Competition and Innovation: ICT- and non-ICT-enabled Product and Process Innovations

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Abstract

The reason for contradictory predictions of the models studying the impact of competition on innovation is the varying assumptions with respect to competition or innovation type. Thus, we study how the impact of competition changes with different types of innovative Output. In particular, we distinguish between non-ICT - and ICT-enabled product and process innovations. To allow for such flexibility, we apply Bayesian inference techniques and use direct measures of innovative that control for the heterogeneity of innovation Output. Our analysis provides evidence that supports the hypothesis that the effect of market competition on innovation is not alike for all types of innovation. We observe an inverse U-shape relationship between competition and non-ICT-enabled and a clear U-shape dependency for ICT-enabled innovations. However, the results become considerably weaker, once industry effects are taken into account. Thus, although the impact of competition on innovation varies with the type of innovation, other factors seem to have a stronger impact on the incentives to innovate.

Keywords: Competition, innovation, Information and communication technologies
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1 Introduction

Innovation can pay large dividends for society. As a result, the determinants of innovative activity have received much attention not only from economists but also from policy makers and business people. However, although the problem of the identification of the industry structure that offers greatest incentives for innovation has been one of the mostly discussed topics in the field of industrial organization, so far there is no consensus on how competition or its lack affects companies' innovative activity (Gilbert (2006)). The reason for this, are different settings and assumptions of the theoretical models that aim at explaining the relationship between competition and innovation. Thus, in this analysis we take a different approach. Instead of looking for the most optimal type of market structure for innovative activity we tackle the question of how market competition affects different types of innovations.

An important element of our analysis is that we take into account the contradicting predictions of theoretical models with respect to competition and firms' innovative behavior (e.g. Schmutzler (2007)). Rather than selecting one type of theoretical model and testing its validity, we acknowledge that most of the models have clear predictions and that they differ with respect to the assumptions made. To allow for such flexibility, we make use of data and an empirical method that take into account the nature of the existing theories. The analysis is based on a unique data set compiling data on innovative activity and a competition measure at the sectoral level for a number of European countries. Our data has two significant advantages. First, it includes the following four direct measures of innovative: non-ICT- and ICT-enabled product innovations and non-ICT- and ICT-enabled process innovations. Thus, in contrast to a large bulk of literature, we use innovation measures that depict real product and process innovations conducted by firms instead of proxies such as R&D expenditures or the number of patents typically used. Furthermore, our measures of innovative output allow us to control for the heterogeneity of innovation output. Due to the fact that the data used in this analysis provides information on whether an innovation conducted by a firm was based on information and communication technology (ICT) or not, we can identify the type of technology that was used in the innovation process. In other words, given the general purpose character of ICT (Bresnahan and Trajtenberg (1996)), we are able to make a distinction between the original technology that an innovation was derived from. Second, our competition variable is based on the concept of economic rents, rather than concentration ratio or market share indicators. Its main advantage over other commonly used indicators is that it does not require the observation of the firm's complete market in order to describe competition. This is particularly important considering that a large share of companies operate in international markets, which poses considerable limitations on other competition measures. Regarding the empirical methodology, we apply Bayesian inference techniques. The most important reason for the choice of Bayesian method is that it enables us to account for the different predictions of the available theory and, consequently, different solutions. By reporting posterior distributions of model parameters, we can subsequently make statements regarding the probability and, consequently, the validity of each theoretical prediction, instead of rejecting any of the competing hypothesis. Furthermore, Bayesian method is less sensitive to the problems regarding small sample size.

As mentioned above, the main motivation of this analysis was to conduct a comprehensive study that would acknowledge the fact that the relationship between competition and innovation is a multifaceted one (Scherer and Ross (1990)). This diversity is reflected in the abundance of theoretical models that deliver contradicting predictions. The source of these inconclusive claims are the differences related to the assumptions made with respect to the competition type and technological characteristics. The very first analysis of market structure and incentives to innovate was conducted by Arrow (1964). Contradicting Schumpeter (Schumpeter (1942)), he formally advanced the claim that a newcomer may have greater incentives to innovate than a monopolistic firm. Arrow's conclusions were, however, revised by subsequent works. For example, the way of thinking about competition and innovation was strongly influenced by Salop (1977) and Dixit and Stiglitz (1977) who argued that intense market competition reduces the incentives to innovate. Similar, Segerstrom and Zolnierek (1999) show that industry leading firms with significant market shares undertake most of the industry innovative activities. A more recent work by Aghion et al. (2005) shows that there is no simple answer to the question of what is the most optimal market structure for the dynamic efficiency. According to the authors, the final effect of competition on innovation depends on the net effect of competition on the pre- and post-innovative profits of firms active in the industry. An interesting overview of a number of theoretical settings and their implications for the relationship between competition and innovation is presented by Schmutzler (2007). He shows that the effects of increasing competition on innovation investments can be positive, negative or non-monotone. In his explanation, he identifies four different transmission channels by which competition affects investments and argues that the number of interactions is a source of ambiguous effects of competition on innovation. Consequently, it is not possible to formulate a universal model that could explain this relationship.

The results of the empirical analysis match the ambiguity of the results of the theoretical works. The studies on the relationship between competition and innovation was pioneered by Frederic M. Scherer. In one of his studies, Scherer (1965) expressed his disapproval of the idea of monopoly being an apt market structure for technological progress. He concluded that innovative output does not seem to exhibit any positive correlation with market power or even with profitability before a successful innovation. Later on, however, Scherer (1967) found that the innovative output tended to increase with the market concentration level. Explaining the discrepancies between both studies, he adhered to the complexity of the relationship and the need to account for inter-industry differences such as technological opportunity. Eventually, he advanced an argument of a threshold, up to which higher industry concentration level promotes innovation competition. The hypothesis of a U-shaped curve, reflecting relations between market power and innovative activity, was partially supported by Comanor (1967) as well. However, he argued that monopoly power may cause higher research efforts only in industries in which product differentiation possibilities are limited and that this relationship does not exist in sectors in which innovation competition plays an important role. Further studies showed little, if any, causality effect between increasing market power and innovation. In a more recent study, Geroski (1994) provided strong support against the concept that monopoly power has a positive and direct effect on innovation. According to him, incomplete treatment of the technological opportunity has lead to biased results of the previous studies. In particular, it seems that the usual methodology of testing the Schumpeterian hypothesis contains a flaw which imparts a distinctly 'pro-Schumpeterian' bias to the results. The study showed that industries with high technological opportunity are characterized by a high concentration ratio, considerable market size, and higher profitability. Mansfield recapitulated the results of empirical research in the following words: *"[a] slight amount of concentration may promote more rapid invention and innovation (...). But beyond a moderate amount of concentration, further increases in concen-*

tration do not seem to be associated with more rapid rates of technological advance."[1] Again, reconciling conclusion can be found in Aghion et al. (2005) who show that there is an inverted U-shape relationship between competition and innovation.

Due to the lack of agreement, Cohen and Levin (1989) pointed out that the research objectives should be refocused from the narrowly defined relationships to the fundamental sources of technological change. Consequently, over the recent decades economists have gradually dispensed with the notions of complete information, profit maximization and predictability (Aghion and Howitt (1995)). Accounting for uncertainty and bounded rationality, the evolutionary approach to economic phenomena has been suggested. According to Gort and Klepper (1982) and Klepper (1996), the innovation process changes together with industry evolution. For example, at the beginning of the industry formation, entrants account for a disproportionate share of product innovations. The diversity of competing versions of the product and the number of major product innovations tend to reach a peak during the growth in the number of producers and then fall. Over time, producers devote increasing effort to process relative to product innovation. Towards the end of an industry life cycle, the advantage of size increases firm's process innovation incentives and efforts.

