Entry and patenting in the pharmaceutical industry[*]: Very Preliminary and Incomplete

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Abstract

We study the impact of incumbents' and own patents on entry in pharmaceutical submarkets in the USA for the period 1988-1998. We relate the variation in the effect of patents on entry to some observable market and firm characteristics and find that own patents never encourage entry. By contrast, patent holdings by incumbents have contrasting effects: on the one hand they act as a barrier to entry, on the other hand they promote entry through the opening of new technologicalopportunities. The two separate effects are identified through a Bayesian approach.

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1. Introduction

Own patents are usually viewed as a stimulus to entry with new products, while patents held by incumbent firms can have an ambiguous effect, and indeed evidence on the role of patents in shaping incumbent/entrant competition is mixed. On the one hand, they can be a be a significant barrier to entry into markets. The patent holder has the exclusive right to make, use or sell the claimed invention, and the costs for entrants to invent around, license, or fight legal disputes relating to a patent can be substantial, thus they may discourage entry. On the other hand, patent holdings in the market can also prove to be a source of useful knowledge, which reduces R&D costs and hence encourages entry.

In this paper we examine the effect of the entrant's and incumbents' patent holdings in a set of narrowly defined pharmaceutical markets on entry into those markets. Our results interestingly show that own patents never improve the chances of entry. By contrast, incumbents' patents may have twofold and contrasting effects. On the one hand, the initial stock of patents held by incumbents has a positive effect on entry, thus suggesting that through patents new knowledge flows to competitors and opens for them new technological opportunities. On the other hand, the most recent patent holdings by incumbents act as a barrier to entry: recent successes by incumbents in the exploitation of existing technological opportunities frustrate entrant's efforts and thus discourage entry. These contrasting effects are separately identified in our empirical analysis.

This paper can give contribution to the recent and intersting debate on the role of patents in spurring innovation and competition. In the recent years there has been an escalation in the number of patents in many industries and an enforcement of their legal protection; on the other side the huge increase of patents don't face an equal increase in the level of R&D expenditures and technological progress (Boldrin and Levine 2013).

From a theoretical and an empirical point of view there is not conclusive evidence in the literature on the role of patents in spurring innovation while there is an inverse relationship between the number of patents and the level of competition of an industry, so usually when the industry reaches a level of maturity there is less competition and more concentration and the number of patents drastically increases (Boldrin and Levine, 2013). In this paper we deal with a reverse question: can the amount of own patents and other companies patents increase the probability to launch a new product? So does the amount of patents increase competition? Precisely can a large amount of patents increase the probability of entry? We address this question in the pharmaceutical sector, which relies heavily on the patent system.

We adopt a bayesian approach, which is particularly suited to the present context for different reasons. First, we do not need to rely on asymptotic results: we obtain a finite sample posterior distribution of the features of interest in the model (parameters, elasticities, etc.). Second, with our specification, we account for heterogeneity in a random coefficient framework. Third, in a simulation-based Probit approach the latent variable is simulated. Conditional on the simulated values of the latent variable, the model becomes linear and therefore much easier to deal with. This is the benefit of using a Gibbs sampling-data augmentation approach (for details see Chib, 2001). Also, average partial effects can be calculated very easily by simulation. Moreover, the model can be easily generalized in different ways to accommodate general assumptions concerning the distribution of error terms. Finally, the bayesian approach, from a computational point of view, allows us to deal with different kinds of regressors which range from strictly exogenous to merely predetermined or endogenous.

2. Literature review

The Pharmaceutical industry is often regarded as the best case for patent protection because the extremely high fixed costs of innovation would discourage the introduction and development of new drugs in the absence of adequate economic incentives. Patents provide such incentives, by granting the exclusive right to produce and commercialize the new drug to the innovating firm. As such the patent system is designed to encourage the introduction of new products into the market (de Figueredo and Kyle, 2006) and patents themselves can be taken as indicators of entrants' technological capabilities, knowledge assets, or innovation success (Cockburn, Henderson, and Stern, 2004). Patent holdings by the potential entrant should therefore positively correlate with the probability of entry.

