The Unexpected Consequences of Asymmetric Competition. An Application to the Pharmaceutical Industry*

Micael Castanheira† Carmine Ornaghi‡ Georges Siotis§
Maria-Ángeles de Frutos¶

October 20, 2017

Abstract

This paper shows that an asymmetric competition shock that leads to a steep price drop in one market segment may benefit substitute products. Consumers move away from the cheaper product triggering a *reverse competition effect*. This result is driven by non-price competition: asymmetric shocks decrease *some* firms' investment in promotion, which cripples their ability to lure consumers. We identify the conditions under which the lower priced product loses volume sales.

To assess the empirical relevance of these findings, we study the effects of generic entry into the pharmaceutical industry. We exploit a large product-level dataset for the US covering the period 1994Q1 to 2003Q4 and find strong empirical support for the model's theoretical predictions. Our estimates rationalize the observation that a molecule that loses patent protection (the originator drug plus its generic competitors) often experiences a drop in the quantity market share –despite being sold at a fraction of the original price.

JEL Classification: D22, I11, L13

Keywords: Asymmetric competition, Pharmaceutical industry, Generic entry

---

*We would like to thank Laurent Bouton, Guilhem Cassan, Christopher Cotton, Raffaele Fiocco, Margaret Kyle, Patrick Legros, Alessandro Lizzeri, Laurent Mathevet, Jacopo Perego, Régis Renault, Patrick Rey, Pablo Querubin, Tobias Salz, Fiona Scott Morton, Denni Tommasi, and Philippe Weil, as well as seminar participants at Oxford University, ECARES, the Paris School of Economics, Queen's University, Universidad Carlos III, Université de Cergy-Pontoise, Université de Lausanne, EARIE2016, and CRETE2016.

†ECARES (Université Libre de Bruxelles - SBS-EM) and CEPR. Micael Castanheira is "Directeur de recherche" FRS-FNRS and gratefully acknowledges their financial support.

‡University of Southampton

§Universidad Carlos III de Madrid and CEPR. Georges Siotis gratefully acknowledges the financial support from the Ministerio Economía y Competitividad (Spain) grants Beca I3 2006/04050/011, ECO2015-65204-P, MDM 2014-0431, and Comunidad de Madrid grant MadEco-CM (S2015/HUM-3444).

¶Maria-Ángeles passed away before being able to complete this project. We owe a lot to her inspiration and enthusiasm, and dedicate this paper to her memory.

1 Introduction

To attract customers, firms selling imperfect substitutes do not only cut prices. They also invest in non-price instruments, such as advertising and brand management. In the presence of product differentiation and *asymmetric* competition shocks, the entry of a firm or the launch of a new product will not squeeze the profit margins of all incumbents in the same manner. Some experience intense margin compression, whereas others remain comparatively shielded.

Our model shows that, if we overlook non-price competition, asymmetric and symmetric shocks always have similar effects: demand shifts towards the cheaper market segment (call it A). Instead, when we take account of the non-price dimension, asymmetric competition shocks may give rise to what we call a *reverse competition effect*.

The reason is that intense competition also cripples firm A's capacity to invest in non-price instruments. This produces an opposite shift in demand, beneficial to the more expensive product segment (call it B). Hence, when non-price instruments are an important determinant of market outcomes, and when one segment (but not the other) moves from imperfect to perfect competition, allocative efficiency can be *reduced*. This holds whether demand eventually moves towards A or towards B. Further, even when non-price instruments do not directly enter consumers' utility, their surplus may be reduced by competition. This only happens when the demand shifts strongly towards B.

This is more than a theoretical construct: using a data trove tracking prices, promotion, and quantities sold, we show that competition by generics in the trillion-dollar pharmaceutical market often fails to put effective pressure on the drugs that remain protected by a patent. Despite price drops as high as 45% for the drug experiencing generic entry, it is often the market share of *competing molecules* that increases. The *volume* market share of the molecule that is now cheaper —the originator drug *plus its chemically equivalent generic version*— drops, on average, by 31% in the pharmacy channel and by 26% for drugs sold in hospitals. As we detail below, both our theoretical and empirical findings show that, quite counter-intuitively, this phenomenon is more pronounced when molecules are close substitutes and when market size is large.

To analyze these effects formally, we propose a stylized model in which two firms, A and B, each produce a differentiated product. Consider, first, the situation in which they compete only in price. Following standard intuition, the more substitutable the goods, the lower initial prices will be. Then, firm A is confronted with the entry of a new competitor that sells a direct substitute for its product. Absent capacity constraints, this competition shock drives the price of A down to marginal cost and forces B to also react with a lower price. In this situation, "competition works as expected".

What happens when the two firms also rely on non-price instruments such as advertising to attract consumers? In this setting, the asymmetric competition shock experienced by A also induces it to cut down investment in the non-price instrument. Whenever the non-price shock dominates the price shock, B sees its residual demand expand.

Under which conditions does this *reverse competition effect* materialize? Quite surprisingly, the problem is more acute when A's and B's products are *closer substitutes*. The reason is that the more substitutable the two goods are, the more aggressively A and B compete prior to the entry of the third firm (before *generic entry* in the case of the pharmaceutical industry). This translates into initially lower prices and higher "promotion" (the non-price instrument that we can measure in our data). In that situation, generic entry has a comparatively small impact on prices; the reduction in promotion dominates. *High* levels of differentiation have the opposite effect: prices are initially high and promotion low. Then, generic entry affects primarily prices: both A's and B's prices drop.

The model also informs us on the expected effects of demand elasticity: we find that a lower price elasticity of demand increases the likelihood that B benefits from the stiffer competition faced by A. The same goes for market size: the reverse competition effect is more likely to hold in large markets because B maintains a high level of promotion.

Clearly, the pharmaceutical industry is a particular one. Yet, it is also an ideal testing ground to assess these predictions. First, we can precisely disentangle asymmetric shocks, caused by the loss of exclusivity (LoE), from the entry of new competing products. Such a clear dichotomy between the launch of new products and the loss of market power for a single product is difficult to observe in other markets. Second, non-price competition is particularly important: for large players, promotion represents 15% to 20% of total sales, about the same

as R&D.[1] Third, agency issues between patients, physicians, and insurances likely increase the sensitivity of demand to non-price instrument relative to prices, which magnifies the effects we are after. Fourth, we find that elasticities differ between hospitals and pharmacies. This allows us to test whether a lower price elasticity of demand indeed benefits B. Fifth, the market is economically relevant: worldwide sales totaled nearly a trillion US dollars in 2013, while the US market stood at 374 billion dollars in 2014.[2] Last, but not least, given the long time span between patent filling and Loss of Exclusivity (LoE), actual market size and the degree of substitutability of competing products cannot be predicted ahead of actual launch. This produces substantial exogenous variation across episodes of generic entry that we exploit in our regressions.

We start with a sample that covers all prescription sales in the U.S. between 1994Q1 and 2003Q4 (40 quarters). From that dataset, we extract all the therapeutic classes ("ATC3 markets") for which data on prices, quantities, and promotional efforts are available. We then crossed these data with that of the FDA to identify episodes of generic entry (see Section 4). This leaves us with 95 episodes of generic entry scattered over 53 different ATC3 markets.

The size of this sample allows us to exploit the (heterogeneous but always large and asymmetric) shocks to competition associated with LoE to identify the coefficients of the demand function. As shown in Section 5.1, the price-to-promotion elasticity ratio is lower in the pharmacy channel than in the hospital channel. We use this difference to test–and confirm–our theoretical predictions relating these elasticities to the evolution of market shares.

After controlling for other possible sources of heterogeneity, we find that, on average, generic entry alone causes a 12% *increase* in market share for molecules that remain on patent. The effect is smaller in the hospital channel: the higher price elasticity reduces the magnitude of this effect by about 3 percentage points. We also propose a novel measure

[1] In the *Oxford Handbook of the Biopharmaceutical Industry*, Harrington (2012) estimates the R&D to be at 17.9% of total net sales for the period 2001-2005, and Kenkel and Mathios (2012) report that the advertising-to-sales ratio was 18% in 2005 in the U.S. As points of comparison, they highlight that, in 2010, advertising stood at 4.5% of total net sales for General Motors (a car producer), 9.5% for Anheuser Busch (a beer producer) and 10.8% for Kellogg (breakfast cereals). The figures are typically smaller for most other R&D-intensive industries. For instance, in 2013, Apple spent 3% of its total net sales on R&D and 0.4% on advertising (Apple 2013: 10-K SEC submission). See also Manchanda *et al.* (2005)

[2] Source: http://www.statista.com/statistics/263102/pharmaceutical-market-worldwide-revenue-since-2001/ and http://www.statista.com/statistics/238689/us-total-expenditure-on-medicine/

of product differentiation for the pharmaceutical industry based on the number of modes of action within a therapeutic class. We argue that the existence of different modes of action to treat a particular condition is indicative of more differentiation. We find that differentiation knocks another 4 percentage points off the market share gain of the competitors. Finally, the market share gain is further reduced by 7 percentage points in "small" markets. Each of these observations is in line with the theoretical predictions sketched out above.

Related literature. Our paper is at the intersection of several literature strands, including industrial organization, advertising, and health economics. With regard to our empirical application, the existing literature on competitive interactions in the pharmaceutical industry has produced a complex, and sometimes contradictory, picture. One group of papers analyzes inter-brand competition when drugs are still patent-protected (see, for instance, Brekke and Kuhn (2006) for a theoretical model and Dave and Safer (2012) for empirics). de Frutos, Ornaghi and Siotis (2013) analyze inter-brand competition when the proportion of brand-loyal consumers is endogenously determined by promotional effort.

Another strand focuses on intra-molecular competition following loss of exclusivity — *i.e.*, when a generic bio-equivalent drug can legally come to market (*e.g.* Scott Morton (2000)).[3] It was in that context that the "generic entry paradox" has been unearthed (the paradox being that the price of the originator drug often goes up following the launch of a competing chemically equivalent generic). This empirical finding has been thoroughly documented (see *a.o.* Caves *et al.* (1991); Regan (2008); Vandoros and Kanavos (2013)).

The few papers that attempted to simultaneously analyze pre- and post-LoE competition have produced a mixed picture. For instance, Stern (1996) provides evidence of intense inter-molecular competition, whereas Ellison *et al.* (1997) reports strong intra-molecular rivalry between the originator and the generic version of the drug, as well as weak (or insignificant) inter-molecular competition.

A related literature focuses on the relative importance of the persuasive and informative roles of promotional effort (Ching and Ishihara (2012)) and on whether detailing and direct-

[3]See Grabowski and Kyle (2007) for a description of generic entry in the US in the period 1995-2005 and Berndt and Dubois (2016) for a comparison of generic penetration across OECD countries for the period 2004-2010.

to-consumer advertising have a market expansion effect (Ching *et al.* (2016); Iizuka (2004, 2005); Fischer and Albers (2010)). Another strand analyzes the effectiveness of promotional effort: Mizik and Jacobson (2004) estimate the long run effect of detailing and sampling on prescriptions for three drugs. Manchanda, Rossi and Chintagunta (2004) assess whether, from a business perspective, detailing is misallocated across individual physicians. Narayanan and Manchada (2009) show that the persuasive effect dominates at the end of a molecule's exclusivity period.

Huckfeldt and Knittel (2011) show that evergreening strategies (the launch of a second-generation product by the same originator) helps explain instances of volume market share drop of the previous generation molecule, despite being sold at a fraction of the original price. Lakdawalla and Philipson (2012) share our motivation (volume sales drop following LoE) and exploit a similar sample. The main difference lies in the fact that we explicitly model competition. This allows us to derive testable hypotheses regarding driving forces underpinning the evolution of post LoE volume market shares.

The remainder of the paper is organized as follows. Section 2 presents some unexpected facts that spur the paper's central research question. Section 3 presents the model and derives testable implications. Section 4 describes the data, while Section 5 presents the empirical results. Section 6 reports rubustness and sensitivity checks. Section 7 concludes by discussing how the presence of non-price instruments can lead to mismatch between consumers and goods when competition is asymmetric.

2 Generic competition: some empirical regularities

2.1 Price, patents, and quantities

Once on the market, the life cycle of a patent-protected pharmaceutical drug can be broken in two distinct stages. The first covers the period spanning market launch until the firm loses exclusivity, which usually stems from patent expiry. During that phase, the producing firm has exclusive rights over the production and distribution of the drug and can exercise market power. The second phase begins after loss of exclusivity (LoE), when generic equivalents can enter the market to compete with the originator firm.

The introduction of a chemically equivalent competitor produces a dramatic change in competitive conditions. Generics are typically sold at a fraction of the price of the original brand and exert strong competitive pressure on the original branded product: Grabowski *et al.* (2014) show that, for branded drugs facing first generic entry in 2011-2012, brands retained, on average, only 16% of the molecule market after one year.

Figure 1 provides another perspective on these evolutions. Lumping together the original product *and* its generic equivalents, it depicts the evolution of the mean and median price and quantity for the 95 molecules that experienced generic entry in our dataset (U.S. data for the period 1994-2003). Time is expressed in quarters, and we denote as "date 0" the quarter in which firms lose exclusivity. We normalize to 1 values at quarter -12.[4] Before patent expiration (quarters -12 to 0), the price of the original molecule is slightly increasing.

Figure 1: Price and Quantity around generic entry

[4]We control for the fact that not all molecules are observed in all quarters (for instance, if a patent expires four quarters before the end of the data, we have only four data points after patent expiration) by: i) computing the price change over two consecutive periods for all available molecules; ii) computing the average of these variations for each quarter before and after patent expiration; and iii) constructing an index that starts at 1 and that varies over time following the average variations computed at stage (ii). We follow the same approach to compute the median price and all the other statistics in this graph.

Then, within a year of the loss of exclusivity (LoE), mean (respectively, median) prices drop by about 30% (20%). Within three years, the drop reaches about 50% (40%).[5]

As Figure 1 makes clear, despite being sold at a fraction of the original price, the *genericized molecule actually experiences a drop in volume* after LoE (black curves): the average and median quantities drop by more than 25% three years after patent expiry. In other words, after LoE, the *combined* volumes of the branded and generic producers are substantially below the volume of the single branded drug when it is sold at a price embodying monopoly power.

