COMMON OWNERSHIP AND MARKET ENTRY: EVIDENCE FROM THE PHARMACEUTICAL INDUSTRY [1]

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Abstract

Common ownership - where several firms are (partially) owned by the same investors - and its impact on product market competition has recently drawn much attention. This paper focuses on its implications for market entry. We consider the entry decisions of generic pharmaceutical firms into drug markets that are opened up by the end of regulatory protection and which were previously dominated by a single firm selling the brand name drug. We find robust evidence that an increase in common ownership leads to a significant reduction in generic entry.

JEL-code: G23, K21, L11, L41, L65
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1 Introduction

Common ownership - where several firms are (partially) owned by the same investors - and its impact on product market competition has recently drawn much attention

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from policy makers and academics alike.[5] In the pharmaceutical industry, common ownership is widespread.[6] Common investors hold shares in both "brand firms," such as Johnson & Johnson, that primarily launch new drugs on the market, and "generic firms," such as Mylan, that primarily produce generic drugs and enter the drug markets of brand firms once patents and other regulatory protection of these markets expire. This fact is illustrated by Table 1 which shows the top 5 largest shareholders in Johnson & Johnson and Mylan. The three largest shareholders in these two firms are the same: BlackRock, Vanguard and State Street, some of the world's largest institutional investors. A controversial question is if, and if so in which way, firms' decision-making is altered by the presence of common ownership as, rather than maximizing their own value, commonly-owned firms may maximize their shareholders' *portfolio* values.

[Insert Table 1 about here]

This article investigates the effect of common ownership on one of the most important decisions firms make: market entry. Specifically, we analyze generics' entry decisions into markets opened up by the end of regulatory protection. Monopolized markets are a vital source of revenue for brand firms. Brand revenues can decline by as much as 90% following generic entry (Branstetter et al., 2016). Moreover, losses to the brands and gains to the generics are highly asymmetric. According to one estimate, brand firms value deterring entry at about $4.3 billion on average (Jacobo-Rubio et al., 2020). In contrast, generic firms value the right to enter at about $204.3 million. This is also true in our sample. As shown by Figure 1, with the event of generic entry, not only brand revenues decrease; also total market revenues decrease, although to a relatively lesser extent.[7] Thus, the market entry decision of a generic firm may crucially depend on whether the owners of this generic firm also have stakes in the brand.[8]

[Insert Figure 2 about here]

[5] For a review of the academic literature see Backus et al. (2019) and Schmalz (2018, 2021).

[6] In Banal-Estanol et al. (2021), we provide a full network analysis of the common ownership patterns in the US pharmaceutical industry over the same sample period used in this paper.

[7] Revenues are proxied by Medicaid reimbursements (see Section 4 for a description of the data).

[8] Our data indicates that top shareholders in generic firms should have a substantial interest in brand profits. For pairs where both the brand and generic firms are publicly listed we see that, on average, the top 10 shareholders in the generic firm collectively own 51%, valued at $3.7 billion, in the *generic* firm. They also collectively own 6.5%, valued at $7.6 billion, in the *brand* firm. In fact, for 75% of the brand-generic pairs, the value held in the brand firm by the top 10 shareholders of the generic firm exceeds the value held in the generic firm. Given the large losses to brand profits upon generic entry, even small stakes in the brand would incentivize the common owners to influence the generic entry decision.

In this paper, we investigate whether a higher level of common ownership between potential generic entrants and the market's incumbent brand reduces the likelihood of generic market entry. Our empirical analysis combines patent and drug approval data from the US Food and Drug Administration's (FDA) Orange Book with ownership data of publicly listed pharmaceutical companies from the Thomson Reuters Global Ownership Database. The US pharmaceutical industry is an attractive industry for studying entry because (i) pharmaceutical markets are well defined, (ii) there are clear entry windows and (iii) US health care expenditure as a percentage of GDP is among the highest in the world and generics are crucial for containing healthcare costs. Indeed, promoting generic entry is an important goal for the FDA and there are hundreds off-patent brand drugs which do not face any generic competition (FDA, 2019).

We first present a simple framework to lay out the effects of common ownership on generic entry, where we consider a set of generic firms that have the possibility to simultaneously enter a market currently dominated by the drug of a brand firm. We analyze how an increase in the levels of common ownership between a focal generic and the brand should affect the individual generic's entry decision. We further propose different pairwise measures of common ownership between generic and brand firms.

Thereafter we empirically test and corroborate the proposition that higher pairwise levels of common ownership between generic and brand firms reduce individual generic entry. Our results hold if we instrument common ownership with stock market pharma index membership. The results are also robust to several measures of common ownership which cover different channels of investor influence, different econometric methods, different definitions of the potential entrant set, different time-horizons and different sets of fixed effects. Our regressions include the controls used in previous literature, including generic prior experience, pre-entry market size and the number of drug substitutes. The average effect is large: a one-standard-deviation increase in common ownership between a given generic and the brand decreases the probability of entry by that generic firm by 13-16%, depending on the measure of common ownership. Furthermore, our results indicate a non-linear impact, with high levels of common ownership, i.e., "strong links," have a much larger impact on generic entry than low levels. Still, as compared to the effect of being a subsidiary of the brand, the effect of any level of common ownership between the generic and the brand is smaller.

To obtain further insights on what drives our results, we perform heterogeneous effect analyses for different types of markets and for different types of potential generic entrants. We find that common ownership has a more pronounced impact on limiting

entry in large markets. Additionally, the negative effects of common ownership on entry are primarily caused by a decrease in the entry of the most experienced generics.

In a next step, we analyze how common ownership impacts overall market outcomes. We find that an increase in market level common ownership, i.e., aggregate measures of links between the potential generics in the market and the brand, has a negative effect on the overall number of entrants for different entry windows. Moreover, common ownership delays generic entry and increases the probability that the brand will face zero generic competition.

Our market level results thus suggest that the reduction of entry, due to an increase in the level of common ownership between a particular generic and the brand, is not (entirely) filled by entry of other generics. While our data is not suited to perform granular analyses at the market level, we use our theoretical framework to propose a tentative explanation for this finding. As we show in an appendix, entry decisions between potential generic entrants may exhibit strategic complementarities in the presence of common ownership. Therefore, an increase in common ownership between a given generic and the brand may also reduce the likelihood of entry of other generics, as long as they also have some common ownership with the brand. The remaining generics, such as less experienced generics, may either be non-strategic or have a too high entry cost to fill the gap. This leads to an overall decrease in the level of entry.