The traditional view of patents as a stimulus to innovation has been somewhat changing in recent years because of concerns over the extent to which the increasing strategic use of patents may actually reduce innovation efforts and outcomes (Boldrin and Levine,2013; Jaffe and Lerner, 2004). Indeed, there exists some evidence that innovators consider patents as a poor mean for protecting innovation (Cohen et al, 2000) and that firms may rather use patents as a strategic device in order to keep or establish their technological position in a given domain and to block rivals from patenting related inventions (Hall and Ham-Ziedonis, 2001). Patents could therefore act as a barrier that restricts or prevents entry by rival products into the market. This may be of particular concern in the pharmaceutical industry, where innovation may have significant effects on the health of individuals. Cockburn and MacGarvie (2011) do find evidence of a detrimental effect of patent holdings on entry in the software industry. Controlling for demand, market structure, average patent quality, and other factors, they find that a 10% increase in the number of patents relevant to market reduces the rate of entry by 3 to 8 percent and that this relationship intensified following expansions in the patentability of software in the mid-1990s.

A negative effect of incumbents' patents on the chance of entry also arises in a world in which firms engage in a "patent race" with each other to reach a particular goal (a new chemical composition or formulation, a new manufacturing process or a new use of a chemical entity). All other things equal, rivals' success imposes an "exhaustion externality" on competitors, and own research productivity will be negatively correlated with competitors' efforts (Reinganum, 1989), thus reducing the chances of introducing new products into the market.

Patents held by inclumbents can however exert also a positive externality on the innovation by rivals. Indeed, a firm may benefit from competitors' research since, all other things equal, extensive spillovers of knowledge between firms can increase the productivity of its research. Patents may improve such spillovers as they allow increased disclosure of the knowledge included in the patent documents, which may turn out to be useful for further discoveries and lead to greater firm and industry wide R&D productivity (Caballero and Jaffe, 1993). The impact of competing firms' efforts on own research productivity is therefore ambiguous. Our aim will be to separately identify the two opposite effects.

3. The dataset

The primary source of data for our analysis is the IMShealth dataset, from which we obtained data on annual sales for all the international companies active in the cardiovascular pharmaceutical submarket in the United States from 1988 to 1998. Sales are available for each company and each submarket up to a 4-digit classification. Real values are obtained using the US GDP deflator[1]. Amisano

[1] Data is collected by IMS Health and was obtained by one of us during a research period at the University of Siena, while working on the EPRIS Project

and Giorgetti (2011) have used the same data to analyze entry at the 1-digit ATC level, which is however too broad to identify independent submarkets and the actual effects of competition. We therefore here analyze entry in 3-digit ATC submarkets and focus our attention on the products belonging to the cardiovascular pharmaceutical submarket.

We also employ patent data from the KITeS-Cespri Patent Database [2] that contains information on all patents applied for at the European Patent Office (EPO) and at the US Patent and Trademarks Office (USPTO). The database includes all the relevant informations available in the patent documents: applicant, inventor, patent class and all citations. We use patents to build the stock of knowledge of each firm in a specific submarket, to proxy for the level of sunk costs. However, while patents can be easily assigned to firms, there is no straightforward correspondence between the IPC patent classification and the ATC classification (available for product sales), i.e. there's no correspondence that allows us to associate each firm's patent to a specific 3-digit ATC class. In order to do that we use information from the following databases: Pharmaceutical Substance (Georg Thieme Verlag), IMS Life Cycle Patent Focus (IMS Health), Adis R& D Insight (Wolter Kluwer Pharma Solutions). These include data on pharmaceutical products, their ATC classification and related patents. For each 3-digit ATC submarket in our sample we obtained all the patents with priority date (i.e. date of first fling) between 1972 and 1998 associated to the products classified in that submarket[3]. We then use patent numbers to associate each patent to the applicant and ultimately to build the stock of knowledge for each of our firms in the relevant submarkets.

Before proceding further, it is worth discussing why we decided to focus our analysis on the cardiovascular pharmaceutical market. A recent and interesting paper by Acemouglu and Linn (2004) analyzed the effect of market size on entry of new drugs and pharmaceutical innovation. Focusing on exogenous changes driven by U.S. demographic trends, they found that a 1 percent increase in the potential market size for a drug category leads to a 4 to 6 percent increase in the number of new drugs in that category. Unfortunately a large part of population suffers from heart diseases, so the potential market for cardiovascular products is huge. It is very attractive for companies to invest in this type of products even if the rate of uncertainty in product development is substantial.

In the period covered by our data there are 45 international companies that

[2] For a detailed description see http://db.kites.unibocconi.it/

[3] This work was performed by N&G consulting.

operates in the US cardiovascular sector. For each year, the sales of each (international) company in each 3-digit ATC cardiovascular submarket are obtained by summing the sales of all companies controlled by it.