As our econometric analysis below shows, this means that generic entry mainly benefits *competing* molecules. This despite the fact that the latter barely adjust their prices. Put differently, few new patients are directed to the cheap genericized molecule, and a number of existing patients switch to competing molecules at the time that their initial treatment becomes cheaper. Neither the rationales for the so-called *generic entry paradox* (*cf.* footnote 5) nor Third Party Payer reimbursement rules can explain why cross-price elasticities suddenly seem to take the "wrong sign".

2.2 Loss of exclusivity and promotion intensity

Turning to non-price competition, Figure 2 shows that LoE also triggers a major drop in the firms' promotional effort (we will use the terms *detailing, promotion* and *advertising* as synonymous). Using data from IMS-Health, we measure the firms' drug-specific spending on personalized visits to general practitioners and hospital specialists, free samples dispensed to physicians, and advertising in professional journals. All these instruments affect the physicians' incentives to prescribe one drug rather than another. The data reveal that promotion falls continuously over the 12-quarter period before patent expiration, with a sharp acceleration around the time of LoE. At time 0, promotion effort has dropped by 50%. Four quarters

[5] Although the *average price of the molecule* (displayed) falls following generic entry, this is not always the case for the price of the branded drug (not separately depicted in Figure 1). Sometimes, the latter remains constant or even *increases*; this is the so-called *generic entry paradox* (for empirical evidence, see Regan (2008) for the U.S. and Vandoros and Kanavos (2013) for the EU). This behavior is usually attributed to the fact that a subset of patients insist on purchasing the brand, even at a higher price. This allows branded producers to keep extracting rents on a (shrinking) subset of patients.

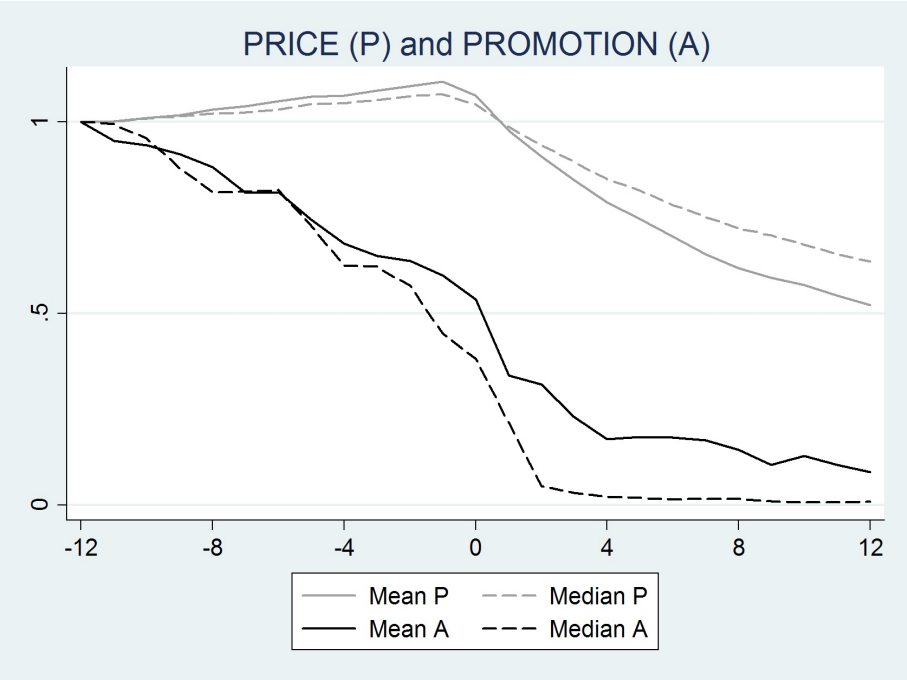

Figure 2: Price and Promotion around generic entry

later, the median drop is close to 95%. At 12 quarters after LoE, median spending is zero.[6]

The fact that price and promotion pull demand in opposite directions was already emphasized by Caves, Whinston and Hurwitz (1991), who observed that "*generic entry brings with it two offsetting effects: first, generic entrants offer significantly lower prices, which tend to expand overall sales of the drug, but their arrival also leads to a significant reduction in the level of advertising for the drug, which acts to counterbalance this price effect*". However, they did not explore the matter further, either theoretically or empirically.

Posterior empirical results have confirmed that total molecule sales can increase or decrease after LoE. Berndt *et al.* (2003) and Lakdawalla *et al.* (2007) find that the market share of the molecule losing exclusivity experiences a fall. Aitken *et al.* (2009, 2013) find the opposite. Duflos and Lichtenberg (2012) find that "the net effect of patent expiration on drug utilization is zero".

[6]The average lies above the median because some molecules continue to be promoted. For instance, high levels of promotions are observed for Prozac (fluoxetine) because Eli Lilly & Co. introduced weekly delayed release capsules of the drug just before LoE in an attempt to stem the post-patent decrease in sales of their daily dosage. Similarly, we observe positive spending for Zantac (ranitidine) and Tagamet (cimetidine), probably because some of their lower-dosage tablets are available over-the-counter (no prescription required).

While it is intuitive that either of two opposite forces may dominate, the literature falls short of explaining when and why one or the other outcome should materialize. Our analysis of asymmetric competition shocks fills this gap: we can identify the precise market structures for which companies' advertising strategy will produce a drop in total volume sales of the molecule losing exclusivity, and the complementary set of parameters that will lead to an increase. We can then test these theoretical implications on pharmaceutical data. The results allow us to attribute these differing evolutions to firms' pricing and promotion strategies.

3 The model

To analyze the effects of asymmetric competition shocks, we propose to build on a textbook model of differentiated Bertrand competition with advertising. That is, (1) initially, two firms sell differentiated products and compete through price and non-price instruments. In contrast with the standard textbook approach, we consider (2) competition shocks that are highly asymmetric: the new entrant is a perfect substitute for *one* good in an otherwise horizontally differentiated industry. (3) In the spirit of Inderst and Ottaviani (2012), consumer decisions are mediated through intermediaries who can be persuaded to modify their purchasing recommendations. In our framework, however, this is only relevant for the normative analysis: realized consumption decisions may differ from those that would maximize the utility of the final consumer.

Formally, two firms, A and B, compete both in prices and in "advertising," or some other type of fixed cost investment that stimulates demand. Starting from that initial situation, we study the effects of the entry of a third firm, G, that produces a perfect substitute for firm A's product? Intuitively, substitutability implies that A's advertising effort produces a positive spillover on G's demand (the way that a brick and mortar store's advertising for a given product also stimulates online demand for the same product). Under these circumstances, competition between A and G causes both the price and advertising effort of A to drop substantially. Our central question is: what happens to the demand for B?

Shifting to a terminology adapted to the pharmaceutical industry, consider a market in which two firms' molecules compete for physicians' prescriptions. We derive the firms'

promotion and *pricing* strategy given the quality θ_J of their molecule, the heterogeneity of treatment responses across patients, e,[7] and the agents' sensitivity to price, δ.[8]

Consider the case of a patient who goes to her physician with a condition that requires treatment. The intrinsic utility of the Patient-Physician-Payer triplet ("P3" henceforth)[9] i's from using treatment A or B is, respectively (we introduce detailing below):

$$U_A^i = \theta_A - \delta p_A + \varepsilon^i, \quad (1)$$

$$U_B^i = \theta_B - \delta p_B - \varepsilon^i, \quad (2)$$

where p_J is the price of molecule $J \in \{A, B\}$; $\varepsilon^i \sim \mathsf{U}\left[-\frac{e}{2}, \frac{e}{2}\right]$ is the relative efficiency of drug A as opposed to B to treat patient i's condition; and U denotes the uniform distribution.[10] A larger value of e implies that patients are more heterogeneous in their response to treatments A and B, and hence that the two molecules are *more distant substitutes*. δ accounts for the triplet's (P3) sensitivity to price.

Note that assumptions such as the linearity of the demand schedule and the uniform distribution of patients would be inappropriate if we were to estimate the model structurally. However, we do not have individual consumption or prescription data (see Section 4), and our questions are rather orthogonal to the ones that structural estimations are meant to address. We thus choose to simplify the model to focus on the market shares of each molecule and, in Section 5, carry out the empirical analysis on the same market variables to test the model's main predictions.

Focusing on market shares, we let patients with a sufficiently good fit with drug A (*i.e.*,

[7] These parameters directly relate to vertical and horizontal product differentiation in classical Industrial Organization analyses. However, product differentiation is not a choice variable in our model.

[8] This model specification fits the industry's description provided by Berndt (2002): "Within many therapeutic classes of drugs, a number of possible substitute medications exist, and in such cases, the market structure is more appropriately depicted by the differentiated product oligopoly framework. In such a setting, it is useful to envisage the optimal profit maximizing price as equaling marginal cost plus a positive margin, where the margin depends on benefits and attributes (including prices) the firm's own drug relative to other drugs in the therapeutic class, on attributes of non-drug therapies, patient heterogeneity and other demand-side considerations."

[9] The "payer" can either be a Third Party Payer (TPP), patient out of pocket expenditure, or a combination of both.

[10] Focusing on a single random variable ε that can be either positive or negative implicitly eliminates patients with negative valuations of the two molecules, who have no reason to consume either of the two drugs. Thus, issues of aggregate under- or over-prescription are beyond what this model can capture.

with ε^i sufficiently positive) buy treatment A, and all the others buy drug B.[11] Letting μ denote market size (or the number of afflicted patients), we identify the patient i who is indifferent between A and B to determine quantities in the absence of detailing:

$$\begin{aligned} Q_A &= \left(1 - F\left[\frac{\Delta\theta_B - \delta\Delta p_B}{2}\right]\right) \times \mu \\ Q_B &= F\left[\frac{\Delta\theta_B - \delta\Delta p_B}{2}\right] \times \mu, \end{aligned}$$

where F represents the CDF of ε^i, $\Delta\theta_B \equiv \theta_B - \theta_A$, and $\Delta p_B \equiv p_B - p_A$. We associate drug A with the oldest molecule, while B is more recent: firm A loses exclusivity before B. For the sake of the argument, we focus on the case $\Delta\theta_B \geq 0$, since more recent drugs (here: B) are expected to be more effective than older drugs (here: A). However, all the results extend to the complementary case of $\Delta\theta_B < 0$. Thus, when they *cannot promote their drugs* (superscript ND for the "No Detailing" case), the two firms' respective profits are:

$$\pi_A^{ND} = p_A \times \left[\frac{1}{2} - \frac{\Delta\theta_B - \delta\Delta p_B}{2e}\right] \times \mu, \tag{3}$$

$$\pi_B^{ND} = p_B \times \left[\frac{1}{2} + \frac{\Delta\theta_B - \delta\Delta p_B}{2e}\right] \times \mu, \tag{4}$$

where the terms between brackets are, respectively, the market shares of A and B when we substitute for the value of F under the uniform distribution.[12]

Generic Entry. This setup describes a duopoly market: each firm's patent gives it

[11] This model specification assumes that all the patients who require a treatment receive one (full market coverage). This requires that the quality θ_J of both molecules is sufficiently high relative to the equilibrium prices–formally, $\theta_A + \theta_B > 2e$ (see Appendix 1). To capture incomplete coverage, we used another model specification that adds the distribution of willingness to pay ω^i into the utility function:

$$U_A^i = \theta_A - \delta p_A + \varepsilon^i + \omega^i, \text{ and } U_B^i = \theta_B - \delta p_B - \varepsilon^i + \omega^i.$$

Solving for the demand for, say, A, then shows that Q_A in equation (3) must be multiplied by: $\left(1 - F_\omega\left(\delta p_A - \theta_A - \frac{\Delta\theta_B - \delta\Delta p_B + e}{4}\right)\right)$ in the simple case where the distribution of ω is also uniform. This term captures the market contraction/expansion effects of higher/lower prices. This does not affect the substance of our analysis of market *shares*. Since we do not have a strong case as to whether there is initially under- or over-provision of drugs, we decided not to incorporate these effects in the model: they make the analysis a lot less tractable, for little benefit.

[12] Formally:

$$F(\varepsilon) = \begin{cases} 0, \forall\varepsilon < -e/2 \\ \frac{\varepsilon + e/2}{e} = \frac{1}{2} + \frac{\varepsilon}{e}, \forall\varepsilon \in [-e/2; e/2] \\ 1, \forall\varepsilon > e/2. \end{cases}$$

and the PDF is $f(\varepsilon) = 1/e, \ \forall\varepsilon \in [-e/2; e/2]$.

exclusivity for the sale of its molecule. Here, we turn to the effects of A losing that exclusivity (LoE), while firm B retains its patent protection and monopoly power

The first case we study is the one in which there is *no detailing.* In the absence of detailing, an equilibrium is characterized by a pair of prices in which firms maximize profits in $(3)-(4)$. Loss of exclusivity implies that chemically equivalent generics can compete directly for A consumers. Based on the evidence (see *a.o.* Grabowski *et al.*, 2014), we let competition among generic producers reduce the price of A down to marginal costs, which we normalize to zero without loss of generality.

The post-generic-entry equilibrium is then characterized by the price that maximizes B's profits when $p_A = 0$. Unsurprisingly, the results in Appendix 1 show that generics competition for the A market can only drive down the price and market share of drug B. We also find that, in an interior equilibrium, price sensitivity determines the magnitude of the price reduction, but does not influence market shares.

Promotion. As discussed in the introduction and in Section 2.2, the pharmaceutical industry stands out for its high promotional intensity. Through their *detailing and sampling* activities, pharmaceutical companies devote substantial resources to inform physicians and provide them with a number of perquisites, sometimes contingent on their prescription behavior. This non-price competition component is also dramatically modified upon generic entry: price competition amongst producers brings detailing down to 0.

We assume that promotion is *persuasive*: it stimulates prescriptions without affecting the patient's intrinsic utility $(1)-(2)$ nor bringing fresh information to doctors. As we discuss below, this reflects the situation at the end of a molecule's life cycle.

