared coefficients are equal to zero for the period 1973-1982, since the χ^2-statistic is 9.64. However, we fail to reject the null hypothesis for the period 1983-1994, since the χ^2-statistic is 2.18.

Table 2.6 shows the coefficients of the regressions considering the two sub-periods and the two type of instruments.

TABLE 2.6: Memory Group without Industry 49 and Structural Break at 1983

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
1973-1982 End. Instruments	260.73 (158.10)	-127.64 (85.95)	-132.71 (72.47)	0.27	49
1983-1994 End. Instruments	73.46 (114.89)	-41.42 (61.11)	-31.01 (54.05)	0.21	55
1973-1982 Ex. Instruments	248.72 (160.23)	-119.06 (88.35)	-129.23 (72.62)	0.27	49
1983-1994 Ex. Instruments	62.88 (114.99)	-36.59 (61.08)	-25.35 (54.17)	0.21	55

Standard errors in parentheses.

Figure 2.8 shows that after dropping industry 49 there is a positive relationship between innovation and competition during the period 1973-1982, when using both the endogenous and the exogenous instruments. We can see that both curves have not only a very similar slope, but also the same level of innovation intensity.

Performing the Sup-Wald test in (2.7), I find two breaks, 1981 and 1991, when including the endogenous instruments[21] and industry 49. There are also breaks at

[21]The sup $W_T(\pi)$ are equal to 7.91 and 8.32 for years 1981 and 1991, respectively.

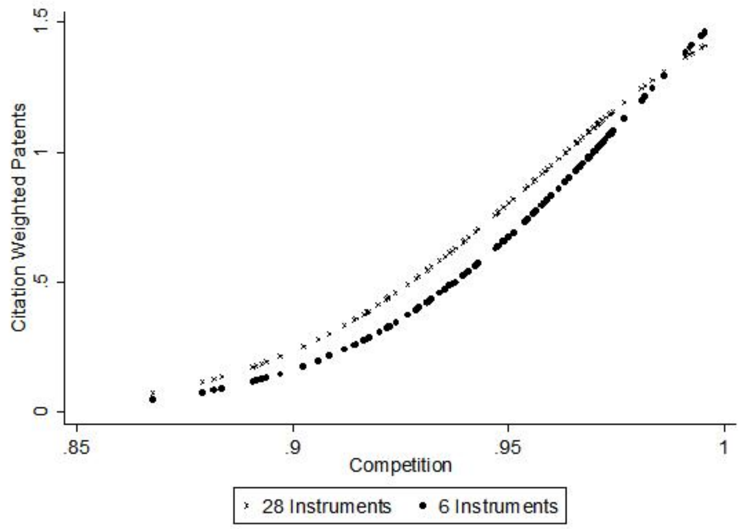


FIGURE 2.8: Memory Group 1973-1982 without Industry 49

1981 and 1991, when using non-endogenous instruments[22] and including industry 49. Excluding industry 49, however, there is a break at 1984 when using endogenous instruments and there are two breaks, 1981 and 1984, when using non-endogenous instruments.[23]

After performing a negative binomial regression for equation (2.1), I test (2.4), both competition and competition squared coefficients are equal to zero, rejecting the null at 5% significance level only for 1973-1983 using endogenous instruments and excluding industry 49.

Table A.3 in appendix A.3 shows the negative binomial regression of equation (2.1) coefficients.[24] Figure 2.9 shows how there is a positive relationship between innovation and competition, using the endogenous instruments and including industry 49, during the period 1973-1983.

Now, I proceed to analyze the memoryless sample. Performing the Chow test in (2.6), we fail to reject the null hypothesis of time stability for the memoryless group, including industry 48, both using the endogenous and the exogenous instruments, since the χ^2-statistics are 1.65 and 1.19 respectively.

Repeating the procedure but excluding industry 48, we also fail to reject the null hypothesis of time stability for the memoryless group, both using the endogenous and the exogenous instruments, since the χ^2-statistics are 1.60 and 1.08 respectively.

After testing the Sup-Wald test in (2.7), we fail to reject the null hypothesis of time stability in any of the cases of the memoryless group. Therefore, we can conclude that the innovation-competition pattern in the memoryless sample is stable over time.

[22]The sup $W_T(\pi)$ are equal to 10.07 and 11.78 for years 1981 and 1991, respectively.

[23]The sup $W_T(\pi)$ are equal to 12.90, 9.01 and 10.65, respectively.

[24]Period 1973-1980, using endogenous instruments and including industry 49, is excluded because of non-concavity of the likelihood function.

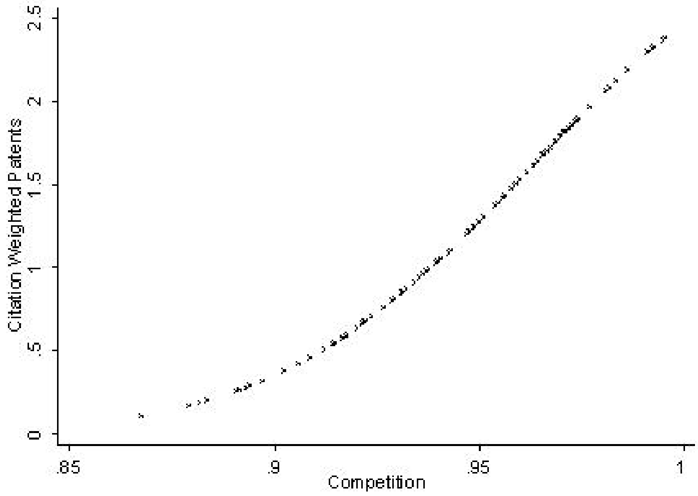


FIGURE 2.9: 1973-1983 with Endogenous Instruments and excluding industry 49

2.3 Conclusion

Most of the empirical studies find a positive relationship between innovation and competition, contradicting the theoretical Shumpeterian models which predict a negative relationship between these two variables. However, most of these models do not take into account that there can be different results for this relationship after considering whether an invention follows a memory process.

ABBGH find an empirical inverted-U relationship between innovation and competition, i.e. more competition increases the level of innovation until a threshold where innovation decreases as competition increases. However, as their theoretical model, they assume that the innovation process is memoryless.

I use the ABBGH dataset to analyze the innovation-competition relationship, regarding that innovation can follow a memory process.

ABBGH include 36 instruments to solve the usual endogeneity problem when regressing innovation on competition. Since after a firm innovates the level of competition also changes (increases or decreases depending on the previous cost level of that firm), ABBGH use a set of instruments to face this mutual causality problem. However, I find that these instruments are endogenous, thus we have an inconsistent estimator of how competition affects innovation.

The ABBGH dataset includes patents granted by the United States Patent and Trademark Office from 1973 until 1994. ABBGH did not take into consideration the establishment of the CAFC in October of 1982. I find a structural break in the early 1980's. After taking this break into account there is a positive relationship between innovation and competition before the CAFC Reform, and no innovation-competition relationship after this reform. However, using non-endogenous instruments, I find that there is no structural break in the data and the relationship between innovation and competition is negative.

Following the theoretical model of chapter 1, I check ABBGH industries in order to determine which industries follow a memory innovation process. After grouping in memory and memoryless industries, I find that there is a positive innovation-competition relationship for the memory group, both using the endogenous and the non-endogenous instruments, before the CAFC Reform and no relationship between innovation and competition for all the other cases.

Therefore, I find that after considering the structural break and instrument endogeneity, the ABBGH empirical inverted-U relationship does not hold. In fact, the empirical finding is more similar to the innovation-competition relationship predicted by my theoretical model developed in chapter 1.

Chapter 3

Patents, Productivity & Competition

Is there any evidence that innovations and technological progress are spurred by competition and contained by monopoly power? Although economists have been for more than 150 years trying to answer this question, it is still among the most controversial in the profession.

The idea that competition affects positively technological progress dates back to Adam Smith, and is based on the belief that competitive pressure leads to reduction in costs, adoption of efficient production methods, and a generally higher rate of innovation. In spite of its classical pedigree, during the last few decades this view has lost ground to the alternative theory, often associated to Schumpeter (1942), according to which technological progress requires the presence of substantial market power. The intuitive argument behind the Schumpeterian hypothesis (see Romer (1990) and Aghion and Howitt (1992) for a contemporary formulation) is that ideas are costly to produce, however, because of their non-rival nature, they can be (almost) freely appropriated and reproduced by competitors: thus only monopoly can provide the incentives and the resources to undergo major changes in technology. Given that no new ideas would be produced without substantial market power, the conventional conclusion of this strand of literature is that patents and copyrights are necessary for innovation and technological progress.

The view that intellectual monopoly granted by governments is a “necessary evil” has been strongly challenged by Boldrin and Levine (2008). They argue that “ideas have value only insofar as they are embodied in goods or people, and that there is no economic justification for the common assumption that ideas are transmitted through costless spillovers”. Under this alternative framework, they show that innovation can thrive under competition while intellectual monopoly can be particularly detrimental to the development of new ideas when these depend on existing innovation (innovation chains).

These conflicting views about innovation and market structure have been recently

This chapter is a joint work with my supervisor Dr. Carmine Ornaghi.

reconciled in an elegant model developed by Aghion et al. (2005), which shows that the relationship between innovation and competition takes the form of an inverted-U. In neck-and-neck industries, competition may increase the incremental profit from innovating and thereby encourage R&D investment (*escape-competition effect*). On the other hand, in unleveled industries, more competition may reduce innovation as the laggard's reward to catching up with the technological leader may fall (the *Schumpeterian effect*). Using a panel of 311 UK manufacturing firms, they find empirical support for the predictions of their model.

