

ISSN: 2281-1346



Department of Economics and Management

**DEM Working Paper Series**

**The impact of submarket concentration in  
the US pharmaceutical industry in  
1987-1998**

Francesca Di Iorio  
(Università di Napoli Federico II)

Maria Letizia Giorgetti  
(Università di Milano)

**# 163 (06-18)**

Via San Felice, 5  
I-27100 Pavia  
[economieweb.unipv.it](http://economieweb.unipv.it)

**June 2018**

# The impact of submarket concentration in the US pharmaceutical industry in 1987-1998 \*

**Francesca Di Iorio**

Dipartimento di Scienze Politiche  
Università di Napoli Federico II  
via L. Rodino' 22, 80138 Napoli  
fdiiorio@unina.it

**Maria Letizia Giorgetti**

Dipartimento di Economia  
Management e Metodi Quantitativi  
Università di Milano  
Via Conservatorio 7 Milano, 20122  
letizia.giorgetti@unimi.it

## Abstract

Global market concentration is the result of the interplay of different sub-markets. According to this view, empirical analysis on the role of concentration as an incentive or as a barrier to entry must be conducted on a sub-market level, where the sub-markets are identified as specific technological trajectories. In this paper we investigate the role of 3-digit submarket concentration in the US pharmaceutical sector in 1987-1998. We take into account several sources of potential entry deterrence including the relative company size to the largest incumbent firm and the number of competing products in each submarket. The estimates of a panel logit model show that a concentrated industry at submarket level seems to act like a barrier to entry. The relative company size is not significant while the number of competing products is significantly positive.

*Keywords:* submarket concentration, pharmaceuticals, product launches, logit

*JEL codes* L25, L65, C23, C25

---

\*We want to thank Massimo Bordignon, Farasat Bokhari, Paolo Bertoletti, Giovanni Dosi, Paolo Garella, Francesco Guala, Rosella Levaggi, Franco Malerba, Franco Mariuzzo, Claudio Piga, Fiona Scott Morton, Carl Shapiro, Geert Van Moer, Barbara Veronese, Marco Vivarelli for helpful comments. Comments and suggestions from participants to the CRESSE Conference 2017 “Advances in the Analysis of Competition Policy and Regulation” (Heraklion, Crete, 30th June - 2nd July, 2017) and to the EARIE conference in Maastricht (31 August – 2 September 2017) are gratefully acknowledged. The usual disclaimers apply.

# 1 Introduction

In recent years the study of concentration is gaining a renewed interest since a reduction of competition has been observed in the United States where huge companies keep increasing their influence in the markets (Shapiro, 2017). A long-standing literature is devoted to global concentration and one of the most discussed aspects is whether should be defined it as an incentive or a barrier, to entry<sup>1</sup>. This paper participates in the debate analyzing the companies behavior in terms of entry and greenfield (i.e. when the company was not previously present in that sub-market) entry at sub-market level using a detailed pharmaceutical dataset at 3-digit classification level. Sutton's (1998) seminal contribution shows that global concentration is the result of the interplay of different sub-markets. Then, according to this view, the analysis of such problems must be conducted on a sub-market basis, where the sub-markets, or group of products, can be seen as technological trajectories originating from a specific R&D line (see also Dosi, 1982<sup>2</sup>).

The main idea is that companies with high investments in R&D are active in many sub-markets, in order to diversify their offering. Their decisions are very often interconnected across sub-markets; as a consequence, sub-market concentration exerts an important impact on entry decision since companies' evaluation in order to launch new products will necessarily be related to it. As it was debated in the literature, the analysis<sup>3</sup> performed until now has considered only global market concentration without disentangling the linkages and interplay among sub-markets. As a matter of fact, submarkets-based investigation requires dataset able to highlight technical trajectories that are in general challenging to identify. Few exceptions refer to studies performed within the chemical and the pharmaceutical sectors where the identification of different technological trajectories is easier.

The pharmaceutical one is a typical example of a sector with many coexisting lines of R&D technological trajectories or submarkets (Sutton, 1998). These coexisting R&D investments allow to gain additional market shares inside each specific submarket. However, the links among submarkets are weak; therefore it is harder to gain additional market shares in related sub-markets. As a consequence the global market concentration doesn't increase too much. In the same work, Sutton (1998) identifies a different group of sectors, characterized by an escalation process of some line of R&D to the detriment of the others, thus implying higher global concentration for these

---

<sup>1</sup>The paper of Ghemawat and Ghadar (2006) deserves interest as regards the renewed attention to global concentration. The paper shows that global integration doesn't necessarily mean higher global concentration.

<sup>2</sup>Dosi(1982) has introduced "technological paradigms", trajectories originated from a research program. Sutton (1998) takes into account Dosi's contribution in his definition of submarkets.

<sup>3</sup>As regards this point it would be useful look at the survey in Nishitateno (2015).

sectors<sup>4</sup>.

We learn from previous theoretical work that there may be various sources of entry deterrence. Under the hypothesis that entry deterrence originates from limit-pricing strategy, the determinants of market entry have been widely studied since the works of Bain (1954) and Sylos-Labini (1962). Key contributions to the development of this literature include Spence (1977), Dixit (1980) who focuses on capacity as deterrence, and Schmalensee (1981) who investigates products proliferation as a barrier to entry. A more recent contribution by Aghion and Bolton (1987) shows that companies rely on long-term contracts to increase barriers to entry. However there is not a large amount of empirical evidence on entry deterrence in Industrial Organization (IO), with the exception of Ellison and Ellison (2011).