Formally, when firm J spends $C(a_J) \equiv a_J^2/2$ on detailing, it produces an autonomous increase in the demand for drug J from θ_J to $\theta'_J = \theta_J + a_J$. Given an action profile $\{a_A, a_B, p_A, p_B\}$, the resulting demands are then:

$$\begin{aligned} Q_A^D &= \left(1 - F\left[\frac{\Delta\theta_B + \Delta a_B - \delta\Delta p_B}{2}\right]\right) \times \mu, \\ Q_B^D &= F\left[\frac{\Delta\theta_B + \Delta a_B - \delta\Delta p_B}{2}\right] \times \mu, \end{aligned}$$

where superscript D denotes *Detailing* and $\Delta a_B \equiv a_B - a_A$. The firms' profits become:

$$\begin{aligned}
\pi_A^D &= p_A \times \left[\frac{1}{2} - \frac{\Delta\theta_B + \Delta a_B - \delta\left(p_B - p_A\right)}{2e}\right] \times \mu - \frac{a_A^2}{2}, \\
\pi_B^D &= p_B \times \left[\frac{1}{2} + \frac{\Delta\theta_B + \Delta a_B - \delta\left(p_B - p_A\right)}{2e}\right] \times \mu - \frac{a_B^2}{2}.
\end{aligned}$$

Discussion of the main assumptions. We made two important assumptions. First, patients do not observe the relative importance of price and promotion in determining their physician's prescription decision. The fact that both prices and promotion may influence prescription behavior is well grounded in facts, and the purpose of the theoretical model by Inderst and Ottaviani (2012), who study how commissions and kickbacks –and the consumers' information about them– influences eventual market outcomes and welfare. Iizuaka (2012) provides evidence that physicians respond to economic incentives in their prescription decisions. The association between payments to physicians and their prescription behavior can also be assessed on the basis of publicly available data (Grochowski, Jones, and Ornstein (2016), Greenway and Ross (2017), and JAMA (2017)). Second, we treat promotion as persuasive. In the context of our paper, the underlying assumption is that the informative component is more relevant earlier in a molecule's life cycle, while the persuasive dimension dominates around LoE, which is the time window we focus on. This is supported by Hurwitz and Caves (1988) and Rizzo (1999), who provide extensive evidence pertaining to the persuasive nature of pharmaceutical detailing, and by Narayanan and Manchada (2009, p. 437), who report that the informative component becomes dominated by the persuasive effect as time passes.

3.1 Equilibrium before generic entry

Before generic entry, each P3 has a choice between two branded molecules. Each firm chooses its price and promotion intensity to maximize its profits. Taking first-order conditions yields the implicit solutions:

$$p_J^D = \frac{2e}{\delta}\frac{Q_J}{\mu}, \tag{5}$$

$$a_J^D = \frac{Q_J}{\delta}. \tag{6}$$

This, in turn, implies:

Result 1 *The price p_J^D is increasing in the molecule's market share (Q_J/μ), and promotion intensity a_J in quantity Q_J. Both are decreasing in the P3's price sensitivity δ.*[13] *Moreover, prices (but not promotion) are increasing with the degree of "horizontal differentiation" e.*

In Appendix 2a, we test this result on our data. We find that prices, promotion and market shares co-move positively, as Result 1 predicts. Importantly, however, this requires proper instrumentation to control for the confounding influence of the demand side of the ledger that affects the raw correlation between prices and market shares. We interpret this result as a confirmation that our theoretical model, even if very simple, does capture the main features of the nature of competition between large pharmaceutical companies.

In Appendix 2b, we analytically show that, when the two molecules are closer substitutes (smaller e), the market share of the superior drug decreases towards 50%, because firm B invests less in promotion, whereas A invests more. Conversely, a larger market size (μ) magnifies the gap between B and A: with higher potential profits, B invests in promotion more aggressively and, hence, increases its market share.

3.2 The effects of generic entry

After LoE, generic entry drives the price of molecule A to $p_A = 0$, and the dissipation of profits produces a drop in detailing: $a_A = 0$. As a consequence, firm B's post-entry profit function becomes:

$$\pi_B^G = p_B \times \left[\frac{1}{2} + \frac{\Delta\theta_B + a_B - \delta p_B}{2e}\right] \times \mu - \frac{a_B^2}{2}.$$

Where superscript G stands for *Generics*: firm B, which still benefits from market power, faces stiffer price competition but looser non-price competition from molecule A. We find:

Proposition 1 *For $Q_A^D, Q_A^G > 0$, the loss of exclusivity on molecule A allows B to* ***increase*** *its market share, promotional effort, and price iff $2\delta e < \mu$.*

[13] This result is in line with, *e.g.*, de Frutos *et al.* (2013) or Brekke and Khun (2006), who write that "*detailing, DTCA and price (if not regulated) are complementary strategies for the firms. Thus, allowing DTCA induces more detailing and higher prices.*" Similarly, Grossman and Shapiro (1984) find that more competitive markets reduce both prices and advertising in a model in which the purpose of advertising is to inform consumers of a product's existence.

Proof. *From Propositions 2 and 3 in Appendix 2, it is relatively straightforward to show that* $Q_B^G - Q_B^D$, $a_B^G - a_B^D$, *and* $p_B^G - p_B^D$ *are all a multiple of* $(2\delta e - \mu)(\delta(\Delta\theta_B - 3e) + \mu)$, *where the second factor is negative whenever* Q_A^D *is positive (see proof of Proposition 2).* ■

It is striking that it is precisely when A and B are closer substitutes (e small enough) that stiffer price competition by the generic versions of A ends up benefiting B. Conversely, only if the two molecules are sufficiently distant substitutes or if market size μ is small, will price competition have the (*a priori* expected) effect of boosting the sales of molecule A.

The rationale for this result stems directly from firm A's pre-LoE behavior: we show in Proposition 2 that, in the pre-generic entry equilibrium, $p_J^*/a_J^* = e/\mu$. Thus, when market size is large and/or the two firms sell close substitutes, A invests comparatively a lot in promotion and/or keeps its price low. As a consequence, generic entry substantially loosens non-price competition (a_A drops from that comparatively high level down to 0) and have a comparatively smaller effect on price (p_A dropping from that comparatively low level to 0). Conversely, when market size is small and A and B are distant substitutes, competition is initially lax (*i.e.*, prices are comparatively higher and promotion lower). In that case, generic entry produces a stronger price drop in comparison to promotion, which dents the demand for B, and forces the latter to react by adopting a more aggressive pricing strategy. Proposition 1 allows us to derive the following:

Testable implication 1 *Generic entry should produce lower gains in market share for* B *in markets where price sensitivity* δ *is higher.*

Testable implication 2 *Generic entry should produce larger gains in market share for* B *in markets where horizontal differentiation* e *is lower.*

Testable implication 3 *Generic entry should produce larger gains in market share for* B *in larger markets.*

The equilibrium outcome whereby close substitutes are most heavily promoted in large markets fits nicely with one observation. Based on Donohue *et al.* (2007), who identify the products most heavily advertised through Direct to Consumer Advertising (DTCA), Kenkel

and Mathios (2012) note that a "striking feature of the US Top 20 list was the number of competing products for the same medical condition." In New Zealand, the other country where DTCA is allowed, the composition of the Top 20 list was different: only four drugs appeared on both countries' lists. This is due to reimbursement rules: in New Zealand, only one product per therapeutic class is subsidized (hence, it makes little sense to advertise the non-subsidized product). There is, however, one condition–erectile dysfunction–for which New Zealand's Pharmaceutical Management Agency (Pharmac) does not subsidize *any* drug. This is also *the* exception in the respective Top 20 lists: contrary to the other product categories, two close substitutes, Viagra and Cialis, are heavily advertised in *both* countries.

In Appendix 3, we extend the model to study allocative efficiency and patient surplus (when the patient does not value promotion directly). First, we find that asymmetric generic entry *never* improves allocative efficiency: the market share of B increases when it is already too large compared to the first best, and it decreases when it is already too low prior to LOE. In other words, the asymmetric shock always distorts the market allocation farther away from the first best. Banning promotion overall would not solve this issue: the results are identical in the absence of promotion. The reason is that the highest quality drug tends to be sold at a higher markup, and generic entry reduces the price of only one molecule, generating inefficient, lopsided competition.

The second result in Appendix 3 aims at evaluating when generic entry increases or decreases *consumer (patient) surplus*. Based on the logic of Inderst and Ottaviani (2012), we acknowledge that promotion influences the behavior of the intermediary (the physician) whereas consumer surplus requires using the utility functions (1) and (2). This implies that promotion does *not* enter directly in the definition of consumer surplus.

We find that the effect of generic entry on consumer surplus varies on a case-by-case basis: even though allocative efficiency worsens, patients benefit from the lower prices of A and, in some cases, of B. We identify that a drop in Q_B is a *sufficient* condition for patients' utility to increase. Conversely, for $\Delta\theta_B = 0$, consumer surplus decreases only if the market share of B increases strongly. We return to these points in the conclusion, once we have assessed actual market responses in the data.

4 The Data

Markets, sub-markets, and product differentiation

We started from a dataset covering quarterly dollar revenues and physical quantities for hundreds of branded and generic prescription drugs sold in the U.S. in virtually all therapeutic areas over the 40-quarter period 1994q1 to 2003q4. These have been obtained from the proprietary database IMS-Health, one of the most important medical-information providers (IMS-MIDAS). All the drugs in IMS-Health are classified according to the Anatomical Therapeutic Chemical (ATC) classification system. The ATC3 level corresponds to a market: it groups the drugs that target a given condition.

In the IMS data, generics have the name of the active ingredient. We thus compiled an initial list of ATC3 markets with generic entry by selecting the markets where some of the drug names are the same as the molecule (*e.g. Fluoxetine* is the active ingredient of *Prozac*, as well as the name of its generic competitors). We double-checked and completed this list with information about LoEs from the FDA and other resources. We then contacted IMS-Heath to obtain drug-level information on promotion expenditure for the selected therapeutic markets, as well as other important ATC3 markets in terms of sales.

Information on promotion was not available for some markets. In spite of this, the final sample we assembled for the empirical analysis includes 53 different ATC3 markets: an unusually rich dataset compared to previous studies on the pharmaceutical industry.

Table 1 shows some descriptive statistics for the 53 markets and related molecules. Our final sample includes 227 drugs initially covered by patent protection, 95 of which lost patent protection between 1994 and 2003. Forty-five of the 53 selected markets experienced the entry of at least one new generic molecule during the observed time window, with one market experiencing six LoEs.

The 53 ATC3 therapeutic areas are further subdivided into ATC4 sub-classes which correspond to different modes of action to treat the same pathology. The complete list of ATC3 markets and ATC4 sub-classes we use in the empirical analysis can be found in Appendix 4. The list includes the most important therapeutic areas, such as lipid regulators, antidepressants, anti-ulcer drugs and hypertension drugs.

Market Descriptive Statistics		**Molecule Descriptive Statistics**	
# ATC3	53	# molecules	227
# ATC4	75	# LoE	95
#Gen. entries	**#Markets in sample**	**#ATC4 in ATC3**	**%age obs'ns**
0	8	1	56.8%
1	22	2	20.2%
2	8	3	13.3%
3	8	4	4.3%
4	3	5	3.7%
5	3	6	1.7%
6	1		
Total:	53	**Total:**	100%

Table 1. Therapeutical Markets, Molecules and Generic Entry

For illustrative purposes, Table 2 reports the list of (plain) lipid regulators for the main two ATC4 subclasses of the ATC3 anti-cholesterol market: statins and bile acid sequestrants.[14] The former has six competing molecules, while the latter has four. Thus, in total, there are up to ten different prescription possibilities for a patient with excess cholesterol. The last column identifies either the quarter in which the drug lost its patent protection (4th quarter of 2001 in the case of Mevacor, for instance) or the date on which the company decided to withdraw the molecule from the market (lethal secondary effects triggered the early withdrawal of Lipobay in 2001).

We use of the structure of these ATC3 markets and ATC4 sub-markets to develop a measure for the degree of horizontal differentiation (e). Since each ATC4 therapeutic sub-group corresponds to a *mode of action* to treat a pathology group identified by the ATC3 level, we conjecture that the higher the number of ATC4 sub-groups in an ATC3 market, the more differentiation there is.[15] We therefore define MoA (for *Modes of Action*) as the

[14]Statins (C10A1) lower cholesterol levels by inhibiting the enzyme HMG-CoA reductase, which plays a central role in the production of cholesterol in the liver. Bile Acid Sequestrants (C10A3) increase the elimination of bile acids which the liver can replace only by converting cholesterol, thus reducing its level in the blood. Note that there are other ATC4 groups in the therapeutic market C10A, such as Fibrates (C10A2). Although we observe quantities and prices for Fibrates, we have promotional data only for the most important ATC4 markets. In fact, quarterly sales of Fibrates in 2000 were around ten million dollars compared to quarterly sales of more than a billion dollars for Statins.

[15]Dubois and Lasio (2017, Table 6) managed to estimate cross-price elasticities for each pair of molecules in one ATC3 market. They do report high cross-price elasticities within an ATC4 market, and close to zero elasticities across ATC4 sub-markets

number of ATC4 sub-groups in each ATC3 market, minus 1. That is, for each drug, we identify the number of rival modes of action to treat the same pathology.

Price, Market Share, and Promotion

For each of the drugs included in the selected markets, we compute deflated revenues (R) by dividing nominal value of sales by the producer price index for the pharmaceutical industry published by the Bureau of Labor Statistics. Quantities (Q) are reported in standard units that represent the number of dose units sold for each product; this corresponds to one capsule or tablet of the smallest dosage or five milliliters of a liquid (*i.e.*, one teaspoon). Standard units allow comparison across different drug forms and dosages, as all different packages are subsumed into the same unit of observation. We then compute the average price of a molecule (P) by dividing R—*i.e.*, the revenues for all the different packages—by total Q.[16] An important feature of our data is that we observe R and Q for two different distribution channels: hospital (HO) and pharmacies (PH).