Similar implications for the innovation process as the industry life cycle has the technological change. For example, in a case study based analysis of innovation patterns in a variety of industries, Christensen (1997) shows that industry leaders often reject important inventions and fail to bring them to the market. Entrepreneurial companies are more likely to exploit these opportunities. What at first sight looks surprising is easy to explain. According to Arend (1999), entrants and incumbents make rational decisions to invest in radical innovations or not. The most obvious reason why incumbents choose not to pursue radical innovations is the fact that at the beginning the market for them is nonexistent or rather small, which makes such investments unattractive or unprofitable for the incumbent firm. Another argument says that the incumbent's incentives to compete with an entrant for a new opportunity are rather low (Reinganum (1983)). This arises due to the cannibalization of its current profits. Incumbents prefer to use the available technology rather than the future one and, consequently, devote resources to the current profits rather to the future ones. Entrants, in contrast, focus on tomorrow's opportunities and choose

[1]Citation in Baldwin, W. L. and Scott, J. T. (1987). 'Market Structure and Technological Change', p. 90.

to compete in the future using future technology.

Considering the interrelations between market evolution, technological change and the process of innovation, it becomes obvious that any analysis studying the relationship between competition and innovation should take into account at least two issues. First, there is a quantitative difference between product and process innovations. Therefore, one can expect that the intensity of each type of innovative activity might vary with competition. Second, technologies evolve and are replaced over the industry life-cycle. Consequently, the relationship between competition, technological shift and the resulting change in the innovative process might be of different nature as compared to a static state.

An example of a technological shift and a transformation of the innovative process is the spread of ICT commonly recognized as a general purpose technology (GPT). GPT is a term describing a new method of producing and inventing that has an extensive impact on a wide range of economic activities (Jovanovic and Rousseau (2005)). Similar to such GPTs as electricity or steam engine, the diffusion of ICT enhances productivity and improves firm performance by enabling development of new products, cheaper production of existing goods, process reorganization and organizational change (e.g. Brynjolfsson and Hitt (2000); Bharadwaj (2000); Köllinger; Nepelski (2009); Venkatraman (1991)). Thus, the ICT-driven technological change moves firms towards a new technological trajectory. In view of the above discussion, it is necessary to ask whether the effect of market competition on innovation changes with the type of innovation.

The scope of innovative activity covered in this study distinguishes it from others that tackle the relationship between innovation and competition. In particular, the inclusion of ICT-enabled innovations makes it absolutely unique. Thus, it is necessary to explain the character and importance of such innovations. According to the literature on user adoption of innovation in ICT, these type of innovations are not primarily cost reducing (Bresnahan and Greenstein (2001)). The use of ICT primarily enables improvements in the quality and the reliability of products and services (Brynjolfsson and Hitt (1996)). Furthermore, novel ICT applications frequently lead to the introduction of entirely new services and products. Regarding ICT-enabled process innovations, this is mainly a result of adopting software, which embeds business processes and organizational structures. Thus, the adoption and business use of ICT applications reinforces the process of process innovation and organizational redesign (Hammer and Champy (1995)).

Our analysis provides evidence that supports the hypothesis that the effect of market competition on innovation is not alike for all types of innovation. First, we observe an inverse U-shape relationship between competition and non-ICT-enabled innovations. Second, a clear U-shape dependency can be observed for ICT-enabled innovations. However, once industry effects are included in the analysis, the results become considerably weaker. Thus, to some extent, we provide evidence that is consistent with the seemingly contradictory predictions of various models and confirm the findings stating that the effect between competition and innovation is only of minor importance. As already indicated in previous studies, other factors seem to have a stronger impact on the innovative activity. Consequently, any implications for innovation policy and further research in this area should take into account the type of innovations, the maturity of the industry and the life cycle of the technology.

The remaining of the chapter is organized as follows. Section 2.2 presents the data used and describes the process of data matching. Section 2.3 discusses the methodology. Section 2.4 presents the results and Section 2.5 concludes.

2 Data sources and data matching

In our analysis we use two data sources to obtain information on innovation activity and competition level at the industry level. The first is the e-Business Watch project and provides measures of innovation activity. The second is the database developed within the EU KLEMS research project and is a source of competition measures.

e-Business Watch is an initiative launched by the European Commission in 2001 with the aim to monitor the adoption, development and impact of electronic business practices in different sectors of the European economy.[2] The enterprise surveys conducted within the e-Business Watch project focused on the availability and usage of ICT and the perceived importance and impact of e-business at the company level. Apart from the numerous questions relating to the usage and relevance of ICT, all data sets contain background information about each firm, e.g. sector, country of origin, number of employees, size class and number of establishments. Since

[2]For more information see www.ebusiness-watch.org

2003, the respondents were asked about their companies' innovative activities. Thus, in this work, we use data from the 2003, 2005 and 2006 surveys. The total number of observations in all three data sets exceeds 26,600 enterprises. Annex gives a detailed description of the surveys and the data sets used in this study together with an overview of sectors and countries covered by each individual survey.

EU KLEMS is a research project that aims at analyzing productivity developments in the European Union at the industry level.[3] One of its product is a database including measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level. The database uses a 63-industry breakdown in accordance to the NACE classification code for the major of the EU's 25 Member States as well as for the US, Japan and Canada, from 1970 onwards. The input measures include various categories of capital, labour, energy, material and service inputs. In addition, the data set includes several measures of knowledge creation. The information on value added and labour compensation enables us to construct a competition measure at the industry level.

In order to match the data from both sources, we followed the sector-country classification of the e-Business Watch and defined our markets accordingly. Then, we matched each observation unit from the e-Business Watch data set with its counterpart in the EU KLEMS data set. Following this matching procedure, we obtained observations which can be defined as single markets, whereas each market is one industry in one country. We included only sectors that can be characterized as ICT-users and excluded industries producing ICT equipment and services, such as the ICT manufacturing or ICT services industries, both covered by the 2006 survey. The justification for this was the fact that it is diffi cult to draw a line between non-ICT- and ICT-enabled innovations in sectors whose primary products are ICT-based, e.g. equipment, services or software.

Due to the fact that sectors covered by the e-Business Watch surveys were very narrowly defined, in many cases it was not possible to find its counterpart in the EU KLEMS data set. Therefore, if that was the case, the sector was excluded from the final analysis. Similarly, some observations were dropped because of a limited number of countries covered in the EU KLEMS data set. Eventually, we obtained a sample of 260 individual markets across the European econ-

[3]For more information see www.euklems.net

omy, out of 363 potential observations originally included in the e-Business Watch database. The final data set includes complete information on innovative activity and competition level. Table 1 shows the final list of sectors included in the analysis together with the NACE classification codes in both data sets.

Table 1: The mapping between e-Business Watch and EU KLEMS sectors

e- Business Watch		EU KLEMS NACE Code
Sector definition	NACE Code	
Survey 2003		
Business Services	74	74
Chemical industries	24, 25	24, 25
Crafts and trade	20, 36	20, 36
Electronics	30, 31, 32	30, 31, 32
Hospital activities	85	N
Retail	52	52
Textile industries	17, 18.1, 18.2, 19.3	17, 18
Tourism	55, 62, 63, 70, 92	H, 63, 92
Transport equipment	34, 35	34, 35
Survey 2005		
Automotive industry	34	34
Construction	45	F
Food and beverages	15	15
Machinery and equipment	29	29
Pharmaceutical industry	24.4, 24.5	24.4
Publishinq and printinq	22	22
Textile industry	17, 18	17, 18
Tourism	55, [62], 63, 92	H, 63, 92
Survey 2006		
Consumer electronics	32	32
Construction	45	F
Food and beveraqes	15	15
Footwear	19	19
Hospital activities	85	N
Pulp, paper and paper products	21	21
Shipbuildinq and repair	35.1	35.1
Telecommunication Services	64	64
Tourism	55, 63, 92	H, 63, 92

2.1 Measuring innovation

There exists no measure of innovation that permits readily interpretable cross-industry comparisons (e.g. Cohen and Levin (1989)). Moreover, the value of innovation is difficult to assess, particularly when the innovation is embodied in consumer products (Griliches (1979)). In order to overcome the shortcomings of traditionally applied measures of innovative activity, we make use of direct measures of innovations. In the e-Business Watch surveys, each respondent was asked a question of whether her company had introduced substantially improved products or services to its customers during the past 12 months prior to the date of the interview. Similarly, survey participants were also asked if the Company had introduced new internal processes during the past 12 months.[4] In addition to the introductory questions on Innovation, the interest was also on the share of innovative activity that is directly related to or enabled by information and communication technology. Therefore, companies that indicated in the introductory questions that they have conducted innovations in the past 12 months were asked follow up questions. Consequently, we are able to distinguish between the following four types of innovations:

- Non-ICT-enabled product innovations,
- ICT-enabled product innovations,
- Non-ICT-enabled process innovations,
- ICT-enabled process innovations.