Closer to the spirit of our work, Breshanan and Reiss (1987, 1991) investigate the impact of both market size and degree of competition on entry decisions. In particular they study how the number of producers in an oligopolistic market varies with changes in demand and market competition conditions. Their empirical results suggest that competitive behavioural changes as quickly as the number of incumbents increases. Berry (1992) shows that aircraft manufacturing companies are more likely to enter markets similar to those where they are active already. Mazzeo (2002) similarly establishes these findings in motel markets.

Not many studies discuss the role of sub-market concentration in entry determinants. Among these are Amisano and Giorgetti (2008) and Giorgetti (2012), where this kind of analysis is developed with a broad level of disaggregation.

The present research aims at understanding whether the concentration may or may not have a barrier effect, in a market characterized by interplay of different sub-markets, that is, if the concentration can affect the decision of launching a new product at the company level in a given sub-market. To this end, we focus on the effect of sub-market concentration in the probability of a new product launch at firm-level using a detailed US pharmaceutical market dataset of annual sales for the period 1987-1998. The products are classified according to ATC classification with a breakdown at 3-digit. This great sub-market detail makes it possible to reproduce the analysis at the same level adopted by the antitrust authorities. Moreover, the sub-market dimension allows to exploit this information in detail and capture companies'

---

<sup>4</sup>Sutton (1998) identifies two groups of sectors: low alpha sectors and high alpha sectors. The first group are sectors with low interactions among different submarkets both on the demand and on the supply side. The second group includes sectors with strong linkages among submarkets. In this case there is an escalation process of a submarket to the detriment of others. A typical example of high-alpha sector, where there are strong linkages among submarkets, is the aircraft sector (Sutton 1998). The advent of jet engines caused the end of the turbo-prop engines, a technological trajectory undermined another one.

heterogeneity.

The paper is organized as follows: in section 2 we discuss the motivation of the study; in section 3 the dataset is presented; the model and the results are discussed in sections 4 and 5; final remarks are in section 6.

## 2 Motivation

Companies may assume several conducts to alter the spontaneous competitive game in the markets, for example: strategic investments to deter entry or product proliferation. The literature is mostly theoretical with reference to strategic investments. One of the few papers that exploit an empirical approach is the above mentioned work by Ellison and Ellison (2011)<sup>5</sup>.

There is, not much empirical literature about the issue of product proliferation as an instrument for strategic entry deterrence. In the pharmaceutical sector many prescription drugs are sold in a large number of “presentations”: *e.g.* the tranquilizer Haldol is sold in 1/2 , 1, 2, 5, 10, and 20 milligram tablets, as a concentrated liquid in bottles, and as a solution for intravenous use in vials, ampules, and disposable syringes. When a drug is produced in many presentations, it would be more expensive for an entrant to replicate the incumbent’s full product line. A potential entrant can (and often does) choose to produce a little subset of presentations offered by the incumbent, thus reducing subsequent profits for potential entrants (Ellison and Ellison, 2011). However, there is an effective alternative: try to offer a larger portfolio in order to do business stealing.

Among the large number of papers in the IO literature on the topic of entry in pharmaceutical markets, the above mentioned Ellison and Ellison (2011), the studies by Kyle (2006) and the paper by Scott Morton (1999) deserve a special interest. Dealing with research questions similar to our own, these studies take into account the role of incumbents as potential deterrence to entry, the number of competing products as a measure of potential product proliferation. Nevertheless, they don’t take into consideration the role of sub-market concentration.

Among the few studies on the role of sub-market concentration, we consider in particular Amisano and Giorgetti (2013a, 2013b). In these papers the submarket characteristics (market size, sunk costs, degree of competition) are exploited to assess company diversification and the choice of markets to enter, while the role of sub-market concentration is ignored.

Inspired by these papers, in our study we investigate the role of pro-deterrence variables (the relative size of the biggest incumbent to each company and the number of competing products) jointly with the role of sub-

---

<sup>5</sup>An interesting paper that analyzes the investment response of incumbents to new entry in 39 chemical product industries refers to post entry investments to deter entry (Liebermann, 1987).

market concentration.

### 3 Data

The detailed dataset, obtained in the framework of the EPRIS Project, University of Siena <sup>6</sup>, refers the annual sales<sup>7</sup> of 57 international companies in USA for the period 1987-1998, and it is the same used by Bottazzi et al. (2001), Bottazzi and Secchi (2005) and Amisano and Giorgetti (2008, 2013a, 2013b).

The original dataset includes information for 15732 units since all pharmaceutical products are considered separately by “presentation” (tablets, ampules, etc) and quantity of the active ingredient (eg 250mg, 500 mg, etc.). The pharmaceutical products are classified according to the ATC classification, based on the EphMRA (European Pharmaceutical Marketing Research Association) Anatomical Classification. The classification breakdown identifies the sub-markets: the 1-digit level, described in Table 1, includes 16 sub-markets according to the Principal Anatomical Group. Each of these 16 sub-markets can be further organized in 2, 3, 4 and 5-digit segmentations. In this paper we focus on the third level of segmentation in order to account for the level of real world competition, according to antitrust authorities. The 3-digit level identifies all the therapeutic pharmacological subgroup; for example the N05B sub-market identifies all the anxiolytic drugs according to the ATC, Anatomical Therapeutic Classification (for more informations on the coding principles see <http://apps.who.int/medicinedocs/en/d/Js4876e/6.2.html>).