The following ones are the ATC3 level submarkets we analyse:

(a) C01C - Cardiac stimulants excl. cardiac glycosides

(b) C02A - Antiadrenergic agents, centrally acting

(c) C03A - Low-ceiling diuretics, thiazides

(d) C04A - Peripheral vasodilators

(e) C05A - Agents for treatment of hemorroids and anal fissures for topical use

(f) C10A - Lipid modifying agents, plain

4. Model and variables

We identify entry by firm i into submarket j in year t with the introduction of a new product by firm i in that submarket, i.e. in a given year t, we observe positive sales for a specific product of firm i in submarket j. When this happens $y_{it}^{(j)} = 1$. Note that this notion of entry covers both entry by greenfield (GF entry), i.e. when the company was not previously present in that submarket, and the choice to expand the range of products being offered.

Entry occurs when net profitability of entry, $\pi_{it}^{*(j)}$, is positive. This is our latent variable and is defined as

$$\pi_{it}^{*(j)} = f\left(\mathbf{X}_{it}^{(j)}\right) + \eta_{it} \tag{4.1}$$

which is assumed to be a function of a set of predetermined variables $\mathbf{X}_{it}^{(j)}$ and a random shock η_{it}.

Our variables, $\mathbf{X}_{it}^{(j)}$, comprise two groups of regressors: firm specific regressors and regressors reflecting prevailing conditions in the submarket:

$$\mathbf{X}_{it}^{(j)} = \begin{bmatrix} \mathbf{X}_{1,it}^{(j)} \\ \mathbf{X}_{2,t}^{(j)} \end{bmatrix} \tag{4.2}$$

According to our specification, $\mathbf{X}_{1,it}^{(j)}$ includes companies characteristics that influence its profitability, size, company's own patents, previous entry and exit choices (which determine the range of products currently offered by the company). $\mathbf{X}_{2,t}^{(j)}$ includes variables that are submarket specific: demand conditions, the degree of competition, the other companies'patents.

If errors η_{it} are assumed Gaussian and the relationship with $\mathbf{X}_{it}^{(j)}$,our observable variables, is linear we have a Probit specification for observed entry, $y_{it}^{(j)}$. For each submarket, we specify a bayesian panel probit model in which the choice of potentially relevant covariates, is inspired by the literature. We follow Bresnahan and Reiss (1993), Hendricks, Piccione and Tan (1997) and Netz and Taylor (2002) and include typical measures of entry-exit reduced form models. Our key interest relies in the effect of patents. Patents are mostly considered as a barrier to entry. There are, however, circumstances under which patents, as sunk costs, may act as an encouragement to entry, as discussed in Cabral and Ross (2008).

With this theoretical agenda in mind, we include the following list of regressors:

1. The dimension of the company in each specific submarket. In our dataset this variable is called `lsalATC3USA` and is obtained summing sales across products in each submarket.

2. Exit decisions of the company in the 3-digit ATC submarket analyzed: `lexit`. It is a dummy variable indicating a reduction in the number of drugs sold by the firm in that submarket with respect to the previous year.

3. Lagged entry decision of the company in the submarket analyzed. This is the lagged dependent variable (`lentry`)

4. A measure of company stock of patents held by a firm in the specific therapeutic area (`spatent)`. This is calculated as the stock of cumulated knowledge, which we obtain accumulating past patented ideas through the perpetual inventory method for each company in each 3-digit ATC submarket. Patents are a widely used measure of innovation output, particularly in the Pharmaceutical sector, where they represent a good mean for protecting innovation.

   The stock of patents is built using the perpetual inventory method as follows:

   $$S(t) = (1-\delta) * S(t-1) + P(t-1) \; and \; S(t=1) = P(t=1)/(g+\delta)$$

where $P(t-1)$ is patents at time $t-1$, g is the average growth rate in patenting (firm and submarket specific) and δ is the depreciation (assumed equal to 0.15, as commonly done in the relevant literature - see, for example, Bottazzi and Peri, 2007). We further present regressions where patents are weighted by family size (`sfam`). A patent family is a set of patent applications taken in multiple countries to protect a single invention by a common applicant and then patented in more than one country. A first application is made in one country – the priority – and is then extended to other offices. Firms will obviously try to protect an innovation in more countries the more relevant is the innovation is, therefore weighting by patent family size is a way to better account for their value.