Promotional data include three main components: visits to office-based practitioners and hospital specialists (*aka* "detailing"); free samples dispensed to physicians (their cost being estimated as the sales price of the drug); and advertising in professional journals. IMS Health data on detailing are constructed using a representative panel of physicians who track

ATC3 class	ATC4 class	Description	Molecule Name	Brand Name	Patent Expiry
C10A	C10A1	Statins	Atorvastatin	Lipitor	
			Cerivastatin	Lipobay	withdrawn 2001
			Fluvastatin	Lescol	
			Lovastatin	Mevacor	2001q4
			Pravastatin	Pravachol	
			Simvastatin	Zocor	
C10A	C10A3	Bile Acid Sequestrant	Colestipol	Colestid	
			Cholestyramine	Questran	1996q3
			Aspartame+ colestyramine	Prevalide	
			Colesevelam	Welchol	

Table 2. Classification of Anti-cholesterol Drugs

[16]This produces a price per standard unit. Note that our empirical specifications control for unobserved differences, such as quality and Defined Daily Dose (DDD), across molecules.

their contacts with sales representatives. The amount spent on free samples is based on a panel of approximately 1200 office staff members in medical practices, while expenditures on advertising in professional journals are computed by tracking ads placed in approximately 400 medical journals and then adding the publisher's charge for those ads. The empirical analysis assumes that promotion to office-based practitioners affects sales in pharmacies, while promotion to hospital physicians affects the use of drugs in hospitals.

The promotion level used in the demand specifications reported in Section 5 is computed with the perpetual inventory method, commonly used for physical capital:

$$A_{it} = (1 - \rho)\ A_{it-1} + I_{it},$$

where I_{it} is the quarterly expenditure in promotion retrieved from IMS, and ρ is the quarterly depreciation rate, assumed to be 0.1–*i.e.*, about 35% per year.[17]

Table 3 reports descriptive statistics for these variables, distinguishing between hospitals and pharmacies. Note that competitors' promotion refers to the sum of the promotion of all other drugs in the ATC3 market, each computed according to the equation above. At the same time, the competitors' price refers to the average price of all the other molecules in the market, including generics, and it is computed as the ratio between total revenues and total quantities in the ATC3 market, after subtracting the revenues and quantities of drug i.

Variables	**Channel**	**Mean**	**SD**	**Min**	**Max**
Market Shares	Hosp	0.117	0.173	0.01	1
	Phar	0.134	0.183	0.01	1
# Competitors	Hosp	13.2	8.17	0	46
(other Molecules)	Phar	12.1	6.62	0	41
Own Price	Hosp	16.73	70.31	0.02	902.8
	Phar	16.78	71.23	0.05	910.1
Own Promotion	Hosp	3269	8101	0	59469
	Phar	11165	24592	0	198027
Competitors' Price	Hosp	8.86	28.32	0.02	197.29
(average price in ATC3)	Phar	4.15	15.19	0.02	122.13
Competitors' Promotion	Hosp	16315	37402	0	231144
(total promotion in ATC3)	Phar	55871	124654	0	891515

Table 3. Summary Statistics

[17] All the results reported in Section 5 are robust to setting $\rho = 0.25$.

To get an initial grasp of the differences between hospitals and pharmacies, the upper part of Table 4 shows that the average quantity dispensed in pharmacies is three times as high as in hospitals. The bottom part reports two different statistics for the drop in volume market shares following generic entry:[18] i) the simple average and ii) the average where each molecule has been weighted by the advertising intensity of competitors in the same ATC3. Table 4 suggests that quantity drops observed after LoE are more pronounced in pharmacies and in markets in which promotion is more prevalent. We will exploit these dimensions of heterogeneity in the econometric analysis.

Distribution of $Q_{PH}/(Q_{PH}+Q_{HO})$		
Mean	0.75	
Median	0.86	
Percentage Change in Market Shares	*PH*	*HO*
Simple Mean	-0.31	-0.26
Weighted by Drug-A Sales	-0.36	-0.25
Weighted by ATC3 Promotion	-0.40	-0.35
Drop in Price (%)	-0.44	-0.45
Drop in Advertising Flow (%)	-0.89	-0.85

Table 4. Distribution: Pharmacists (PH) & Hospitals (HO)

5 Empirical Analysis

In this section, we first estimate the demand equation for prescription drugs still covered by patent protection (Section 5.1). We find that demand behavior matches the main hypotheses underlying the model and that the elasticity of demand with respect to both a company's and its competitors' price and promotion are large and significant. Then, Section 5.2 empirically assesses the model's *testable implications*. We confirm that the heterogeneous patterns found in the data are largely explained by the predictions of the model. The caveat is that, while Proposition 1 makes predictions about market shares, prices, and promotion, we had to focus the empirical analysis on market shares. The reason is that identification is weak with regard

[18] The changes are calculated based on the evolution between three years before and after patent expiration. When patent expiration is either closer to the beginning or to the end of the sample period 1994Q1-2003Q4, we take the first (last) available observation for the pre-expiration (post-expiration) period.

to the other variables, and the results (available upon request) were rarely significant–this may be due to more important measurement errors for prices and promotion.[19]

5.1 Demand prior to LoE: hospitals and pharmacies

We start our empirical analysis by evaluating the parameters of the demand for branded drugs. This allows us to assess the relative importance of promotion separately for the hospital and the pharmacy channel. Since we focus on the pre-LoE period, we estimate demand using an unbalanced panel of active ingredients until one quarter before LoE.[20] This means that all firms in this subsample face competition only from imperfect substitutes (that can be generic or branded).

We estimate the elasticity of a given branded drug's market share with respect to its own price and promotion effort, as well as the cross-elasticities for competing drugs. We use this simple econometric framework as opposed to other models of differentiated products demand – *e.g.* Almost Ideal Demand System, nested logit or random coefficient models in the spirit of Berry *et al.* (1995) – for different reasons. First, we do not have consumer-level purchase data nor do we observe product characteristics that have a straightforward economic meaning (unlike engine horsepower, a 10mg dosage is not necessarily superior to a 5mg one). Recall that our aim is to understand how (own and cross) price elasticities compare to promotion elasticity across a large sample of branded drugs, several of which are in their final years of patent protection. It is *not* to retrieve price-cost margins, or to carry out merger simulations. Second, empirical results (not reported here) suggest that the competitive constraints that drugs exercise on each other vary with exclusivity.[21] In that context, it would make little sense to fix the nest structure *a priori*.

Defining a market as a given ATC3 group, equation (7) describes the P3s' demand for a particular molecule i at time t. In this and all the other estimations reported in the remainder

[19] We thank Fiona Scott Morton for drawing our attention to the acuteness of this issue.

[20] The results reported below have been obtained with quantity market shares (relative quantity in the ATC3 market) as the dependent variable. The results with (absolute) quantity as the dependent variable are similar and available upon request. Our preference for relative quantity is that most of these markets are growing in both value and volume.

[21] This could explain the somewhat conflicting results among papers that empirically analyse both inter- and intra-molecular competition (*e.g.* Stern 1996 and Ellison *et al.* 1997).

of this paper, errors have been clustered at the ATC3 level.

The demand equation is estimated in first-differences in order to remove all time-invariant, drug-specific fixed effects, such as quality differences:[22]

$$\begin{aligned} \Delta ms_{i,t} \;=\; & \alpha_0 + \alpha_1\ \Delta p_{i,t} + \alpha_2\ \Delta p_{-i,t} + \alpha_3\ \Delta a_{i,t} + \alpha_4\ \Delta a_{-i,t} \\ & + \alpha_5\ GEN_{-i,t} + \alpha_6\ NbComp_{i,t} + \alpha_7\ TE_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $\Delta ms_{i,t}$, $\Delta p_{i,t}$ and $\Delta a_{i,t}$ respectively refer to the quarterly growth of the quantity market share, price, and promotion effort of branded drug i in the ATC3 market (to repeat, our unbalanced panel includes molecules i until one quarter before LoE). Similarly, $\Delta p_{-i,t}$ and $\Delta a_{-i,t}$ are the competing molecules' evolution of prices and promotion in the same ATC3 market (the products in $-i$ may either be branded or generic). All of these variables are in logarithms, implying that the coefficients can be interpreted as elasticities. $GEN_{-i,t}$ is the number of these competing molecules in the ATC3 market that lost exclusivity during the observed time period. We do *not* expect it to be significant: according to our hypotheses, generic entry affects demand only through its effect on prices and promotional effort. The variable $NbComp$ is the number of competing molecules present on the market (be they protected or genericized). Hence, this regressor captures the launch of new molecules in the market. Finally, the variable $TE_{i,t}$ (Time to Expiration) counts the number of quarters left to patent expiration, to account for the impact of the drug's life cycle on demand.[23]

The regressors are likely affected by two different problems. The first one is that feedback from market-share shocks to future prices and advertising may produce endogeneity issues (reverse causality). The second problem is errors in the measurement of both prices and promotion effort. The price actually paid may differ from the price we observe in the IMS database because the latter does not reflect off-invoice ex-post rebates that pharmaceutical companies grant to large buyers in return for some performance component, such as reaching a target volume of sales (see Berndt (2012)). Errors in the measurement of promotion effort stem from the difficulty to observe and quantify monetarily the work of sales representatives

[22] Results using FE are qualitatively similar, but we could not identify a set of instruments that simultaneously pass the relevant tests for under-identification/weak-identification and the Hansen J test for the exogeneity (orthogonality) of the instruments.

[23] We use negative values so that the variable is increasing as we approach patent expiration. For instance, -10 and -1 refer, respectively, to ten quarters and one quarter before LoE.

when they visit physicians. Both measurement errors are likely to create an attenuation bias when estimating (7) using OLS.[24]

To address these two problems, we instrument prices and advertising with: the number of packages (linear and squared);[25] the average price of drugs sold by firm i in quarter t in other ATC3 markets ("Hausman" instruments); and a dummy indicating whether a branded drug has experienced the entry of a generic competitor before LoE, following a successful "Paragraph IV" challenge.[26] This choice of instruments is validated by the Kleibergen-Paap rk-statistic (K-P) for under-identification, the Angrist-Pischke (A-P) F-test for weak instruments, the Hansen J-test for the orthogonality conditions, and the C-statistic to test the exogeneity (endogeneity) of one or more instruments (regressors).[27,28]

[24] In the words of Griliches and Hausman (1986), "Errors of measurement will usually bias the first difference estimators downward (toward zero) by more than they will bias the within estimators." This problem has been largely discussed in the empirical literature on the estimation of production function (see Griliches and Mairesse (1995), among others). It is not by coincidence that the estimation of the demand elasticity to promotion is affected by the same problem of the elasticity of production with respect to capital. In fact, in both cases, econometricians need to construct a measure of "effective stock" looking at account data on past and present expenditures on physical capital or promotional effort.

[25] The number of packages has been used by Chaudhuri, Goldberg and Jia (2006) and Branstetter, Chatterjee and Higgins (2014), among others. The variable is related to the average price p, as variations in p stem in part from variations in the set of packages available in each period. First-stage results show that this variable is also highly correlated with promotion. This is because the introduction of a new posology or delivery mode is often accompanied by a resurgence in promotional effort. For instance, Ely Lilly started a huge marketing campaign to promote Prozac Weekly, a once-weekly formulation of Prozac. Another example is Paxil CR, a controlled-release version of Paxil. Other examples abound.

[26] Paragraph IV of the Hatch-Waxman Act allows generic manufacturers to attempt to enter the market before patent expiration of the original branded drug, either by claiming non-infringement or invalidity of the branded product's patent. A successful Paragraph-IV challenge represents an exogenous shift in the promotional effort of branded drugs uncorrelated with demand shocks or measurement errors. Branstetter, Chatterjee and Higgins (2011) investigate the welfare effect of accelerated generic entry via Para-IV challenges for hypertensive drugs.

[27] Our IV strategy is also supported by the fact that our estimates of price-elasticities are lower but not too far off the order of magnitude reported by Dubois and Lasio (2017), They use IMS data for France, where problems of measurement errors, and the resulting attenuation bias, are less important given the regulatory constraints of the pharmaceutical industry.

[28] These tests lead us to use slightly different instruments for the two channels. Concretely, the average firm prices in other markets can be used only for hospitals, while for the pharmacy channel we use the price of the molecule sold in hospitals.

Regression Results

We estimate the empirical model in (7) separately for hospitals and pharmacies in order to unearth channel-specific idiosyncrasies.[29] Columns (1) and (3) of Table 5 report the estimates obtained without instrumenting for prices and promotion. Comparing these results with those in Columns (2) and (4) confirms the existence of an attenuation bias due to errors in measuring prices and promotion intensity.

A number of interesting findings emerge from the IV results. First, the estimated elasticities *w.r.t.* own-price are in the upper of the range reported in the literature when using U.S. data, but are not uncommon (Narayanan and Manchanda (2005); see also footnote 27). We defer the discussion of the "high" estimate for promotion to Section 6.2.

Second, the elasticity of demand *w.r.t.* prices is higher in hospitals than in pharmacies. The coefficient pertaining to the price of competitors ($Price\_Comp$) is about three times as large in the hospital channel and more precisely estimated, which reinforces the message that hospitals are more price-sensitive than private practice doctors.[30] This difference probably results from the moral hazard problems that arise between third-payers, physicians, and patients. Private practice doctors do not directly benefit when patients buy a cheaper alternative (possibly, they even lose some perks offered by pharmaceutical companies) and, at the same time, these patients pay only a fraction of the drug's price, thanks to third-party payer coverage. By contrast, hospitals are residual claimants: their margin depends one-for-one on procuring drugs at a discount since they then charge the patient a pre-determined reference price.[31] Such mechanisms, highlighted in Inderst and Ottaviani (2012) are "blackboxed" in our textbook model. Yet, we see that their symptoms are apparent in our data.

A third finding is that the coefficients for own- and cross-promotion elasticity are of the right sign, large, and precisely estimated in both channels. When instrumented, the point estimates increase substantially, confirming the extent to which this variable is affected by

[29] Berndt (2002) provides a detailed explanation as to why arbitrage between different (cf. hospitals and retail pharmacies) cannot occur.

[30] A Wald test rejects the hypothesis that the coefficients of the company's price and competitors' price could be the same for the two channels (p-value: 0.01).

[31] This is in line with what Berndt (2002) reports: "Next lowest are prices to hospitals (...) prices charged pharmacies for their cash-paying customers are discounted off "list" price the least".