Then, all the sales collected in the dataset are classified in 267 3-digit sub-markets. Table 2 shows the 1-digit composition, that is how many 3-digit classes are in each 1-digit class.

According to the usual practice, we eliminate all the observations belonging to 1-digit sub-markets B, K, T and V<sup>8</sup>. In addition, after a preliminary screening of missing values and unreliable records, our final dataset refers to 56 company and 205 3-digit sub-markets. Since we are interested in company decisions of launching new products at sub-market level, we consider the product observations aggregated at the company level in each sub-market summing for each year the sales for each drugcode. In this way, we are able to study the main effect of sub-markets concentration on the entry decision in a given sub-market with new products, without differentiating if the entry happens with one or more products. Then, the *Entry* event covers both the greenfield entry and the choice to expand the range

---

<sup>6</sup>The data have been collected by IMS Health, which is the world’s leading provider of information solutions to the pharmaceutical and healthcare industries.

<sup>7</sup>Sales figures are not transformed here in real terms since we consider just market share in the following.

<sup>8</sup>This is done because of the potential unreliability in the data collection in these classes.

Table 1: ATC classification, 1-digit level

---

A	‘Alimentary Tract and metabolism’ products
B	‘Blood and Blood Forming Organs’
C	‘Cardiovascular system products
D	‘Dermatological’ products
G	‘Genito-Urinary System and Sex Hormones’ products
H	‘Systemic hormonal preparations(excluding sex hormones)’ products
J	‘General Anti-Infective-Systemic’ products
K	‘Hospital Solutions’
L	‘Antineoplastic and Immunomodulating agents’ products
M	‘Musculo-Skeletal System’ products
N	‘Central Nervous System’ products
P	‘Parasitology’ products
R	‘Respiratory System’ products
S	‘Sensory Organs’ products
T	‘Diagnostic Agents’
V	‘Various’

---

Table 2: 3-digit breakdown for 1-digit class

1-digit	A	C	D	G	H	J	L	M	N	P	R	S	Total
Freq.	37	25	14	20	10	23	10	9	16	4	19	17	204
Percent	18.1	12.3	6.9	9.8	4.9	11.3	4.9	4.4	7.8	1.9	9.3	8.3	100

Table 3: Number of any-entry by year

year	88	89	90	91	92	93	94	95	96	97	98	Total
any-entry	135	136	102	107	120	132	111	116	139	146	87	1331

Table 4: Number of any-entry by 1-digit submarket

1-digit	A	C	D	G	H	J	L	M	N	P	R	S	Total
any-entry	198	193	96	76	17	129	64	93	217	9	185	54	1331

Table 5: 1-digit submarket market share descriptive statistics over years

1-digit	A	C	D	G	H	J	L	M	N	P	R	S
mean	16.41	21.30	3.99	6.09	1.30	14.10	3.70	4.33	16.85	0.18	9.91	1.84
stdev	0.59	0.96	0.51	0.12	0.17	0.54	0.77	0.82	2.24	0.04	0.66	0.37
min	15.33	20.23	3.12	5.93	1.12	13.22	2.53	3.25	14.34	0.13	8.81	1.26
max	17.35	22.87	4.68	6.40	1.67	15.01	4.56	5.49	20.70	0.25	10.87	2.47

of products being offered. We can name this definition of entry as “any-entry”. Then when a new product enters the sub-market, the sales may go from zero to a positive value. As a result, in our case, the units of analysis are “companies per sub-markets”, which means that we consider the sales of company  $i$  in sub-market  $j$  at time  $t$ . Since not all the companies are in all the sub-markets, our dataset includes 1703 observations.

A further description of the dataset characteristics can be found in the following tables. Table 3 describes the distribution of entries during the period of our study, while Table 4 shows the number of the entries by 1-digit sub-market. Table 5 shows the main descriptive statistics over the years of the market share for the 1-digit class. Classes (A), (B) and (N) collect in mean almost the 55% of the global market in the sample period. Class (N) shows the greater variability of the yearly market shares. The *Entry* values are more or less equally distributed across the time period considered, while a higher number of entries occurs in the 3-digit sector of pharmaceutical products related to diseases of the alimentary tract and metabolism organs (A), the cardiovascular apparatus (C), the nervous and respiratory systems (N) and (R) respectively. It is well known that pharmaceutical companies address their decisions of launching products to markets characterized by frequent and not rare diseases.

Tables 6 shows the distribution of the companies by the number of products launched. We can observe a lot of variety concerning different companies; in particular 15 firms made more than 30 launches of products. The modal value of *any-entry* concerns 17 international companies that carry out launches of products in a number between 11 and 20. Table 7 describes the distribution of the entries by submarket: the companies act in a heterogeneous way: for 26 submarkets there are any-entry values equal to zero, the number of submarkets interested by a small number of entries (less than 6) are 102, and just in 2 submarkets we observe more than 50 entries. The submarkets with more than 50 entries of new products are sub-market *M1A* (Anti-inflammatory and Anti-rheumatic Products, Non-Steroids) with 62 entries and sub-market *N2B* (Other Analgesics and Antipyretics) with 51 entries respectively. These tables show the impact of additional information that we can extract by focusing on narrower sub-market segmentation. Figure 1 describes by boxplot the variability of of the Herfindhal index by 1-digit. In general, the median of the Herfindhal index takes values between 0.3 and 0.6 between the classes. All the distributions show a certain asymmetry and the outliers for 1-digit class are mostly in the first two classes.