Because this study is at a sector level, we had to aggregate companies' answers to the questions of interest. Therefore, in order to compute innovation rates for each sector-country cell, we first summed up companies' positive answers to the questions regarding their innovation activity and divided by the number of all firms in the relevant sector-country cell. The final innovation measures are indices for each type of innovation that can take any value between 0 and 1. If the value of an index is 0, none of the companies belonging to a certain market covered by the survey has conducted any of the relevant innovation. In contrast, if an index takes value of 1, it means that all companies in the market have introduced a particular type of innovation.

As in other studies, our measures suffer from some limitations.[5] First, we need to rely on respondents' perceptions. Second, we are not able to quantify the value of different innovations. Nevertheless, compared to commonly used innovations measures, such as the number of patents or R&D spending, the most obvious advantage of our innovations indicators is the fact that we use a direct measure of innovative activity that is related to the innovative Output. Furthermore, we are able to control for the heterogeneity of innovation type. The latter is decisive for obtaining

[4] The questions regarding a firm's innovative activities were adopted from the Community Innovation Survey (CIS 2004) to determine the share of companies that recently introduced product or process innovations.

[5] See Cohen and Levin (1989) for a discussion of the drawbacks of patents and R&D input as measure of innovation.

a consistent picture of the relationship between competition and firms' innovative activity type, which is a distinct feature of this study.

2.2 Measuring competition

The measurement of profits and consequently market competition at the macroeconomic level is subject to a high degree of uncertainty and may also reflect measurement problems associated with other economic variables. Empirical studies analyzing the relationship between competition and innovation are marked by considerable deficiencies in capturing the level of competition (Cohen and Levin (1989)). The most important problem of these studies was the choice of an appropriate indicator of market level competition and finding empirical data that could allow for an extensive study of the issue. Thus, the measure of competition applied in this study is based on the concept of economic rents, rather than concentration ratio or market share indicators. One problem with applying a measure of economic rents as a proxy for market power is that a high gross margin is a natural feature of dynamic, innovation-driven industries and its mere existence is not a basis to conclude that there is monopolization (Geroski (1994)). Despite this limitation, a measure of market competition based on economic rents has some straightforward advantages over other indicators, such as market shares or Herfindal index, commonly used in studies of competition and innovation. Computing economic rents does not require the observation of the firm's complete market in order to describe competition. This is particularly important considering that a large share of companies operate in international markets. In such cases, traditional market competition measures quickly reach their limitations. Thus, as in Aghion et al. (2005), the Lerner index is very attractive as a measure of market competition. However, given that the direct empirical measurement of the Lerner index is quite difficult since firms' marginal costs are not observable, we make use of gross margin as a proxy of market competition. The gross margin is defined as the ratio of sales minus cost of goods sold to sales (Gitman (1994)).

In order to create a proxy for a gross margin at the industry level by using the EU KLEMS data, we define our measure of competition as the difference between value added and labour compensation as a proportion of value added, i.e.:

$$GM_{ij} = \frac{VA_{ij} - LC_{ij}}{VA_{ij}}, \quad (1)$$

where *LCij* is the labour compensation and *VAij* is total value added of industry *j* in country *i*. Examples of using the concept of gross margin as a measure of competition include Cowley, P.R. (1985), Holdren (1965), Livingston and Levitt (1959) and Nevo (2001) and a similar approach to the measurement of competition by using macroeconomic data can be found in Crespi and Patel (2007) and ECB (2006). To make the Interpretation of the following analysis more intuitive, we use

$$c_{ij} = 1 - GM_{ij}, \quad (2)$$

where c_{ij} Stands for competition level in country *i* and industry *j*. The values of c_{ij} can range between 0 and 1 and it can be interpreted in a reverse way to the Lerner index. As c_{ij} increases, so does the competition level.

In order to reduce the problem of endogeneity, we lagged the data on competition by two periods relatively to the observation on innovation. Thus, as companies were asked about innovation activity in the last 12 months before the survey, the Information on competition level comes from at least a year before any innovation took place. For example, the data from the 2003 survey was matched with the EU KLEMS data from 2001.

3 Method

3.1 Empirical model

The main question of the current analysis is what kind of relationship exists between innovation and competition, i.e. what is the shape of $g(c_{ij})$? In contrast to previous studies discussed above, we make a qualitative distinction between different types of innovation. Thus, for each type of innovative activity we model innovation intensity in country *i* and industry *j* in the following way:

$$I_{kij} = \alpha + g(c_{ij}) + \beta x_j + \varepsilon_{ij} \quad (3)$$

where I_{kij} denotes Innovation rate of Innovation type $k = 1,..., 4$, i.e. non-ICT-enabled and ICT-enabled product and process innovations, a is a constant and Xj is a complete set of industry dummy variables. Following other studies (e.g. Aghion (2005)), we refrain from imposing any particular form of $g(c_{ij})$. Instead, we allow for a flexible functional form of the dependency between innovation and competition. In the proceeding section we make use of visual data analysis techniques, which will allow us to identify the shape of $g(c_{ij})$.

An important concern regarding the model specified above is the problem of endogeneity. It is a well known fact that there is a two-way causality effect between market structure or market power and innovation.[6] In other words, just as competition influences the intensity of innovative behavior, innovation influences market competition. Thus, in order to minimize the endogeneity problem, data on competition was lagged by two periods, relatively to the data on innovation.

A number of studies shows that once additional variables are introduced the effect of competition on innovation activity diminishes or disappears completely (see, for example, Geroski (1994)). Thus, in order to account for other factors that might have an influence not only on the innovation intensity but also on the type of innovations, we control for industry effects by including sector dummies in one of the specifications.

3.2 Bayesian method

The literature survey presented above reveals that the economic theory of innovation and competition is very inconclusive and, depending on the assumptions, leads to different conclusions. Thus, instead of asking what is the optimal level of competition for innovative Output, our analysis focuses on how the impact of competition on innovation changes subject to the type of innovation. The main purpose of this analysis is to operationalize and validate the exist-ing pieces of seemingly contradicting hypotheses in order to obtain a consistent picture of the relationship between competition and innovative activity.

A logical step in reexamining this issue is the choice of an appropriate empirical method, which can take into account the nature of the existing theories. It is evident that the difference in theoretical conclusions stems from the assumptions made with respect to the characteristics of innovation or technology used. Thus, an appropriate method should allow for a study of

[6]For a review on the interplay between competition and innovation see Nepelski (2003).

innovation and technological phenomena, as they can determine the impact of competition on innovative activity. However, most of the empirical studies in this area use some variations of regression analysis estimated by using traditional statistical techniques (for a literature overview see, for example, Kamien and Schwartz (1982) or Baldwin and Scott (1987)). The major focus of these studies is to test whether there is a relationship between competition and innovation measured by an aggregated measure such as R&D expenditures or the number of patents. Consequently, the results of these studies indicate only that, on average, competition negatively or positively affects the studied measure of innovation and they do not allow to make any comment with respect to a specific probability that such a relationship exists for a particular type of innovation. In order to fill this gap, we propose Bayesian inference.

3.2.1 The principles of Bayesian interference

The Bayesian approach is characterized by the use of external information sources, which is called prior information. This information is usually captured in terms of probability distribution based on previous studies or historical information. Despite its convenience of use and intuitive presentation of results, Bayesian methods have become widely used only in the last two decades. Until recently, mainly due to computational requirements, there were only few classes of models for which the posterior could be computed. Furthermore, many researchers disputed the quality of an approach in which subjective prior information is used. To tackle this problem and to increase the robustness of the results, most of the analyses include various assumptions regarding the priors. In addition, the widespread use of such simulation methods as Markov Chain Monte Carlo (MCMC) eliminated most of the computational obstacles for a number of models and reduced the concern of the influence of the prior on the coefficient estimates. In particular, the possibility of conducting a large number of simulations considerably reduced the influence of priors on the final results. As a result, Bayesian methods have been intensively used in a number of disciplines. Some examples from the economics studies in which Bayesian inference techniques were used are Fryar, Arnold and Dunn (1988) and Mountain and Illman (1995). Applications in other disciplines, such as management, include, among others, Hansen et al. (2004), Block and Thams (2007). Furthermore, an overview of studies in marketing, in which Bayesian techniques were used, can be found in Rossi et al. (2003).