Common ownership is a pervasive feature not only of pharmaceutical companies, but of many industries in the US as well as Europe (Backus et al., 2021b; Fichtner et al., 2017; Seldeslachts et al., 2017; Boot et al., 2022). Although large institutional investors may own "only" 5-8% of a single company, this is often enough to position them as a top investor with privileged access to the firms' management (Malenko and Shen, 2016). There is evidence that institutional investors engage in discussions with companies' management with a view to influence companies' strategies (e.g., Fichtner et al., 2017). Specifically, in pharmaceutical markets, institutional investors with common holdings can be seen taking an active interest in the corporate decision-making.[9]

However, institutional investors do not need to actively influence companies to have an impact on firm strategies. They may employ "selective omission," encouraging actions that increase both firm and portfolio values and remaining silent when this is not the case (Hemphill and Kahan, 2019). They may also influence competition between firms through managerial incentives (Antón et al., 2023). Moreover, managers of firms

[9]We present some anecdotal evidence in Appendix A that confirms this view. Further examples of interventions by common owners are documented by Shekita (2022).

that are largely owned by shareholders that also have sizeable stakes in competitors might just simply act in these shareholders' interest, maximizing the return of their shareholders' portfolios rather than their own firm profits (Azar, 2017). In our conceptual framework, we present different measures of common ownership that reflect the different channels by which common ownership might influence firms' behavior.

This article is, to our knowledge, the first to directly consider the influence of common ownership on market entry. Previous empirical studies on common ownership have often centered on price effects (e.g. Azar et al., 2018; Backus et al., 2021a). Whereas pricing decisions are typically made on a regular basis by specialized pricing teams, market entry is a one-off decision with substantial consequences for the firm. Common ownership may be especially relevant for this type of decision. Another advantage of the current article over other empirical studies is that we do not only look at the effects of common ownership at the market level, but also consider pairwise common ownership links (between individual generics and the brand).

The article is organized as follows. Section 2 provides a literature overview of entry in pharmaceutical markets, on the one hand, and common ownership, on the other. Section 3 introduces the conceptual framework. Section 4 describes the data. Section 5 presents the sample and variables. Section 6 shows the empirical analysis and results of the effect of common ownership on the individual entry decision. Section 7 deals with the effect of common ownership on market outcomes. Section 8 concludes. We include appendices on (A) anecdotal evidence on how institutional investors influence firms' decisions in the pharmaceutical sector, (B) a simple theoretical model of strategic interaction, (C) alternative measures of common ownership, (D) database construction, (E) identification, (F) heterogeneous effects, (G) empirical robustness checks, and (H) tentative welfare implications.

2 Literature

We separately discuss the most relevant articles on the entry decisions of generic firms in pharmaceutical markets and common ownership.

Generic entry. Several articles have considered the determinants of generic entry decisions in off-patent drug markets. A common finding from this literature is that generic entry increases with the size of the branded drug's market prior to the loss of patent protection, where market size is commonly measured as brand-generated

revenues (Scott Morton, 1999; Moreno-Torres et al., 2008; Appelt, 2015).

Scott Morton (1999) considers other aspects of generic entry decisions in US pharmaceutical markets. She finds that generic firms are more likely to enter markets in which they have previous experience in drug form, therapy class or ingredient. Kyle (2006) and Appelt (2015) similarly confirm the importance of generic firm characteristics. Scott Morton (1999) also highlights the role of the characteristics of the drugs e.g. drug form/route. Appelt (2015) examines the impact of authorized generics, i.e., the distribution and marketing of the brand product under a generic label through an authorized generic distributor (typically just before the loss of the patent). She finds that authorized generic entry has no significant effect on the likelihood of "independent" generic entry.[10]

Scott Morton (2002) analyzes how direct ownership links between the brand firm and a generic firm influences the likelihood of generic entry. She finds that generics owned by the original innovator (i.e., the brand company) are less likely to enter the market. In the US, generic firms can enter markets early by legally challenging the brand's patents via Paragraph IV of the Hatch-Waxman Act. Helland and Seabury (2016) investigate the link between Paragraph IV challenges, settlements and entry. They find that a Paragraph IV challenge increases generic entry, although a settlement effectively reverses the effect. Hovenkamp and Lemus (2018), finally, confirm that settlements after Paragraph IV challenges cause generics to stay out of the market.

Common ownership. In terms of theoretical work, a number of early authors have remarked that shareholder diversification can lead firms to internalize the externalities they impose on rivals; see Schmalz (2018, 2021) for an overview. These models show that common ownership reduces incentives to compete as the gains of aggressive competition come at the expense of other firms in the investors' portfolio. Consequently, common ownership is predicted to lead to higher prices and boost profits. On the other hand, Lopez and Vives (2019) find that common ownership may lead to a higher welfare in a context of cost-reducing R&D investment in the presence of spillovers.

[10]There are also a few papers providing empirical structural models of generic entry that provide for interesting policy experiments. Gallant et al. (2010) document the spillover effect of a firm's past entry decisions on its future entry costs. Ching (2010a) develops and estimates a dynamic oligopoly structural model to capture (i) generic firms' entry decisions, (ii) both brand-name and generic firms' dynamic pricing decisions, and (iii) consumer and firm learning about the generic drug quality over time. Wang et al. (2023) incorporate heterogeneity in generic entrants' characteristics, by distinguishing between leaders and non-leaders in terms of number of FDA approvals. They find that manufacturing complexity significantly reduces the likelihood of generic entry.

Previous empirical studies on common ownership have often centered on price effects. Focusing on the US airline industry, Azar et al. (2018) use the modified Herfindahl-Hirschman index (MHHI), developed by O'Brien and Salop (2000), which provides a measure of the extent of common ownership at the market level. They find that ticket prices are about 3-12% higher than would be the case under separate ownership. Backus et al. (2021a) focus on the ready-to-eat cereal industry. Their results show that while the potential magnitude of common ownership effects on prices could be large, standard own-firm profit maximization is more consistent with the data for this industry. Boller and Scott Morton (2020) study the effect of common ownership on stock prices. They show that increases in common ownership cause increases in stock returns, consistent with the hypothesis that common ownership raises profits.

Xie and Genakos (2020) find that institutional investors' common holdings between US generic and brand companies increase the likelihood of settlement agreements after generic companies have disputed the brand's patent validity through a Paragraph IV challenge. Schmalz and Xie (2022) also find that an increase in common ownership increases the probability of settlement. These studies, thus, are complementary to this article as they showcase a plausible way through which entry can be deterred in pharmaceutical markets.