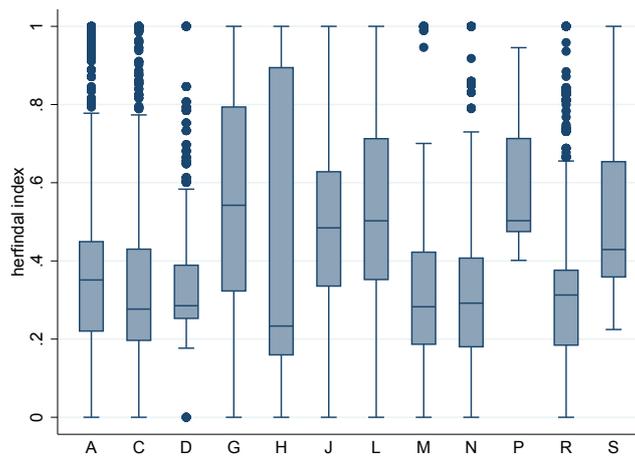
Table 6: Firms by number of any-entry

Any-entry	num. of firms
$\leq 5$	8
6-10	8
11-20	17
21-30	8
31-50	8
$> 50$	7
Total	56

Table 7: Sub-markets entered by number of any-entry

num. any-entry	num. submarkets
0	26
1-5	102
6 -10	32
11- 20	33
21 -30	7
31 -50	3
$>50$	2
Total	205

Figure 1: Variability of Sub-market Herfindhal index by 1-digit level



## 4 The Model

Concentration may or may not exert a barrier effect, and the decision of launching a new product, at the company level, in a given sub-market is one of the possible measures of this effect. In particular, we focus our attention on the effect of sub-market concentration on the probability of new products' launch at firm-level. To this aim, we define the event *Entry* as the launch in the sub-market of one or more products that can be a real greenfield (i.e. when the company was not previously present in that sub-market), or an expansion of the range of products being offered. This *Entry* event is identified when the sales for a specific drugcode become greater than zero. In this way, we do not consider the number of new products launched by a company but just the entry decision into a given sub-market  $j$  by company  $i$  at time  $t$ . Then, the *Entry* decisions at firm level are represented by a dummy variable  $y_{ij,t}$  that takes value 1 if the firm  $i$  decides to launch new products into a given sub-market  $j$  a time  $t$ , and zero otherwise. It is important to keep in mind we are not able to discriminate if the product launched is a *me-too drug* or a new chemical entity. In our panel we count 1331 entries. Among these, we have only 83 New Chemical Entities (NCE), with a percentage of 6.2% and more than the 50% of NCE entries take place in the last three years of our observation period. Moreover, we collapsed the information down to obtain a panel at "company-submarket" level losing the information at product level, so a specific analysis for NCE is scarcely exploitable in an immediate and clear way.

To analyze the effect of sub-market concentration on the firm entry decision, we adopt the panel-logit model defined as follows:

$$Pr(y_{ij,t} = 1) = \Lambda(\beta_0 + \beta_1 x_{1ij,t-1} + \dots + \beta_k x_{kij,t-1} + c_i) \quad (1)$$

where  $i$  refers to company,  $j$  to sub-market,  $t$  to time,  $\Lambda(z) = \frac{e^z}{1+e^z}$ , and  $c_i$  represents the unobserved heterogeneity. It is well known that a method to incorporate unobserved heterogeneity in a logit or probit model is to include a set of subject-specific parameters  $c_i$  (see, among others: Wooldridge 2005, 2010, 2011; Halaby 2004) that may be treated as fixed or random. The panel includes 1703 units; it is recognized that, in such a situation, Fixed Effect could lead to the incidental parameters problem. Moreover, as pointed out by Wooldridge (2010, pag. 286) if the key explanatory variables do not vary much over time, Fixed Effect estimator can lead to imprecise estimate, that is it have a greater variance. These considerations and the nature of the available data suggest a Random Effect Logit model. Maximum Likelihood estimates are obtained by the adaptive Gauss-Hermite quadrature, using STATA14. The assumption of normal distribution for  $c_i$  allows us to evaluate the population average effect (APE) (Wooldridge 2010).

All the explanatory variables in the model are considered lagged of order

1 to take into account that the decision of launching a product is determined both by firm and sub-market characteristics that preempt this decision. Furthermore, it is well known that the launch of new pharmaceutical products is a long process that has to overtake many decisions internal to the company and many authorization phases. The choice of one lag period is thus due to the necessity of not losing too much information and in order to shorten the panel length. Among the regressors we consider variables that are not commonly used in this framework, in particular: the number of products offered by each company in each specific sub-market, the number of competing products in the same sub-market, the number of sub-markets entered by each company and the relative size of each company compared to the biggest incumbent in each sub-market, and a measure of individual market specification.

The behavior of general demand for pharmaceutical goods is taken into account by considering the growth rate of the per-capita real total prescription drug expenditures in US in the observed period. The total prescription drug expenditures come from National Health Expenditure Accounts (NHEA)<sup>9</sup> expressed in nominal terms and not adjusted to remove the impact of changes in health care prices. Although a price index for Personal Health Care goods and services is available, there is not a corresponding price index for the aggregate NHE, so the data are transformed in real terms by using the US CPI. The differences in the annual growth rates of the NHE reflect trends in the factors that affect health care spending, including technological developments, changes in the age and sex composition of the population (demographic effects), changes in the use of health care goods and services and changes in prices for health care goods and services. In more detail, the variables employed in our model are:

1.  $SMS_{ij,t-1}$ , the sub-market market share, namely the lagged (at t-1) value of the market share of each company in each sub-market.
2.  $MS_{i,t-1}$ , the general market share, namely the lagged (at t-1) market share of each company in the whole pharmaceutical sector (all the sub-markets).
3.  $Natc3_{i,t-1}$ , the lagged number of sub-markets in which each company is present. This is a measure of the diversification already achieved.
4.  $IH_{j,t-1}$ , the lagged Herfindhal index, the concentration level in each sub-market.
5.  $NIS_{j,t-1}$ , the lagged number of competing incumbent companies in each sub-market, a measure of competition.