As we have seen in the previous chapters, both the theoretical and empirical ABBGH models are not robust. The ABBGH inverted-U prediction is overturned when allowing for the possibility that innovation follows a memory process, where the current probability of introducing a new innovation increases when firms have successfully introduced an innovation in the previous period. Taking into account the structural break in the data generation process of patents (the variable used to measure innovation), in coincidence with the establishment of the CAFC in October 1982, there is a positive innovation-competition relationship before this institutional change and no relationship at all after it.

Empirical evidence on what market structure favors technological progress is surprisingly narrow. Using a panel dataset of UK firms, Nickell (1996) finds that corporate performance, measured as TFP growth, is positively affected by different measures of competition, namely market share, concentration, import penetration, a competition survey and the average rents normalized on value added. Similarly, Geroski (1990) and Blundell et al. (1999) also find a positive relationship between competition and innovativeness in the UK using data on innovation counts.[1]

Most of the available empirical evidence on market structure and technological progress refers to the UK and it dates back to the eighties or early nineties. They also use either productivity or innovation counts as a measure of innovativeness. The objective of this research is then to produce fresh and robust evidence on the relationship between innovation and competition using data on both patent statistics and Total Factor Productivity growth. To this aim, we construct a dataset that includes, among other measures, patent counts and patent citations for 220 4-digit SIC code industries over the period 1990-2003 and Total Factor Productivity for 85 4-digit NAICS code industries over the period 1987-2008. Because the sources of innovation may be rapidly changing, some may argue that past findings might be irrelevant to understand today's drivers of technological progress. Although we share Stigler's view that "The very essence of scholarly irresponsibility is the assertion that the past is irrelevant to the future" (1956, "Industrial Organization and Economic Progress"), the time window considered in this study makes our findings particularly important and compelling.

[1]These studies use the number of significant technically and commercially successful innovations retrieved from the Science Policy Research Unit. Blundell et al. (1999) also use patent counts of UK firms registered at the USPTO. While Blundell et al. (1999) use firm data, Geroski (1990) uses data at the industry level.

Our approach is empirical in nature and is based on the estimation of a reduced-form equation of innovation and competition. While we make no attempt to estimate a structural model of market structure and firms' investment and innovation decisions, our regressions are inspired by the most recent empirical works produced in this area. Following ABBGH, we will estimate a Poisson model for the number of patents (one first measure of innovative activity) using a hazard rate specification which is assumed to be a non-linear function of our measure of competition. We will also present fresh evidence on the relationship between competition and innovation by using productivity as an alternative measure of technological progress.

The raw data used to construct our dataset come from different sources. Firm balance-sheet and financial data available in Compustat are matched with firm level data on patents retrieved from the National Bureau of Economic Research (NBER) Patent Data Project, described by Hall et al. (2001). Industry information on output, inputs and productivity are obtained from the US Bureau of Labor Statistics (BLS). Total industry output data are collected from the NBER and US Census Bureau's Center for Economic Studies (CES) Manufacturing Industry Database.[2] Finally, we retrieve information on US imports for different industries from the US Department of Commerce and the US International Trade Commission.[3]

This large dataset will allow us to construct a more accurate measure of innovation and competition and test the robustness of our finding when using different variables to capture those forces. In particular, innovation will be measured with two different sets of variables. The first set consists of number of patents and number of citations received by those patents. Differently from a simple patent count, citations can capture not only the quantity of ideas produced but also the quality of those ideas. The main advantages of patents compared to other R&D indicators are that they provide a measure of successful research output and they are objective in so far as they are not influenced by accounting practices. At the same time, there are a number of limitations in measuring innovation through patents. As stated by Cohen et al. (2000), many firms prefer to avoid disclosure of their innovations and to rely on trade secrecy instead. Patents can then measure only a fraction of the research output. Moreover, patents cannot account for efficiency gains due to the adoption of the most efficient technologies and best managerial practices. In order to overcome these limitations and to provide a check of robustness of our findings, the second variable we use to capture technology advances refers to firms' productivity computed as Total Factor Productivity (TFP).

One of our main concerns for our empirical exercise is that competition and market power are at the same time a cause and an effect of innovation. Industries that experience positive shocks to innovation are likely to experience an increase in market power too. To the extent that this is true, Ordinary Least Squares estimates will be biased and will not uncover the true functional relationship between competition

[2] See Bartelsman and Gray (1996) for further details.

[3] In order to match the SIC with the NAICS comparable industries we use the bridge provided by the US Census Bureau.

and innovation. In order to deal with this endogeneity problem, we will use advertising intensity and import penetration as instrumental variables for our measure of competition.

The results presented in this chapter cast serious doubts on the concept that monopoly power is necessary to foster technological progress when innovation follows a memory process. On the contrary, we estimate that competition, as measured by our indexes, substantially increases technology adoption and productivity. This implies that, contrary to much established wisdom, market power and a monopolistic position do not seem to favor innovation and technological change when past innovations matter.

The structure of this chapter is as follows. In the next section we present the data and discuss some methodological issues. The econometric model used to study the relationship between innovation and competition is defined in the second section, while the results are presented in the third section. The last section summarizes the main findings and concludes the chapter.

3.1 Data and Variables

The dataset we use for the empirical analysis is constructed using different sources: firm-level data from Standard & Poor's Compustat and the NBER Patent Data Project files are merged with industry-level data from BLS, the NBER-CES Manufacturing Industry Database, and the US Department of Commerce and the US International Trade Commission imports data.

The accounting data retrieved from Compustat include sales S (item 12), gross capital K (item 7), operating profits π (item 13) and advertising expenditure A (item 45) for the period 1990-2006. The data we use refer to all firms in the manufacturing sector; this includes 7,432 firms, divided in 220 industries, according to the 4-digit Standard Industrial Classification (SIC4).

Following ABBGH, competition is measured by an index of the average profits in the industry. We first compute the profitability ρ_{it} of firm i at period t as

$$\rho_{it} = \frac{\pi_{it} - rK_{it}}{S_{it}},$$

where r is the cost of capital rate and, as in ABBGH, assumed to be 0.085.

Considering gross capital instead of net capital has the advantage that is not contaminated with the fact that firms use depreciation methodologies to differ taxes. It is also noted that with the adequate maintenance a machine can work at its efficiency level during its whole service life. Since our sample includes manufacturing industries only and the period covered is not significantly long, the ABBGH assumption of a constant cost of capital rate seems to be acceptable in this context.

Ideally, we would measure the market power of a firm using the Lerner Index.[4] But prices and marginal costs are not observed. Firms' profitability defined above can be considered the best approximation to firms' market power with the data at hand. ρ takes values from zero to one.[5] The larger the ρ, the higher the market power.

Using the SIC4 that Compustat assigns to each firm, we compute our measure of competition, denoted c_{jt}, as the unweighted average of profitability across all firms in the industry j as

$$c_{jt} = 1 - \frac{1}{n_{jt}} \sum_{i \in j} \rho_{it},$$

where n_{jt} is the number of firms in industry j at year t and $c_{jt} \in [0, 1]$. The higher the measure of competition, the stronger the competition in the industry.[6]

Patent statistics are obtained from the publicly available NBER Patent Data Project files, described by Hall et al. (2001). This dataset comprises detailed information on all US patents granted between 1963 and 2006. The information retrieved from these files are patent numbers, application year, name of the inventors and the number of citations received by each patent.[7] Patent data can be merged with Compustat's financial data using a specific file that reports the Committee on Uniform Security Identification Procedures (CUSIP) code of the inventor if this is a company traded in US stock markets.

The information contained in the NBER Patent Data Project files is used to compute the total number of patents p_{it} obtained by the Compustat firm i at period t, the corresponding total number of citations received by those patents including self-citations R_{it}^{in} and the number of citations excluding self-citations R_{it}^{ex}. Citation counts are useful to check the robustness of our results when we use a measure that can capture not only the quantity of innovative ideas produced but the quality of those ideas. Summing the number of patents and citations across all the firms in each SIC4 industry, we obtain the variables used in our empirical estimation as $p_{it} = \sum_{i \in j} p_{it}$ and $R_{it} = \sum_{i \in j} R_{it}$.

It must be noticed that both patent counts and patent citations are affected by a truncation problem. As we use the application year for granted patents, the number of filed patents that are not granted increases as we approach to the last year of the dataset. We have a patent bias as during the last years of the sample there are filed patents which are not granted.[8] Similarly, we have a citation bias since the patents of the last years of our sample do naturally have fewer citations. Although

[4] Price minus marginal cost over price.

[5] We assume $\rho = 0$ when firms have negative profits.

[6] As in ABBGH we use the unweighted average of profitability since most of the firms in our sample compete in international markets, thus market shares are not known.

[7] There is also information of citations excluding self-citations, i.e. excluding citations made by the same company who owns the cited patent.

[8] Bloom and Van Reenen (2002) state that the lag between applying for and granting a patent is about two years.

the NBER dataset provides a truncation index that can be used to adjust the number of citations, the dramatic decrease in the number of citations shown in table 3.1 suggests that the truncation corrected variable does not seem to be a good indicator after 2000.[9] For these reasons, we use patent counts until 2003 and patent citations until 2000.