Some empirical studies highlight the positive effects of common ownership. Antón et al. (2021) examine how common ownership positively affects R&D investments and innovation output. Geng et al. (2016) find that vertical common-ownership links can mitigate hold-up problems, which in turn is correlated with more innovation. The findings of Eldar and Grennan (2020) suggest that common ownership by VC investors helps weaker startups to improve their performance and raise more capital.

There is also a body of literature in corporate finance that investigates channels through which institutional investors might have an impact on governance, policies and strategic decisions of firms (e.g., Aghion et al., 2013; Malenko and Shen, 2016; Brav et al., 2018; Antón et al., 2023). Appel et al. (2016) find that passive mutual funds have a significant and positive impact on board composition and anti-takover provisions, and suggest that a key mechanism by which these investors exert their influence is through their large voting blocks.

3 Conceptual framework

We now present a simple framework to lay out the effects of common ownership on market entry. We consider a set of generic firms that have the possibility to simultaneously enter a market currently dominated by the product of a brand firm.[11] We then analyze how an increase in the levels of common ownership between a focal generic and the brand should affect this individual generic's entry decision. We further propose several pairwise measures of common ownership between generic and brand firms. In Section 7 we will consider the effects of common ownership on market level outcomes.[12]

Common ownership and individual entry. Consider a set of N (≥ 1) generic firms, assumed symmetric for notational simplicity, that can simultaneously enter the market of a brand firm b.[13] We focus on the decision of one of these generic firms, the *focal* generic g, as a function of its beliefs about the entry decisions of the other generics. Denote by p_k the probability, assigned by this (risk-neutral) focal generic, to the event that a number k of the *other* generic firms enter the market, where $k = 0, ..., N-1$ and $\sum_{k=0}^{N-1} p_k = 1$. Denote by π_g^k the focal generic's profits in a market that includes k other generic firms (the market contains in total $k+2$ firms, when also counting the brand firm). Profits π_g^k may also include fixed costs of entry, and are thus net of these entry costs. Profits in the absence of entry are normalized to 0, so π_g^k is also the gain or loss in profits upon entry. Denote by $\Delta\pi_b^k (< 0)$ the loss in profits of the brand firm b due to an increase from k to $k+1$ in the total number of generic entrants in the market.

[11] Our conceptual and empirical framework considers, as the seminal paper of Scott-Morton (1999), entry decisions to be simultaneous. Indeed, our main empirical setup specifies an entry window of six quarters, where most entries occur (see Figure 3). During this time frame, entry decisions should be considered as simultaneous. This is because the entire application process for generic drugs takes six quarters on average. Information on ANDA's received by the FDA is kept secret until approval and manufacturers do not reveal their entry plans due to strategic business considerations.

[12] Throughout the paper, we disregard the common ownership links among generic firms. Banal-Estanol et al. (2021) show that the common ownership network of generic firms is very sparse and stays that way over the span of the sample period. Instead, as we also show later in this paper and more in detail in Banal-Estanol et al. (2021), the common ownership links between brands firms, on the one hand, and generic firms, on the other, are more dense and have increased in density over time.

[13] Note that the Waxman-Hatch gives the first generic exclusivity for two quarters. Our simple symmetric setup can be easily extended to accommodate ex-post first-mover advantages. Suppose that, despite taking the entry decisions simultaneous, one of the generic entrants in our model becomes (randomly) first in obtaining ANDA approval, thus enjoying higher ex-post profits because of the two-quarter exclusivity rights conferred by the Waxman-Hatch Act. Even if the ex-post generic entrant profits are asymmetric, the ex-ante expected profits from entry (the relevant objective for the decision) can still be symmetric. One would just need to replace the profits π_g^k of the main formulation by corresponding expected profits. The results of the analysis would be the same.

We posit that any possible gain the focal generic can obtain with entry is lower than the losses suffered by the brand, as generic competition reduces brand firm's profits significantly (Branstetter et al., 2016). In other words, although a generic firm's profits may increase with entry, i.e., π_g^k may be positive, joint profits decrease, i.e., $\pi_g^k + \Delta\pi_b^k < 0$, independently of the number k of other generics that decide to enter the market. This is consistent with the evidence we provide in Figure 1 on the relationship between number of entrants, and brand and total market revenues.[14]

Common ownership between the focal generic and the brand firm makes the generic's entry decision non-trivial. Indeed, shareholders of the generic that also own shares in the brand should also care about the reduction of joint profits. As a result, the decision-makers of generic g may also take into account the reduction of joint profits when deciding whether to enter. Formally, let us denote by δ the weight the decision-makers of g place on joint profits, rather than on individual generic firm profits. Generic g should enter the market if the expected net gains from entry Π_g are positive, where

$$\Pi_g(p_0, ..., p_{N-1}, \delta) \equiv \sum_{k=0}^{N-1} p_k[(1-\delta)\pi_g^k + \delta(\pi_g^k + \Delta\pi_b^k)].^{15} \quad (1)$$

An increase in common ownership between g and b will naturally increase δ, and thus δ can also be viewed as a measure of common ownership. In the absence of common ownership between g and b, the generic g should place no weight on joint profits, and thus $\delta = 0$. Entry should occur as long as the generic's profits increase with entry, $\pi_g^k > 0$. At the other extreme, in the case where common ownership is so high that joint profits are as important as individual generic profits, $\delta = 1$, entry should not occur, as $\pi_g^k + \Delta\pi_b^k < 0$ for any k. More generally, the expected net gains from entry of a generic g should decrease in its level of common ownership with the brand, as

$$\partial\Pi_g(p_0, ..., p_{N-1}, \delta)/\partial\delta = \sum_{k=0}^{N-1} p_k \Delta\pi_b^k < 0 \text{ for any } p_0, ..., p_{N-1}. \quad (2)$$

Thus, an increase in the level of common ownership between a generic and the brand should reduce the likelihood of entry by this individual generic. Indeed, the entry of the focal generic reduces the brand firm's profits, independently of the entry decisions

[14]It also means that the business stealing effects caused by generic entry on the brand firm are larger than any market expansion effect. This should hold true for markets with low demand elasticity of which pharmaceutical markets are a primary example (Duggan and Scott Morton, 2010).