---

<sup>9</sup>Data are available at: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html>

6.  $NFC_{j,t-1}$ , the lagged number of products offered by competing incumbents in each specific sub-market.
7.  $DISrel_{ij,t-1}$ , the relative size of each company compared to the biggest incumbent in each sub-market.
8.  $PCEX_{t-1}$  the growth rate of the per-capita real total prescription drug expenditures in US in the considered period. Since this variable is constant across units it can also play the role of time dummies.
9.  $PI_{ij,t-1}$ , the lagged number of products offered by each company in each specific sub-market.
10.  $Diver_{i,t-1}$ , a technological diversification indicator, the lagged number of 2-digit submarkets entered by firm  $i$  at time  $t-1$ .

The variable  $Diver_{i,t-1}$  increases (or decreases) its value only if the entry (or exit) happens in a 3-digit submarket that belongs to a new 2-digit submarket for the firm. In this way, we capture the technological diversification decisions and we can disentangle an expansion through new lines of business (a new 2-digit submarket) from an expansion due to the increase of the range of products being offered in the same 2-digit submarket (the same line of business). This measure implies a definition of diversification that is different from that implied by simply considering greenfields. A new product can be launched into a subsector belonging to the same 2-digit group in which the company is already present. The effort required for such diversification would be less expensive compared to the launches of products in new lines of business, that is launches in 2-digit submarkets where the company has no product. This indicator should capture some technological diversification.

This index is different from the  $Natc3_{i,t-1}$ , which doesn't allow to take into account the technological diversification.

Time dummies are not explicitly considered, since, as mentioned before, the growth rate of the per-capita real total prescription drug expenditures  $PCEX$  is constant across units then it also play the role of time dummies. Table 8 collects descriptive statistics of the explanatory variables.

Exploiting the contribution by Wooldridge (2005) for the unobserved heterogeneity and following Amisano and Giorgetti (2013) the potential endogenous variables enter the model with their initial conditions. The covariates are divided into 3 groups:  $x_{(1i)}$  includes the strictly exogenous regressors,  $x_{(2i)}$  includes the regressors that are not strictly exogenous (of course among them we have the lagged dependent variable) and  $x_{(3)}$  the regressors which do not vary across units, such as for example the intercept term, the growth rate of of the per-capita real total prescription drug expenditures. The distribution of the random effects  $c_i$  is conditioned on all the average

Table 8: Explanatory variables descriptive statistics

Var.	Mean	Std. Dev.	Min	Max
MS	.06	.20	0	3.91
SMS	.11	.23	0	1
PI	1.56	1.73	0	15
IH	.40	.23	0	1
NIS	11.11	6.66	0	29
NFC	21.61	19.73	0	98
DISrel	.71	.40	0	1
Natc3	39.80	23.40	0	91
PCEX	6.74	3.37	1.3	11.03
Diver	24.93	12.31	0	53

sample<sup>10</sup> values of the regressors in  $x_{(1i)}$  as well as on the initial values of  $x_{(2i)}$ .

The resulting specification is:

$$c_i = \gamma_1' \bar{\mathbf{x}}_{(1i)} + \gamma_2' x_{(2i)} + \alpha_i \quad (2)$$

$$\bar{\mathbf{x}}_{1i} = \frac{1}{T} \sum_{t=1}^T \mathbf{x}_{(1it)} \quad (3)$$

In particular, as in Wooldridge (2005), we assume that

$$(c_i | \mathbf{X}_{(1i)}, \mathbf{x}_{(2i0)}, \boldsymbol{\theta}) \sim N(f(\mathbf{X}_{(1i)}, \mathbf{x}_{(1i0)}, \boldsymbol{\theta}), \sigma_c) \quad (4)$$

and we use a linear specification for the conditional expectation.

In our case we have no exogenous variable with the exception of the per-capita expenditure growth rate. The endogenous variables considered with their initial conditions are the sub-market share, the global market share, the entry, the number of own products in each sub-market, the number of products by competitors in each sub-market, the number of sub-markets entered, the relative size of each company compared to incumbent, the diversification measure, all calculated at the initial year of observation (1988)  $x_{(2i)} = [MS_{i0}, SMS_{i0}, PI_{i0}, NFC_{i0}, Natc3_{i0}, DISrel_{i0}, Diver_{i0}]$ .

Since in our dataset the number of the events *Entry* is just 7.3% of the total observations, our data could be affected by rarity of events, i.e. the number of the any-entry may be small compared to the total number of observations. King and Zeng (2001, pag. 693) classify the rare events as “binary dependent variables characterized as by dozens to thousands of times fewer ones than zeroes (nonevents)”.

<sup>10</sup>To reduce the number of regressors, the value of exogenous regressors enter with the mean value, with an approach due to Mundlak (1978) and further used in Heckman (1981).