TABLE 3.1: Patents and Citations Mean

Year	Patents (1)	Citations (2)	Ratio (2/1)
1990	125.31	1,801.77	14.38
1991	128.90	1,929.95	14.97
1992	129.75	2,051.80	15.81
1993	140.73	2,286.41	16.25
1994	162.85	2,694.59	16.55
1995	203.10	3,261.78	16.06
1996	200.80	3,335.16	16.61
1997	240.51	3,734.85	15.53
1998	239.54	3,342.22	13.95
1999	261.65	3,078.29	11.77
2000	285.83	2,525.80	8.84
2001	290.36	1,720.66	5.93
2002	254.28	1,043.72	4.10
2003	176.19	440.15	2.50
2004	88.98	96.22	1.08
2005	24.29	8.34	0.34
2006	1.05	0.00	0.00

One concern that is often expressed about using patent counts is that they may not be comparable across industries because of significant differences in the propensity to patent. This and other source of unobserved differences across industries can affect the estimation if they are not orthogonal to the competitive structure of the industry. All specifications control for any time-invariant heterogeneity across industries by including industry fixed effects. Inclusion of industry fixed effect implies that identification comes from comparing changes in market competition to changes in innovation within each specific industry.

There is an important feature of Compustat and the NBER Patent data that must be noticed. While most of the companies in our dataset have their production and research activities concentrated in the US, some of the companies and inventors are multinational corporations. For instance, Pfizer Inc. is a US pharmaceutical company with offices, manufacturing facilities and research laboratories spread all over the world. Pfizer's financial data reported in Compustat refer then to its global sales and profits and, similarly, Pfizer's patent counts capture the innovative activities of all its laboratories. Depending on the degree of openness of the industry, our measures of competition and innovation can capture industry dynamics beyond the US border. The inclusion of industry fixed-effect will also control for this source of unobserved heterogeneity, under the assumption that they are, somehow, constant over the period

[9] We can see in table 3.1 that while the average number of citations is more than 14 times the average number of patents in 1990, during 2001 this relation is less than 6 times.

considered.

Our major concern for our empirical research is that competition and innovation are mutually endogenous. While we are interested in assessing how competition affects technological progress, we must keep in mind that innovation is also a cause of market power. This is likely to introduce a bias toward finding a negative relationship between innovation and competition in so far that patents ensure that inventors can charge prices above "some competitive equilibrium". We address this problem by using two variables that, we believe, provide exogenous variation in the degree of industry-wide competition: advertising intensity Ai and import penetration Ip. The first variable is computed as the ratio of the sum of the advertising expenditure (item 45 in Compustat) and the sum of sales (item 12 in Compustat) across all the firms in each SIC4 industry as

$$Ai_{jt} = \frac{\sum_{i \in j} A_{it}}{\sum_{i \in j} S_{it}}.$$

Similarly, import penetration is computed as the ratio of general imports value[10] to total value of industry shipments in each SIC4 industry. Data on value of imports at industry level are retrieved from the US Department of Commerce and the US International Trade Commission, while total value of shipments are obtained from the NBER-CES Manufacturing Industry Database.[11]

By informing consumers about the unique characteristics of a product or influencing the perceived quality for brands that are very similar in their physical characteristics, advertising is one of the most important tools to communicate and create products' differentiation, thus relaxing competition and increasing firms' market power. At the same time, there is large both theoretical and empirical evidence on the competitive pressure exercised by imports on the price-cost margins of local producers. For instance, Melitz and Ottaviano (2008) theoretically show that more integrated markets exhibit lower mark-ups. Domowitz et al. (1986) find that imports accounted for a quarter of the decline in margins in highly concentrated industry. In a more recent empirical study, Kee and Hoekman (2007) find that industries with higher import exposure tend to be more competitive. Our econometric approach, discussed in section 3.2, confirms that these two variables are significantly correlated with our competition index. Differently from our measure of competition, Ai and Ip are unlikely to be simultaneously determined with innovation. While there are industries like pharmaceuticals that have high advertising outlays and numerous patents, there are also industries with high advertising intensity and few patent filings (e.g. ready-to-eat cereals and soft drinks) and vice versa. Similarly, shocks to innovation at period t are likely to have (almost) no effects on the flow of imports in that year. However, as we cannot rule out that shocks to innovation may still feed back to current value of

[10] Including cost, insurance and freight.

[11] The source of this database is the Annual Survey of Manufactures, carried out by the US Census Bureau. For more details see Bartelsman and Gray (1996).

advertising and imports, we take a conservative approach and use lagged values of the two instruments at $t-1$ when estimating our specifications.

In order to check the robustness of our results, we use information on TFP for 85 different NAICS-4 manufacturing industries over the period 1990-2008 published by the BLS.[12] TFP growth is a more comprehensive measure of technological progress than patents in so far as only a small number of innovations are actually covered by intellectual property rights. The BLS productivity data are the outcome of a long research program started at the beginning of the eighties. They use the Solow residual as a measure of TFP, i.e. the change part in output which is not capture by changes in inputs (See Dean and Harper (1998)). After almost three decades of improving the quality of the data and the methodology used to elaborate those data, the BLS statistics on TFP can be considered one of the most precise measures of productivity available for the US.

Measure of productivity at industry-level offers an important advantage compared to firm-level data in our empirical exercise. At firm-level productivity may be positively correlated by construction with profitability, our measure of competition. Intuitively, in the absence of detailed information on firm-level prices, outputs are computed as deflated revenues. The productivity of firms that enjoy some market power, and charge higher prices than other firms in the industry, is then overestimated. As stated by Katayama et al. (2009), this leads to an "artificial" positive correlation between productivity and profitability. At industry level, we can assume that deflated revenue is a better measure of the quantity produced.

Together with the TFP, BLS publishes data on value of output VO, cost of intermediary inputs CM, and cost of labor CL and stock of capital SK.[13] This information is used to construct a new, however very similar, measure of competition as

$$c2_{jt} = 1 - \frac{VO_{jt} - CM_{jt} - CL_{jt} - rSK_{jt}}{VO_{jt}}.$$

The competition index $c2$ takes values between 0 and 1, where a lower value of $c2$ indicates that firms in industry j have relatively more market power while higher values suggest stronger competition among producers.[14]

The variable used to instrument $c2$ is import penetration. Data on imports at NAICS-4 are available only from 1997 onward. To construct the NAICS-4 imports data before 1997, we use data on imports at SIC4 level for the period 1987-2001 and we then match the SIC4 codes to their equivalent NAICS-4 using the correspondence table provided by U.S. Census Bureau. The time window of overlapping data (1997-2001)

[12] Both Compustat and the NBER Patent Data Project use the SIC4 classification instead.

[13] Notice that in order to calculate the financial cost of capital we use the same cost of capital rate r as in our main approach.

[14] When the sum of intermediary inputs, cost of labor and financial cost of capital is higher than the value of output, we assume $c2$ equal to 1.

is used to check any important discrepancies between the two series of data.[15]

Descriptive statistics of the variables used in the empirical analysis are reported in table 3.2.

TABLE 3.2: Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Skewness	Kurtosis
Patents p	3,300	195.25	676.08	7.90	91.80
All citations R^{in}	3,300	2,742.65	10,617.86	8.78	111.12
Citations R^{ex}	3,300	2,222.89	8,474.76	7.96	89.07
Competition c	3,247	0.93	0.04	-2.24	14.87
Competition $c2$	1,892	0.89	0.10	-2.45	14.34
Advertising Int.	3,669	0.01	0.02	2.90	12.86
Import Pen. Comp.	1,727	0.44	1.25	8.55	87.29
Import Pen. BLS	1,700	0.40	0.98	7.12	64.50
TFP	1,892	102.12	15.71	2.01	60.62

3.2 Econometric Model and Estimation

Our initial specification uses patents (or citations) as measure of innovation. Assume that the number of patents p in any point in time has a Poisson distribution

$$\Pr(p = h|\lambda) = \frac{\exp\{-\lambda\}\lambda^h}{h!},$$

where the parameter λ represents the expected number of patents (citations)[16] and it is assumed to depend on the competition measure c according to

$$\lambda_{jt} = E[p_{jt}|c_{jt}, D_t] = \exp\left\{g(c_{jt}) + \beta_0 + \sum_{t=1}^{T}\gamma_t D_t\right\}, \tag{3.1}$$

where D is a dummy variable taking the value of 1 at year t and 0 otherwise (time effects). In order to control for differences in the patent activities across industries that have no direct causal relationship with competition, we use fixed effects.[17] The exponential function in (3.1) ensures that the expected number of patents is non negative for any linear combination of the predictors. To investigate the shape of the relationship between innovation and competition at industry level, we approximate the function $g(c)$ in equation (3.1) by a quadratic specification. Accordingly, the loga-

[15]We find that the two series of data are very similar for most of the industries. The overall results do not change when we drop the industries where the average difference between the actual NAICS-4 and the constructed data for the period 1997-2001 is more than 50% larger or smaller.

[16]We check the robustness of number of patents using the number of patents weighted by the number of firms. As expected, the results are the same, since our sample is constructed with manufacturing Standard & Poor's companies during the 1990-2003 period. Therefore, it is unlikely to have large variation of companies within industries.

[17]Appendix B.1 shows the methodology used.

rithm of the mean of patents is modeled as

$$\ln \lambda_{jt} = \beta_1 c_{jt} + \beta_2 c_{jt}^2 + x_{jt}^{'}\delta, \tag{3.2}$$

where x represents a complete set of non-stochastic elements, i.e. the constant and time effects. Equation (3.2) is generally known as mean function and can be estimated using fixed effects and the Maximum Likelihood Estimator (MLE).