5. A measure of the stock of patents of incumbent firms (`lotherpatents`), obtained by summing the patents stocks of all other firms in the market. Also in this case we use the stock of other firms' patents weighting by patent family size (`lotherfam`).
6. Submarket size - a proxy for demand - equal to the sales of all the companies in the specific ATC3 submarket (`lsott`).
7. The number of incumbents active in the submarket (`limp`), as a proxy for the intensity of competition *among firms*.
8. The degree of competition between products (`lprodcomp`): the number of competing products in the same ATC3.

All covariates are one-year lagged and can therefore be safely considered as predetermined.

5. Econometric specification

We use a bayesian panel probit and account for heterogeneity by allowing for unit-specific intercepts (random effects). We also allow unobservable heterogeneity to be potentially correlated with the regressors. More specifically, the probit model can be written as follows:

$$
\begin{aligned}
p(y_{it} &= 1|I_{t-1}, c_i, \boldsymbol{\theta}) = p_{it} = \Phi(c_i + \mathbf{x}_{it}^{'}\boldsymbol{\lambda}) \\
\Phi(x) &= \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp(-z^2/2) dz \\
i &= 1, 2, .., n \text{ (units)}, \ t = 1, 2, ..., T \text{ (time)}
\end{aligned} \tag{5.1}
$$

where the dependent variable, y_{it} is the dichotomous variable measuring entry in a given submarket , I_{t-1} is the information set that includes the past values of covariates. The vector $\boldsymbol{\theta}$ is the vector of free parameters in the model.

In its simplest specification the random effects (c_i) are assumed to be independent of regressors, with the following assumption:

$$
c_i \backsim N(0, (h)^{-1}) \tag{5.2}
$$

Notice that when $h \to \infty$ we have perfect pooling (no heterogeneity), whereas when $h \to 0$ we allow for maximum heterogeneity. In this case we basically have no assumption on the unit specific intercepts and therefore this is tantamount to using a fixed effects model.

It should also be noted that, given that the covariates include an intercept term, identification requires that the mean of c_i be equal to zero.

In the simplest specification, initial conditions (i.e. observations at time $t = 0$) are treated as fixed and random effects are assumed independent from regressors. This last assumption is clearly unreasonable; hence we assume that random effects are dependent on covariates and on the initial condition as proposed by Wooldridge (2005) and model unobservable heterogeneity specifying a distribution for unit-specific intercepts conditional on the initial values and on the values of the covariates:

$$
p(c_i|y_{i0}, \mathbf{X}_i, \boldsymbol{\theta}) \tag{5.3}
$$

Covariates can be divided into 3 groups: $\mathbf{X}_i^{(1)}$ includes strictly exogenous regressors, $\mathbf{X}_i^{(2)}$ includes regressors that are not strictly exogenous (among these, the lagged dependent variable) and, finally, $\mathbf{X}^{(3)}$ includes regressors which do no vary across units, such as the intercept term and time dummies.

The distribution of the random effects c_i is conditioned on all sample values of the regressors in $\mathbf{X}_i^{(1)}$ and only on the initial (pre-sample, at $t = 0$) value of the $\mathbf{X}_i^{(2)}$

$$p(c_i|\mathbf{X}_i^{(1)}, \mathbf{x}_{i0}^{(2)}, \boldsymbol{\theta}), i = 1, 2, ..., n \tag{5.4}$$

where $\mathbf{X}_i^{(1)}$ is a $(T \cdot k \times 1)$ vector with all the sample values of all exogenous variables for unit i, i.e. all regressors for each year and $\mathbf{x}_{i0}^{(2)}$ is a $(k \times 1)$ vector with the initial (i.e. pre-sample) observations for the predetermined variables.

In particular, as in Wooldridge (2005), we assume a Gaussian distribution and a linear specification for the conditional mean. Thus, since in our application we have no strictly exogenous variables, we have the following specification for random effects

$$\begin{aligned} c_i &= \boldsymbol{\gamma}_2^{'} \mathbf{x}_{i0}^{(2)} + \alpha_i && (5.5) \\ \alpha_i &\backsim N(0, h_\alpha^{-1}) && (5.6) \end{aligned}$$

which implies

$$\begin{aligned} P(y_{it} &= 1|I_{t-1}, \boldsymbol{\theta}, \alpha_i) = \Phi(\alpha_i + \boldsymbol{\beta}^{'} \mathbf{z}_{it}) = p_{it} && (5.7) \\ \Phi(\alpha_i + \boldsymbol{\beta}^{'} \mathbf{z}_{it}) &= \int_{-\infty}^{\alpha_i + \boldsymbol{\beta}^{'} \mathbf{z}_{it}} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{\omega^2}{2}\right\} d\omega && (5.8) \\ \boldsymbol{\beta} &= \left[\boldsymbol{\lambda}^{'}, \boldsymbol{\gamma}_2^{'}\right]^{'}, \mathbf{z}_{it} = [\mathbf{x}_{it}^{'}, \mathbf{x}_{i0}^{(2)'}]^{'} && (5.9) \end{aligned}$$