In particular, the main problem when a great number of units in a panel have no events (i.e. a great number of units that never show  $y = 1$ ) is that logit coefficients are biased in small samples (less than 200). Of course, the simplest way of correcting the problem is by decreasing the rarity of the event, increasing the efficiency of subsequent data collections changing the optimal trade-off between gathering more observations and including better or additional variables, as suggested by King and Zeng (2001). They also suggest a “Prior correction”, that is a correction of the logistic estimated using a factor based on prior information about the fraction of events (the “ones”) in the population. Unfortunately, both of these strategies are not applicable in our case. Notice that our dataset has 1703 observations, so at least it is not small.

## 5 Results

Table 9 presents the results for two different model specifications: in the specification labeled (*Mod1*) we consider all the variables mentioned before, while (*Mod2*) is a restricted specification. All the variables, with the exception of relative size with respect to the biggest incumbent  $DISrel_{i,j,t-1}$  and technological diversification  $Diver_{i,t-1}$ , are statistically significant. For the remaining variables the estimated coefficients in the two specifications are similar. The signs are in line with the expectations. More precisely, the general market share ( $MS_{i,t-1}$ ) in all the US pharmaceutical sub-markets increases the probability to launch a new product, so the largest companies have higher chances to introduce products into specific 3-digit sub-market. The (lagged) sub-market share ( $SMS_{i,j,t-1}$ ) is significant with a negative sign, as the lagged number of products ( $PI_{i,j,t-1}$ ) introduced by each company.

These results are in line with the previous literature: the company’s size, ( $MS_{i,j,t-1}$ ), measured, in this case, as the global market share, induces companies to launch new products, that is, larger firms have a well-known tendency towards a continuous growth. On the contrary, the market share into a specific sub-market ( $SMS_{i,j,t-1}$ ) reduces the probability to launch additional products, that is, companies are interested in reaching a certain “optimal presence in the sub market”. In case this sub-market share has been reached, companies seem to reduce the new products launches.

The initial number of products ( $PI_{i0}$ ) in each sub-market is significant and positive while the lagged number of products launched is negatively significant. Again, it seems that companies are interested in entering a certain number of sub-markets, and, when a certain presence has been reached, the probability to launch a new product is decreasing.

The Herfindhal index ( $IH_{j,t-1}$ ) is a barrier to the launch of “new” products; this result confirms the findings in previous studies (Amisano and Giorgetti,

2008, Giorgetti 2012) with a lower level of disaggregation, the 1-digit ATC classification. In the present case, by taking into consideration a deeper level of segmentation, the Herfindhal index has a significant and negative impact on the decision of launching new products. The idea that the possibility to exploit sub-market power could encourage the introduction of products is completely misleading. According to our results, entry is inversely correlated with the level of concentration: higher concentration, and consequently less competition, implies less entry. Our results can also offer some contribution to the old debate, in the literature, on the relationship between entry and competition (Breshnan and Reiss, 1991).

The number of incumbent companies ( $NIS_{j,t-1}$ ) is a disincentive to the launch of new products, as suggested by the literature (Netz and Taylor, 2002): the number of companies is a standard proxy for the level of competition in all the entry-exit reduced form models: companies are discouraged to launch their first product or to add a further product when there is a strong competition.

The company's presence in many sub-markets ( $Natc3_{j,t-1}$ ) is an incentive to launch a new product into a specific sub-market, this regressor presents a considerable elasticity, more than 1. It can be argued that a greater level of diversification pushes companies to launch more products. While the lagged number of sub-markets entered  $Natc3_{i,t-1}$  is significant and positive, the initial number ( $Natc3i0$ ) is significant and negative. If in the initial period a company has not entered a considerable number of sub-markets, it will continue avoid to launch additional products. Otherwise this tendency could be overturned during the period of observation and the presence of a lagged diversification ( $Natc3_{i,t-1}$ ) will increase the probability of launching additional products.

The relative size of the biggest incumbent compared to each potential entrant  $DISrel_{ij,t-1}$ , that is our proxy for potential predation, is not significant. In theory a bigger incumbent company could carry out predation strategies more easily (Benoit, 1984<sup>11</sup>, and Holmstrom and Tirole, 1997). In a situation where a firm is financially stronger than another, the former can use its deeper pockets (long purse) to force the latter out of the industry. This lack of significance could be partially explained by a large heterogeneity among the 3-digit sub-markets studied. However it was not possible to analyze separately each specific sub-market because of the small number of entries in all the pharmaceutical sectors.

The estimated coefficient for the number of products ( $NFC_{i,j,t-1}$ ) offered in the same sub-market by competitors suggests that this is an incentive to launch another product. This result, at first sight, could be counterintuitive, since pharmaceutical companies usually offer the same product in many pre-

---

<sup>11</sup>Benoit (1984) deals with a simple model of predation, Holmstrom and Tirole (1997) deals with a model of predation in imperfect markets.