A variable modeled as a Poisson process is assumed to have an expected value equals to its variance $\lambda_{jt} = E[p_{jt}|c_{jt}] = Var[p_{jt}|c_{jt}]$. This is an untenable assumption for our patent counts whose sample variance is more than 2 thousand times the sample mean.[18] In the presence of overdispersion, the estimated variance covariance matrix of the Poisson MLE is incorrect, thus making statistical inference suspicious. The solution we adopt to deal with this problem is to estimate specification (3.2) using a negative binomial regression. Under this alternative approach, the expected value for the mean function does not change but the variance can now be adjusted independently of the mean according to the overdispersion parameter θ

$$Var[p|c] = E[p|c](1 + \theta E[P|c]),$$

with $\theta \geq 0$. The negative binomial converges to the Poisson model as θ tends to zero.

The main concern in estimating our empirical models is the possible endogeneity problem due to the fact that market structure can be at the same time, a determinant and an outcome of innovation. Although the inclusion of industry fixed effect can control for systematic differences between our measures of innovation and competition, it is possible that shocks to patent counts can cause changes in the relative profitability across industry, thus biasing the results against the competitive hypothesis.

To have consistent estimates of the competition parameters, we use the first lag value of advertising intensity and import penetration as instruments for competition. The first-step of the IV regression confirms the conjecture discussed in section 3.1 that Ai_{t-1} and Ip_{t-1} are strongly correlated with our measure of competition. At the same time, the nature of these two instruments and the particular timing used should ensure that they are orthogonal to the shocks in patent counts.

Following ABBGH, our econometric estimation uses the control function approach where we add the residuals $\hat{v}$ from a first-stage regression of the competition index c on the instrumental variables to equation (3.2) above.[19] The first-stage of this approach consists of estimating a reduced form equation for competition using our two instruments Ai_{jt-1} and Ip_{jt-1}, as

$$c_{jt} = \zeta_1 Ai_{jt-1} + \zeta_2 Ip_{jt-1} + x_{jt}^{'}\psi + v_{jt}, \tag{3.3}$$

[18] As it can be seen in table 3.2, this is even more problematic when considering citations.

[19] Notice that since we use the first lag of the instruments to construct the control function, the second stage regression uses data from the period 1991-2003 when using patents as measure of innovation and the period 1991-2000 when using citations as measure of innovation.

where the residuals v capture any variation in competition that is not explained by the instruments and the other exogenous regressors. The estimated residuals $\hat{v}$ are then added to equation (3.2) to control for any correlation between shocks of innovation and competition, leaving the remaining variation in c exogenous

$$\ln \lambda_{jt} = \beta_1 c_{jt} + \beta_2 c_{jt}^2 + x_{jt}^{'}\delta + \phi\hat{v}_{jt}. \tag{3.4}$$

The inclusion of $\hat{v}$ in the estimation of the expected number of patents, as stated by ABBGH, is "sufficient to remove all spurious correlation and recover the correct structural relationship $g(c)$". Using fixed effects, equation (3.4) is the empirical model that we estimate with our data.

The specification we use to check the robustness of our results use TFP as dependent variable, the competition index $c2$, defined in section 3.1, on the right hand side and import penetration as (the only) instrument. While the variables in equation (3.4) are defined for SIC4 manufacturing industries, the new measures of competition and innovation refer to the NAICS-4 classification.

Using fixed effects and the control function approach,[20] we derive the second empirical model as

$$TFP_{jt} = \alpha_1 c2_{jt} + \alpha_2 c2_{jt}^2 + x_{jt}^{'}\tau + \varphi\hat{v}_{jt}, \tag{3.5}$$

where $\hat{v}$ refers again to the residuals of a first stage regression of competition $c2$ on import penetration at $t-1$.

3.3 Empirical Results

3.3.1 Patents and citations

We regress the first stage of our empirical model, equation (3.3). Table 3.3 reports the coefficients of the first stage regression. As expected, there is a negative correlation between competition and advertising intensity while the correlation between competition and import penetration is positive.

TABLE 3.3: Competition and Instruments

Competition	Advertising Intensity	Import Penetration	Constant	Fixed Effects	Year Effects	Observations
Coefficients	-0.023	0.013	0.913	Yes	Yes	1,698
	(0.066)	(0.002)**	(0.004)**			

Standard errors in parentheses. ** significant at 1% level.

[20] Analogously as when using the Compustat data, since we use the first lag of the instruments to construct the control function, the second stage regression uses data from the period 1991-2008 when using TFP as measure of innovation.

To check the relevance of our instruments we test

$$\begin{aligned} H_0 &: \zeta_1 = \zeta_2 = 0, \\ H_1 &: \text{otherwise.} \end{aligned} \tag{3.6}$$

As the F-statistic is 25.82, we reject the null hypothesis of weak instruments.

Now, we perform negative binomial regressions of our specification in equation (3.4), using patents and citations as dependent variables. Table 3.4 reports the outcome of these regressions. We can see that there is a convex innovation-competition relationship when using patents as measure of innovation, while the relationship is concave when using citations as innovation indicator.

TABLE 3.4: Innovation and Competition

Innovation	Competition	Competition Squared	Constant	Fixed Effects	Year Effects	Observations
Patents p	-8.36	6.06	3.66	Yes	Yes	1,442
No Instruments	(9.19)	(5.14)	(4.11)			
Patents p	-12.09	12.35	2.05	Yes	Yes	1,442
Instruments	(11.36)	(6.41)	(5.14)			
All citations R^{in}	38.74	-19.64	-18.80	Yes	Yes	1,159
	(20.84)	(11.48)	(9.49)*			
Citations R^{ex}	38.62	-19.52	-18.85	Yes	Yes	1,159
	(20.96)	(11.55)	(9.54)*			

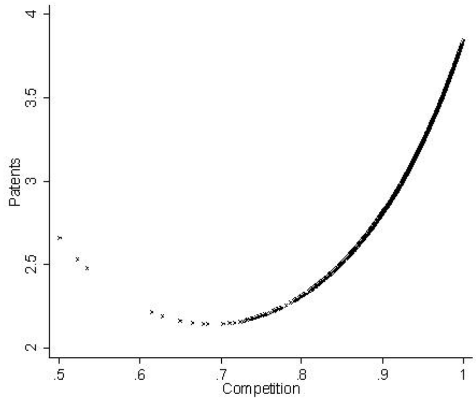
Standard errors in parentheses. * significant at 5% level.

Now, we test

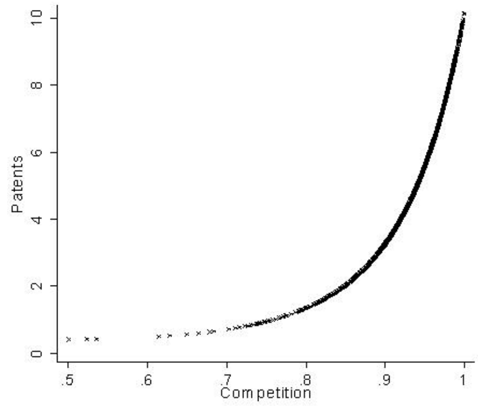
$$\begin{aligned} H_0 &: \beta_1 = \beta_2 = 0, \\ H_1 &: \text{otherwise;} \end{aligned} \tag{3.7}$$

for patents, all citations and citations regressions, rejecting the null hypothesis that both competition and competition squared coefficients are equal to zero, at 5% significance level, in the three cases as the χ^2-statistics are 33.96, 7.47 and 7.76 respectively.

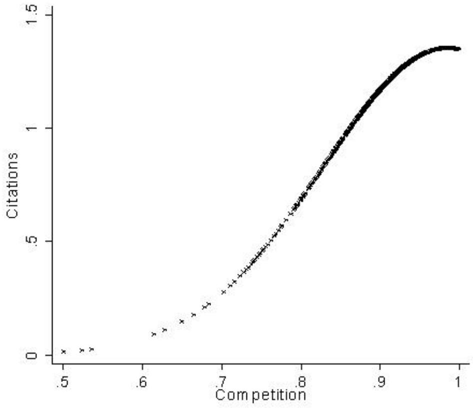
Figure 3.1 shows the relationship between the predicted values of innovation and the competition index for the three innovation indicators. We can see that there is a positive relationship in the three cases. Therefore, we do not see evidence of an inverted-U innovation-competition relationship using the overall sample. We can also notice that when not using the instruments there is a negative innovation-competition relationship for low level of competition and the slope is more flat.



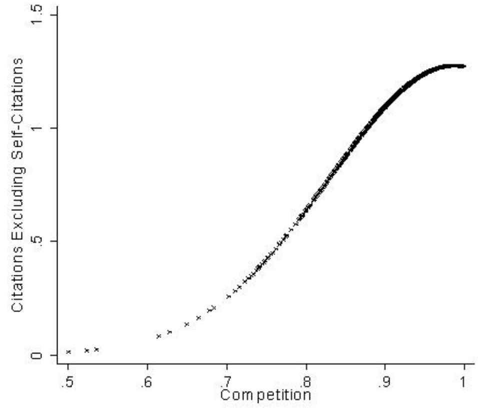
(A) Patents and Competition (No Instruments)



(B) Patents and Competition (Instruments)



(C) All Citations and Competition



(D) Citations and Competition

FIGURE 3.1: Innovation and Competition

3.3.1.1 Memory sample

As in chapter 2, in order to define a memory industry we first perform a negative binomial regression

$$P_t^{(j)} = \exp\left\{\varsigma_0^{(j)} + \lambda^{(j)} t^{(j)} + \sum_{s=1}^{k} \varsigma_s^{(j)} P_{t-s}^{(j)} + \varepsilon_t^{(i)}\right\}, \tag{3.8}$$

where $P_t^{(j)}$ represents each innovation indicator (patents, all citations and citations for the Compustat database). Then, as in Hayashi (2000), we use the sequential rule to test

$$\begin{aligned} H_0 &: \varsigma_k^{(j)} = 0, \\ H_1 &: \text{otherwise}, \end{aligned} \tag{3.9}$$

beginning with $k = 5$.