Hence the joint density of the sample, conditional on covariates, coefficients and random effects is

$$p(\mathbf{y}_1, .., \mathbf{y}_n |\mathbf{Z}_1, .., \mathbf{Z}_n, \alpha_1, ..., \alpha_n, \boldsymbol{\theta}) = \prod_{i=1}^{n} \prod_{t=1}^{T} p_{it} \tag{5.10}$$

Therefore we have a panel probit model structure with a properly augmented set of regressors. A clear advantage of using this approach to model unit heterogeneity is that, unlike in non-parametric approaches, the average partial effects can be easily calculated. Its disadvantage is that it is based on very restrictive hypotheses: the Gaussianity of the conditional distribution of c_i and the linear dependency of its expected value on the values of regressors but these assumptions can nevertheless be weakened.

6. Results

As already mentioned, the debate on the role of patents has not yet reached a clear agreement on their effect on entry and competition. In the following tables we present the estimation results, using simple patent counts as well as patents weighted by their family size, to account for their quality.

In all our regressions own patents never improve the chances of entry. This is the case for both recent and the initial patent holdings. Interestingly, we instead find significant effects on entry for patents holdings by incumbents in submarket C1C, C3A with both simple patent counts and patents weighted by family size, and in submarket C4A when we use simple patent counts. On the one hand, when significant, the initial stock of patents held by incumbents has a positive effect on entry. This suggests that patents promote knowledge flows to potential competitors and the opening of new technological opportunities, which promote industry dynamics, a sort of spillover effect. On the other hand, the most recent patent holdings by incumbents have a negative effect on entry and hence act as a barrier to entry (this also happens in sector C5A). This could emphasize the property rights effect of patents: recent successes by incumbents in the exploitation of existing technological opportunities frustrate entrant's efforts and thus discourage entry. These results give an important contribution to the debate on the role of patents in shaping competition, precisely entry conditions.

We also find that in some submarkets the number of competing products has a negative and significant effect (see submarket C5A, C2A, C3A, C1C -families and submarket C1C, C3A,C5A-patents). This result is in line with the literature: the number of competing products in narrowly defined submarkets reduces the probability that new products will be introduced. Finally, submarket size is positive and significant in submarket C3A (both for family weighted and simple patents measures) as foreseen by the literature.

Table 1: patents weighted by families

C1C

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	0,020754251	0,916037	0,007812	0,001868	1	0,000286
lsfam	-0,341108746	0,97503	0,028689	0,02127	0	0,000974
lsott	0,160362859	0,876914	-0,00132	0,000397	1	-4,6E-05
lprodcomp	-0,092124213	1,009355	-0,4681	0,144951	1	-0,01685
lentry2	-0,060559976	1,098248	-0,74723	0,473911	0	-0,03024
lexit2	0,135019122	0,96155	0,963095	0,49822	1	0,038143
lotherfam	0,118447826	1,039646	-0,04775	0,012169	1	-0,00168
intercept	0,009487418	0,988064	0,042235	0,96042	0	0,003795
initial_lsalATC3USA	0,111741633	1,019359	-0,00869	0,004799	1	-0,00032
initial_lsfam	-0,009978872	0,97386	0,046495	0,04279	0	0,001631
initial_lentry2	0,003740273	1,096724	0,163912	0,817901	0	0,00234
initial_lexit2	-0,056191118	1,041014	0,257099	0,9488	0	0,012377
initial_lotherfam	0,009114523	1,035067	0,140596	0,036357	1	0,004946
precision \alpha	0,477169011	0,624278	1,222254	0,941431	1	0
confidence level		0,95				
correlation btw p^ and y		0,63783				
proportion correct forecasts		0,716667				