All Bayesian methods rely on Bayes' theorem of probability theory (Lancaster, (2004)), which can be expressed as

$$\Pr(\theta \mid y) = \frac{\Pr(y \mid \theta)\Pr(\theta)}{\Pr(y)}, \tag{4}$$

where θ represents the set of unknown parameters, and *y* represents the observed data. Pr(θ) is the prior distribution of the unknown parameters. Pr(*y* | *θ)* is the likelihood function, which is the probability of the data *y* given *θ.* Pr(*y*) is the marginal distribution of the data, and Pr(θ| *y)* represents the posterior distribution, which is the probability of the parameter *θ* given the data *y*.

When testing a hypothesized relationship between two variables, Bayesian analysis proceeds in the following steps. First, a priori beliefs about the relationship of interest, i.e. Pr(θ), are formulated. Next, a probability of occurrence of the data given these beliefs, i.e. Pr(*y* | *θ),* is assumed. In the second step, data is used to update these beliefs. The result is the posterior distribution, i.e. Pr(θ | *y),* of all parameters included in the model specification. Thus, Bayesian inference allows for statements in terms of *likely* and *unlikely* parameter values or effects on the dependent variable.

In practice, Bayesian probability statements regarding the parameters conditional on the data are often interpreted in a similar way to classical confidence statements about the probability of random intervals covering the true parameter value. This is however not correct (Sims (1988); Sims and Uhling (1991)). According to the frequentists approach, a population mean is not known, but can be estimated from a sample. Thus, by knowing or assuming the distribution of the sample mean, confidence interval is constructed that is centred at the sample mean. Then, the only statement that can be made is that 95% or 90%, accuracy level depends on arbitrary preferences, of similar intervals would contain the population mean, if each interval was constructed from random samples. In contrast, the Bayesian approach proceeds by constructing a credible interval that is centred around the sample mean. Eventually, by using the Bayesian approach, one can state that there is, for example, 95% or 90% probability that this interval contains the mean.

Another implication of Bayesian econometrics is that it is less concerned with the sampling issue, compared to the frequentist approach. Instead, Bayesian econometrics rely on the data at hand. This brings the focus of the analysis to more fundamental questions like, for example, what is the relation between the available data and the model or how to deal with the discrepancies between the empirical results and what the theory suggests?

These characteristics of Bayesian inference have some clear advantages for our analysis. First, we do not assume that there are any true and fixed coefficients, which allows us to account for the differences in the dependency of innovative activity on competition. This is useful because the theory describing the relationship between competition and innovation is far from being consistent and includes competing hypotheses. Bayesian analysis states the probability or the extent to what a particular hypotheses can be confirmed by the observations. Consequently, it allows us to determine which hypothesis describes our data with a higher probability, instead of rejecting any hypotheses as being not relevant at all.

3.2.2 Bayesian calculations and Marcov chain Monte Carlo Simulation

As mentioned above, one of the main reasons for the late take-off of the Bayesian techniques use was the computational difficulty. The Joint posterior distribution, i.e. $\Pr(\theta \mid y)$, is in many Situation hundred- or thousand-fold dimensional, which makes it very complex and unavailable in closed form (Lunn et al. (2000)). As it is shown in the next section, Bayesian inference involves the estimation of various summary statistics of the posterior distributions, such as mean, Standard deviation or quantiles. In order to obtain these measures, one needs to integrate functions that involve $(\theta| y)$ with respect to θ, which considerably limits the use of Bayesian method. MCMC Simulation allows one to overcome this problem, i.e. it substitutes for multidimensional Integration as a means to parameter estimation (e.g. Chib and Greenberg (1996) and Kloek and van Dijk (1978)).

In Bayesian interference, MCMC Simulation methods are used to evaluate integrals from a Marcov chain that is constructed in a way that its stationary distribution is the posterior. For that purpose, there are two commonly used Simulation algorithms: Gibbs and Metropolis sampler (Lancaster (2004)). Both algorithms proceeds by iterative Simulation from the füll conditional distributions of each unknown stochastic quantities taking into account the current values of all other terms of the model. The Gibbs sampler is implemented in the WinBUGS algorithm (Lunn et al. (2000)), which was used to conduct computation included in the current analysis.

4 Empirical analysis

4.1 Descriptive statistics

Table 2 shows mean values of innovation rates for each type of innovation activity and competition levels broken down by sectors. Regarding process innovation, 14% of all process innovations were not ICT-enabled and only 24% were in some way driven by ICT. Such discrepancy does not exist in the case of product innovations. There are however significant variations in the type of innovation activity between industries. For example, whereas in the telecommunication sector nearly one half of all product innovations were enabled by ICT, in the construction or pharmaceutical sectors such innovations accounted for only around 10% of all product innovations. Similar patterns can be observed for process innovations. Furthermore, the large value of standard deviations and the discrepancies between minimal and maximum values of all innovation measures indicate that there are considerable differences between the markets (see table 5A, Annex). To some extent, this can be explained by the discrepancies in the use of ICT across sectors. At the same time, however, this is also a reflection of differences in the demand for various types of technologies that firms use and technological regimes they operate in. This indicates also to what extent new technologies, such as ICT, can be used in different sectors to introduce new products or improve production processes.

Table 2: Innovation activity by innovation type and competition level across sectors

Sector	Non-ICT-enabled innovations		ICT-enabled innovations		Competition
	product	process	product	process	
Automotive industry	0.35	0.19	0.15	0.28	0.63
Business Services	0.25	0.24	0.23	0.21	0.57
Chemical industries	0.16	0.18	0.46	0.28	0.45
Construction	0.12	0.09	0.11	0.19	0.54
Consumer electronics	0.18	0.10	0.31	0.23	0.61
Crafts and trade	0.06	0.05	0.31	0.13	0.53
Electronics	0.24	0.22	0.30	0.26	0.58
Food and beverages	0.38	0.16	0.11	0.23	0.55
Hospital activities	0.15	0.18	0.31	0.27	0.77
Machinery and equipment	0.34	0.17	0.15	0.24	0.71
Pharmaceutical industry	0.52	0.20	0.11	0.30	0.54
Publishing and printing	0.18	0.10	0.26	0.41	0.62
Pulp, paper and paper products	0.22	0.12	0.15	0.23	0.54
Retail	0.23	0.26	0.39	0.19	0.48
Shipbuilding and repair	0.14	0.15	0.12	0.11	0.88
Telecommunication Services	0.09	0.03	0.46	0.42	0.39
Textile industries	0.25	0.13	0.21	0.19	0.69
Tourism	0.20	0.13	0.20	0.23	0.52
Transport equipment	0.15	0.16	0.35	0.25	0.56
Total	0.22	0.14	0.23	0.24	0.57

Regarding competition levels, it can be seen that, on average, the telecommunication and chemical industries are the least competitive. On the other extreme, the hospital activities and shipbuilding sectors exhibit the highest levels of competition within the studied sample. A closer look at the detailed statistics reveals that the competition level strongly varies in our sample (see table 5A, Annex). Although the mean and median values are slightly higher than 0.5, the minium and maximum values, c = 0.11 and c = 0.97 respectively, indicate that our sample includes both types of markets, i.e. nearly monopolies and perfectly competitive markets.

Some insights into the relationship between competition and innovation activity delivers the analysis of the correlation coefficients (see table 6A, Annex).[7] Whereas there is a positive, though not significant, correlation between competition and both non-ICT-enabled innovation

[7]Considering that the values of correaltion cofficients are relatively moderate, the multicollinerity should not be an issue in the forthcoming analysis.

types, the reverse is true for ICT-enabled innovations. Both types of ICT-enabled innovations are negatively correlated with the competition measure. Taking all these facts together, it can be assumed that an increasing market competition decreases firms' propensity to adopt ICT tools and, as a result, to use ICT in their innovation process.