Among the 220 industries, we find that there are 149 industries showing memory in the process of innovation when using patents as innovation measure, 139 industries when using all citations and 135 industries when using citations excluding self-citations.[21]

Using the same estimated residuals from equation (3.3), we perform negative binomial regressions of equation (3.4) for each indicator of innovation, using the memory industries sample. The outcome of these regressions can be seen in table 3.5. We can notice that this time only do all citations have a concave innovation-competition relationship.

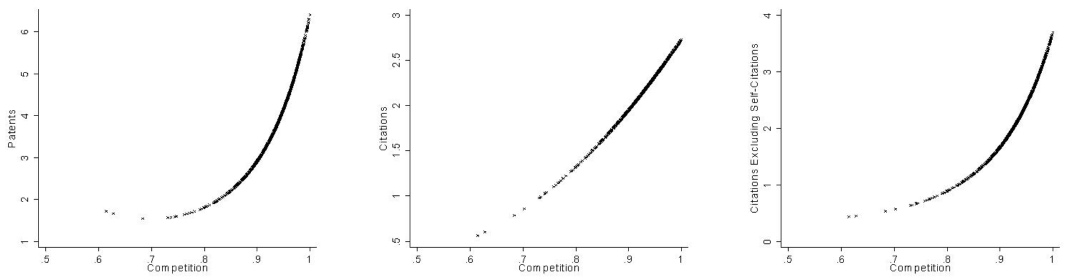
TABLE 3.5: Innovation and Competition Memory

Innovation	Competition	Competition Squared	Constant	Fixed Effects	Year Effects	Observations
Patents p	-22.02 (9.50)*	15.75 (5.64)**	8.12 (4.19)	Yes	Yes	1,019
All citations R^{in}	8.21 (14.79)	-2.54 (8.40)	-4.66 (6.56)	Yes	Yes	777
Citations R^{ex}	-8.28 (13.66)	8.56 (7.82)	1.02 (6.02)	Yes	Yes	793

Standard errors in parentheses. ** significant at 1% level. * significant at 5% level.

Testing (3.7) for patents, all citations and citations regressions, we reject the null hypothesis that both competition and competition squared coefficients are equal to zero, at 5% significance level, in the three cases as the χ^2-statistics are 11.43, 6.71 and 19.89 respectively.

As it can be seen in figure 3.2, the relationship between innovation (using either of the three indicators) and competition is positive for the memory industry sample. As we can notice, in the case of citations, the memory sample innovation-competition relationship is steeper than the overall sample's at higher levels of competition.



(A) Patents and Competition (B) All Citations and Competition (C) Citations and Competition

FIGURE 3.2: Innovation and Competition Memory Sample

[21]There are 12 industries with memory using all citation but without it using citations excluding self-citations. There are 8 industries with memory using citations excluding self-citations but without it using all citations. Among the 12 all citations memory industries there are no import penetration data for 9 of them, while among the 8 citations excluding self-citations memory industries there are no import penetration data for 3 of them. The latter explains why there are more observations for the citations excluding self-citations sample than in the all citations sample as it can be seen in table 3.5.

3.3.1.2 Memoryless sample

We define as memoryless industries all industries which are not in the memory sample. The empirical results of the negative binomial regression of equation (3.4), using the memoryless sample, can be seen in table 3.6.

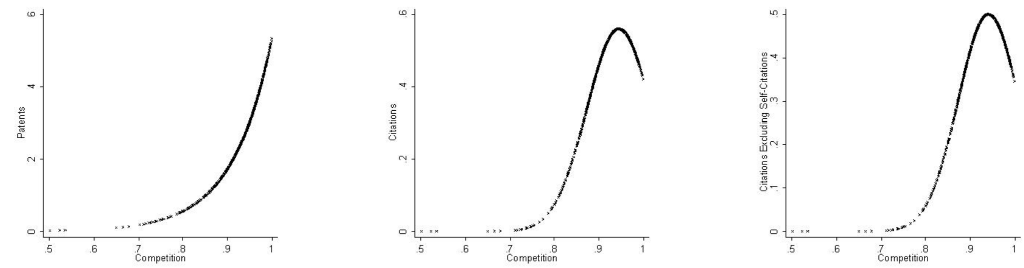
TABLE 3.6: Innovation and Competition Memoryless

Innovation	Competition	Competition Squared	Constant	Fixed Effects	Year Effects	Observations
Patents p	10.63 (26.74)	0.43 (14.96)	-9.39 (12.11)	Yes	Yes	423
All citations R^{in}	182.32 (70.94)*	-96.38 (38.78)*	-86.80 (32.43)**	Yes	Yes	382
Citations R^{ex}	204.01 (77.28)*	-108.31 (42.25)*	-96.76 (35.32)**	Yes	Yes	366

Standard errors in parentheses. ** significant at 1% level. * significant at 5% level.

Now, we test (3.7) for patents, all citations and citations regressions, and we reject the null hypothesis that both competition and competition squared coefficients are equal to zero, at 5% significance level, in the three cases as the χ^2-statistics are 10.84, 9.72 and 9.75 respectively.

As we can see in figure 3.3, the relationship between patents and competition is similar as the one found in both the overall sample and the memory sample. However, the relationship between citations and competition differs from the memory sample's innovation-competition relationship. In this case, although it is not a well-shaped inverted-U relationship as predicted by the ABBGH memoryless model, there is a non-negligible part of the curve with a negative relationship at high level of competition.



(A) Patents and Competition (B) All Citations and Competition (C) Citations and Competition

FIGURE 3.3: Innovation and Competition Memoryless Sample

3.3.2 Productivity

Regressing equation (3.3), using $c2$ as measure of competition, but this time using only the first lag of import penetration as instrument, we can see in table 3.7 that, as expected, there is a positive correlation between competition and import penetration. We, then, compute the predicted residuals $\hat{v}$ to use them in the second stage.

TABLE 3.7: Competition and Instruments BLS

Competition	Import Penetration	Constant	Fixed Effects	Year Effects	Observations
Coefficients	0.019 (0.002)**	0.900 (0.005)**	Yes	Yes	1,615

Standard errors in parentheses. ** significant at 1% level.

After regressing equation (3.5), outcome which can be seen in table 3.8, we test

$$\begin{aligned} H_0 &: \alpha_1 = \alpha_2 = 0, \\ H_1 &: \text{otherwise}; \end{aligned} \tag{3.10}$$

whether both competition and competition squared coefficients are equal to zero. We reject the null hypothesis at 5% significance level as the F-statistic is 30.29.

TABLE 3.8: Productivity and Competition

Productivity	Competition	Competition Squared	Constant	Fixed Effects	Year Effects	Observations
TFP	251.07 (49.60)**	-154.71 (19.93)**	-1.59 (35.41)	Yes	Yes	1,615

Standard errors in parentheses. ** significant at 1% level.

Figure 3.4 shows the relationship between TFP and competition. We can see that there is a positive concave relationship, with a small decreasing part at high level of competition, however, not an inverted-U at all.

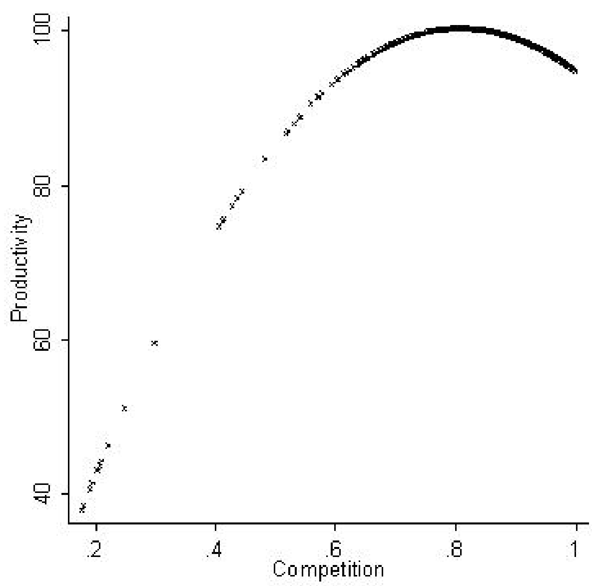


FIGURE 3.4: Productivity and Competition

To check whether there is also a different innovation-competition relationship between memory and memoryless industries, we perform OLS regressions of equation (3.8), using TFP level as P, and test (3.9) to define the memory industries. We find that there are 74 memory industries and 12 memoryless industries.