Table 5. Demand of Branded Drugs in Hospital and Pharmacy channel

Depend Vbl: Market Shares		**Hospital**		**Pharmacies**	
Specification:		FD	FD-IV	FD	FD-IV
	Coeff.	(1)	(2)	(3)	(4)
Own Price	α_1	−1.280***	−2.629*	−1.003***	−1.725***
		(0.18)	(1.55)	(0.22)	(0.65)
Own Promotion	α_2	0.084***	1.994***	0.096***	1.998***
		(0.02)	(0.48)	(0.04)	(0.71)
Price_Comp	α_3	0.844***	0.914***	0.260**	0.310*
		(0.15)	(0.25)	(0.13)	(0.17)
Promotion_Comp	α_4	-0.061***	-1.436***	-0.067**	-1.528***
		(0.02)	(0.36)	(0.03)	(0.54)
Generic Entry	α_5	0.005***	0.002	0.004**	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)
Nmb of Competitors	α_6	-0.031**	-0.002	-0.033**	-0.005
		(0.01)	(0.02)	(0.01)	(0.02)
Time to Expiration	α_7	-0.004***	-0.003***	-0.003***	-0.001*
		(0.00)	(0.00)	(0.00)	(0.00)
Observations		5046	5046	5032	5032
K-P Underidentification[a]			.0101		.0124
AP_F-test - Promotion[b]			.0020		.0102
AP_F-test - Price[b]			.0324		.0082
Hansen J test (df)[c]			.362 (3)		.511 (3)
C-test - Endogeneity[d]			<.0001		.0013
C test - Exogeneity[d]			.5027		.3449

Notes: Robust standard errors clustered at market level in parentheses. * significant at 10% level; ** significant at 5%; *** significant at 1%. All specifications in First Differences. Endogenous variables: Own price and promotion. Five instruments: #Packages (linear and squared), Average Price charged by same firm, Dummy for new products by same firm, Indicator for Paragraph IV challenges. [a] P-value for the Kleibergen-Paap rk statistics testing the null hypothesis that the model is underidentified. [b] P-value for the Angrist-Pischke F-test for excluded instruments testing for weak instruments in the first stage regressions of promotion and price. [c] Hansen J test of overidentifying restrictions with degrees of freedom reported in parentheses. [d] P-value of C (GMM distance) test of endogeneity for own price and promotion and test of exogeneity for price and promotion of competitors.

endogeneity problems. Section 6 discusses in detail why, in our opinion, such elasticities are the correct ones when assessing the effects of generic entry.

The coefficients on the headcount of genericized molecules and on the number of competitors are statistically insignificant once we properly control for endogeneity (and economically minute in columns (1) and (3)). These result confirm our theoretical hypothesis that *(a)* generic entry affects demand exclusively through the price and promotion of a given molecule. *(b)* Market share movements of incumbents are not driven by the launch of new molecules above and beyond the latter's effects on price and promotion.

5.2 The effects of LoE (testable implications 1-3)

The results of the previous section provide us with a proxy for high *vs.* low price-to-advertising elasticity ratio: hospitals are comparatively more price sensitive than pharmacies. We also have the variable MoA (modes of action, see p18) as a proxy for horizontal differentiation, and we can capture ATC3 market and molecular vertical differentiation through molecule fixed effects. We thus have all the elements to test implications 1-3 derived in Section 3.2.

To test these predictions, we use the following specification:

$$\begin{aligned} ms_{i,t} &= \gamma_0 + \rho\, ms_{i,t-4} + \gamma_1 GEN_{-i,t} + \gamma_2 Hosp\; GEN_{-i,t} + \gamma_3 MoA_t\; GEN_{-i,t} \\ &\quad + \gamma_4 S_{i,t}\; GEN_{-i,t} + \beta' X_{i,t} + \gamma_i + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

where $ms_{i,t}$ is the market share of the patent-protected drug in the ATC3 market, and $GEN_{-i,t}$ counts the number of molecules that lost exclusivity in the same market. $Hosp$ is a dummy for the hospital channel, and MoA_t is our proxy for horizontal differentiation. To proxy the importance of drug i, we identify the top 25% selling drugs during the entire time period and define the indicator variable S (for small) for drugs that do *not* belong to that blockbuster group. The specification includes the one-year lag of the dependent variable (*i.e.*, four quarters) to capture dynamic autoregressive processes. The set of control variables X includes the number of competing molecules to proxy the intensity of competition, a time trend (TE), and a complete set of time dummies. As for other specifications, the data for $ms_{i,t}$ pertain to branded drugs until one quarter before patent expiration.

According to **testable implication 1**, following the LoE of some molecule A, the market share of a still-patent-protected molecule B should increase less (or decrease more) if δ is higher. In light of the results of Section 5.1, that elasticity is higher in hospitals. We thus expect γ_2 to be negative. According to **testable implication 2**, we also expect γ_3 to be negative: the market share of molecule B should increase less (or decrease more) if the ATC3 market features more horizontal differentiation. Finally, **testable implication 3** predicts that γ_4 should be negative: on-patent drug B should be more likely to lose market share if the revenue it generated is small prior to LoE. As indicated previously, we do not report the results for prices and promotion because they are rarely significant, probably due to measurement errors in the data.

In Table 6 (columns 1 and 2), we first report standard random and fixed effects estimations without instrumenting. As expected, the more precise estimates are the ones that control for drug-level fixed effects. However, because of the presence of the lagged dependent variable, the use of fixed effects leads to a downward bias (known as "Nickell bias") in the point estimate of ρ, which can be transmitted to the other coefficients. To tackle this problem, we use the GMM estimator with the forward orthogonal deviation (FOD) transformation proposed by Arellano and Bover (1995). The reason for preferring the FOD over the First Difference estimator is that some of the regressors do not vary (*e.g.* $Hosp$) or vary little over time (*e.g.* MoA). Accordingly, First Difference estimations would not capture the transition from the pre-entry to post-LoE equilibrium as defined in our theoretical model.

The instruments we use are composed of lags of the number of competitors and the Herfindahl-Hirschman concentration index. Because the number of instruments generated by our GMM framework is quadratic in T, we try to avoid the problem of using "too many weak instruments" by experimenting with two approaches. In column (3), we use lags of the instruments from period $t-4$ to $t-8$, but we collapse them as in Roodman (2006). In column (4) we use the standard (un-collapsed) instruments, but we limit the lags to period $t-4$.

The IV strategy leads to an increase in the point estimate of the lagged dependent variable. Estimates for the coefficients of interest are consistent with our testable implications. The first finding is that we observe mainly instances of branded drugs increasing their volume market

		GEN				GEN^{IMP}	
	Coeff.	RE (1)	FE (2)	FOD-IV(3) (3)	FOD-IV(4) (4)	FOD-IV(1) (5)	FOD-IV(2) (6)
GEN	γ_1	0.068**	0.158***	0.123***	0.131***	0.237***	0.243***
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Hosp*GEN	γ_2	-0.021	-0.016	-0.035*	-0.030*	-0.089***	-0.082***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
MoA*GEN	γ_3	-0.006	-0.038***	-0.041***	-0.041***	-0.084***	-0.081***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Small*GEN	γ_4	-0.023	-0.098***	-0.063*	-0.071**	-0.164***	-0.172***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Time to Expiration		-0.003	-0.016***	-0.018***	-0.018***	-0.017***	-0.017***
		(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Competitors		-0.015	-0.013	-0.012	-0.013	-0.014	-0.014
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lagged Dependent Variable	ρ	0.635***	0.551***	0.754***	0.708***	0.771***	0.732***
		(0.04)	(0.05)	(0.11)	(0.10)	(0.11)	(0.10)
Hosp		-0.004					
		(0.06)					
MoA		-0.225					
		(0.14)					
Small		-0.726***					
		(0.12)					
Observations		8622	8622	8622	8622	8622	8622
Hansen J-test (df)a				0.333 (9)	0.697 (69)	0.348 (9)	0.999 (69)

Notes: Robust standard errors clustered at ATC3-market level in parentheses. *significant at 10% level; **significant at 5%; ***significant at 1%. Endogenous variable: lagged dependent vbl one year before. Instrument: lags of number of competitors and market concentration. a P-value of Hansen J-test of overidentifying restrictions with degrees of freedom reported in parentheses

Table 6. Effect of a competitor's genericization on on-patent drugs

share following the genericization of a competitor. Indeed, the coefficient γ_1 is positive and precisely estimated. As already discussed, the reason is that generic entry also drastically reduces promotional effort, which more than compensates for the price drop. Importantly, and in line with the higher elasticity of demand estimated in Section 5.1, this effect is more limited in the hospital channel: in both columns (3) and (4), the interaction between the two dummies ($HOSP*GEN$) is significantly negative, reducing by roughly a quarter the market share gain for the drugs remaining on patent. The negative coefficient γ_3 confirms that markets characterized by a higher degree of horizontal differentiation experience a smaller increase in market share. The interaction between the revenue size indicator variable and the generic count (γ_4) is also significant and of the expected sign.

To check the robustness of these findings, we define an alternative generic entry count variable that considers LoE experienced by only the most important molecules. More precisely, the new variable $GEN^{IMP}_{-i,j,t}$ pertains only to the LoE of the 20 drugs (out of 95 drugs) with the largest average sales over the sample period.

Results when using this new variable are reported in Columns 5 (with "collapsed" instruments) and 6 (instruments lagged $t-4$) of Table 7. We note that coefficient signs do not change when we focus solely on these "important" drugs. In line with the intuition, the absolute value of the point estimates increases substantially. Yet note that the relative magnitude of the different coefficients remains similar. Interestingly, the precision of the estimates improves markedly as compared to columns (3)-(4).

6 Robustness and Sensitivity

This section addresses two issues. First, we check whether our results are robust to evergreening strategies. We do this by reestimating our empirical model excluding instances of LoE experienced by a drug whose originator also owned a second-generation product in the same market. Second, we assess whether the elasticities reported in Table 5 do a good job in predicting observed post LoE developments. In addition we compare the "performance" of these estimates with those typically found in the literature

6.1 Evergreening (follow-on / second-generation launches)

"Evergreening" refers to a fairly common practice consisting in introducing new formulations or second-generation drugs, also known as "product hopping" by patients (see Huckfeldt and Knittel (2011) for a detailed analysis). One may contend that this is the main rationale for the reduction in market shares we document.

The first thing to note is that evergreening strategies rely on promotion to migrate patients onto the second generation molecule. Clearly, strategic launch of follow-on products will be more profitable if supported by substantial promotion efforts to induce a switch in prescription/consumption habits towards the new molecule. Hence, the mechanism we document is not incompatible with evergreening. Rather, the latter is particularly attractive when the promotion of a second generation product can be expected to be most effective.

Table 7 shows that our results still hold even in the absence of evergreening episodes: we re-estimated the regressions in Table 5, excluding the episodes of LoE in which the firm that experiences the LoE episode also owned marketing rights for another drug in the same ATC3. This reduces our sample size by about 10%, which reduces the significance of some coefficients. Yet, the coefficients on own and competitors' promotion remain largely unchanged. This provides strong support to the idea that ever-greening cannot be the whole story behind the market share loss of molecules losing exclusivity.

6.2 Assessing demand elasticities: an out-of-sample exercise

Our estimates for promotion and, to a much lesser extent, price elasticities are higher than what is generally reported in the literature. We conjecture that there are three main reasons for this: **1)** Our sample includes a substantially larger number of LoE events over a long time horizon. Patent expiration represents a significant (exogenous) shock that produces a larger-than-usual variation in prices and promotional effort, with more visible changes in prescription behavior. **2)** We control for both own- and cross-price and promotion effects, which addresses a potential omitted-variable bias due to the arms-race nature of promotion. Note that, if the slope of the promotion reaction function is close to 1 (the actual correlation between own and competitors promotion is above 0.6), then the sum of the own and cross promotion elasticities

Table 7. Re-estimating Demand without Evergreening

Depend Vbl: Market Shares		**Hospital**		**Pharmacies**	
Specification:		FD	FD-IV	FD	FD-IV
	Coeff.	(1)	(2)	(3)	(4)
Own Price	α_1	-1.246***	-2.061	-1.007***	-1.495***
		(0.18)	(1.32)	(0.23)	(0.54)
Own Promotion	α_2	0.085***	1.713***	0.083**	1.723***
		(0.03)	(0.44)	(0.04)	(0.61)
Price_Comp	α_3	0.850***	0.896***	0.280**	0.308*
		(0.16)	(0.24)	(0.13)	(0.17)
Promotion_Comp	α_4	-0.065***	-1.220***	-0.058**	-1.294***
		(0.02)	(0.34)	(0.03)	(0.46)
Generic Entry	α_5	0.005***	0.001	0.004**	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)
Nmb of Competitors	α_6	-0.030**	-0.001	-0.032***	-0.008
		(0.01)	(0.02)	(0.01)	(0.02)
Time to Expiration		-0.004***	-0.003***	-0.003***	-0.002**
		(0.00)	(0.00)	(0.00)	(0.00)
Observations		4571	4571	4559	4559
K-P Underidentification[a]			.0121		.0130
AP_F-test - Promotion[b]			.0018		.0098
AP_F-test - Price[b]			.0469		.0062
Hansen J test (df)[c]			.491(3)		.581(3)
C-test - Endogeneity[d]			<.0001		<.0001
C test - Exogeneity[d]			.5701		.4612

Notes: Robust standard errors clustered at market level in parentheses. * significant at 10% level; ** significant at 5%; *** significant at 1%. All specifications in First Differences. Endogenous variables: Own price and promotion. Five instruments: #Packages (linear and squared), Average Price charged by same firm, Dummy for new products by same firm, Indicator for Paragraph IV challenges. [a] P-value for the Kleibergen-Paap rk statistics testing the null hypothesis that the model is underidentified. [b] P-value for the Angrist-Pischke F-test for excluded instruments testing for weak instruments in the first stage regressions of promotion and price. [c] Hansen J test of overidentifying restrictions with degrees of freedom reported in parentheses. [d] P-value of C (GMM distance) test of endogeneity for own price and promotion and test of exogeneity for price and promotion of competitors.

yields a figure very close to what is typically reported in the literature. In that respect, it is worth noting that promotion elasticities are typically obtained without including competitors' promotion in the regression analysis (*e.g.* Mizik and Jacobson 2004). **3)** We use a rich set of instrumental variables: our initial estimates in columns (1) and (3) display significantly lower estimates for promotion elasticities. This is largely due to measurement errors for promotion efforts. Moreover, around one third of the drugs in our sample are not actively promoted on the basis of IMS data, which may also contribute to biasing the estimates towards zero. Our instruments appear to address these issues satisfactorily.