C2A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	-0,076611073	1,082874	-0,00203	0,000759	1	-0,00022
lsfam	0,070751684	0,977159	0,014314	0,014333	0	0,001725
lsott	-0,040166838	1,045423	-0,00019	5,14E-05	1	-2,1E-05
lprodcomp	-0,15137758	0,982186	-0,16051	0,05241	1	-0,01801
lentry2	-0,03191339	1,144849	-0,3215	0,386715	0	-0,03481
lexit2	-0,133496089	0,895929	0,200689	0,392281	0	0,021322
lotherfam	0,129970884	1,051737	0,009767	0,003276	1	0,001078
intercept	-0,013257865	1,097857	0,020849	1,04536	0	0,000849
initial_lsalATC3USA	-0,019626019	1,090044	0,00064	0,001256	0	7,52E-05
initial_lsfam	-0,12775196	1,132511	0,019492	0,017066	0	0,00206
initial_lentry2	0,14313599	0,938342	0,005052	0,533251	0	0,002921
initial_lexit2	0,058072616	1,003106	0,157954	0,856869	0	0,018821
initial_lotherfam	-0,215107342	0,928478	0,017421	0,007708	1	0,001963
precision \alpha	0,366931944	0,607027	0,868309	0,467443	1	0
confidence level		0,95				
correlation btw p^ and y		0,429864				
proportion correct forecasts		0,595455				

C3A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	-0,043360154	1,020834	-0,00036	0,001018	0	-4,6E-05
lsfam	0,070269984	0,935827	-0,0224	0,011997	0	-0,00248
lsott	-0,019996935	0,991659	0,000157	4,87E-05	1	1,76E-05
lprodcomp	-0,22178402	1,03414	-0,11004	0,045463	1	-0,01228
lentry2	0,189998259	0,933565	-0,3833	0,329968	0	-0,0434
lexit2	0,192146996	0,988566	0,212476	0,276361	0	0,024146
lotherfam	-0,049951966	0,988243	-0,01562	0,00565	1	-0,00175
intercept	-0,070247955	1,088423	-0,11644	1,012371	0	-0,01584
initial_lsalATC3USA	0,073523665	0,953869	-0,00064	0,001052	0	-6,4E-05
initial_lsfam	-0,063801424	1,026295	0,018454	0,044554	0	0,002082
initial_lentry2	0,038144044	1,03469	0,405588	0,445935	0	0,047264
initial_lexit2	0,017412779	1,013244	0,03518	0,587928	0	0,002003
initial_lotherfam	0,049526863	0,994223	0,038596	0,033123	0	0,004285
precision \alpha	0,46307459	0,622915	1,640727	0,775213	1	0
confidence level		0,95				
correlation btw p^ and y		0,443346				
proportion correct forecasts		0,648148				

C4A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	-0,04619872	0,982833	-0,00168	0,003101	0	-0,00011
lsfam	0,065894263	0,930004	0,002319	0,006414	0	0,000203
lsott	0,047731597	0,946446	-0,00092	0,000413	1	-7,5E-05
lprodcomp	-0,037467986	0,967868	-0,00471	0,039471	0	-0,0004
lentry2	0,069917968	1,046608	-1,45705	0,714433	1	-0,11449
lexit2	-0,020466012	0,981557	0,591264	0,452514	0	0,047022
lotherfam	0,066992161	1,00964	-0,00546	0,002477	1	-0,00044
intercept	0,160294516	0,957693	0,001503	0,92213	0	-0,001
initial_lsalATC3USA	-0,123252279	0,922687	0,000647	0,004157	0	2,31E-05
initial_lsfam	0,000533135	0,908033	0,006203	0,009599	0	0,000499
initial_lentry2	0,077997819	1,11636	0,031099	0,812423	0	0,006322
initial_lexit2	-0,022161881	0,976915	0,317834	0,598386	0	0,024345
initial_lotherfam	-0,020996876	0,956518	0,012602	0,005772	1	0,001021
precision \alpha	0,519216422	0,978723	1,545977	0,985583	1	0
confidence level		0,95				
correlation btw p^ and y		0,439994				
proportion correct forecasts		0,666667				

C5A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	-0,104839908	0,997172	-0,00886	0,003845	1	-0,00073
lsfam	0,022306822	1,164268	0,009904	0,014545	0	0,000932
lsott	-0,081736823	1,131937	0,000101	6,72E-05	0	8,27E-06
lprodcomp	-0,021671412	0,872293	-0,16916	0,073176	1	-0,01384
lentry2	-0,134233659	0,926274	-0,67708	0,662185	0	-0,05858
lexit2	0,114060815	0,839285	0,801414	0,414888	1	0,068242
lotherfam	-0,127846287	1,042437	-0,00753	0,004396	0	-0,00063
intercept	0,081172918	1,083511	0,127784	0,918788	0	0,0058
initial_lsalATC3USA	0,002433342	0,94502	0,011725	0,004948	1	0,000979
initial_lsfam	0,033471545	1,028805	-0,00231	0,042819	0	-0,0002
initial_lentry2	0,166101761	0,998742	0,087169	0,531198	0	0,007138
initial_lexit2	0,000987428	1,01949	0,018731	0,695762	0	0,003721
initial_lotherfam	-0,129244299	0,912741	0,01233	0,036256	0	0,001033
precision \alpha	0,474878095	0,519061	1,546859	0,763272	1	0
confidence level		0,95				
correlation btw p^ and y		0,38502				
proportion correct forecasts		0,621429				