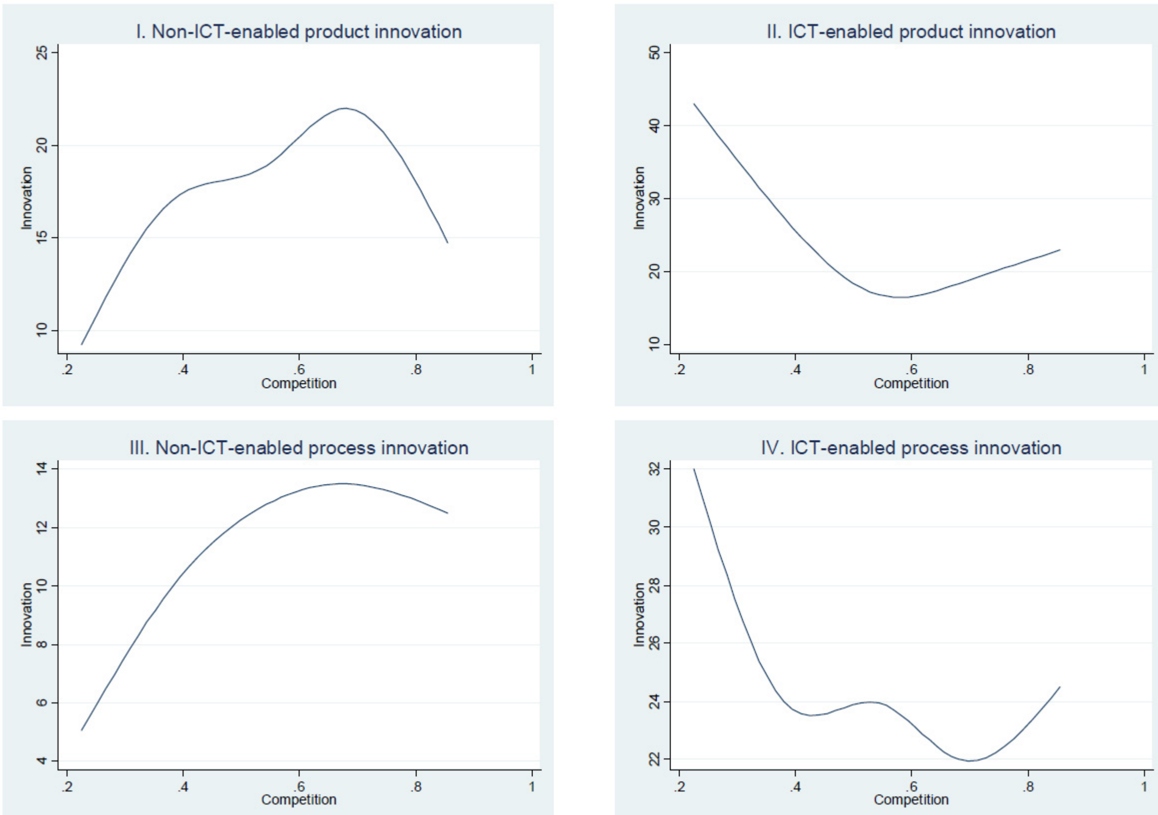
4.2 Univariate analysis

Before proceeding with a regression analysis, we start with exploring the relationship between competition and all four types of innovations in a univariate analysis by inspecting a series of data plots. For each type of innovation we illustrate the dependency between competition and innovation rate by fitting a median spline function. A median spline function is a semiparametric method that aims at fitting a function that matches the relationship between the dependent and independent variables (Smith (1979)). This is done in two steps. First, the independent variable is split into equally spaced intervals.[8] Second, cross medians are calculated and used as knots to fit a cubic spline. The resulting spline is graphed as a line plot. By using such a method, we can get a first insight into the shape of the function describing the dependency between competition and all four innovation types.

Figure 1 shows the results of spline estimations. The shape of these curves indicates that there is a considerable heterogeneity across different types of innovation with respect to competition. On the one hand, we can observe a positive relation between non-ICT-enabled innovation. Although far from an inverted U shape, the lines indicate that the propensity to conduct both product and process non-ICT-enabled innovations increases at a decreasing rate with the competition level. This reminds of the results obtained in some of the previous studies (see for example Scherer (1967) and Aghion et al. (2005)). On the other hand, however, when analyzing ICT-enabled innovations, it is clear to see that there is a negative relationship between innovative activity and competition. For both types of innovation, the highest rate of innovative activity can be observed in the least competitive markets. Then, as competition increases, the innovative activity decreases at an increasing rate to reach its minimum between .5 and .7 and to increase slightly in the region of the highest competition.

[8]Here we present the case where the number of intervals is equal to 5. We checked alternative other cases and the results were qualitatively not different.

Figure 1: Innovation and competition, semiparametric estimation (median splines)



Similar to Aghion et al. (2005), we can conclude that the relationship between innovation and competition is not linear. However, once we can control for the type of innovation, it becomes evident that for some types of innovation, non-ICT-enabled ones, the function is concave and for others, ICT-enabled ones, it is convex. Because we do not control for other factors that might influence firms' innovative behavior, the above results are only approximations of the possible relationships between different types of innovation and competition. Thus, we now proceed to a more thorough analysis in which we estimate a number of models in which we control for other factors that might influence the innovative process. Furthermore, by including additional variables, we want to test the strength of the relations established above.

4.3 Bayesian estimations

Taking into account the results of the spline analysis (figure 1), we start the examination of the relationship between competition and various types of Innovation by estimating three models. First, we start with a basic model in which function $g(c_{ij})$ is linear. In order to focus only on the dependency between the two variables of interest, we do not include sector dummies. Thus, the first equation to be estimated can be expressed by

$$I_{kij} = \alpha + \beta_1 c_{ij} + \varepsilon_{ij} \tag{5}$$

where I_{kij} denotes innovation rate of innovation type, $k = 1,\ldots,4$, α is a constant, c_{ij} is our measure of competition and ε_{ij} represents an error term. In the second model, following the observation in the previous section (figure 1), we relax the assumption that there is a linear relationship between competition and innovative activity. Consequently, in the next analysis, we want to estimate a model in which $g(c_{ij})$ takes a quadratic form, i.e. $g(c_{ij}) = \beta_1 c_{ij} + \beta_2 c^2_{ij}$. Our last specification goes beyond examining the relationship between competition and innovation and includes sector effects as well.

All priors for the model parameters carry little Information, i.e. they are assumed to be normally distributed with $\mu = 0$ and $\tau = 0.001$. In other words, in order not to influence the results by assumptions on priors, we state that there is no relationship between the dependent and independent variables. The motivation behind using such a conservative approach are varying theoretical predictions with respect to the relationship between our two variables and the first results of the spline analysis. Such prior specification ensures that we eliminate the bias towards any of the hypotheses. The initial state of *no dependency* is further validated in the regression. Any deviation from the initial assumptions can be interpreted as evidence for the presence of some dependency between the variables of interest.

To estimate the three models, all computations were done by using MCMC Simulation method. The number of draws was set at 11,000 and the first 1,000 draws were discarded. One of the main advantages of the Bayesian estimation is that it provides Information about the posterior distributions of each model parameter, which contains more Information than a single metric reported by traditional techniques. These distributions can be of course presented in a graphical way, making the Interpretation of the results even more intuitive.

