Unveiling the effects of sunk costs: barrier to entry vs. commitment*

Preliminary and Incomplete

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Abstract

Sunk costs are generally considered a barrier to entry. However, if the sunk investments required to entry are huge, sunk costs could become a commitment inducing incumbents to be less aggressive. If sunk costs become an "encouragement" to entry, the Cabral-Ross effect takes place.

We study the impact of sunk costs on entry in pharmaceutical submarkets in the USA for the period 1988-1998. We relate the variation in the effect of sunk costs on entry to some observable characteristics that make

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predation by incumbents less or more likely to occur. Among these, we control for the relative size of the entrant vs. the incumbents and the degree of direct competition between the entrant and the incumbents' products.

The preliminary results show a positive impact of sunk costs on entry.

JEL classification: L11, L65, C11, C23, C25.

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1. Introduction

In markets characterized by high sunk costs, the impact of sunk costs on entry may be controversial. Sunk costs could act as a barrier to entry if there is an incumbent likely to retaliate entry by preying on the entrant. In such case, an incumbent company acts strategically in order to maintain market power and to discourage entry: sunk costs are a barrier to entry. In other cases sunk costs can be a deterrent to predation if they serve to commit entrants to staying in the market and thereby induce the incumbent to adopt a more accommodating strategy. This is called the Cabral-Ross effect (Cabral and Ross, 2008).

In a related paper Amisano and Giorgetti (2011) find a positive relationship between entry and sunk costs in many 1 digit ATC (Anatomical Therapeutical Classification) submarkets of the pharmaceutical sector. In this paper, we try to detect if the relationship, when positive, can be explained by regressors associated with factors that make predation less likely to occur. In particular, we control for the difference in size between the entrant and the largest incumbent, and by the degree of competition between the new product and incumbents' products. Besides controlling for more theoretically grounded regressors, in this paper we also model entry into a specific submarket by adopting a narrow submarket segmentation and identify pharmaceutical submarkets at the 3-digit ATC classification level in the broader 1-digit cardiovascular pharmaceutical submarket.

Finally, in Amisano and Giorgetti (2011) sunk costs were measured following Tybout and Roberts (1997) as the time elapsed since last entry. In this paper we adopt a different measure and sunk costs are measured following Sutton (1998) as the level of R&D required to enter in a given submarket with a new product. Because company data on R&D expenditures by product line are unavailable, we measure sunk costs as the stock of cumulated knowledge, which we obtain using past patented ideas through the perpetual inventory method. We claim that one major novelty of this paper consists of the way sunk costs are measured to cast light on the above specified controversial impact of sunk costs on entry.

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.

2. A brief review of the literature

Sunk costs are considered an entry barrier in the traditional industrial organization literature. By contrast, the strategy literature emphasizes their role as commitment (Ghemawat, 1991) and that "the ability to make the right kind of commitment can be the source of a firm's competitive advantage" (Cabral and Ross, 2008). Sunk costs are irreversible investments that induce strategic behavior by the incumbents: as exit for the entrant becomes unattractive when sunk costs are high, predation by the incumbent may become unprofitable. High sunk costs could then have a positive effect on entry.

The standard view of sunk costs as barriers to entry relies on two different set of assumptions: 1) sunk costs can be an obstacle if entry is followed by quick exit; 2) large sunk capacity serves to commit the incumbent to higher output rates (e.g., Spence, 1977; Dixit, 1980; Milgrom and Roberts, 1982), thus lowering post-entry price and profits for prospective entrants (Cabral and Ross, 2008). Incumbents can undertake predatory pricing in order to eliminate competitors.

Predatory pricing is the practice of cutting your prices so low as to bankrupt your competition. Afterwards the predator raises back his prices and earns monopoly profits. Some authors, such as Edlin (2010) believe that predatory pricing can, under certain circumstances, be a profitable business strategy. Others (close to the Chicago School), suggest that predatory pricing is rarely rational and thus unlikely to be practiced[1]. At the basis of predatory pricing is a trade-off between lower profit in the short run due to aggressive pricing and higher profit in the long run due to reduced competition.

Finally, according to the "deep pocket" model developed by Bolton and Scharfstein (1990), predation can be borne by potential entrants if they have major fi-

[1] Large firms also incur in great losses, when they increase price ex-post entry will start again (unless entry fixed/sunk costs).

nancial resources to resist to incumbent's first periods predation. Therefore, the possibility by incumbents to prey on the entrants must be analyzed accounting for potential financial costraints met on internal capital markets by the entrants.