[15]Equivalently, δ is the weight that the decision-makers of the generic place on the change of profits of the brand relative to the weight they place on the change in profits of the generic itself, $\Pi_g(p_0, ..., p_{N-1}, \delta) = \sum_{k=0}^{N-1} p_k[\pi_g^k + \delta\Delta\pi_b^k]$.

of the other generic firms (and the beliefs the focal generic may have over these).[16]

Common ownership measures. We propose three measures that aim to capture how common investors' interests in the two firms affect the weight that the generic firm's decision-maker places on joint rather than on individual firm profits. We posit that ownership of the brand provides common investors with *incentives* to steer decisions towards joint profits and ownership of the generic provides them with the *ability* to influence such decisions (Posner et al., 2017). The main difference between our measures is how incentives and ability to influence decisions are taken into account. In Appendix C we present additional common ownership measures.

SIZE-BASED MEASURE. This approach assumes that there exists a "joint profit steering index," which (i) increases with the size of the common investors' shareholdings in the brand (incentive), and (ii) increases with the size of the common investors' shareholdings in the generic (ability). A higher value of the index steers the decision-maker in the generic towards joint profit maximization (as illustrated in equation (1)). We assume further that the marginal effect of an increase in incentives does not depend on the level of ability, and vice versa.[17] Formally, assuming a symmetric treatment of incentives and ability, we posit that

$$\delta_S(g,b) \equiv \frac{\sum_{i\in C}(\gamma_{ig}+\gamma_{ib})}{\sum_{i\in C\cup NC}(\gamma_{ig}+\gamma_{ib})}, \tag{3}$$

where γ_{ig} and γ_{ib} are the shareholdings of investor i in the generic and brand, respectively, and C stands for the set of common shareholders whereas NC stands for the set of shareholders with ownership stakes in only one of the two firms ("non-common investors").[18] Note that the measure ranges between zero and one. The generic firm will place no weight on joint profits ($\delta_S = 0$) if there are no common shareholders, and it will place full weight on joint profits ($\delta_S = 1$) if all the shareholdings are common.[19]

[16] In Appendix B, we present a simple model of strategic interaction. We illustrate the type of strategic effects that may appear in this setting and characterize the equilibrium entry decisions of N symmetric generics as a function of their level of common ownership with the brand.

[17] As we will show in Appendix C, we obtain similar results if we use an alternative measure in which incentives require ability, and vice versa (i.e., where the shareholdings in the two firms are complementary). In practical terms, our size-based measure does not penalize unequal shareholdings in the two firms, whereas the alternative complements measure does.

[18] In both our conceptual framework and empirical analysis, we only consider the "relevant shareholdings," i.e., those with a minimum ownership stake above that which one can arguably have influence on firm decision-making (set at 1% in the empirical analysis). That is also why the denominator in (3) may be smaller than two.

[19] Note that we are also implicitly assuming that common investors coordinate their collective decision making. This assumption makes sense if common owners have similar interests. For example, a

A relevant threshold is when more than half of the total ownership in the pair is in the hands of the common investors (i.e., if $\delta_S > 0.5$), as the majority of shareholders are common owners. This threshold will be used in the empirical analysis, as further below explained.

RANK-BASED MEASURE. Our second approach assumes that only the top investors have the ability and incentive to steer decisions towards joint profit maximization. We consider that the presence of a common investor increases the joint profit steering index if and only if it is a top 5 investor in both the generic and brand firms. However, we assume that within the group of the top 5 investors, they all count equally. Therefore, we build the ratio of the top 5 investors in the generic that are also one of the top 5 investors in the brand firm.[20]

$$\delta_R(g,b) \equiv \textstyle\sum_i I(\gamma_{ig} \geq \gamma_{(5)g} \text{ and } \gamma_{ib} \geq \gamma_{(5)b})/5,$$

where γ_{ig} and γ_{ib} are the shareholdings of investor i in the generic and brand, respectively, $\gamma_{(5)g}$ and $\gamma_{(5)b}$ are the 5-th largest shareholdings in the generic and brand firm, and $I()$ is the indicator function which is equal to 1 if the argument is true, and 0 otherwise.[21]

WEIGHTED SUM OF INTERESTS MEASURE. Our third approach, often called "Kappa," following O'Brien and Salop (2000), Backus et al. (2019) and Boller and Scott Morton (2020), assumes that the decision-makers maximize a weighted sum of the interests of *all* the shareholders of the generic firm. That is, the interests of any (common or non-common) shareholder i of the generic, who has holdings γ_{ig} and γ_{ib} are given by $\gamma_{ig}\pi_g + \gamma_{ib}\pi_b$, where γ_{ib} can be zero. The weight of each investor in a generic firm's decision-making is equal to her degree of control of the generic firm. Assuming that control is proportional to ownership, the degree of control of each shareholder is given by γ_{ig}. Decision-makers of the generic firm should therefore maximize

$$\textstyle\sum_i \gamma_{ig} \left[\gamma_{ig}\pi_g + \gamma_{ib}\pi_b\right].$$

Straightforward algebra shows that maximizing this function is equivalent to maximiz-

case study of a shareholder vote at the company DuPont indicates how common investors can group together to implement their objectives (Schmalz, 2015)

[20] As we will show in Appendix C, we obtain similar results if we use an alternative rank-based measure on the basis of the top 10 investors, instead of the top 5.

[21] The scale is between zero and one. The generic firm will place no weight on joint profits ($\delta = 0$) if there are no top 5 common shareholders, and a condition for full-weight on joint profits ($\delta = 1$) is that all top 5 shareholders are common.

ing $(1-\delta_L)\pi_g + \delta_\kappa(\pi_g + \Delta\pi_b)$, where

$$\delta_\kappa(g,b) \equiv \frac{\sum_i \gamma_{ig}\gamma_{ib}}{\sum_i \gamma_{ig}^2}.$$

This measure captures the the shareholdings in the generic (ability) and shareholdings in the brand (incentives) taking into account the ownership concentration of the generic.[22]

4 Data

We explain both the pharmaceutical and common ownership data in this section. More details on the data and the construction of the dataset can be found in Appendix D.

Entry in the pharmaceutical industry. Broadly speaking, pharmaceutical firms can be categorized as brand or generic firms.[23] Brand firms undertake costly research and development to discover new medications and bring them to market, and must apply for FDA approval through the new drug application (NDA) procedure. Once a brand has received FDA approval, it is awarded "data exclusivity" for a period of three, five or seven years, depending on the drug type. Data exclusivity protects the underlying clinical data and runs concurrently with patent protection. The period that spans between the end of data exclusivity and the expiration of the last patent, if any, is commonly referred to as "market exclusivity."