Table 2: patents

C1C

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	0,02977	1,03842	0,00379	0,002101	0	0,000296
lspatent	-0,07157	0,94737	0,272059	0,357109	0	0,019893
lsott	-0,19474	0,878152	-0,00031	0,00021	0	-2,5E-05
lprodcomp	-0,01191	1,156765	-0,21995	0,104324	1	-0,01864
lentry2	-0,00045	0,986223	-0,38033	0,546631	0	-0,03332
lexit2	-0,15845	1,171273	1,05271	0,480719	1	0,086112
lotherpatents	0,039201	1,035856	-0,30659	0,105675	1	-0,02545
intercept	0,096807	0,931936	-0,00286	0,961551	0	-0,00333
initial_lsalATC3USA	-0,01646	1,008291	-0,00525	0,004262	0	-0,00039
initial_lspatent	0,138244	0,888306	0,456684	0,595515	0	0,041234
initial_lentry2	-0,00222	0,977933	0,243268	0,773626	0	0,022085
initial_lexit2	0,159929	1,091608	0,025397	0,939865	0	-0,00293
initial_lotherpatents	0,094104	0,947196	0,922426	0,499453	1	0,076051
precision \alpha	0,604376	1,193727	1,115776	1,128864	1	0
confidence level		0,95				
correlation btw p^ and y		0,510608				
proportion correct forecasts		0,675				

C02A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	0,02977	1,03842	-0,00053	0,000363	0	-5,64E-05
lspatent	-0,07157	0,94737	0,007437	0,243261	0	0,000801
lsott	-0,19474	0,878152	-0,0002	9,20E-05	0	-2,31E-05
lprodcomp	-0,01191	1,156765	-0,11255	0,058351	0	-0,01269
lentry2	-0,00045	0,986223	-0,08994	0,277072	0	-0,01104
lexit2	-0,15845	1,171273	-0,02959	0,397048	0	-0,00328
lotherpatents	0,039201	1,035856	0,147632	0,083749	0	0,016989
intercept	0,096807	0,931936	0,190231	1,04794	0	0,019417
initial_lsalATC3USA	-0,01646	1,008291	0,001502	0,001	0	0,000165
initial_lspatent	0,138244	0,888306	-0,35072	0,470434	0	-0,03797
initial_lentry2	-0,00222	0,977933	0,45969	0,451657	0	0,053626
initial_lexit2	0,159929	1,091608	-0,09227	0,733893	0	-0,01181
initial_lotherpatents	0,094104	0,947196	0,457279	0,282792	0	0,051367
precision \alpha	0,604376	1,193727	1,925164	0,934721	1	0
0,95						
0,390394702						
0,55						

C3A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	0,027283	1,033549	-6,3E-05	0,000711	0	-1,3E-05
lspatent	0,02344	0,996433	-0,62592	0,394099	0	-0,09397
lsott	0,062827	0,884822	8,88E-05	3,01E-05	1	1,32E-05
lprodcomp	-0,02287	0,980114	-0,03688	0,016478	1	-0,00552
lentry2	0,061968	0,998463	-0,25711	0,243076	0	-0,03935
lexit2	-0,00904	1,035828	0,0944	0,262169	0	0,014509
lotherpatents	-0,08701	1,048674	-0,48989	0,192187	1	-0,07347
intercept	-0,07646	1,005884	-0,17809	1,000656	0	-0,02329
initial_lsalATC3USA	-0,0321	0,9545	-0,00068	0,000584	0	-9,8E-05
initial_lspatent	0,114972	1,063965	-0,39924	0,628183	0	-0,05999
initial_lentry2	-0,14089	0,970377	0,460433	0,411942	0	0,067185
initial_lexit2	-0,05736	1,01841	-0,03803	0,455752	0	-0,00542
initial_lotherpatents	0,048826	0,94351	0,076415	0,448835	0	0,011362
precision \alpha	0,601298	0,768003	2,972141	1,22326	1	0
confidence level		0,95				
correlation btw p^ and y		0,438248				
proportion correct forecasts		0,574074				