Figure 2: The effect of competition on innovation by innovation type: Basic specification, Bayesian estimation

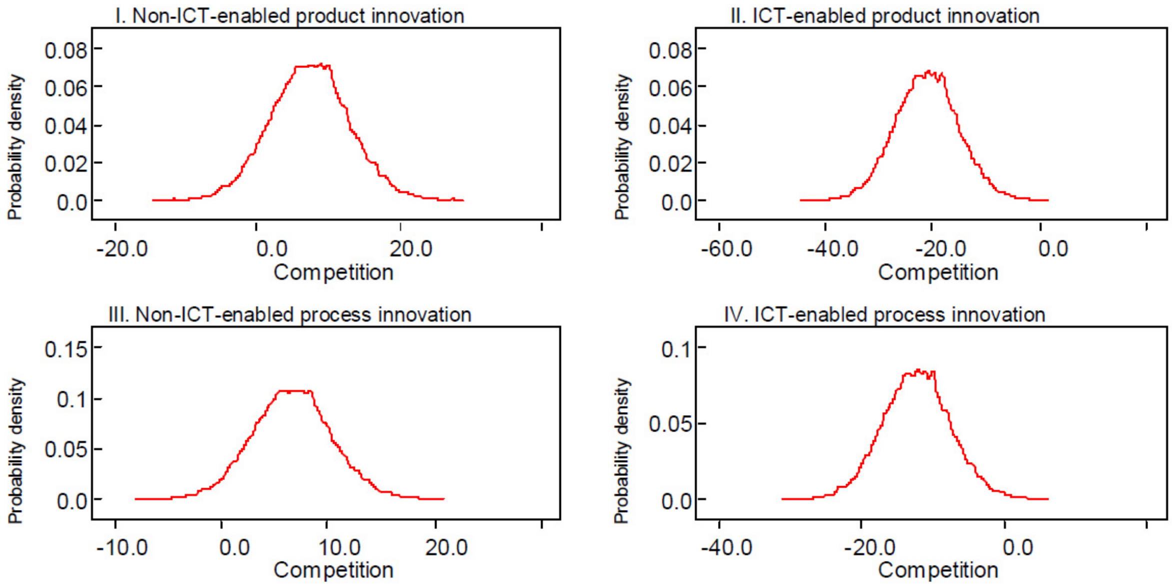
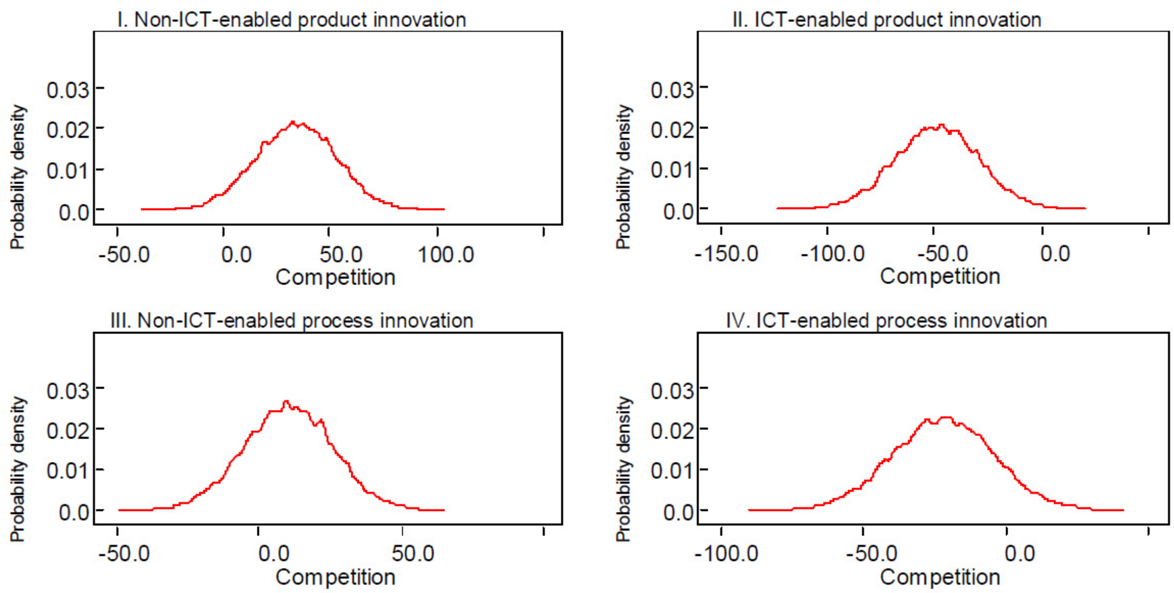


Figure 2 shows posterior distributions of competition variable estimated for the basic model for each type of innovation. Regarding non-ICT-enabled product innovations, over 90% of the surface of the distribution function lies to the right from zero. This represents the probability of a positive effect of competition on this particular type of innovations. The remaining part of the curve, to the left from zero, shows the probability of competition having a negative effect on non-ICT-enabled product innovations. In other words, there is over 90% probability that competition has a positive effect on non-ICT-enabled product innovations. A similar conclusion can be made with respect to non-ICT-enabled process innovations. Turning to ICT-enabled innovations, however, it can be seen that a reverse pattern can be observed. Both posterior distribution curves lie to the left from zero, which suggests that there is a negative relationship between competition and innovations derived from ICT. These results are consistent with the outcomes of the univariate analysis in previous section.

Along graphical presentation, the results of Bayesian estimation can be presented in a conventional way by using metrics as well. Table 3 presents the distributions of posteriors for each parameter across the three models. For each posterior distribution, five quantiles of the

probability density functions are reported, i.e. 5%, 25%, 50%, 75% and 95%. Regarding the basic estimation, it can be seen that the probability that competition positively influences the likelihood of introducing non-ICT-enabled product innovation case is over 0.9. In contrast, the opposite can be said about ICT-enabled product innovations. There, it can be seen that there it is certain that increasing competition has a negative implication for the intensity of ICT-enabled product innovations. Regarding process innovations, we can again see the same pattern as above. Whereas there is a large probability of a positive impact of competition on non-ICT-enabled innovations, the opposite effect can be observed for ICT-enabled ones.

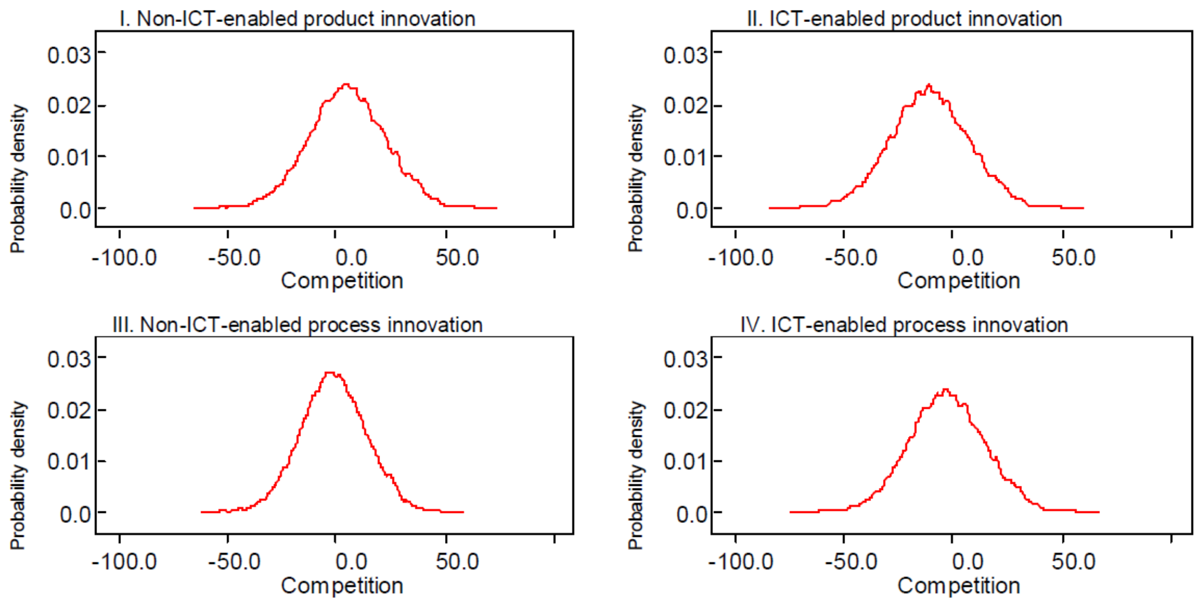
Figure 3: The effect of competition on innovation by innovation type: Qadratic specification, Bayesian estimation



Regarding the second specification, in which $g(c_{ij}) = \beta_1 c_{ij} + \beta_2 c^2_{ij}$, it can be seen that despite some changes in the coefficient values, there are no strong qualitative deviations from the previous observations (see figure 3 and table 3, second column). In particular, the results for both types of product innovations remain unchanged and we can still observe a clear negative (positive) impact of competition on (non)-ICT-enabled innovations. There is, however, a small difference in the way the competition coefficient reacts to the inclusion of the quadratic term. Whereas, the duality of the impact of competition on product innovations becomes even more

polarized, its effect on process innovations becomes less heterogenous than before. Regarding the coefficient values of the quadratic term, consistently with the previous observation reported in figure 1, we can observe that the rate of non-ICT-enabled innovations increases at a decreasing rate and that the reverse holds for ICT-enabled innovations.