Generic firms produce bio-equivalent replications of brand drugs at a much lower cost, after they have already been marketed as brand-name products. Generic firms are able to enter a particular drug market once the regulatory protections afforded to the brand product have expired. During the market exclusivity period, generics can challenge the monopoly rights of the brand in court through Paragraph IV certification. Generic companies can also apply for FDA approval once all patents are expired. In both instances, an abbreviated new drug application (ANDA) must be submitted to the FDA. The protection conferred to new drugs is illustrated in Figure 2.

[22]See O'Brien and Waehrer (2017) and Backus et al. (2019) for a thorough discussion of this measure. As opposed to our previous two measures, δ_κ is not symmetric with respect to the two ownership stakes. Furthermore, δ_κ can be larger than one. This would imply that the decision-makers of the generic put more weight on the profits of the brand than on those of the generic itself. This might lead to the phenomenon of "tunneling," i.e., a transfer of profits from generic to brand to the benefit of the common owners.

[23]Note that we define firms as being a "brand" or a "generic" on a drug market basis. It is possible that the same firm is a potential generic entrant for one market and the brand company in another market. This can occur because some companies produce both branded drugs and generic drugs.

[Insert Figure 2 about here]

We use ANDA FDA approval as an indicator of generic entry, in line with several articles on the topic (e.g., Helland and Seabury, 2016; Hovenkamp and Lemus, 2018; Scott Morton, 1999). We consider a market to be open for generic entry at the earlier of either the date of first generic entry or the end of the market exclusivity period.[24] We term this date the "end of regulatory protection."[25] We focus on entry that occurs within six quarters after the end of regulatory protection, as generics prefer to enter a market as early as possible (Wang et al., 2022, Scott Morton, 1999) and it indeed captures most of the actual generic entries in our sample (see Figure 3). However, given the potential sensitivity of results to our time window, we will show that results are robust to other entry period definitions.

[Insert Figure 3 about here]

Pharma data. We obtain data on NDAs and ANDAs from the FDA Orange Book (FDA, 2017a; FDA, 2001-2016). The FDA Orange Book provides data on all launched pharmaceutical products in the United States since 1982. The data includes information on the launching company, type of drug (NDA or ANDA), associated patents, list of ingredients, drug form/route, strength, approval date and status (prescription, over-the-counter, or discontinued). Information on the submission class of the brand product is merged in from the Drugs@FDA database (FDA, 2017b) using the FDA application number. Products are linked to their therapeutic field using the ATC/DDD Index (WHO Collaborating Centre for Drug Statistics, 2017) using exact text matching, based on compound-name.[26] Drug markets are defined at the ingredient-form level.[27]

[24] If we observe FDA approval of the first generic entrant before the end of the market exclusivity period, then a generic successfully challenged the brand's patent through a Paragraph IV procedure. Other generics can then enter too, although possibly with a delay of two quarters due to temporary monopoly rights conferred to the first paragraph IV filer (see e.g., Hovenkamp and Lemus, 2018).

[25] That is, we consider a market to be open for generic entry at the earlier of either the date at which the *last* patent listed in the Orange Book for the drug expires or the date of first generic entry. We use the phrases "open for entry" and "end of regulatory protection" interchangeably to refer to this point in time. To check the robustness of our results to an alternative definition of the date of end of regulatory protection, we use information on the type of patent. Results hardly change, as we will show in the robustness checks section.

[26] The ATC/DDD Index categorizes all chemical compounds used in any therapeutic field according to a five-level hierarchical system, called the Anatomical Therapeutic Chemical (ATC) Classification System.

[27] For example, the drug with the brand-name Zyrtec in syrup form with the ingredient Cetirizine Hydrochloride 5mg/5ml is considered to be in the same drug market as Zyrtec in syrup form with the ingredient Cetirizine Hydrochloride 10mg/10ml. However, the product Zyrtec Allergy with the ingredient Cetirizine Hydrochloride 10mg in the form of a tablet constitutes a different market. The therapeutic field in which Zyrtec falls, at the ATC-2 level, is "Antihistamines for systemic use."

We match the brand product (NDA) with the sample of potential generic entrants to form a brand product-generic pair. The sample of potential generic entrants in the market includes all pharmaceutical companies that launched at least one generic product in our drug markets and have previous experience in launching generic drugs of the same form/route (i.e. oral, injection etc.) as the relevant brand drug. Results are robust to a set of different definitions of the entrant set, as we will show in the robustness section.

Common ownership data. We use the Thomson Reuters Global Ownership Database (Thomson Reuters Global One, 2015), which includes holdings by each shareholder in each publicly listed firm worldwide for every year-quarter. For US-listed firms Thomson Reuters collects ownership information from 13F, 13D and 13G filings, and forms 3, 4, and 5. For companies outside the US, information is sourced from stock exchange filings, trade announcements, company websites, company annual reports and financial newspapers.

For each pharmaceutical firm and for each quarter in the period 2003-2014, we extract data on all the shares held by each investor. We define the quarterly shareholdings of each (ultimate) investor as the fraction of shares held by that investor in that quarter, relative to the total number of shares held by all the investors in our database.[28] We then compute yearly shareholdings, averaging the quarterly shareholdings over the four quarters. We keep the "relevant" shareholdings, i.e., those that represent at least 1% of the total number of shares. A common shareholder in a brand-generic pair is then defined as an investor that owns at least 1% of the shares in each of the two firms while a non-common shareholder is an investor that owns at least 1% in one of the two firms but not in the other.

The advantages with regard to datasets used by most other papers on common ownership in the US, which use Thomson's Spectrum database, are considerable (but see Amel-Zadeh et al. 2022, and Azar and Ribeiro, 2022, for recent papers that use similarly complete databases). That database is limited to 13F filings, which contains only large investors in US companies, whereas some pharma companies are not listed on a US stock market. Moreover, the Thomson's Spectrum database shows holdings assigned to the owner that filed the 13F. This is what is commonly referred to as an "as-filed view." Our database utilizes a "money-manager view." With this view, the

[28]For a detailed explanation of our data and dynamic assignment of ultimate owners, see Newham et al. (2024) and data repository https://www.openicpsr.org/openicpsr/project/120781/version/V1/view attached to the paper Banal-Estañol et al. (2020), available at: https://doi.org/10.1257/pandp.20201026

database combines together one or more filings to link the holdings to the actual firm that manages the investments. In other instances, it might break apart a single filing in order to accomplish the same. The holdings would then be assigned to one or more of the managers listed on the file.

5 Sample, variables and descriptive statistics

Our final sample consists of 395 drug product markets and 34,144 potential generic-branded drug pairs. We consider drug products that faced generic entry or patent expiry between 2004 and 2014, as this is the range for which we have data on all relevant variables. In total there are 93 unique brand companies and 10,453 unique generic-brand pairs. We now describe the variables used in the empirical analysis.