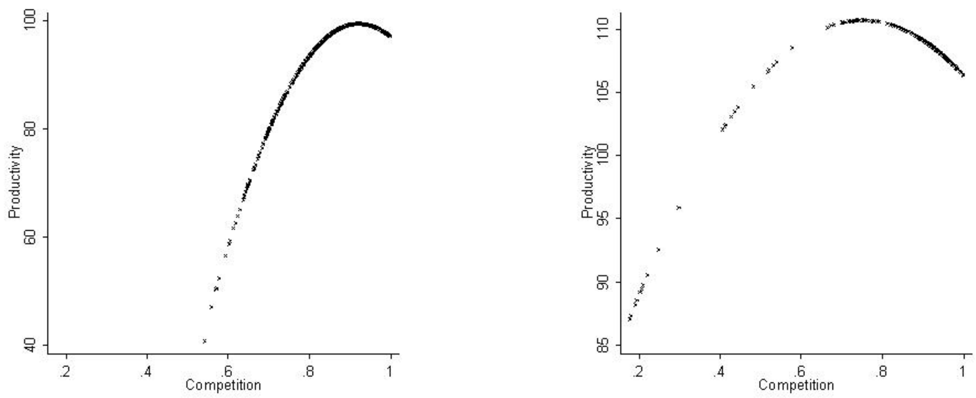
Table 3.9 shows the outcome of regressing equation (3.5). Testing (3.10) that competition and competition squared coefficients are equal to zero, we reject the null hypothesis at 5% significance level for the memory and memoryless industries as the F-statistics are equal to 21.94 and 21.61, respectively.

TABLE 3.9: Productivity and Competition (Memoryless and Memoryless)

Productivity	Competition	Competition Squared	Constant	Fixed Effects	Year Effects	Observations
Memory	732.20 (121.78)**	-396.23 (59.83)**	-238.88 (69.76)**	Yes	Yes	1,387
Memoryless	107.09 (23.92)**	-71.06 (10.83)**	70.33 (16.44)**	Yes	Yes	228

Standard errors in parentheses. ** significant at 1% level.

Figure 3.5 shows the relationship between TFP and competition. We can see a positive concave relationship between innovation and competition for both memory and memoryless samples. However, the memoryless curve presents a decreasing part at high level of competition. We can also notice that the memory curve is steeper than the memoryless curve.



(A) Memory (B) Memoryless

FIGURE 3.5: Productivity and Competition (Memory and Memoryless)

3.4 Conclusion

Most of the empirical models which have studied the relationship between innovation and competition use patents as a measure of innovation and UK industry panel data. In this chapter we build a 220 industries panel database using information of 7,432 Standard & Poor's firms for the period 1990-2006.

We find that there is a positive relationship between innovation and competition. We use patents, all citations and citations excluding self-citations as measure of innovation. Citations are corrected with and index to address the truncation problem. However, this index is not reliable for the last years of our sample, since it tends to underestimate the number of citations received by a patent.

We also find that industries which have memory in the innovation process tend to be more innovative with more competition, result which is consistent with the theoretical model of chapter 1. However, in the case of memoryless industries, there is a negative relationship between citations and competition at high level of competition. This result gives some support to the theoretical ABBGH model. Although it is not an inverted-U there is a significant part of the curve at high level of competition where the innovation-competition relationship is negative.

We check the robustness of our result using TFP as a measure of innovation. Using a panel data of 86 US industries, we find a positive concave relationship between innovation and competition. As when using patents and citations as measure of innovation, we find a positive relationship between TFP and competition when innovation follows a memory process. Even though that in the case of memoryless industries there is a part of the curve, at high level of competition, where the innovation-competition relationship is negative, this part is not as significant as when using citations as a measure of innovation.

Appendices

Appendix **A**

Appendix to Chapter 2

A.1 Mutual causality problem

Assuming that the relationship between innovation and competition follows a Poisson regression

$$p = \exp\{W\delta + \beta_1 c + \beta_2 c^2 + u\}, \tag{A.1}$$

where W is a matrix containing non-stochastic elements. Rewriting (A.1) as a linear transformation we get

$$y = W\delta + \beta_1 c + \beta_2 c^2 + u, \tag{A.2}$$

with $y \equiv \log p$.

Now, it is assumed that

$$\begin{aligned} c &= W\lambda + \alpha y + \epsilon, \\ c^2 &= W\varpi + \theta y + \varepsilon. \end{aligned}$$

Hence,

$$\begin{aligned} cov(c, u) &= cov(W\lambda + \alpha y + \epsilon, u), \\ cov(c, u) &= \lambda cov(W, u) + \alpha cov(y, u) + cov(\epsilon, u). \end{aligned} \tag{A.3}$$

$$\begin{aligned} cov(c^2, u) &= cov(W\varpi + \theta y + \varepsilon, u), \\ cov(c^2, u) &= \varpi cov(W, u) + \theta cov(y, u) + cov(\varepsilon, u). \end{aligned} \tag{A.4}$$

Assuming that $cov(W,u)=0$, $cov(\epsilon,u)=0$ and $cov(\varepsilon,u)=0$, (A.3) and (A.4) turn to

$$\begin{aligned}
cov(c,u) &= \alpha cov(y,u),\\
cov(c,u) &= \alpha cov(W\delta+\beta_1 c+\beta_2 c^2+u,u),\\
cov(c,u) &= \alpha[\delta cov(W,u)+\beta_1 cov(c,u)+\beta_2 cov(c^2,u)+\sigma_u^2],\\
cov(c,u) &= \frac{\alpha[\beta_2 cov(c^2,u)+\sigma_u^2]}{1-\alpha\beta_1}. \qquad \text{(A.5)}\\
cov(c^2,u) &= \theta cov(y,u),\\
cov(c^2,u) &= \theta cov(W\delta+\beta_1 c+\beta_2 c^2+u,u),\\
cov(c^2,u) &= \theta[\delta cov(W,u)+\beta_1 cov(c,u)+\beta_2 cov(c^2,u)+\sigma_u^2],\\
cov(c^2,u) &= \frac{\theta[\beta_1 cov(c,u)+\sigma_u^2]}{1-\theta\beta_2}. \qquad \text{(A.6)}
\end{aligned}$$

Replacing (A.6) in (A.5) we have

$$\begin{aligned}
cov(c,u) &= \frac{\alpha[\theta\beta_2\frac{\beta_1 cov(c,u)+\sigma_u^2}{1-\theta\beta_2}+\sigma_u^2]}{1-\alpha\beta_1},\\
cov(c,u) &= -\frac{\alpha\sigma_u^2}{(\alpha\beta_1-1)(\theta\beta_2-1)(\alpha\beta_1+\theta\beta_2-1)}. \qquad \text{(A.7)}
\end{aligned}$$

Therefore, $\alpha\beta_1\neq 1$, $\theta\beta_2\neq 1$ and $\alpha\beta_1+\theta\beta_2\neq 1$ are necessary conditions for $cov(c,u)$ to be defined. If $cov(c,u)$ exists, $\alpha\neq 0$ is necessary and sufficient condition for $cov(c,u)\neq 0$.

Now, replacing (A.7) in (A.6) we have

$$\begin{aligned}
cov(c^2,u) &= \frac{\theta[-\alpha\beta_1\frac{\sigma_u^2}{(\alpha\beta_1-1)(\theta\beta_2-1)(\alpha\beta_1+\theta\beta_2-1)}+\sigma_u^2]}{1-\theta\beta_2},\\
cov(c^2,u) &= -\frac{\theta\sigma_u^2[(\alpha\beta_1-1)(\theta\beta_2-1)(\alpha\beta_1+\theta\beta_2-1)-\alpha\beta_1]}{(\alpha\beta_1-1)(\theta\beta_2-1)^2(\alpha\beta_1+\theta\beta_2-1)}.
\end{aligned}$$

We can notice that whenever $cov(c,u)$ is defined, $cov(c^2,u)$ is also defined. If $cov(c^2,u)$ exists, $\theta=0$ and $\theta\sigma_u^2(\alpha\beta_1-1)(\theta\beta_2-1)(\alpha\beta_1+\theta\beta_2-1)=\alpha\beta_1$ are sufficient conditions for the regressors to be orthogonal to the disturbance term.

A.2 J test of overidentifying restrictions

After an OLS regression of

$$c_{jt}=W\delta+Z\alpha+\nu_{jt},$$

where W and Z are matrices containing non-stochastic elements and instrumental variables respectively, we compute the predicted values of competition as

$$\hat{c}_{jt}=W\hat{\delta}+Z\hat{\alpha}.$$

Performing a Poisson regression of

$$p_{jt} = \exp\{W\psi + \beta_1 \hat{c}_{jt} + \beta_2 \hat{c}_{jt}^2 + u_{jt}\},$$

we compute the predicted values using competition and competition squared, before being adjusted by the instrumental variables, as

$$\hat{p}_{jt} = \exp\{W\hat{\psi} + \hat{\beta}_1 c_{jt} + \hat{\beta}_2 c_{jt}^2\}.$$

We, then, generate $\hat{u}_{jt} = p_{jt} - \hat{p}_{jt}$ and perform the OLS regression of

$$\hat{u}_{jt} = W\gamma + Z\delta + \epsilon_{jt}.$$

Finally, we test

$$\begin{aligned} H_0 &: \delta = 0, \\ H_1 &: \text{otherwise}, \end{aligned}$$

with the J-statistic equals to mF, where m is the number of instruments and F is the F-statistic. Rejection of the null hypothesis leads to instrument endogeneity.