Figure 4: The effect of competition on innovation by innovation type: Qadratic specification with industry effects, Bayesian estimation



Turning to the results of the last specification, the posterior distribution curves are shown in figure 4 and the values of the median and individual quantiles in the last column of table 3. It can be seen that the impact of competition on any type of innovative activity becomes considerably weaker once we include industry effects. In particular, in contrast to product innovations, the discrepancy in the impact of competition on different types of process innovations diminishes. The shape of the density curves of the competition variable suggests that the areas indicating positive and negative relationship are roughly equal. In other words, the probability of a positive vs. negative effect of competition on both types of process innovations is equal. It has to be noted that this is different from saying, as in a classical approach, that there is no effect at all. Thus, at this example it becomes straightforward that the Bayesian methodology delivers a considerable larger amount of information than single metrics reported in classical inference.

Although smaller, the drop in the competition coefficient value in both product innovations specifications does not allow us to make any clear conclusion on the effect of competition on product innovation. The different signs of competition coefficients still remain, but the strength of this relationship becomes much weaker. With respect to the quadratic term of competition variable, it can be said that the inverted U shape established in the first regression remains visible for non-ICT-enabled innovations. For the other type of innovation, the inclusion of additional control variables centers the posterior distribution function around zero.

Table 3: Competition and innovation; Bayesian estimations

	Non-ICT-enabled product innovations														
	Basic estimation					Quadratic estimation					Quadratic estimation with industry effects				
Quantiles	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%
Constant	11.91	15.14	17.27	19.44	22.54	1.75	6.95	10.66	14.48	19.77	9.761	14.66	18.16	21.55	26.48
Competition	-1.47	3.78	7.48	11.07	16.65	3 .00	21.36	34.24	46.96	64.34	-23.08	-6.458	4.91	16.53	34.01
Competition^2						-51.65	-36.03	-24.82	-13.61	3.12	-33.71	-18.21	-7.37	3.09	18.38
Industry effects													Yes		
	Non-ICT-enabled process innovations														
Quantiles	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%
Constant	6.24	8.39	9.80	11.24	13.30 0.71	1.73	5.89	8.85	11.88	16.10 -	5.95	10.16	13.13	15.99	20.15
Competition	4.19	6.65	9.03	12.74		15.33	-0.04	10.43	20.98	35.29 -	-25.69	-11.28	-1.44	8.76	24.04
Competition^2						25.38	-12.61	-3.51	5.75	19.38	-23.77	-10.25	-0.88	8.25	21.44
Industry effects													Yes		
	ICT-enabled product innovations														
Quantiles	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%
Constant	28.82	32.28	34.56	36.90	40.22	32.04	37.61	41.46	45.43	50.84 -	18.55	23.59	27.22	30.70	35.82
Competition	-30.55	-24.97	-20.98	-17.14	-11.18	81.00	-61.81	-48.63	-35.69	-17.09 -	-39.60	-22.52	-10.82	1.28	19.31
Competition^2						2.04	14.13	25.74	37.40	54.41	-26.95	-10.97	0.22	10.94	26.65
Industry effects													Yes		
	ICT-enabled process innovations														
Quantiles	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%	5%	25%	50%	75%	95%
Constant	26.46	29.22	31.04	32.91	35.57	25.23	30.10	33.52	37.02	41.89	13.76	18.71	22.24	25.65	30.62
Competition	-19.85	-15.37	-12.17	-9.11	-4.32	-51.20	-33.90	-21.88	-9.92	6.60	-31.05	-14.32	-2.85	8.94	26.63
Competition^2						-16.26	-1.66	8.87	19.55	34.90	-22.96	-7.36	3.55	14.08	29.46
Industry effects													Yes		

N=260
All estimations done by using MCMC method. Number of draws was set at 11,000; the first 1,000 draws were discarded.
All priors were assumed to follow normal distribution with μ=0 and τ=0.001.

To some extent, the above results are consistent with the findings of previous studies (e.g. Scherer (1965), Cohen and Levin (1989), Geroski (1994)). Although at a first glance one is able to establish some relationship between competition and innovative activity, once controlled for other elements of technology or industry environment, the initial findings become considerably weaker. An important insight of this study is, however, the finding that, if any, there is no homogenous relationship between competition and in particular product innovations derived from different technologies. Here, this contrast was demonstrated for ICT- and non-ICT-enabled innovations.

5 Conclusions

Concluding, a detailed analysis that takes into account the heterogeneity of innovation activity reveals that there is no simple answer to the question of what is the optimal market structure or competition level for innovation. The results indicate that the statement that there is an inverted U-shape relationship between innovation and competition is only partially true. Such a relation holds only for some types of innovation, e.g. non-ICT-based innovations. For other types of innovations, for example ICT-based innovations, a negative impact of increasing competition on innovative activity can be observed. Consequently, in light of the results of the previous studies, these outcomes cast completely new light on the relationship between innovation and competition. However, similar to some previous studies, our results lead to the conclusion that it is not the competition level that primarily affects innovation activity. As indicated before (e.g. Kamien and Schwartz (1982); Cohen and Levin (1989)), these are other technology- and industry-related elements that influence firms' incentives to innovate.

6 Annex: Data and variables

6.1 e-Business Watch surveys

e-Business Watch is an observatory initiative launched by the European Commission in late 2001. The e-Business Watch monitors the adoption, development and impact of electronic business practices in different sectors of the European economy. The purpose of the project is to provide reliable and methodically consistent empirical information about the extent, scope, and factors affecting the speed of e-business development at the sector level in an internationally comparative framework, information which have previously not been available from official statistics.

Until the end of 2007, the e-Business Watch initiative had conducted five large scale enterprise survey rounds. Each survey had a different coverage of industrial sectors and countries. The surveys are based on independently drawn random samples from pre-specified country-sector combinations, stratified by three enterprise size classes (<49 employees, 50-250 employees, >250 employees) to enable a representative representation of the respective country-sector findings. A consistent survey method was used, interviewing decision makers in companies (e.g. IT managers, managing directors or the owner) by computer-aided telephone interviews (CATI). Each interview collected basic information about the company, including confirmation of sector membership, number of employees, number of establishments, and basic financial information such as turnover development. The majority of questions related to the availability and usage of various ICT and e-business technologies.

During the course of the project, changes have also been made to the questionnaire that was used for the surveys.[9] These changes partially reflected prior experience with survey results, identification of additional aspects that deserved more attention, but also changes in the technological environment due to newly emerging trends that needed to be reflected in the questionnaire. The implemented changes led to inconsistencies between the surveys, which makes them difficult to compare. Only some questions remained unchanged over the entire project life cycle. Thus, in this study we use data from three surveys, i.e. the Nov/Dec 2003, 2005 and 2006 surveys.

[9] The questionnaires and methodological reports of all surveys can be downloaded from the e-Business W@tch website (www.ebusiness-watch.org/about/methodology.htm).