Table 9: Logit Coefficient estimates

var	Mod1			Mod2		
	estim.	z-ratio		estim.	z-ratio	
$MS_{i,t-1}$	.778	(2.30)	**	.688	(2.10)	***
$SMS_{ij,t-1}$	-1.349	(-2.85)	***	-1.214	(-2.96)	***
$PI_{ij,t-1}$	-.316	(-4.59)	***	-.302	(-4.53)	***
$IH_{j,t-1}$	-.799	(-2.96)	***	-.772	(-3.38)	***
$NIS_{j,t-1}$	-.030	(-2.18)	**	-.034	(-2.72)	***
$NFC_{j,t-1}$	.049	(6.97)	***	.048	(7.20)	***
$Natc3_{ij,t-1}$	.041	(5.80)	***	.041	(5.95)	***
$DISrel_{ij,t-1}$	-.015	(-0.12)		–	–	
$Diver_{i,t-1}$	-.0002	(-0.04)		–	–	
$PCEX_{t-1}$	.0213	(1.77)	*	0.018	1.58	
$MS_{i0}$	-.256	(-0.67)		-.151	(-0.42)	
$SMS_{i0}$	.865	(1.60)		.922	(2.30)	**
$PI_{i0}$	.437	(6.00)	***	0.438	(6.24)	***
$NFC_{i0}$	-.040	(-5.40)	***	-.0397	(-5.58)	***
$Natc3_{i0}$	-.039	(-5.20)	***	-.041	(-5.54)	***
$DISrel_{i0}$	-.160	(-0.61)		–	–	
$Diver_{i0}$	0.006	(0.74)		–	–	
<i>const</i>	-2.868	(-10.43)	***	-2.782	(-14.99)	***

sentations: liquid, oral and etc. This could be an obstacle for a new entrant, that can enter only with a subset of products. A large number of products by competitors could be an obstacle but in the present application we find the opposite. The high number of products offered by competitors increases the probability to launch additional products. This can be explained by the attempt of each company to offer comparable portfolios of products to other incumbent companies and to do business stealing to the same competitors<sup>12</sup>. The elasticity for this variable is close to 1 for both specifications. The growth rate of per-capita real total prescription drug expenditures in US ( $PCEX_{t-1}$ ) is positively significant at 10%.

The variable  $Diver_{i,t-1}$ , aimed at measuring technological diversification, is not significant. This is mainly due to the difficulty to enter completely different lines of business (different therapeutical groups, 2-digits ATC classification). As a matter of fact diversification needs a long period of time in research, authorization procedure and a large amount of money with an uncertain profitability. This result anyway confirms the same evidence obtained by Bottazzi and Secchi (2005) who do not identify a precise diversification pattern in the pharmaceutical industry worldwide.

<sup>12</sup>We consider this variable as endogenous because companies decide their portfolio by taking into account the portfolio choice of their competitors.

Table 10: Logit APE and elasticity

var	Mod1				Mod2			
	APE		Elast		APE		Elast	
$MS_{i,t-1}$	.049	**	.038	**	0.043	**	.034	**
$SMS_{ij,t-1}$	-.084	***	-.128	***	-.076	***	-.123	***
$PI_{ij,t-1}$	-.019	***	-.392	***	-.019	***	-.387	***
$IH_{j,t-1}$	-.050	***	-.283	***	-.049	***	-.276	***
$NIS_{j,t-1}$	-.002	***	-.287	**	-.002	***	-.330	***
$NFC_{j,t-1}$	.003	***	0.913	***	0.003	***	0.900	***
$Natc3_{ij,t-1}$	.003	***	1.370	***	0.003	***	1.386	***
$DISrel_{i0}$	-.9e-3		-0.009		–		–	
$Diver_{i0}$	.2e-4		-0.006		–		–	
$PCEX_{t-1}$	.001	***	.103	*	0.001		0.876	***

The corresponding average partial effect and elasticity for all variables are reported in table 10.

The main results can be summarized as follows. The number of sub-markets entered, by each company, increases the probability to launch additional product. The sub-market concentration acts as barrier to entry, the relative size of the biggest incumbent compared to each potential entrant is not significant, the number of competing products induces the launch of an additional product.

The role played by competing products is positively significant. This counter-intuitive result, at first sight, can be explained by a business stealing effect. Firms have to present to customers a comparable range of products. The last important result concerns the number of sub-markets entered by each company: companies that experienced, with one-year lag, a certain propensity towards diversification, overcome with more facility the barrier to entry of sub-market concentration.

Unfortunately, in our current analysis, we are not able to differentiate among NCE and me-too-drugs; this could help us to further differentiate the role of sub-market concentration in case of products protected by patents.

## 6 Conclusions

The paper investigates the role of sub-market concentration in entry decision in the pharmaceutical sector in the USA by taking into account other several potential entry deterrence variables. Following previous papers dedicated to this topic, we analyse the companies' decisions of launching products in US pharmaceutical sub-markets in the period 1988-1998 adopting a deep level of segmentation, identified according to the 3-digit breakdown of the ATC classification.

The contribution of this paper is twofold: to analyse sub-market concentration, a topic scarcely considered in the literature, with a good level of disaggregation, and to propose a way for analysing other sectors with high investments in R&D where the strength of linkages among submarkets play a big role.

In this paper we focus our attention on a typical low-alpha sector, that is a sector with weak linkages among sub-markets (Sutton, 1998). A study on entry decisions, conducted in a similar way for a high-alpha sector could help to investigate the presence or the absence of regularities as regards the role of sub-market concentration in high R&D investments sectors.

In order to disentangle the “potential” role played by the concentration from other potential deterrence variables, we introduced some specific regressors as the number of competing products and the relative size of each company compared to the biggest company in each sub-market.

Our findings suggest that, in analysing the sub-market entry determinants, it is extremely important to take into account, not only submarket concentration but also other rival company strategies as the diversification of potential entrants and potential predation by incumbents.

In fact, the number of products by competitors in the same sub-market increases the probability to launch new products in order to have comparable products portfolio, while the relative size of companies compared to the biggest incumbent, our proxy of potential deterrence is not significant.