A.3 Additional tables

TABLE A.1: Group of Years Regressions

Citation Weighted Patents	Competition	Competition Squared	Constant	Pseudo R^2	Observations
1973-1976	700.07 (238.02)**	-371.16 (129.13)**	-329.74 (109.79)**	0.78	60
1977-1980	107.31 (283.64)	-53.00 (150.11)	-70.40 (1603.32)	0.74	68
1981-1984	-209.32 (519.23)	126.02 (274.02)	86.22 (245.85)	0.70	64
1985-1988	302.52 (356.37)	-166.85 (194.94)	-152.48 (1222.71)	0.69	65
1989-1994	7.55 (133.16)	-9.58 (69.05)	4.63 (64.48)	0.75	97

Standard errors in parentheses. ** significant at 1% level.

TABLE A.2: Negative Binomial Regression to Define Memory and Memoryless Industries

Industry	5th Lag	4th Lag	3rd Lag	2nd Lag	1st Lag
22	-0.17	-0.07	-0.08	-0.00	0.02
	(1.18)	(0.33)	(0.45)	(0.00)	(0.05)
23	-0.20	-0.16	0.16	-0.19	0.22
	(2.37)	(5.97)*	(9.92)**	(8.41)**	(6.94)**
24	-0.05	-0.03	0.00	0.06	0.02
	(0.31)	(0.12)	(0.00)	(0.57)	(0.04)
25	-0.02	-0.01	-0.00	0.01	0.02
	(0.77)	(0.43)	(0.04)	(0.32)	(4.44)*
31	-2.06	-4.98	-1.06	2.21	4.18
	(0.04)	(0.22)	(0.01)	(0.07)	(0.35)
32	-0.47	-0.27	-0.05	0.03	0.28
	(0.49)	(0.21)	(0.01)	(0.00)	0.27
33	-0.00	-0.03	0.00	0.02	0.06
	(-.00)	(0.84)	(0.00)	(0.52)	(4.79)*
34	-0.01	-0.08	0.01	0.00	0.04
	(0.01)	(1.23)	(0.03)	(0.00)	(0.40)
35	0.01	-0.01	0.03	-0.01	0.03
	(0.06)	(0.13)	(2.31)	(0.13)	(15.86)**
36	-0.05	0.04	0.03	-0.00	0.02
	(1.76)	(0.98)	(0.55)	(0.01)	(0.20)
37	-0.09	-0.10	-0.12	-0.28	-0.14
	(0.01)	(0.11)	(0.15)	(0.87)	(0.34)
41	-0.21	0.04	0.04	0.02	0.11
	(4.50)*	(0.39)	(0.42)	(0.12)	(4.97)*
42	-0.01	-0.01	-0.02	0.02	0.00
	(0.45)	(0.23)	(1.36)	(1.74)	(0.02)
43	0.34	-0.73	-0.51	-1.14	0.40
	(0.02)	(0.11)	(0.05)	(0.24)	(0.04)
47	0.05	NC	0.34	NC	0.09
	(0.00)		(0.03)		(0.00)
48	ZA	NC	NC	NC	-0.50
					(0.74)
49	-0.01	NC	NC	0.10	0.23
	(0.58)			(3.89)*	(4.56)*

Standard errors in parentheses. ** significant at 1% level; * significant at 5% level.

NC non-concavity of likelihood function; ZA dependent variable is zero for all observations.

TABLE A.3: Memory Group and Sup-Wald Structural Breaks

Citation Weighted Patents	Comp.	Comp. Sqrt.	Const.	Ind. 49	Pse. R^2	Obs.	$\beta_1 = \beta_2 = 0$ χ^2-statistic
1981-1990	194.12	-102.78	-89.05	Yes	0.17	52	0.7
28 Instruments	(268.83)	(145.33)	(124.44)				
1973-1980	294.06	-155.47	-154.59	Yes	0.34	44	2.6
6 Instruments	(186.03)	(101.14)	(1320.44)				
1981-1990	172.11	-91.57	-78.30	Yes	0.17	52	0.49
6 Instruments	(255.77)	(137.53)	(119.05)				
1973-1983	264.19	-128.74	-134.56	No	0.27	54	27.74
28 Instruments	(144.76)	(78.88)	(66.21)*				
1984-1994	81.34	-46.45	-33.70	No	0.21	50	2.04
28 Instruments	(117.26)	(62.36)	(55.19)				
1973-1980	296.17	-153.08	-142.42	No	0.30	40	2.86
6 Instruments	(186.80)	(101.16)	(87.11)				
1984-1994	71.00	-42.00	-27.86	No	0.21	50	3.18
6 Instruments	(118.34)	(62.75)	(55.87)				

Standard errors in parentheses. * significant at 5% level.

TABLE A.4: Industries

SIC Code	Industry
22	Metal Manufacturing
23	Extraction of Other Minerals
24	Non-Metallic Mineral Products
25	Chemicals
31	Manufacture of Metal Goods
32	Mechanical Engineering
33	Office & Computing Machinery
34	Electrical & Electronic Engineering
35	Motor Vehicles
36	Manufacture of Other
37	Instrument Engineering
41	Food Manufacture
42	Sugar Beverages & Tobacco
43	Textiles
47	Paper, Paper Products & Printing
48	Rubber & Plastic Products
49	Other Manufacturing

TABLE A.5: Instruments

Number	Instrument	Type	Number	Instrument	Type
1	Industry R&D/ Y USA	Foreign-industry	19	Markup USA squared	Foreign-industry
2	Industry R&D/ Y USA squared	Foreign-industry	20	Output - variable costs/ Output USA	Foreign-industry
3	Industry TFP USA	Foreign-industry	21	Output - variable costs/ Output USA squared	Foreign-industry
4	Industry TFP USA squared	Foreign-industry	22	Markup France	Foreign-industry
5	Industry R&D/ Y France	Foreign-industry	23	Markup France squared	Foreign-industry
6	Industry R&D/ Y France squared	Foreign-industry	24	Output - variable costs/ Output France	Foreign-industry
7	Industry TFP France	Foreign-industry	25	Output - variable costs/ Output France squared	Foreign-industry
8	Industry TFP France squared	Foreign-industry	26	SMP high impact	Policy
9	TFP France dummy for SIC2 49	Foreign-industry	27	SMP medium impact	Policy
10	Industry imports/ Y USA	Foreign-industry	28	Car industry	Policy
11	Industry imports/ Y USA squared	Foreign-industry	29	Periodicals industry	Policy
12	Industry imports/ Y France	Foreign-industry	30	Brewing industry	Policy
13	Industry imports/ Y France squared	Foreign-industry	31	Telecoms industry	Policy
14	Industry exports/ Y USA	Foreign-industry	32	Pharmaceuticals industry	Policy
15	Industry exports/ Y USA squared	Foreign-industry	33	Textiles industry	Policy
16	Industry exports/ Y France	Foreign-industry	34	Razor industry	Policy
17	Industry exports/ Y France squared	Foreign-industry	35	Steel industry	Policy
18	Markup USA	Foreign-industry	36	Ordnance industry	Policy

Appendix **B**

Appendix to Chapter 3

B.1 Fixed effects

As in equation (2.1), it is assumed that the relationship between innovation and competition follows a Poisson regression

$$p_{jt} = \exp\Big\{\beta_0 + \beta_1 c_{jt} + \beta_2 c_{jt}^2 + \phi \hat{v}_{jt} + \sum_{j=1}^{n} \alpha_j D_j + \sum_{t=1}^{T} \gamma_t D_t + u_{jt}\Big\}. \tag{B.1}$$

Defining $y_{jt} \equiv \ln p_{jt}$, we ca rewrite (B.1) as

$$y_{jt} = \beta_0 + \beta_1 c_{jt} + \beta_2 c_{jt}^2 + \phi \hat{v}_{jt} + \sum_{j=1}^{n} \alpha_j D_j + \sum_{t=1}^{T} \gamma_t D_t + u_{jt}. \tag{B.2}$$

Taking the average within industry in (B.2) we have

$$\begin{aligned} \frac{1}{T}\sum_{t=1}^{T} y_{jt} &= \beta_0 + \beta_1 \frac{1}{T}\sum_{t=1}^{T} c_{jt} + \beta_2 \frac{1}{T}\sum_{t=1}^{T} c_{jt}^2 \\ &\quad + \phi \frac{1}{T}\sum_{t=1}^{T} \hat{v}_{jt} + \sum_{j=1}^{n} \alpha_j D_j + \frac{1}{T}\sum_{t=1}^{T} \gamma_t + \frac{1}{T}\sum_{t=1}^{T} u_{jt}. \end{aligned} \tag{B.3}$$

Subtracting equation (B.3) from equation (B.2) we have

$$\begin{aligned} y_{jt} - \frac{1}{T}\sum_{t=1}^{T} y_{jt} &= \beta_1 \Big(c_{jt} - \frac{1}{T}\sum_{t=1}^{T} c_{jt}\Big) + \beta_2 \Big(c_{jt}^2 - \frac{1}{T}\sum_{t=1}^{T} c_{jt}^2\Big) \\ &\quad + \phi \Big(\hat{v}_{jt} - \frac{1}{T}\sum_{t=1}^{T} \hat{v}_{jt}\Big) + \sum_{t=1}^{T} \gamma_t D_t - \frac{1}{T}\sum_{t=1}^{T} \gamma_t + u_{jt} - \frac{1}{T}\sum_{t=1}^{T} u_{jt}. \end{aligned} \tag{B.4}$$

From (B.2) we have that

$$\frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} y_{jt} = \beta_0 + \beta_1\frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt} + \beta_2\frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt}^2 + \phi\frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T}\hat{v}_{jt} + \frac{1}{n}\sum_{j=1}^{n}\alpha_j + \frac{1}{T}\sum_{t=1}^{T}\gamma_t + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} u_{jt}. \tag{B.5}$$