Individual entry decision. We define *Entry* as an indicator variable equal to 1 if the generic has entered within six quarters after the end of regulatory protection, and equal to 0 if not. In the robustness checks, we will show that results are robust to other entry period definitions.

Pairwise common ownership. We construct the measures introduced in the conceptual framework: δ_S, δ_R and δ_κ. Figure 4 shows the evolution of these measures over time. It is evident that common ownership has increased significantly from 2003 to 2014. The growth was relatively low until the beginning of 2010. However, in the last four years of our sample the average level of common ownership almost doubled.[29]

[Insert Figure 4 about here]

Our main setup uses common ownership measured in the year prior to the end of regulatory protection, as entry requires time to acquire an approved source of materials and suitable production facilities. Indeed, about one to two years before filing an ANDA application, the generic firm should start preparing to enter (Reiffen and Ward, 2005). However, as it is unclear at exactly what point time the final entry decision of

[29]Common ownership is an increasingly pervasive pattern in many other sectors, including airlines and banking (see e.g. Azar et al., 2018), as well as more generally across all the S&P 500 firms (Backus et al., 2021) and across all publicly listed firms in the US (Banal-Estanol et al., 2022b), particularly since the 2007-2008 great financial crisis (Banal-Estanol et al., 2022a; Lewellen and Lowry, 2021). Banal-Estanol et al. (2022b) argue that the increasing levels of common ownership can be explained by the increase in the money holdings of more diversified passive investors.

the generic firm is made, we also check and confirm that our results are robust to the use of common ownership measured two and zero years prior to the end of regulatory protection.

To investigate whether greater levels of common ownership have a larger impact, we construct categorical variables of common ownership. We start with the size-based measure δ_S, which presents natural thresholds. We define the following indicator variables: $I(0 < \delta_S \leq 0.3)$ which takes on the value 1 if $\delta_S \in (0; 0.3]$, $I(0.3 < \delta_S \leq 0.5)$ which takes on the value 1 if $\delta_S \in (0.3; 0.5]$, and $I(\delta_S > 0.5)$ which takes on the value 1 if $\delta_S \in (0.5; 1]$.[30] As stated above, especially $I(\delta_S > 0.5)$ is of interest, as it is the category where the common investors are the majority shareholders. We also construct indicator variables for the weighted sum of interest measure δ_κ, where we use numerical thresholds that correspond to the percentiles used for δ_S.[31,32] Note that our rank measure δ_R is already categorical, and, hence, does not need to be transformed to investigate non-linearities.

Furthermore, we pay particular attention to the case in which the potential generic entrant is a subsidiary of the brand firm. We create an indicator variable that takes on the value 1 if the potential generic entrant is a subsidiary of the brand and 0 if it is not.[33] In the former scenario, common ownership measures are set to zero, as we assume direct ownership trumps common ownership (which will be confirmed later in our results).

Descriptive statistics. Table 2 (see rows 1-5) presents summary statistics for the individual entry decision, the pairwise measures of common ownership and the subsi-

[30]Note that there are 582 unique generic-brand pairs with δ_S greater than 0.5 in our sample. This is 5.6% of all brand-generic pairs. There are 2,394 unique pairs in the lowest category and 1,046 unique pairs in the middle category.

[31]In particular, $\delta_S = 0.3$ and $\delta_S = 0.5$ correspond to the $65th$ and $87th$ percentiles, which in turn correspond, approximately, to $\delta_\kappa = 0.2$ and $\delta_\kappa = 0.5$.

[32]For private firms, i.e., not listed on a stock-exchange, we assume that they do not have common investors with any other firm. We checked ownership data for our private companies in the Refinitiv VentureXpert database. We found only three common ownership links among private brand-generic pairs. Moreover, according to Refinitiv VentureXpert, the three largest common owners in public companies in our database (Blackrock, State Street and Vanguard) show no holdings into our private companies. However, the database seems to be incomplete. We note that this dimension is an interesting avenue for future research.

[33]We consider a firm X to be subsidiary of a firm Y if firm Y has a direct ownership stake of more than 50% in firm X. For the vast majority of subsidiary pairs (92%), firm Y owns 100% of firm X. In the remaining cases the stake lies between 53-95%. We could in principle also identify minority shareholdings, i.e., where one firm has an ownership stake of less than 50% in another firm. However, in the dataset used for the main analysis, there are no pairs with minority shareholding links.

diary variable. The unconditional probability of entry is 2.8%.[34] On average, common owners have a share of ownership δ_S equal to 8%, where the range is between 0 and 95%. The mean values for δ_R and δ_κ are 0.054 and 0.067 respectively. For 84 pairs (0.246%) there is a parent-subsidiary relationship.

Generic-market control variables. Controlling for generic firm characteristics has shown to be crucial (Scott Morton, 1999; Scott Morton, 2002; Kyle, 2006). Prior experience in the relevant market is one of the key characteristics of the potential generic entrants. *Experience Route* serves as a proxy for the potential entrant's experience in the brand drug form/route, by counting the number of products, with the same route of administration as the brand product, previously launched by the generic one quarter prior to the end of regulatory protection. Similarly, *Experience ATC2* serves as a proxy of the generic's experience in the relevant therapeutic field at the ATC2 level. *Experience New Drug* is constructed as a count of the generic's previously launched new (brand) drugs. Generic entrants that are also active in producing new drugs may hold some patents that ease entry. *Breadth of Experience* accounts for the breadth of the generic's portfolio, by counting the number of distinct therapeutic fields in which the generic has been active in one quarter prior to the end of regulatory protection.

Table 2 (see rows 6-9) provides descriptive statistics of the experience and breadth variables, calculated using the full FDA Orange Book. All counts are divided by 10. Counts start in 1994, 10 years before the start of the sample (although our results are robust to other starting points). As can be seen in the table, the average potential generic entrant has launched about 21 generic products of the same route/form as the brand and is active in about 14 therapeutic fields.

Drug market control variables. Following prior literature, we construct variables to control for relevant drug market characteristics (Scott Morton, 1999; Kyle, 2006; Moreno-Torres et al., 2009; Appelt, 2015). We proxy for drug market size using a measure of the brand's pre-generic-entry revenues obtained from Medicaid reimbursements (Centers for Medicare and Medicaid Services, 2001-2018; available publicly from the Medicaid website).[35] We match the drugs in our sample with Medicaid reimburse-

[34]Both the number of potential entrants and realized entry opportunities are comparable with previous studies: In our sample, on average there are 86 potential entrants per market. In Scott Morton (1999) and Appelt (2015) there are on average 123 and 100 potential generic entrants per drug market respectively. In Scott Morton (1999) 2-7% of entry opportunities are realized, in Kyle (2006) 2.5% of entry opportunities are realized, and in Appelt (2015) 10% of entry opportunities are realized.