Further analysis that verifies a role of sub-market concentration as barrier to entry could be improved by differentiating entry with respect to “the me-too-drugs” or NCE. If the company decides to launch a new chemical entity, will concentration be again a barrier to entry? This will be the object of ongoing studies.

## References

- Aghion P., Bolton P. (1987) Contracts as a Barrier to Entry, *The American Economic Review*, 77, pp. 388-401.
- Amisano G., Giorgetti M.L. (2008), Entry into New Pharmaceutical Submarkets: The Role of Submarket Concentration, *SSRN Electronic Journal*, April 2008 .
- Amisano G., Giorgetti M.L. (2013a) Entry into pharmaceutical Submarkets: A Bayesian Panel Probit Analysis, *Journal of Applied Econometrics*, 28, pp. 667-701.
- Amisano G., Giorgetti M.L. (2013b) Diversification by entry into a new submarket? *Applied Economics*, 45, pp. 1507-1518.

- Bain J. (1954). Economies of Scale, Concentration, and the Condition of Entry in Twenty Manufacturing Industries. *American Economic Review*, 44, pp. 15-39.
- Benoit, J.P. (1984) 'Financially constrained entry into a game with incomplete information', *Rand Journal of Economics*, 15, pp. 490-499.
- Berry S. (1992) Estimation of a Model of Entry in the Airline Industry. *Econometrica*, 60, pp. 889-917.
- Bottazzi G., Dosi G., Lippi M., Pammolli F., Riccaboni M. (2001) Innovation and corporate growth in the evolution of the drug industry. *International Journal of Industrial Organization*, 19, pp. 1161-1187.
- Bottazzi G., Secchi A. (2005) Growth and Diversification Patterns of the Worldwide Pharmaceutical Industry, *Review of Industrial Organization* 26: pp. 195-216.
- Bresnahan T., Reiss P. (1987) Do entry Conditions vary across markets? *Brookings Papers on Economic Activity: Microeconomics*, pp. 833-871.
- Bresnahan T., Reiss P.(1991) Entry and Competition in Concentrated Markets, *Journal of Political Economy*, pp 977-1009.
- Dixit A. (1980) The role of investment in entry-deterrence, *The Economic Journal*, 90, pp. 95-106.
- Dosi G. (1982) Technological paradigms and technological trajectories, *Research Policy*, 11, pp.147-162
- Ellison G., Ellison, S. F. (2011) Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration. *American Economic Journal: Microeconomics*, 3, pp. 1-36.
- Ghemawat P., Ghadar F. (2006) Global integration  $\neq$  global concentration, *Industrial and Corporate Change*,15,pp.595-623.
- Giorgetti M.L. (2012) Entry and submarket concentration: empirical evidence from the pharmaceutical industry, *Economia e politica industriale*, 3, pp. 5-29.
- Holmstrom B., Tirole J. (1997) "Financial Intermediation , Loanable Funds, and the Real Sector, *Quarterly Journal of Economics*, 112, pp. 663-692.
- King G., Zeng L. (2001) Logistic Regression in Rare Events Data, *Political Analysis*, 9, pp. 137-163.

- Kyle M.K., (2006) The role of firm characteristics in pharmaceutical product launches, *The Rand Journal of Economics*, Vol. 37(3), pp. 602-618.
- Halaby C.N. (2004) Panel Model in Sociological Research: Theory into Practice. *Annual Review of Sociology*, 30, pp.507-544.
- Heckman J.J. (1981) Statistical model for discrete panel data, in *Structural Analysis of Discrete Data and Econometric Applications*, Monski,C. and McFadden, D. Eds, Cambridge (MA), MIT Press.
- Liebermann M.B. (1987) Postentry Investment and Market Structure in the Chemical Processing Industries, *The Rand Journal of Economics* Vol.18(4), pp. 533-549.
- Mazzeo M. (2002) Product choice and oligopoly market structure, *Rand Journal of Economics*, 33, pp. 1-22.
- Mundlak Y. (1978) On the Pooling of Time Series and Cross Section Data, *Econometrica*, 46, pp. 69-85.
- Netz J.S., Taylor B.A. (2002) Maximum or minimum differentiation? Location patterns of retail outlets. *The Review of Economics and Statistics*, 84, pp. 162-175.
- Nishitatenno S. (2015) *Market Structure and Entry: Evidence from the intermediate goods market*, RIETI Discussion Paper Series 15-E-081.
- Schmalensee R. (1981) Economies of Scale and Barriers to Entry, *Journal of Political Economy*, 89, pp. 1228-38.
- Scott Morton F.M. (1999) Entry decisions in the generic pharmaceutical industry, *The RAND Journal of Economics* , 30, pp. 421-440.
- Shapiro C.(2017), Keynote speaker, Cresse Conference "Advances in the Analysis of Competition Policy and Regulation" 2017, Creta
- Spence M. (1977) Entry, Investment and Oligopolistic Pricing, *The Bell Journal of Economics*, 8, pp.534-544.
- Sutton J. (1998) *Technology ad Market Structure*, Cambridge (MA), MIT Press.
- Sylos-Labini, P (1962), *Oligopoly and Technical Progress*, Cambridge (MA), Harvard University Press.
- Wooldridge J.M. (2005). Unobserved heterogeneity and estimation of average partial effects. in *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pp. 27-55.

Wooldridge J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*, second edition, Cambridge (MA), MIT Press.

Wooldridge J.M. (2011) A simple method for estimating unconditional heterogeneity distributions in correlated random effects models, *Economics Letters*, 113, pp. 12-15.