The commitment power of sunk costs, which we shall refer to as the *Cabral Ross effect*, can make exit unattractive for potential entrants, and can therefore soften predation by incumbents. In this case it is important to control for competition between incumbents and potential entrants. If competition is tougher, predation is more likely: effective entry may disclose an higher commitment power of sunk costs. The other element to evaluate is the relative size of incumbents and potential entrants. If the incumbents is much bigger than the potential entrant, this could shred the commitment power of sunk costs: the possibility to obtain illimitate and low-cost financial resources enforces a predatory conduct by the incumbent. "A large firm might drive a small competitor out of the market by waging a price war that gives losses to both. But the small competitor has limited resources ("a small pocket") and will therefore be unable to survive such losses for a long time. Sooner or later, it will have to give up and leave the industry, allowing the large firm to increase prices and recoup losses" (Motta, 2004). Once we observe a positive impact of sunk costs on entry, the Cabral-Ross effect is greater when competition between the entrant and the incumbent is tougher. In such cases, incumbents' reaction should be more likely but if the commitment role of sunk costs prevails on the entry barrier role, this implies a greater Cabral-Ross effect.

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[2]. Amisano 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

[2] 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

pharmaceutical submarket. We then move down to the 4-digit ATC level in order to capture relevant substitution effects between entrant and existing products.

We also employ patent data from the KITeS-Cespri Patent Database [3] 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[4]. 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 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.

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

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

The following ones are the ATC3 level submarkets we choose to analyse:

(a) C01C - Cardiac stimulants excl. cardiac glycosides

(b) C02A - Antiadrenergic agents, centrally acting

(c) C02B - Antiadrenergic agents, ganglion-blocking

(d) C03A - Low-ceiling diuretics, thiazides

(e) C04A - Peripheral vasodilators

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

(g) C05B - Antivaricose therapy

(h) C09B - Ace inhibitors, combinations

(i) C10A - Lipid modifying agents, plain

Our choice was based on the availability, within each of the aboce 3-digit ATC classes, of at least two 4-digit submarkets that allow us to capture direct competition between new and existing products. The introduction of a new product into a 3-digit ATC submarket should induce a tougher reaction from the incumbents if the existing products belong to the same 4-digit ATC subclass, i.e. if they are closer substitutes.

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, previous entry and exit choices (which determine the range of products currently offered by the company), interactions with other markets and the level of entry sunk costs faced by the single firm at any given time. $\mathbf{X}_{2,t}^{(j)}$ includes variables that are submarket specific: demand conditions, the degree of competition and the size at which economies of scale kick in.

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 measures of: demand, costs, intensity of competition and linkages across submarkets. Our key interest relies in the effect of sunk costs on entry. As we already mentioned, sunk costs are mostly considered as a barrier to entry. There are, however, circumstances under which sunk costs may act as an encouragement to entry, as discussed in Cabral and Ross (2008). In particular, in order for the Cabral-Ross encouragement effect to occur it is important that there be an incumbent likely to retaliate entry by preying on the entrant. We then need to identify observable market characteristics that proxy for the likelihood of a preying incumbent. We propose that predation is more likely if (a) the entrant directly challenges incumbents (i.e. both drugs are within the same therapeutic 4-digit ATC submarket), (b) The relative size of the entrant with respect to the incumbent is small. The question is then whether we observe a positive effect of sunk costs on entry related to the above characteristics.

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

1. The dimension of the company in all the global pharmaceutical market to account for the overall company size. This is a measure of more favourable financing conditions that larger companies may enjoy compared to smaller

companies. In our dataset this variable is called `lsal` and is obtained summing sales across products/submarkets.

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. The ratio between the global sales of the largest incumbent company in the specific 3-digit ATC submarket and the global sales of each company that is a potential entrant (`lefin`).

5. A measure of company sunk costs (`sunk_costs`). These are 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. Ideally, we would like to measure sunk costs with R&D investment. However, it is not possible to obtain information on the amount of R&D devoted by a firm to the conception and development of products in a specific therapeutic area. We therefore proxy sunk costs with the stock of patents held by a firm in the specific therapeutic area. Patents are a widely used measure of innovation output, particularly in the Pharmaceutical sector, where they represent a good mean for protecting innovation. Patents are also strongly and positively associated with R&D investment, hence potentially a good proxy for it.

   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). Patents are weighted by forward citations to better account for their value.

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 (lcomprod): for each ATC4 submarket, we calculate the ratio between the sales of the biggest company (at the ATC4 level in the US market) and its sales at the superior ATC3 level (always in the US market). This allows us to detect for the most important incumbent, the weight of each specific lines of business (identified by ATC4 submarket) on the global company portfolio at the ATC3 submarket level. If the ATC4 submarket where a company introduces a new product represents a large share of the incumbent's portfolio we consider competition between the incumbent and the entrant's products to be tougher. Because of the presence of at least two ATC4 submarkets in each ATC3 submarket, for each company we use the ratio calculated for the ATC4 submarket where the entrant has introduced the new product. If the entrant introduces products in different ATC4 submarkets we calculate the same ratio as average. The same measure is adopted if the company doesn't introduce any product.