[35]Medicaid is the US public health insurance program for people with low income. In 2014, Medicaid

ment data using National Drugs Codes (NDC) (FDA, 2019) which are unique product identifiers for drugs in the US. The *Market Size (ln)* variable used in the analysis is the logged dollar value in billions of total national Medicaid reimbursements for the brand drug in the two years before the end of regulatory protection.

We further include a set of indicator variables. The variable *Authorized Generic* (FDA, 2017c) takes on the value 1 if the brand firm has launched an authorized generic in that particular market.[36] *New Chemical Entity* takes the value 1 if the drug is a novel chemical entity and has been granted new chemical entity exclusivity by the FDA. Second, *Pediatric Drug*, takes the value 1 if the drug can be used in children and has been granted pediatric exclusivity by the FDA; and *Orphan Drug*, takes the value 1 if the drug treats a rare disease and has been granted orphan drug exclusivity by the FDA.[37] These included variables control for the different characteristics and exclusivity periods of these drugs. New clinical investigations are granted a 3-year period of exclusivity. A 5-year period of exclusivity is granted to new chemical entities. Orphan drugs receive 7 years of exclusivity. Pediatric drugs receive an additional 6 months of protection at the end of the listed patents and/or exclusivity period.

In order to control for the intensity of inter-molecular competition in the therapeutic field we construct the variable *Substitutes on Patent* which provides a count of the number of on-patent substitutable active ingredients listed in the same therapeutic field at the ATC-2 level in the quarter prior to the end of regulatory protection. Similarly, *Substitutes off Patent* measures the number of off-patent substitutable active ingredients. Counts are divided by 10. Further market characteristics include the therapeutic field of the drug (ATC-2 level), submission class of the brand product, drug form/route and year of the end of regulatory protection.[38,39] Summary statistics for the drug market

covered 19.5% of Americans (ca. 65 million enrollees); see Statistica, "Percentage of U.S. Americans covered by Medicaid 1990-2022." Medicaid spending on outpatient prescription drugs accounts for approximately 5% of the total Medicaid spending, which in turn accounts for approximately 17% of the total national health expenditures (see macpac.gov and cms.gov). While Medicaid reimbursement data does not provide an accurate measure of market size in absolute terms, it arguably provides a good proxy of relative market sizes and is, therefore, suited for our purposes.

[36]Note that our left-hand variable is independent generic entry. Authorized generics can be launched without FDA approval and at any point in time (typically shortly before patent expiry). An authorized generic may be launched by a partially-owned generic or subsidiary of the brand, and hence would not enter as an independent generic

[37]This information is obtained by looking at the exclusivity rights granted to the drug in the FDA Orange Book. The excluded category, captured by the intercept, is new clinical investigations.

[38]Submission classes include Type 1 New Molecular Entity, Type 2 New Active Ingredient, Type 3 New Dosage Form, Type 4 New Combination, Type 5 New Formulation or Other Differences.

[39]We recode the FDA form/route variable to construct five form/route classes namely oral, injection, topical, ophthalmic and inhalation.

controls for the 395 drug markets can be found in Table 2 (rows 10-16).

[Insert Table 2 about here]

6 Individual entry decisions

We investigate the impact of the pairwise common ownership linkages between a given generic and the brand firm on that particular generic's entry decision for a variety of different empirical specifications. However, it is important to note that – as in our conceptual framework – other potential generic entrants are part of the analysis through their inclusion in the set of potential entrants. We first present the empirical implementation and main results, including instrumental variable (IV) estimations, then non-linear effects of common ownership, heterogeneous effects and, finally, robustness checks.

Empirical implementation. The binary dependent variable contains the individual entry decision of generic firm g in market m of brand firm b. The resulting equation to be estimated is:

$$Pr[Entry_{gbm} = 1] = \beta_0 + \beta\delta(g, b) + \gamma X_{gm} + \eta Z_m + A_m + A_g + \mu_t + \epsilon_{gbm}.$$

$Entry_{gbm}$ takes on the value 1 when generic g enters market m within six quarters after the end of regulatory protection. δ is one of the measures of common ownership between the generic and brand firm of the market, i.e., δ_S, δ_R or δ_κ. X_{gm} is the vector of generic-market control characteristics and Z_m is the vector of market level controls. A vector of fixed effects A_m is included for drug form/route, submission class and therapeutic field (ATC-2 level). A_g is a fixed effect for the region of the generic's company headquarters, and μ_t is a fixed effect for the year of the end of regulatory protection.

Ordinary least squares. Columns 1-3 of Table 3 present the results of estimating a linear probability model.[40] The estimates of β, across all measures of common ownership δ, are negative and significant (at the 1% level). Thus we find that common ownership between the relevant generic and the brand significantly reduces the likelihood of that

[40]Coefficients and marginal effects for probit and logit models are reported in Appendix G. Note that there are several therapeutic fields at the ATC2 level which do not experience any entry in our sample, thus the dummy indicators for these ATC2 fields become perfect predictors for a zero outcome. These observations are thus dropped in the logit and probit models, unlike in the main OLS model.

generic entering the market. The coefficients should be interpreted bearing in mind that the unconditional probability of entry for the sample of firms and markets is 2.8% (see Table 2). For example, an increase of one standard deviation as measured by δ_S implies a $0.16 \times 0.025 = 0.004$ decrease in the probability of entry *ceteris paribus*. This is therefore a $0.004/0.028 = 14\%$ reduction in the unconditional probability of entry. Similarly, an increase of one standard deviation in δ_R and δ_κ imply a 13% and 16% decrease, respectively, in the probability of entry.

[Insert Table 3 about here]

The effect of common ownership is much smaller than the effect of being a subsidiary of the brand. If we set δ_S, for instance, to 1 – that is, all shareholders of the generic and brand are common owners – then the probability of entry falls by 2.5 percentage points. On the other hand, if the relationship is parent-subsidiary then the probability of entry falls by 5.5 percentage points *ceteris paribus*. Thus, the negative effect from being a subsidiary vs. being 100% commonly owned is about double the size in magnitude. This difference, we believe, is intuitive as parent companies most likely have a higher degree of control as compared to common investors.