C04A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	-0,0098	1,123763	-0,00177	0,002465	0	-0,00016
lspatent	-0,08502	1,020173	0,000209	0,191902	0	-0,00035
lsott	0,017467	0,93063	-0,00057	0,000383	0	-5,1E-05
lprodcomp	-0,09155	0,932653	-0,00884	0,035671	0	-0,00052
lentry2	-0,02242	0,861355	-1,07921	0,573051	1	-0,10157
lexit2	-0,03906	1,071352	0,729697	0,378134	0	0,06562
lotherpatents	0,001566	1,033749	-0,00568	0,089645	0	-0,00045
intercept	0,162805	0,975875	0,119057	1,019973	0	0,013641
initial_lsalATC3USA	-0,0084	0,928599	0,00212	0,003231	0	0,000192
initial_lspatent	-0,16173	1,033416	0,089499	0,241844	0	0,008079
initial_lentry2	0,124245	0,961185	0,11541	0,716495	0	0,007337
initial_lexit2	-0,06962	1,00662	0,287856	0,566346	0	0,022636
initial_lotherpatents	0,060593	0,950051	0,098982	0,198276	0	0,008155
precision \alpha	0,533385	0,686541	1,684132	1,007057	1	0
confidence level		0,95				
correlation btw p^ and y		0,360293				
proportion correct forecasts		0,566667				

C5A

regressor	prior mean	prior std	post mean	post std	significant	APE
lsalATC3USA	0,02977	1,03842	-0,01523	0,009671	1	-0,00069
lspatent	-0,07157	0,94737	0,874414	0,401	0	0,049034
lsott	-0,19474	0,878152	7,96E-05	8,53E-05	0	3,59E-06
lprodcomp	-0,01191	1,156765	-0,17358	0,077441	1	-0,0087
lentry2	-0,00045	0,986223	-0,95719	0,497213	1	-0,05625
lexit2	-0,15845	1,171273	0,778972	0,459452	0	0,039682
lotherpatents	0,039201	1,035856	-0,30387	0,140371	1	-0,0157
intercept	0,096807	0,931936	0,24374	0,897787	0	0,009581
initial_lsalATC3USA	-0,01646	1,008291	0,017222	0,01035	1	0,000817
initial_lspatent	0,138244	0,888306	-0,10062	0,897663	0	-0,0021
initial_lentry2	-0,00222	0,977933	0,514702	0,512751	0	0,030168
initial_lexit2	0,159929	1,091608	0,260862	0,691634	0	0,019933
initial_lotherpatents	0,094104	0,947196	0,667808	0,820502	0	0,032852
precision \alpha	0,604376	1,193727	1,568079	1,107769	1	0
confidence level		0,95				
correlation btw p^ and y		0,463857				
proportion correct forecasts		0,628571				

7. Conclusions

Our results interestingly show that own patents never improve the chances of entry. This is the case for both recent and the initial patent holdings. This does not necessarily suggest that entry is not explained by the firm's ability to innovate and its initial conditions, which are certainly difficult-to-measure and associated with the firm's initial allocation of resources and capabilities (Cockburn et al, 2000). It may rather suggest that the positive effect on entry of innovation and initial conditions are not well captured by own patents. By contrast, incumbents' patents are found to have twofold and contrasting effects. On the one hand, the initial stock of patents held by incumbents has a positive effect on entry, thus suggesting that through patents new knowledge flows to competitors and opens for them new technological opportunities. Therefore patents do seem to effectively promote product and industry dynamics as innovation comes from building on what came before, using the building blocks provided by previous innovations by incumbents.

On the other hand, the most recent patent holdings by incumbents do appear to act as a barrier to entry. Recent successes by incumbents in the exploitation of existing technological opportunities frustrate entrant's efforts and thus discourage entry. The use of a Bayesian framework allows us to separately identify the two contrasting effects: spillover effect versus property rights effect.

Our findings can contribute to the recent debate on the role of patents in enforcing or reducing competition and innovation. Patents grant a monopoly power that may discourage other companies from innovating (Boldrin and Levine, 2013). This is confirmed by our results. However, knowledge contained in patents held by other companies may also facilitate entry with a new product by enlarging the set of technological opportunities and thus favour competition. This is also confirmed by our results. Patents may thus increase social welfare through but also beyond their role of providing incentives to the innovator.

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