Regarding (own) price elasticities, we want note that the findings of an elasticity below 1 are difficult to reconcile with profit maximization. By contrast, our point estimates in Table 5, Columns (2) and (4), are compatible with price-cost margins in the 40-55% range. This order of magnitude is in line with the price reductions observed following generic entry, and it is also close to the results reported by Rizzo (1999), and more recently, by Narayanan *et al.* (2005). More precisely, the latter report (p. 286) own-price elasticities ranging from 2.18 to 2.61 for three antihistaminics.[32]

With regard to promotion elasticities, the meta-analysis by Kremer *et al.* (2008) reports that estimates ranging from a negative value (Venkataraman and Stremersch 2007) and 1.39 (Berndt, Pindyck and Azoulay 2003), and the average of all estimates is 0.35. More recently, Dave and Saffer (2012, Table 2) report an elasticity *w.r.t.* detailing comprised between 0.44 and 0.52. While such elasticities are certainly accurate to describe how prescription behavior reacts to marginal changes in promotion effort (*e.g.* comparing a doctor who received two visits per month with another who received only one), we argue that they cannot appropriately capture the effects of a long-term, nation-wide, effort by companies to shift the doctors' attention from an old molecule to a new one.

Formally, we check whether the promotion elasticities reported in the literature can be made consistent with the observed shift in prescription behavior post-LoE. The evolution of

[32]The elasticities reported by Dubois and Lasio (2017, Table 4) are much higher and range from values of 4.06 for the U.S. and 5.5 for Germany.

a molecule's sales (or market share when total market size is normalized) must be such that:

$$\frac{\Delta Q}{Q} \simeq \eta_P \cdot \frac{\Delta P}{P} + \eta_A \cdot \frac{\Delta A}{A},$$

where η_P is the price elasticity, and η_A the advertising elasticity.

Table 4 indicates that LoE produces an average price drop of about 44-45% depending on the channel, and an average drop in the *flow* of promotion between 85 and 90%. We calculate that, once converted into *stocks*, these correspond to a drop of respectively 69.4% and 72.9% three years after LoE. Taking the pharmacy channel as an example, the predicted change in the market share of the now generic molecule should thus be:

$$\frac{\Delta Q}{Q} \simeq \eta_P \cdot (-0.45) + \eta_A \cdot (-0.694)\,.$$

If we take a lower reasonable bound of $\eta_P = 1$, and use the estimates for η_A reported in the meta-analysis by Kremer *et al.* (2008), it turns out that 55 of the 58 reported elasticities are incompatible with any drop in the molecule's market share, and therefore with actual observations. The same applies for the elasticities reported in Dave and Saffer (2012, Table 2, column 7).

If instead we use our IV-regression results from Table 5, we find that, in hospitals, the predicted change in market share is: $-2.629 \cdot (-0.45) + 1.994 \cdot (-0.694) = -0.201$, which compares to an actual average drop of about -0.26 (see Table 4). Following the same procedure for pharmacies, the predicted evolution is: $-1.725 \cdot (-0.44) + 1.998 \cdot (-0.729) = -0.697$ (actual average drop about -0.31). Thus, regression results in Table 5 predict (i) a drop in market shares for both segments and (ii) a larger drop for pharmacies. Note that the predicted drop in pharmacies is substantially larger than observed levels. This is compatible with the third party payers' active promotion of generics use.

Beyond this technical point, it should be recalled that the large pharmaceutical corporates spend 15-20% of their revenue on promotion in various forms. If detailing were not effective, it would hard to justify such spending by important, well established, and sophisticated firms. Their behavior can only be compatible with profit maximization if advertising elasticities are north of 0.2 in the case of constant returns to promotional effort, or significantly higher in

the presence of steeply increasing marginal cost of detailing ($MC \gg AC$). Berndt *et al.* 2003), and Manchanda, Rossi and Chintagunta (2004) provide convincing evidence of such fast decreasing returns to detailing, and Chressanthis *et al.* (2014) document that detailing agents face increasing difficulties to access physicians.

7 Conclusions and Welfare Implications

This paper analyzes the consequences of asymmetric competition in imperfectly competitive markets. Our research question was prompted by the puzzling observation that intense intra-molecular price competition following generic entry typically does not lead to increased volume sales for the molecule that experiences Loss of Exclusivity (LoE).

Why would substantially lower prices end up repelling consumers? Is that phenomenon related to specificities of generic competition or caused by broader forces? We posit that the key to this "reverse competition" effect is the presence of non-price instruments combined with an asymmetry in the competitive shock associated with generic entry. Our model shows that a product selling at much reduced price-cost margins may end up selling less, simply because the firm hit by stiffer competition stops promoting its product (or, by extension, reduces its investments in non-price instruments).

This phenomenon helps explain why, despite generics accounting for 75-90% of the market for the molecules that have lost exclusivity,[33] their overall effect on the market has fallen short of expectations. Legislators and purchasers on both sides of the Atlantic have had to actively promote generic penetration, and yet expenditures on drugs kept on rising.

Our model identifies the circumstances under which the molecule facing generic entry should experience a market share drop. This is when the market is large, the price elasticity of demand is low and, strikingly, when horizontal product differentiation is not pronounced. These theoretical predictions are largely confirmed by our empirical analysis.

Going one step further, the model allows us to make some inferences regarding allocative efficiency. In Appendix 3, we extend the analysis to patient/consumer surplus. Following the logic in Inderst and Ottaviani (2012), our model reckons that promotion does influence

[33]Source: http://pharmaphorum.com/views-and-analysis/greek_nhs_the_battle_continues_to_rage/

physicians' prescription behavior. But this influence may not directly benefit patients. Using a definition of consumer surplus that does not attribute any *direct* benefit of promotion to the patients, we find that a sufficient condition for patient (consumer) surplus to increase after generic entry is that the market share of molecules remaining on-patent decreases *in equilibrium* (the price of both molecules then falls). As we saw, this condition is rarely met in practice, meaning that asymmetric competition typically *hurts* patients according to that definition of surplus. The model also allows us to assess when the change in market shares produced by generic entry brings the market allocation closer to the first best (Proposition 5 in Appendix 3). The answer is *never*, and a ban on promotion would not solve the problem.

US Third Party Payers (TPPs) have started providing increasingly high-powered incentives to promote generic use, limiting (or even reversing) the market share gains of drugs that remain on patent (in Europe, that has been done by social security systems). However, note that in the case of bio-pharmaceuticals, TPPs activism is bound to be much less effective, as bio-generics are not considered perfect substitutes. In addition, the approval process for generics lasts longer and it is more complex and costly. Under these circumstances, doctors' discretionary choices will remain central. It is not unreasonable to think that promotion spend will continue to be a key determinant of prescription behavior, even after LoE. This is an area for future research.

References

Aitken, M., L., Berndt, E. R., and Cutler, D., M., (2009). "Prescription Drug Spending Trends In The United States: Looking Beyond The Turning Point", *Health Affairs* 28, no.1: w151-w160

Aitken, M., L., Berndt, E. R., Bosworth, B., Cockburn I. M., Frank, R., Kleinrock, M. and Shapiro, B., (2013). "The Regulation of Prescription Drug Competition and Market Responses: Patterns in Prices and Sales Following Loss of Exclusivity". NBER Working Paper 19487.

Apple (2013). UNITED STATES SECURITIES AND EXCHANGE COMMISSION, Form 10-K, September 28. http://investor.apple.com/secfiling.cfm?filingid=1193125-13-416534&cik=#D590790D10K_HTM_TOC590790_1

Arellano, M. and Bover, O. (1995). "Another look at the instrumental-variable estimation of error-components models". *Journal of Econometrics*, 68, pp. 29–52

Berndt, E.R. (2002). "Pharmaceuticals in U.S. Health Care: Determinants of Quantity and Price". *Journal of Economic Perspectives*, Vol. 16(4), pp. 45–66.

Berndt, E.R. and Dubois P. (2016). "Impacts of Patent Expiry of Pharmaceutical Treatments in Eight OECD Countries, 2004-2010". *International Journal of the Economics of Business*, vol. 23(2):125–147.

Berndt, E. R., Kyle, M., and Ling, D., (2003). "The Long Shadow of Patent Expiration: Generic Entry and Rx-to-OTC Switches," in *Scanner Data and Price Indexes*, ed. R. Feenstra and M. Shapiro University of Chicago Press, pp. 229–267

Branstetter, L.G., Chatterjee C. and Higgins M.J. (2011). "Regulation and Welfare: Evidence from Paragraph IV Generic Entry in the Pharmaceutical Industry". NBER Working Paper No. 17188

Branstetter L.G., Chatterjee, C. and Higgins M.J. (2014). "Starving (or Fattening) the Golden Goose? Generic Entry and the Incentives for Early-Stage Pharmaceutical Innovation". NBER Working Paper 20532.

Brekke, K., Kuhn, M. (2006). "Direct to Consumer Advertising in Pharmaceutical Markets". *Journal of Health Economics*, 5(1), 102–130.

Caves, R.E., Whinston, M.D., and Hurwitz, M.A. (1991). "Patent expiration, entry, and competition in the U.S. Pharmaceutical Industry". *Brookings papers on Economic Activity: Microeconomics*, pp. 1–23

Chaudhuri, S., Goldberg, P. K., and Jia, P. (2006). "Estimating the Effects of Global Patent Protection in Pharmaceuticals: A Case Study of Quinolones in India". *The American Economic Review*, Vol. 96(5): 1477-1514

Ching, A. T., and Ishihara, M. (2012). "Measuring the informative and persuasive roles of detailing on prescribing decisions". *Management Science*, Vol. 58(7), 1374-1387.

Ching, A. T., Clark, R., Horstmann, I., and Lim, H. (2016). "The effects of publicity on demand: The case of anti-cholesterol drugs". *Marketing Science*, Vol. 35(1), 158-181.

Chressanthis, G., Sfekas, A., Khedkar, P., Jain, N. and Poddar, P. (2014). "Determinants of pharmaceutical sales representative access limits to physicians". *Journal of Medical Marketing*, Vol. 14849, pp. 220-243.

Dave, D. and Saffer H. (2012). "The Impact of Direct-to-Consumer Advertising on Pharmaceutical Prices and Demand". *Southern Economic Journal*, 79, 1. 97-126.

de Frutos, M.A., Ornaghi C. and Siotis G. (2013). "Competition in the pharmaceutical industry: how do quality differences shape advertising strategies?" *Journal of Health Economics*, 32, 268-285

Donohue, J.M., Cevasco M. and Rosenthal M.B. (2007). "A Decade of Direct-to-Consumer Advertising of Prescription Drugs". *The New England Journal of Medicine*. 357:673-81.

Dubois, P., and Lasio L.. (2017). "Identifying Industry Margins with Unobserved Price Constraints: Structural Estimation on Pharmaceuticals". *mimeo*.

Duflos, G. and Lichtenberg F. R.. (2012). "Does competition stimulate drug utilization? The impact of changes in market structure on US drug prices, marketing and utilization". *International Review of Law and Economics*, 32(1), 95-109.

Elison, S., Cockburn I., Griliches, Z. and Hausman J. (1997). "Characteristics of Demand for Pharmaceutical Products: An Exploration of Four Cephalosporins". *RAND Journal of Economics*, 28(3), 426-446.

Fischer, M., Albers, S., (2010). "Patient- orPhysician-Oriented Marketing: What Drives Primary Demandfor Prescription Drugs?", *Journal of Marketing Research*, Vol. XLVII, 103–121

Grabowski H., and Kyle, M. (2007). "Generic Competition and Market Exclusivity Periods in Pharmaceuticals". *Managerial and Decision Economics* 28(4-5), 491-502.

Grabowski H., Long G., and Mortimer R. (2014). "Recent trends in brand-name and generic drug competition". *Journal of Medical Economics*. 17(3):207-14.

Greenway, T. and Ross, J.S. (2017). "US drug marketing: how does promotion correspond with health value? ". *BMJ* 357:j1855

Griliches, Z and Hausman A.J. (1986). "Errors in Variables in Panel Data". *Journal of Econometrics* 31: 93-118.

Griliches, Z. and Mairesse J. (1995). "Production Function: The Search for Indentification". NBER Working Paper, No. 5067

Grochowski Jones, R. and Ornstein, C. (2016). "Matching Industry Payments to Medicare Prescribing Patterns: An Analysis". *ProPublica*. (The undelying data is avalaible at:

https://projects.propublica.org/docdollars/)

Grossman, G.M, Shapiro, C. (1984). "Informative Advertising with Differentiated Products". *The Review of Economic Studies*, Vol. 51, No. 1 (Jan.), pp. 63-81

Harrington, S.E. (2012). "Cost of Capital for Pharmaceutical, Biotechnology, and Medical Device Firms". *Oxford Handbook of the Economics of the Biopharmaceutical Industry.*

Huckfeldt P. J. and Knittel C.R. (2011). "Pharmaceutical use following generic entry: paying less and buying less". NBER Working Paper 17046.

Hurwitz, M.A. and Caves, R. E. (1988). "Persuasion or Information? Promotion and the Shares of Brand Name and Generic Pharmaceuticals". *Journal of Law and Economics* 31, No. 2, 299–320

Iizuaka, T. (2004). "What Explains the Use of Direct-to-Consumer Addvertising of Prescription Drugs?", *Journal Economics and Management Strategy* Vol. 14(3))

Iizuaka, T., Zhe Jin, G. (2005). "The Effect of Prescription Drug Advertising on Doctors Visits", *The Journal of Industrial Economics* Vol. LII(3)

Iizuaka, T. (2012). "Physician Agency and Adoption of Generic Pharmaceuticals", *American Economic Review* 102(6), 2826-2858

Inderst, R., and Ottaviani, M. (2012). "Competition through Commissions and Kickbacks". *American Economic Review*, 102(2): 780-809.