Table 1A: Country-sector coverage e-Business W@tch survey Nov/Dec 2003

	Textile industries	Chemical industries	Electronics	Transport equipment	Crafts & Trade	Retail	Tourism	ICT services	Health & social services	Business services
Belgium		100				100				100
Den mark						66	67		67	
Germany	100	100	100	100	100	100	100	100	100	100
Greece	75		75	75	75		75			
Spain	100	100	100	100	100	100	100	100	100	100
France	100	100	100	100	100	100	100	100	100	100
Ireland		70					70	70		
Italy	100	100	100	100	100	100	100	100	100	100
Netherlands	100							100	100	
Austria				100			100		100	
Portugal				100		100				100
Finland	75		75					75		
Sweden		75	75	75						75
United Kinqdom	100	100	100	100	100	100	100	100	100	100
Cyprus						50				
Czech Republic		50		50			75	75	50	
Estonia	50	50	50	50	50	50	50	50	50	50
Hunqary				80	80					80
Lithuania						50				
Latvia	50	50				50				
Malta							50			
Poland	80	80	80	80	80	80	80	80	80	80
Slovenia			50				50	50	50	50
Slovakia	50		50			50				50
Norway	50					50				

The Nov/Dec 2003 survey covered ten sectors in 25 European countries. In sum, the data set contains 7,302 valid observations. Regarding the geographical scope of the survey, 4,670 were conducted in the old EU and Norway and the remaining 2,632 in the Acceding Countries. Within each sector, sampling was adjusted according to the relative size of sub-sectors measured by value-added. Thus, sub-sectors with a relatively larger share of contribution to national GDP were included with a proportionately larger number of interviews, allowing to get an approximately representative picture at the country-sector level. Table 1A shows the number of successfully completed interviews in each country-sector cell for the e-Business Watch survey which was carried out in Nov/Dec 2003. All 10 sectors were covered only in the five largest European countries (France, Germany, Italy, Spain and the UK) and two accessing countries (Estonia and Poland). Consequently, only these seven countries which exhibit a complete and homogeneous sector coverage that enables cross-country and cross-sector comparisons.

Table 2A: Country-sector coverage e-Business W@tch survey 2005

	Food and beverages	Textile industries	Publishing and printing	Manufacture of pharmaceuticals	Manufacture of machinery and equipment	Automotive industry	Aerospace industry	Construction	Tourism	IT services
France	80	80	80	76	77	80	39	80	80	78
Germany	80	76	80	83	80	80	38	81	80	80
Italy	86	81	79	81	84	81	23	80	82	82
Spain	82	81	82	81	81	81	15	83	82	82
UK	75	75	75	75	75	75	25	75	76	75
Czech Republic	85	85	84	54	85	85	20	84	84	84
Poland	83	83	83	82	83	83	3	83	83	84
TOTAL	571	561	563	532	565	565	163	566	567	565

The e-Business Survey 2005, which was the third survey after those of 2002 and 2003, had a scope of 5,218 telephone interviews with decision-makers in enterprises from seven EU countries. In contrast to the surveys of 2002 and 2003, the survey of 2005 considered only companies that used computers. Thus, the highest level of the population ("base") was the set of all computer-using enterprises which were active within the national territory of one of the respective countries, and which had their primary business activity in one of the sectors specified by NACE Rev. 1.1 categories. The sample drawn was a random sample of companies from the respective sector population in each of the seven countries, with the objective of fulfilling strata with respect to company size class and no cut-off was made in terms of minimum size of firms. Strata were to include a share of at least 10% of large companies (250+ employees) per country-sector cell, 30% of medium sized enterprises (50-249 employees), 25% of small enterprises (10-49 employees) and up to 35% of micro enterprises with less than 10 employees. Table 2A shows the number of successfully completed interviews in each country-sector cell for the survey which was carried out in 2005. Within this survey, all 10 sectors were covered in each country, which gives a complete and homogeneous sector-country coverage.

Table 3A: Country-sector coverage e-Business W@tch survey 2006

	Food and beverages	Footwear	Pulp and Paper	ICT Manufacturing	Consumer electronics	Shipbuilding and repair	Construction	Tourism	Telecom-munications	Hospital activities
France	78	26	132	190	20	8	75	70	72	80
Germany	53	68	163	169	66	15	51	54	60	101
Italy	50	200	85	182	30	21	50	48	50	40
Poland	50	135	75	76	141	3	50	50	75	97
Spain	49	181	117	132	17	23	49	46	103	37
UK	59	20	140	167	59	8	59	57	147	34
Austria	116		20	24			119	121		
Belgium	112			38	9	1	100		118	22
Bulgaria	115	20		25			120	120		
Cyprus	50						79	80		
Czech Republic	74	70	105	99	130	2	75	75	70	50
Den mark	100		30			2	101	110	60	
Estonia				24			120	132	38	
Finland	149	18	66	104	9	4	141	134	95	32
Greece	102	32				1	120	119	17	16
Hungary	153	40	50	95	19	2	152	141	60	60
Ireland	54			36	1		119	178	12	
Latvia				54			130	132	61	55
Lithuania			38	50	15		122		121	58
Luxembourg							62	55		
Malta							33	68		
Netherlands	60	11	31	63	16	12	52	50	97	8
Norway				11		35	184	140	22	9
Portugal	138	50	20			2		140		50
Romania	106		20			4	121	102	87	
Slovakia		32			46		127	150	45	
Slovenia	33		11	21			168	167		
Sweden			55	77	37			126	95	10
Turkey		75		50	50		75		75	75
Total	1701	978	1158	1687	665	143	2654	2665	1580	834

The e-Business Watch survey 2006 was the fourth survey after those of 2002, 2003 and 2005 and had a scope of 14,081 interviews with decision-makers in enterprises from 29 countries, including the 25 EU Member States, EEA and Candidate Countries. The design of the questionnaire builds on the ones used in the previous surveys from 2002 to 2005. As in 2005, the survey considered only companies that used computers. Thus, the highest level of the population was the set of all computer-using enterprises which were active within the national territory of one of the 29 countries covered, and which had their primary business activity in one of the 10 sectors specified on the basis of NACE Rev. 1.1.

No cut-off was made in terms of minimum size of firms. The sample drawn was a random sample of companies from the respective sector population in each of the seven countries, with the objective of fulfilling minimum strata with respect to company size class per country-sector cell. Strata were to include a 10% share of large companies (250+ employees), 30% of medium sized enterprises (50-249 employees), 25% of small enterprises (10-49 employees) and up to 35% of micro enterprises with less than 10 employees. Samples were drawn based on widely recognized business directories and databases. In most countries, between 400 and 750 interviews were conducted. Table 3A shows the number of successfully completed interviews in each country-sector cell for the e-Business Watch survey which was carried out in 2006.

6.2 Variables description and descriptive statistics

Table 4A: Variable definitions

Variable	Definition
Competition	The difference between 1 and industry-level gross margins, i.e. the difference between value added and labour cost as a Proportion of value added.
Non-ICT-enabled product innovation	If a Company introduced new or substantially improved products or Services to its customers during the past 12 months, the following question was asked: "Has any of your product / Service innovations over the past 12 months been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)". All negative answers were aggregated to form an average value for each market.
ICT-enabled product innovation	If a Company introduced new or substantially improved products or Services to its customers during the past 12 months, the following question was asked: "Has any of your product / Service innovations over the past 12 months been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)". All positive answers were aggregated to form an average value for each market.
Non-ICT-enabled process innovation	If a Company introduced new Company internal processes during the past 12 months, the following question was asked: "Has any of your product / Service innovations over the past 12 months been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)". All positive answers were aggregated to form an average value for each market.
ICT-enabled process innovation	If a Company introduced new or substantially improved products or Services to its customers during the past 12 months, the following question was asked:"- Has any of your Company internal process innovations been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)". All positive answers were aggregated to form an average value for each market.
Source: e-Business Watch surveys are source of all variables, except Competition variable, whose source is EU KLEMS.	

Table 5A: Descriptive statistics

Variable	N	Mean	Median	S.D.	Min	Max
Non-ICT-enabled product innovation	260	21.58	18.70	13.28	0.00	70.00
ICT-enabled product innovation	260	22.69	18.79	14.62	0.00	85.00
Non-ICT-enabled process innovation	260	13.61	12.37	8.75	0.00	49.00
ICT-enabled process innovation	260	24.17	23.80	11.46	0.00	75.00
Competition	260	0.57	0.58	0.15	0.11	0.97

Table 6A: Correlation matrix

	Variable	1	2	3	4	5
1	Non-ICT-enabled product innovation	1				
2	ICT-enabled product innovation	-0.38*	1			
3	Non-ICT-enabled process innovation	0.54*	-0.09	1		
4	ICT-enabled process innovation	-0.05	0.49*	-0.18*	1	
5	Competition	0.08	-0.23*	0.11	-0.17*	1
* signifficant at .01 level						

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