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:

$$\begin{aligned} p(y_{it} &= 1|I_{t-1}, c_i, \boldsymbol{\theta}) = p_{it} = \Phi(c_i + \mathbf{x}_{it}^{\prime}\boldsymbol{\lambda}) \\ \Phi(x) &= \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp(-z^2/2)dz \\ i &= 1, 2, .., n \text{ (units)}, \; t = 1, 2, ..., T \text{ (time)} \end{aligned} \tag{5.1}$$

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

$$c_i = \boldsymbol{\gamma}_2' \mathbf{x}_{i0}^{(2)} + \alpha_i \tag{5.5}$$

$$\alpha_i \backsim N(0, h_\alpha^{-1}) \tag{5.6}$$

which implies

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

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

We present results for one submarket: C01C (Cardiac Stimulants excl. Cardiac Glycosides). As a consequence, we emphasize that these results have to be interpreted with caution because they are relative to a single ATC3 submarket and cannot be generalized to all submarkets.

The results are in line with the literature and with our expectations: competition at the firm level (`limp`) confirms that the lagged number of companies in the same ATC3 submarket is a disincentive to entry, the ratio of the size of the largest incumbent on the size of each potential entrant is positively correlated to entry (`lefin`), the sign is negative but the sales of each potential entrant are at the denominator of the regressor `lefin`, showing a positive relationship between the relative size of potential entrant versus the largest incumbent. This shows that according to the deep pocket argument bigger companies are more likely to find the necessary resources to bear a potential predation by incumbents and, therefore, to enter.

These preliminary results also confirm the positive impact of initial sunk costs, measured as patents whegheted by citations, on the decision to enter, confirming the commitment power of sunk costs (Cabral and Ross, 2008) versus their entry barrier role. The submarket size is not significant, this doesn't confirm the results by Acemoglu and Linn (2004), the same holds for the lagged entry regressor.

Submarket C01C CARDIAC STIMULANTS EXCL. CARDIAC GLYCOSIDES

coeff.	regressor	prior mean	prior std	post mean	post std	lower	median	upper	significant	APE
\beta_1	limp	0,002329	1,001485	-1,20069	0,621255	-2,50829	-1,18342	-0,03786	1	-0,00219
\beta_2	lefin	-0,00853	1,003061	0,235167	0,116501	0,053746	0,219046	0,5018	1	0,000551
\beta_3	lentry1	0,008032	1,002842	-1,17181	0,794534	-2,77405	-1,14491	0,34056	0	-0,00316
\beta_4	lsott	0,010131	1,00406	0,051041	0,542925	-1,00964	0,046493	1,105439	0	0,000208
\beta_5	lsunkcit	-0,0113	1,006513	0,08367	0,566258	-1,05754	0,090475	1,184647	0	-0,00037
\beta_6	intercept	-0,00776	1,00262	-0,07734	0,993926	-2,02777	-0,07423	1,874699	0	-0,00028
\beta_7	initial_lefin	0,00531	0,997638	0,107922	0,426458	-0,79675	0,126019	0,911189	0	-0,00021
\beta_8	initial_lentry1	0,018102	0,999304	-0,04427	0,998121	-2,00514	-0,03879	1,891166	0	-0,00012
\beta_9	initial_lsunkcit	0,019419	1,014657	1,106689	0,563151	0,067445	1,086967	2,268207	1	0,001403
h_\alpha	precision \alpha	0,510152	0,727772	0,778805	0,803406	0,06079	0,508418	3,03087	1	
confidence level	0,95									
correlation btw p^ and y	0,67923									
proportion correct forecasts	0,890909									

7. Conclusions

In markets characterized by high sunk costs, the impact of sunk costs on entry may be controversial. On the one hand, sunk costs could act as a barrier to entry if there is an incumbent likely to retaliate entry by preying on the entrant. On the other hand, sunk costs can be a deterrent to predation if they serve to commit entrants to staying in the market and thereby induce the incumbent to adopt a more accommodating strategy (Cabral and Ross, 2008).

We study the effect of sunk costs on entry on pharmaceutical submarkets and innovatively measure sunk costs using citation weighted patent stocks. We also control for competition between incumbents and potential entrants and for their relative size (to account for the effect of internal capital markets).

Our preliminary results show a positive impact of initial sunk costs on the decision to enter, thus confirming their commitment power.

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