JAMA (2017). "Conflict of Interest Theme Issue", *Journal of the American Medical Association*, 317(17), May, 1707-1812

Kenkel, D. and Mathios, A. (2012). "Promotion to Physicians and Consumers". *Oxford Handbook of the Economics of the Biopharmaceutical Industry.*

Kremer, S., Bijmolt, T., Leeflang, P., Wieringa, J. (2012). "Generalizations on the effectiveness of pharmaceutical promotional expenditures". *International Journal of Research in Marketing,* 25, 234–246.

Manchanda, P., Rossi, P.R. and Chintagunta, P.K. (2004). "Modelling with Nonrandom Marketing-Mix Variables". *Journal of Marketing Reserach*, 41(4), pp. 467-478.

Mizik, N. and Jacobson, R. (2004). "Are Physicians "Easy Marks"? Quantifying the Effects of Detailing and Sampling on New Prescriptions". *Management Science*, 50(12): 1704-1715.

Narayanan, S. and Manchanda, P. (2009). "Heterogeneous Learningand the Targeting of Marketing Communication for New Products". *Maarketing Science*, 28(3) pp.427-441.

Lakdawalla, D, and Philipson, T. (2012). "Does Intellectual Property Restrict Output? An Analysis of Pharmaceutical Markets". *Journal of Law and Economics,* 55(1): 151-187.

Regan, T.L. (2008). "Generic entry, price competition, and market segmentation in the

prescription drug market". *International Journal of Industrial Organization*, 26, 930–948.

Rizzo, J. (1999). "Advertising and competition in the ethical pharmaceutical industry: The case of antihypertensive drugs". *Journal of Law and Economics,* 42(1) 89–116.

Roodman, D. (2006). "How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata". *Centre for Global Development*, Working paper 103.

Scott Morton, F. M. (2000). "Barriers to entry, brand advertising, and generic entry in the US pharmaceutical industry" *International Journal of Industrial Organization* 18(7), 1085-1104.

Stern, S. (1996). "Market Definition and the Returns to Innovation: Substitution Patterns in Pharmaceutical Markets," *mimeo.*

Vandoros S. and P. Kanavos (2013). "The generics paradox revisited: empirical evidence from regulated markets". *Applied Economics*, 45:22, 3230-3239

Venkataraman, S., and Stremersch, S. (2007). "The debate on influencing doctors' decisions: are drug characteristics the missing link?". *Management Science*, 53(11), 1688-1701.

Appendix 1.
Benchmark: generic entry in the absence of promotion

This section presents the case in which firms cannot use detailing and can compete only on prices. One of the main reasons for promoting generics is to make drugs more affordable. The expectation is two-pronged: first, the entry of a generic version of molecule A should put substantial pressure on the price of molecule A. As we saw in Section 2, this effect is unquestionably present. Thus, we assume that generic entry does produce such strong competition on molecule A that the price of drug A drops to the marginal cost of production, which we normalized to 0. This is the direct effect of generic entry.

The second, indirect, effect is the price reaction of firm B. We can check how each of these effects operates when firms can compete only on prices–that is when we impose that firms cannot use promotion: $a_A = a_B \equiv 0$.

Deriving firms' respective reaction functions is straightforward:

$$p_A = \frac{1}{2\delta}\left(e - \Delta\theta_B + \delta\ p_B\right) \tag{9}$$

$$p_B = \frac{1}{2\delta}\left(e + \Delta\theta_B + \delta\ p_A\right). \tag{10}$$

Hence, in the pre-entry equilibrium,

Pre-entry benchmark:
Before generic entry and in the absence of detailing, for $\theta_A + \theta_B > 2e$, and $|\Delta\theta_B/e| \leq 3$, the equilibrium is such that:

$$p_A = \frac{1}{\delta}\left(e - \frac{\Delta\theta_B}{3}\right) \text{ and } Q_A = \left(1 - \frac{\Delta\theta_B}{3e}\right) \times \frac{\mu}{2},$$

$$p_B = \frac{e}{\delta} + \frac{\Delta\theta_B}{3\delta} \text{ and } Q_B = \left(1 + \frac{\Delta\theta_B}{3e}\right) \times \frac{\mu}{2}.$$

The drug with highest quality θ_J, sells more and at a higher price. Moreover, both prices increase in patient heterogeneity e and decrease in price elasticity, δ.

In that benchmark, the condition $\theta_A + \theta_B > 2e$ is necessary and sufficient to ensure that all patients obtain their treatment in equilibrium. For lower values of θ_J, some patients would find both treatments unaffordable. Note that this condition does not depend on price sensitivity δ because, in the absence of price constraints, firms vary their price exactly to compensate a variation in price sensitivity. In other words, if health insurances double their intervention, total prices will double as well, and the patient will pay the same final price. Second, the condition $|\Delta\theta_B/e| \leq 3$ ensures that both firms sell positive quantities for the price levels derived in benchmark 1.

Upon generic entry, the price of A falls to 0. As a consequence, by (10) , the equilibrium becomes:

Post-entry benchmark:
After generic entry and in the absence of detailing, an interior equilibrium is such that:

$$p_A = 0 \text{ and } Q_A = \left(\frac{3}{2} - \frac{\Delta\theta_B}{2e}\right) \times \frac{\mu}{2},$$

$$p_B = \frac{e + \Delta\theta_B}{2\delta} \text{ and } Q_B = \left(\frac{1}{2} + \frac{\Delta\theta_B}{2e}\right) \times \frac{\mu}{2}.$$

Note that for any interior solution (*i.e.*, for $0 < \Delta\theta_B/e < 3$), the price of B must decrease, and the market share of A must increase in comparison to the pre-entry benchmark. Hence, the only question is the magnitude of this change: the more vertically superior is molecule B, the less generic entry influences market shares and equilibrium prices.

Appendix 2

Appendix 2a. Empirical Test of Result 1

Here, we test the initial prediction of Section 3, which identifies key correlations that should result from the strategic interactions among firms when they still benefit from exclusivity.

Based on Result 1, we expect that a producer with a higher-quality molecule will (a) sell more, (b) charge a higher price, and (c) promote its molecule more intensely than its lower-quality competitors. In addition, (d) both promotional effort and price should be decreasing in price sensitivity δ. In light of the differences in price elasticities identified in Section 5.1, we expect lower prices in hospitals than in pharmacies. Last, (e) prices should be increasing in the degree of "horizontal differentiation", as defined in Section 4.

Empirically, predictions (a-c) compare different molecules/firms in a particular market. However, we cannot directly observe the relative quality or other differences between molecules. Hence, we use a specification in first-differences to test whether an increase in market share is, indeed, associated with higher promotion and prices. Firm i's behavior in market j at quarter t is described by the following equation:

$$\Delta y_{i,t} = \beta_0 + \beta_1 \Delta q_{i,t} + \beta_2 Hosp + \beta_3 MoA_{j,t} + X_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where, based on equation (5) (resp. (6)) in Section 3.1, y is price (resp. promotion) and q is market share (resp. quantity). $Hosp$ is a dummy taking value 1 for the hospital channel and zero otherwise. $MoA_{j,t}$ has been defined above, and the control variables X include a trend that identifies the number of quarters before patent expiration of brand i (time to expiration, TE), and a complete set of time dummies. As in Section 5.1, we focus on branded drugs until one quarter before LoE.

	Dep. Variable:	**Promotion**	**Promotion**	**Price**	**Price-IV**
	Coeff.	FD(1)	FD(2)	FD(3)	FD(4)
Quantity	β_{1q}	0.251***			
		(0.054)			
Market-Shares	β_{1ms}			-0.037***	0.038**
				(0.008)	(0.020)
Price	β_{1p}		0.339**		
			(0.184)		
Hospital	β_2	-0.006	-0.001	-0.003***	-0.005***
		(0.005)	(0.004)	(0.001)	(0.002)
Modes of Action: "e"	β_3	-0.070	-0.067	-0.006**	-0.003
		(0.061)	(0.058)	(0.003)	(0.004)
Time to Expiration		-0.001	-0.002**	-0.001	0.001***
		(0.001)	(0.001)	(0.001)	(0.000)
Observations		10345	10345	10345	10345
R-squared		.235	.228	.050	
Under-identification[a]					< 0.001
Hansen J-test (df)[b]					0.438 (1)

Notes: Robust standard errors clustered at ATC3-market level in parentheses. * significant at 10% level; ** significant at 5%; *** significant at 1%. In Model (4), we control for endogeneity of price using promotion and number of competitors as demand shifters. [a]P-values of F-test for excluded instruments in the first stage. [b]P-value of Hansen J-test of overidentification.

Table 8. Market Share, Price and Promotion under Patent Protection

The results are reported in Table 8. Specification (3) in the table suffers from the classic identification problem that both demand and supply influence that relationship. To address this issue, we exploit the results in Section 5.1, which showed that promotion produces an outward shift of demand. Therefore, in column (4), we use promotion as an instrument to isolate supply-side effects.

In line with Result 1, we find that prices, promotion and market shares co-move positively over time.[34] Next, the price response is lower in hospitals (prediction d), although the effect for promotion is not significant. In line with the theoretical model, e does not directly influence promotion. However, in contrast with our predictions, we do not find a significant impact of e on price. The reason is probably that most of the data variation for *Modes of Action* comes from differences across markets and not over time.[35]

Appendix 2b. Equilibrium before and after generic entry

Here, we derive the explicit solutions for the equilibrium levels of prices, promotion, and quantities before and after generic entry. We work under the following condition, which ensures that solutions are interior (*i.e.*, the market share of A before entry is strictly positive):

Condition 1 $\mu < (3e - \Delta\theta_B)\,\delta$ *or, equivalently:* $\Delta\theta_B < 3e - \mu/\delta$.

Before generic entry.

Letting $K_J \equiv 1 + \frac{\theta_J - \theta_{-J}}{3\delta e - \mu}\delta$ and solving explicitly yields:

Proposition 2 *Under Condition 1, the equilibrium* prior to generic entry *is unique and such that:*

$$p_J^D = \frac{e}{\delta}K_J \tag{12}$$

$$a_J^D = \frac{\mu}{2\delta}K_J \tag{13}$$

$$Q_J^D = \frac{\mu}{2}K_J, \tag{14}$$

for $J \in \{A, B\}$. Hence, the most advanced molecule, B, has a higher price, advertisement level and market share than A.

Proof. *Everything follows directly from the FOCs:*

$$\begin{aligned}\frac{\partial \pi_A}{\partial a_A} &= \frac{\mu p_A}{2e} - a_A = 0\\ \frac{\partial \pi_B}{\partial a_B} &= \frac{\mu p_B}{2e} - a_B = 0.\end{aligned}$$

Hence:

$$\Delta a_B = \frac{\mu}{2e}\Delta p_B.$$

Next:

$$\frac{\partial \pi_A}{\partial p_A} = \left[\frac{1}{2} - \frac{\Delta\theta_B + \Delta a_B - \delta\,(p_B - 2p_A)}{2e}\right] \times \mu = 0 \Leftrightarrow p_A = \frac{e}{\delta}\left[\frac{1}{2} - \frac{\Delta\theta_B + \mu\frac{p_B - p_A}{2e} - \delta p_B}{2e}\right]$$

$$\frac{\partial \pi_B}{\partial p_B} = \left[\frac{1}{2} + \frac{\Delta\theta_B + \Delta a_B - \delta\,(2p_B - p_A)}{2e}\right] \times \mu = 0 \Leftrightarrow p_B = \frac{e}{\delta}\left[\frac{1}{2} + \frac{\Delta\theta_B + \mu\frac{p_B - p_A}{2e} + \delta p_A}{2e}\right]$$

[34] In column (3), we observe that the demand side of the ledger dominates the raw correlation between prices and market shares. Once market shares are properly instrumented for in column (4), the coefficient changes sign and is precisely estimated.

[35] Only 10 of the 53 ATC3 markets register an increase in the number of *Modes of Action* during the time window we consider.

Solving jointly for p_A and p_B yields:

$$\begin{aligned} p_A &= \frac{e}{\delta}\left(1 - \frac{\Delta\theta_B\delta}{3\delta e - \mu}\right) \\ p_B &= \frac{e}{\delta}\left(1 + \frac{\Delta\theta_B\delta}{3\delta e - \mu}\right) \end{aligned}$$

Finally, Condition 1 follows from the fact that $Q_A \geq 0$ iff:

$$\begin{aligned} 1 &\geq \frac{\Delta\theta_B + \Delta a_B - \delta\left(p_B - p_A\right)}{e} \\ e &\geq \Delta\theta_B + \frac{\mu}{2e}2\frac{e}{\delta}\frac{\Delta\theta_B\delta}{3\delta e - \mu} - 2\delta\frac{e}{\delta}\frac{\Delta\theta_B\delta}{3\delta e - \mu} \\ \frac{e}{\Delta\theta_B} &\geq 1 + \frac{\mu}{3\delta e - \mu} - \frac{2\delta e}{3\delta e - \mu} = \frac{3\delta e - \mu + \mu - 2e\delta}{3\delta e - \mu} = \frac{\delta e}{3\delta e - \mu} \\ \Delta\theta_B &\leq \frac{3\delta e - \mu}{\delta} \end{aligned}$$

■

After generic entry.

Profit maximization yields:

Proposition 3 *Post generic entry, the unique equilibrium is given by:*

$$\begin{aligned} p_A^G &= a_A^G = 0 \\ p_B^G &= 2e\frac{\Delta\theta_B + e}{4\delta e - \mu} \\ a_B^G &= \frac{\mu}{2e}p_B^G \\ Q_B^G &= \frac{\mu}{2}\left[1 + \frac{2\delta\Delta\theta_B - (2\delta e - \mu)}{4\delta e - \mu}\right] \end{aligned} \tag{15}$$

Proof. Perfect competition amongst generics implies that $p_A = a_A = 0$. Taking first-order conditions of the maximization of π_B with respect to p_B and a_B yields the Proposition. ■

Appendix 3. Outcome efficiency and patient surplus

The results in Section 3.2 can be exploited to analyze how generic entry influences static allocative efficiency and patient (consumer) surplus. The fact that our results focus on *static* efficiency is important to note: our analysis considers firm behavior for pre-existing molecules, around the time of patent expiration. As we know, patents are essential to provide the incentives to pharmaceutical firms to develop these molecules in the first place. Yet, extending the analysis to dynamic allocative efficiency and welfare would require accounting for the endogenous R&D investments by different firms, which is beyond the scope of this paper.