Summing equation (B.4) and equation (B.5) we have

$$\begin{aligned} y_{jt} - \frac{1}{T}\sum_{t=1}^{T} y_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} y_{jt} &= \beta_0 + \sum_{t=1}^{T}\gamma_t D_t + \beta_1\Big(c_{jt} - \frac{1}{T}\sum_{t=1}^{T} c_{jt} \\ &\quad + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt}\Big) + \beta_2\Big(c_{jt}^2 - \frac{1}{T}\sum_{t=1}^{T} c_{jt}^2 + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt}^2\Big) \\ &\quad + \phi\Big(\hat{v}_{jt} - \frac{1}{T}\sum_{t=1}^{T}\hat{v}_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T}\hat{v}_{jt}\Big) \\ &\quad + u_{jt} - \frac{1}{T}\sum_{t=1}^{T} u_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} u_{jt} + \frac{1}{n}\sum_{j=1}^{n}\alpha_j, \end{aligned} \tag{B.6}$$

where using fixed effects estimates equation (B.6) under the constraint that $\frac{1}{n}\sum_{j=1}^{n}\alpha_j = 0$. Therefore, we can rewrite equation (B.6) as

$$\begin{aligned} y_{jt} - \frac{1}{T}\sum_{t=1}^{T} y_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} y_{jt} &= \beta_0 + \sum_{t=1}^{T}\gamma_t D_t + \beta_1\Big(c_{jt} - \frac{1}{T}\sum_{t=1}^{T} c_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt}\Big) \\ &\quad + \beta_2\Big(c_{jt}^2 - \frac{1}{T}\sum_{t=1}^{T} c_{jt}^2 + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} c_{jt}^2\Big) \\ &\quad + \phi\Big(\hat{v}_{jt} - \frac{1}{T}\sum_{t=1}^{T}\hat{v}_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T}\hat{v}_{jt}\Big) + \epsilon_{jt}, \end{aligned}$$

where $\epsilon_{jt} = u_{jt} - \frac{1}{T}\sum_{t=1}^{T} u_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} u_{jt} + \frac{1}{n}\sum_{j=1}^{n}\alpha_j$.

Bibliography

Acemoglu, Daron and Joshua Linn, "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry," *Quarterly Journal of Economics*, 2004, *119* (3), 1049–1090.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Structural Identification of Production Functions," 2006.

Aghion, Philippe and Peter Howitt, "A model of Growth Through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

_ , Christopher Harris, Peter Howitt, and John Vickers, "Competition, Imitation and Growth with Step-by-Step Innovation," *Review of Economic Studies*, 2001, *68* (3), 467–492.

_ , Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: An Inverted-U Relationship," *Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

Andrews, Donald W. K., "Test for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica*, 1993, *61* (4), 821–856.

_ , "Test for Parameter Instability and Structural Change with Unknown Change Point: A Corrigendum," *Econometrica*, 2003, *71* (1), 395–397.

Bartelsman, Eric J. and Wayne Gray, "The NBER Manufacturing Productivity Database," 1996. National Bureau of Economic Research Technical Working Paper No. 205.

Bloom, Nicholas and John Van Reenen, "Patents, Real Options and Firm Performance," *Economic Journal*, 2002, *112* (March), C97–C116.

Blundell, Richard and Stephen Bond, "GMM Estimation with persistent panel data: an application to production functions," *Econometric Reviews*, 2000, *19* (3), 321–340.

_ , Rachel Griffith, and John Van Reenen, "Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms," *Review of Economic Studies*, 1999, *66* (3), 529–554.

Boldrin, Michele and Davide K. Levine, “Perfectly Competitive Innovation,” *Journal of Monetary Economics*, 2008, *55* (3), 435–453.

Boone, Jan, “A New Way to Measure Competition,” *Economic Journal*, 2008, *118* (August), 1245–1261.

Cameron, Colin and Pravin K. Trivedi, *Regression Analysis of Count Data*, New York: Cambridge University Press, 1998.

Cohen, Wesley M., Richard R. Nelson, and John P. Walsh, “Protecting Their Intellectual Assets: Appropriability Conditions And Why U.S. Manufacturing Firms Patent (Or Not),” 2000. National Bureau of Economic Research Working Paper No. 7552.

Dean, Edwin R. and Michael J. Harper, “The BLS Productivity Measurement Program,” 1998. Bureau of Labor Statistics.

Domowitz, Ian, R. Glenn Hubbard, and Bruce C. Petersen, “Business Cycles and the Relationship between Concentration and Price-Cost Margins,” *RAND Journal of Economics*, 1986, *17* (1), 1–17.

Doraszelski, Ulrich, “An R&D Race with Knowledge Accumulation,” *RAND Journal of Economics*, 2003, *34* (1), 20–42.

_ **and Jordi Jaumandreu**, “R&D and productivity: Estimating endogenous productivity,” 2009.

Geroski, Paul A., “Innovation, Technological Opportunity, and Market Structure,” *Oxford Economic Papers*, 1990, *42* (3), 586–602.

Gilbert, Richard and David Newbery, “Preemptive Patenting and the Persistence of Monopoly,” *American Economic Review*, 1982, *72* (3), 514–526.

Greene, William H., *Econometric Analysis*, New Jersey: Prentice Hall, 2003.

Griliches, Zvi, “Productivity Puzzles and R&D: Another Nonexplanation,” *Journal of Economic Perspectives*, 1988, *2* (4), 9–21.

Hall, Bronwyn H., “Innovation and Market Value,” in “Productivity, Innovation and Economic Performance,” New York: Cambridge University Press, 2000, pp. 177–198.

_ **, Adam B. Jaffe, and Manuel Trajtenberg**, “The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools,” 2001. National Bureau of Economic Research Working Paper No. 8498.

_ **, Zvi Griliches, and Jerry A. Hausman**, “Patents and R and D: Is There a Lag?,” *International Economic Review*, 1986, *27* (2), 265–283.

Hansen, Lars Peter, “Large Sample Properties of Generalized Method of Moments Estimators,” *Econometrica*, 1982, *50* (4), 1029–1054.

Hausman, Jerry A., Bronwyn H. Hall, and Zvi Griliches, "Econometric Models for Count Data with an Application to the Patents-R&D Relationship," *Econometrica*, 1984, *52* (4), 909–938.

Hayashi, Fumio, *Econometrics*, New Jersey: Princeton University Press, 2000.

Jaffe, Adam B. and Josh Lerner, *Innovation and its Discontents*, New Jersey: Princeton University Press, 2004.

Jones, Charles I., "Sources of U.S. Economic Growth in a World of Ideas," *American Economic Review*, 2002, *92* (1), 220–239.

Katayama, Hajime, Shihua Lu, and James R. Tybout, "Firm-level productivity studies: Illusions and a solution," *International Journal of Industrial Organization*, 2009, *27* (3), 403–413.

Kee, Hiau Looi and Bernard Hoekman, "Imports, entry and competition law as market disciplines," *European Economic Review*, 2007, *51* (4), 831–858.

Klette, Jakob, "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data," *Journal of Industrial Economics*, 1999, *47* (4), 451–476.

_ **and Zvi Griliches**, "The Inconsistency of Common Scale Estimators When Output Prices are Unobserved and Endogenous," *Journal of Applied Econometrics*, 1996, *11* (4), 343–361.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 2003, *70* (2), 317–341.

Melitz, Marc J. and Giancarlo I.P. Ottaviano, "Market Size, Trade, and Productivity," *Review of Economic Studies*, 2008, *75* (1), 295316.

Moser, Petra, "How do Patent Laws Influence Innovation? Evidence from Nineteenth-Century World's Fairs," *American Economic Review*, 2005, *95* (4), 1214–1236.

Nickell, Stephen J., "Competition and Corporate Performance," *Journal of Political Economy*, 1996, *104* (4), 724–746.

Olley, Steven and Ariel Pakes, "Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms," *Econometrica*, 1996, *64* (6), 1263–1297.

Pakes, Ariel and Zvi Griliches, "Patents and R&D at the Firm Level: A First Look," 1980. National Bureau of Economic Research Working Paper No. 561.

Reinganum, Jennifer F., "Uncertain Innovation and the Persistence of Monopoly," *American Economic Review*, 1983, *73* (4), 741–748.

Romer, Paul M., "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98* (5), S71–S102.

Sargan, J.D., "The Estimation of Economic Relationships using Instrumental Variables," *Econometrica*, 1958, *26* (3), 393–415.

Schumpeter, Joseph A., *Capitalism, Socialism and Democracy*, New York: Harper and Brothers, 1942.

Scotchmer, Suzanne, *Innovation and Incentives*, Massachusetts: The MIT Press, 2004.

Shy, Oz, *Industrial Organization: Theory and Applications*, Massachusetts: The MIT Press, 1995.

Stigler, George J., "Industrial Organization and Economic Progress," in "The State of the Social Sciences," Chicago: University of Chicago Press, 1956.

Stock, James H. and Mark W. Watson, *Introduction to Econometrics*, Addison-Wesley, 2007.

Tirole, Jean, *The Theory of Industrial Organization*, Massachusetts: The MIT Press, 1988.

Wooldridge, Jeffrey M., *Econometric Analysis of Cross Section and Panel Data*, Massachusetts: The MIT Press, 2003.