Keeping this in mind, static efficiency is reached when both firm A and B face perfect competition. In this first-best case (FB), the price of both molecules is driven down to marginal costs, $p_A^{FB} = p_B^{FB} = 0$, and promotion consequently drops to zero: $a_A^{FB} = a_B^{FB} = 0$. The resulting quantities are:

$$Q_J^{FB} = \frac{\mu}{2}\left(1 + \frac{\Delta\theta_J}{e}\right), \tag{16}$$

and patient/consumer surplus is maximized.

Quite trivially, we would reach first best as soon as all molecules have lost exclusivity; it is just a matter of time. In reality, new vintages of old treatments (so-called "me too" drugs) and new treatments appear constantly. In our quarterly data, for instance, there is at least one molecule still under patent protection for all "anatomic therapeutic classes" and periods. That is, reality is best described either by situation D or situation G that we analyzed above. Our purpose here will be to identify when the movement from D (only patent-protected molecules) to G (some patent-protected molecules) improves market efficiency and/or consumer surplus. We find that:

Proposition 4 *Whether a pharmaceutical firm can (D), or cannot (ND), use detailing, generic entry* ***never*** *brings the market equilibrium closer to the first-best allocation* (16).

Proof. First, let us concentrate on the case in which firms can use detailing and focus on the quantities sold by B, since A serves the rest of the market. Consider, first, the case in which $q_B^D > q_B^{FB}$ – *i.e.*, B sells too much prior to generic entry. By (14) and (16) this only happens if:

$$\frac{\delta}{3\delta e - \mu} > \frac{1}{e} \Leftrightarrow 2\delta e < \mu,$$

which is the exact condition in Proposition 1 for $q_B^G > q_B^D$. Hence, generic entry produces an increase in the quantities sold by B precisely when convergence to the first best requires a drop. By the same token, the reverse is true for $2\delta e > \mu$.

Second, let us turn to the case in which firms cannot use detailing. As shown in Appendix 1, the quantities before and after generic entry are, respectively:

$$\begin{aligned} Q_B^D &= \frac{\mu}{2}\left(1 + \frac{\Delta\theta_B}{3e}\right) \\ Q_B^G &= \frac{\mu}{4}\left(1 + \frac{\Delta\theta_B}{e}\right) = \frac{Q_B^{FB}}{2}, \end{aligned}$$

and the condition for Q_B^D and Q_B^G to be less than the whole market (μ) is: $\Delta\theta_B < 3e$. It is straightforward to check that, for such parameter values, we always have $Q_B^G < Q_B^D < Q_B^{FB}$. ■

The main reason for this result is the same as for Proposition 1: generic entry produces a very asymmetric type of competition, in which one molecule becomes cheaper but is no longer promoted and the other remains protected against direct competition. As we saw, when molecules are distant substitutes and/or market size is small ($2\delta e > \mu$), the genericization of A intensifies competition for B, which loses market share, and cuts down prices and promotion as a result. This is exactly the intended purpose of generic competition. The problem is that this happens precisely when B's market share is initially lower than in the first best.

Conversely, when the two molecules are close substitutes and/or market size is large ($2\delta e < \mu$), the genericization of A actually relaxes the competitive pressure on B. This allows firm B to actually gain market power and market share. In this case, firm B also grabs the opportunity to increase its prices and its detailing effort. This only happens when B's market share was already initially too high.

Interestingly, prohibiting detailing altogether would not be a panacea. In that case, the market share of the more advanced molecule B is *always* too low (except in the corner solutions in which it grabs 100% of the market), and the genericization of A further reduces it.

From a policy perspective, being confronted with explosive expenditures on healthcare, authorities have actively promoted the use of generics, partly in an effort to contain the costs borne (directly or indirectly) by patients. In addition, competition authorities have, *de facto*, adopted a *consumer surplus standard*. We define consumer surplus as their utility minus the price they pay for the molecule they actually buy. Importantly, their utility depends on the actual quality of the molecule, θ_J, whereas which molecule they actually buy also depends on promotion effort, which is rather targeted at the physicians or is spent on the representatives' wages, etc. Thus, we calculate consumer surplus as the integral of the patients' utilities (1-2) when they

actually consume the quantities Q_J^D before, and Q_J^G after, generic entry.[36] We find that:

Proposition 5 *Generic entry necessarily increases consumer welfare when B's market share (weakly) decreases after generic entry* (i.e.*, for $\mu < 2\delta e$). For $\Delta\theta_B = 0$, consumer surplus decreases upon generic entry when $\mu > \frac{2\delta e}{3}\left(7 - \sqrt{10}\right) \simeq 2.56\ \delta e$, in which case B gains substantial market share, and increases prices and promotion intensity.*

Proof. After tedious algebra (see supplementary material), we find that:

$$2\delta e = \mu \Rightarrow CW^G - CW^D = \frac{(e-1)^2}{2} \geq 0,$$

where CW^D is consumer surplus when both A and B benefit from patent protection, and CW^G is consumer surplus when only B still benefits from patent protection. When μ is smaller, prices must be decreasing for all consumers, and their welfare increases.

Imposing $\Delta\theta_B = 0$ for the sake of tractability, one can also identify the value of μ for which this difference in consumer surplus is zero. The threshold is: $\mu = \frac{2\delta e}{3}\left(7 - \sqrt{10}\right)$. For any values of μ below that threshold, consumer surplus increases upon generic entry. ■

[36] The derivations of consumer surplus are available upon request. We do not present them here because they are tedious but rather straightforward.

Appendix 4: Supplementary tables

Table A1: list of ATC3 markets

ATC3	*ATC4*	*ATC4_name*	*ATC3*	*ATC4*	*ATC4_name*
A10B	A10B1	Sulphonylurea Antidiabetics	J1D	J1D1	Cephalosporins,Oral
A10B	A10B2	Biguanide Antidiabetics	J1G	J1G1	Oral Fluoroquinolones
A10B	A10B3	Comb Sulph+Biguan Antidiabetics	J2A	J2A0	Syst Antifungal Agents
A10B	A10B4	Thiazolinedione Antidiabetics	J4A	J4A1	Anti-Tb, Single Ingred
A10B	A10B5	Alpha-Gluc.Inhib. Antidiabetics	J5B	J5B0	Antivirals Excl Anti-Hiv
A10B	A10B9	Other Oral Antidiabetics	L1A	L1A0	Alkylating Agents
A2B	A2B1	H2 Antagonists	L1B	L1B0	Antimetabolites
A2B	A2B2	Acid Pump Inhibitors	L1C	L1C0	Vinca Alkaloids
A2B	A2B9	All Other Antiulcerants	L1D	L1D0	Antineoplas. Antibiotics
B1C	B1C2	Adp Recep Antag Plat Inhibitors	L1X	L1X1	Adj Prep For Cancer Ther
B1C	B1C4	Pl Camp Enh Plat Ag Inhibitors	L1X	L1X2	Platinum Compounds
C10A	C10A1	Statins - Hmg-Coa Reduct. Inhibitors	L1X	L1X9	All Oth. Antineoplastics
C10A	C10A3	Bile Acid Sequestrant	L2B	L2B1	Cyto Anti-Oestrogens
C10A	C10A9	All Oth Chol/Triglyc Red	L2B	L2B2	Cyto Anti-Androgens
C1B	C1B0	Antiarrhythmics	L2B	L2B3	Cytostat Aromatase Inhibitors
C1F	C1F0	Positive Inotropic Agent	L4A	L4A0	Immunosuppressive Agents
C1X	C1X0	All Other Cardiac Preps	M1A	M1A1	Antirheumatics Non-S Pln
C2A	C2A1	Antihyper.Pl Mainly Cent	M1A	M1A3	Coxibs
C2A	C2A2	Antihyper.Pl Mainly Peri	M1C	M1C0	Spec Antirheumatic Agent
C3A	C3A2	Loop Diuretics Plain	M5B	M5B1	Oral Bisph Bone Calc Reg
C3A	C3A3	Thiazide+Analogue Plain	N1A	N1A2	Inject Gen Anaesthetics
C4A	C4A1	Cereb/Periph Vasotheraps	N2A	N2A0	Narcotic Analgesics
C7A	C7A0	B-Blocking Agents,Plain	N2B	N2B0	Non-Narcotic Analgesics
C8A	C8A0	Calcium Antagonist Plain	N3A	N3A0	Anti-Epileptics
C9A	C9A0	Ace Inhibitors Plain	N4A	N4A0	Anti-Parkinson Preps
C9B	C9B1	Ace Inhibitors Comb+A-Hyp/Diur	N5A	N5A1	Atypical Antipsychotics
C9B	C9B3	Ace Inhibitors Comb+Calc Antag	N5B	N5B1	Non-Barbiturate Plain
D10A	D10A0	Topical Anti-Acne Preps	N5C	N5C0	Tranquillisers
D11A	D11A0	Other Dermatological Prd	N6A	N6A1	Antidepress.Excl Herbals
D1A	D1A1	Topical Dermat Antifung	N6B	N6B0	Psychostimulants
D6D	D6D1	Topical Antivirals	P1D	P1D1	Antimalarials Single Ing
D6D	D6D9	Oth Top Prds Viral Inf	R1A	R1A1	Nasal Cortic W/O Anti-inf
D7A	D7A0	Top.Corticosteroid Plain	R1A	R1A6	Nasal A-Allergic Agents
G4A	G4A1	Urinary Antibiot/Sulphon	R1B	R1B0	Systemic Nasal Preps
G4B	G4B3	Erectile Dysfunction Prd	R3G	R3G4	A-Chol+B2-Stim Comb,Inh
G4B	G4B4	Urinary Incontinence Prd	R6A	R6A0	Antihistamines Systemic
G4B	G4B9	All Oth Urological Prods	S1D	S1D0	Anti-Viral Agents -Eye
J1C	J1C1	Brd.Spect.Penicill.Oral			

TABLE A2: List of Branded Drugs losing patent protection

Brand Name	*Generic Name*	*Quarter Generic Entry*
anafranil	clomipramine	1996q4
ansaid	flurbiprofen	1994q2
augmentin	amoxicillin+clavulanic acid	2002q3
axid	nizatidine	2001q3
betapace	sotalol	2000q2
blenoxane	bleomycin	1996q3
bumex	bumetanide	1995q1
buspar	buspirone	2001q2
capoten	captopril	1995q4
capozide	captopril+hydrochlorothiazide	1997q4
carafate	sucralfate	1996q4
cardene	nicardipine	1996q3
cardura	doxazosin	2000q4
ceclor	cefaclor	1994q4
cerubidine	daunorubicin	1998q2
ciproxin	ciprofloxacin	2003q2
clarinase	loratadine+pseudoephedrine	2002q3
claritine	loratadine	2002q3
condylox	podofilox	2002q1
cordarone	amiodarone	1998q2
cyclocort	amcinonide	2002q2
cylert	pemoline	1999q2
daypro	oxaprozin	2001q1
diprivan	propofol	1999q2
dormicum	midazolam	2000q2
drogenil	flutamide	2001q3
dtic-dome	dacarbazine	1998q4
duricef	cefadroxil	1996q1
eldepryl	selegiline	1996q3
elocon	mometasone	2002q1
floxstat	ofloxacin	2003q3
floxyfral	fluvoxamine	2000q4
glucophage	metformin	2002q1
glucotrol	glipizide	1994q2
heitrin	terazosin	1999q3
imuran	azathioprine	1995q3
inocor	amrinone	1998q3
lariam	mefloquine	2002q2
leponex	clozapine	1997q4
lodine	etodolac	1997q1
loniten	minoxidil	1996q2
losec	omeprazole	2002q4
mevacor	lovastatin	2001q4
mexitil	mexiletine	1995q2
micronase	glibenclamide	1994q2
mutamycin	mitomycin	1995q2
myambutol	ethambutol	2000q2
navelbine	vinorelbine	2003q1

Brand Name	Generic Name	Quarter Generic Entry
nizoral	ketoconazole	1999q2
nolvadex	tamoxifen	2002q4
normodyne	labetalol	1998q3
pepcidine	famotidine	2001q2
permax	pergolide	2002q4
pevaryl	econazole	2002q4
platinol	cisplatin	1999q4
prostin vr	alprostadil	1998q1
prozac	fluoxetine	2000q3
psorcon	diflorasone	1998q2
questran	colestyramine	1996q3
relifex	nabumetone	2001q3
retin-a	tretinoin	1998q2
rivotril	clonazepam	1996q3
rynatan mepo	chlorpheniramine+mepyramine	1994q4
sandimmun	ciclosporin	1998q4
sectral	acebutolol	1995q2
seroxat	paroxetine	2003q3
serzone	nefazodone	2003q3
somnatrol	estazolam	1997q3
stadol	butorphanol	1997q2
staril	fosinopril	2003q4
sufenta	sufentanil	1996q1
tagamet	cimetidine	1994q2
talwin nx	naloxone+pentazocine	1997q2
tambocor	flecainide	2002q1
taxol	paclitaxel	2000q4
temovate	clobetasol	1994q3
tenex	guanfacine	1995q4
ticlid	ticlopidine	1999q2
toradol	ketorolac	1997q2
trental	pentoxifylline	1997q3
ultram	tramadol	2002q2
unat	torasemide	2002q2
univasc	moexipril	2003q2
vaseretic	enalapril+hydrochlorothiazide	2001q3
vasotec	enalapril	2000q3
viroptic	trifluridine	1996q2
voltaren	diclofenac	1995q3
wytensin	guanabenz	1994q3
zantac	ranitidine	1997q3
zaroxolyn	metolazone	2003q3
zavedos	idarubicin	2002q3
zestoretic	hydrochlorothiazide+lisinopril	2002q2
zestril	lisinopril	2002q2
zinnat	cefuroxime axetil	2002q1
zovirax	aciclovir	1997q2