Furthermore, the control variables carry the expected signs. In line with the literature, we find that market size and previous experience are key drivers of generic entry. New chemical entities face less generic entry in comparison to new clinical investigations (NCIs).[41] On the other hand, we find that authorized generic entry and the number of molecular substitutes on and off-patent do not have a significant impact on entry.

To compare the effect of common ownership to the effect of market size we refer to Table G4 in Appendix G where we adopt an indicator variable to measure market size that takes the value 1 for drugs in the top 100 in terms of US sales. There, we find that if a drug drops out of the top 100, the average entry rate decreases by 2.1 percentage points. This drop is similar in magnitude to the effect of being 100% commonly owned (vs. no common ownership) which decreases the probability of entry by 2.7 percentage points. Thus, moving out of the top 100 markets in terms of sales and going from no to full common ownership have a similarly sized negative impact on entry.

Overall, we find similar effects for our three proposed common ownership measures, both in terms of significance and economic magnitude. This is in fact not surprising

[41] This may indicate higher entry and production costs associated with new chemical entities. A reason for this could be, for example, generics do not have prior experience with new chemical entities, hence it may require additional effort to procure the active ingredients to produce the drug as opposed to NCIs which may simply be new indications and dosing regimens using existing chemical entities.

as, empirically, our measures of common ownership are highly correlated with each other.[42] Thus, although our measures can conceptually capture different mechanisms of influence, the empirical counterparts are similar across brand-generic pairs.

Identification. If investors adjust their holdings in response to entry opportunities, common ownership might be endogenous. The direction of the potential bias is a priori not clear. For example, if investors in the brand increase investment in generics with entry plans, common ownership between the generic and brand will increase before entry, causing β to be biased upwards. Alternatively, if investors with shareholdings in generic firms reduce the size of their stakes in brand firms with drugs that face impending generic entry, then common ownership will decrease before entry, causing β to be biased downwards.

To investigate the concern of potential endogeneity, we perform IV estimations and instrument for common ownership with financial index membership at the pair level.[43] We use information on the holdings included in the Dow Jones US Select Pharmaceutical Index during the 2006-2014 period. Our data on the composition of the Dow Jones US Select Pharmaceutical Index comes from historical data on the composition of BlackRock's iShares US Pharmaceutical exchange-traded fund (ETF) (iShares.com, 2017) which tracks the Dow Jones US Select Pharmaceutical Index.

Figure E1 in Appendix E provides a snapshot of the top 10 investments of the fund as of November 2013. As can be seen, both generic and brand firms are present; e.g., Mylan primarily produces generic drugs whereas Johnson & Johnson is a brand company. On average, the fund has been comprised of 39 pharma holdings over time.[44] Since May 2006, each listed company has been included in the ETF for an average of four years. The fund has been marked by various periods of high entrance and exit – for instance, more than six companies dropped out and entered the fund in the last quarter of 2013 and the third quarter of 2015, respectively – and periods of no change.

[42]The correlations between our three measures are Corr(δ_S,δ_R): 0.85; Corr(δ_S,δ_κ): 0.88; Corr(δ_R,δ_κ): 0.83.

[43]A similar approach has been applied by several other studies. For example, Aghion et al. (2013) use the inclusion of a firm in the S&P 500 as an instrument for institutional ownership. Bena et al. (2017) instrument foreign institutional ownership with stock additions and deletions to the MSCI all country world index. Schmidt and Fahlenbach (2017) instrument passive institutional ownership with switches between the Russel 1000 and Russel 2000 indexes. Boller and Scott Morton (2020) use instances of a stock entering the S&P 500 index to test if an increase in common ownership changes future expected profits of the entering firm and its product market rivals.

[44]A detailed description of how the Dow Jones US Select Pharmaceutical Index is constructed can be found at: https://www.spglobal.com/spdji/en/documents/methodologies/methodology-dj-us-select-sector-specialty.pdf

Our resulting instrument, *Index Presence* is an indicator equal to 1 if both firms are listed on the Dow Jones US Select Pharmaceutical Index at the point in time when common ownership is measured. We expect that if both companies in the pair appear in the index, common ownership will increase by virtue of the fact that investors who track the index, so-called *index investors*, will hold shares in both companies. The summary statistics and binned scatter plot, Figure E2, in Appendix E shows that our IV performs well in terms of relevance: broadly, it correctly identifies which brand-generic pairs are connected through common ownership. The first-stage results, reported in Table E2, confirm that the instrument is highly relevant and positively correlated with all measures of δ (see the F-stats of excluded instruments).

The results of the IV regressions are presented in columns 4-6 of Table 3. These IV results are very similar to the OLS results in terms of size of the coefficients (although their significance is lower). The Durbin-Wu-Hausman tests show that we cannot reject the hypothesis that δ is exogenous, and this for all our measures of δ. This suggests that the potential endogeneity of common ownership is not a large concern in our context. To bolster this claim, we discuss identification in greater detail in Appendix E, the content of which is summarized below.

The identifying assumption for our IV is that joint inclusion in the pharmaceutical index is exogenous to a particular market entry, except through its effect on common ownership. This is the case provided that the index is not created with potential entry opportunities in mind and that, controlling for other factors, addition to the index does not directly affect entry decisions except through common ownership. This exclusion restriction cannot be directly tested and has to be assumed. Nonetheless, we provide supporting evidence for this assumption. To this end, we test whether our instrument varies around the time that the market becomes open for entry using a similar event-study analysis as in Schmalz and Xie (2022) adapted to our setting. As can be seen in Figure E3 in Appendix E, we fail to detect any systematic changes in index presence around an entry opportunity which suggests that our instrument is not driven by entry opportunities.

This result is consistent with the notion that index inclusion is not caused by entry opportunities. To provide a reason for why this is the case, one could follow Boller and Scott-Morton (2020), who provide convincing arguments that entry into the S&P 500 index is an exogenous event. Following and adapting their reasoning to our setting, we could argue that a company's index inclusion is to some extent random and, therefore, does not depend on its size/value, nor on the (future) attractiveness of a particular

pharmaceutical drug market.

Similarly, we investigate variations in common ownership surrounding a market entry opportunity. Figure E4 illustrates that there are no significant changes in common ownership around entry opportunities. One explanation for this observation is that a large share of common investors in our dataset are index investors and hence adjust their holdings in generic or brand firms based on their presence in indices such as the Dow Jones US Select Pharmaceutical Index, rather than direct entry opportunities.

Thus, both common ownership (our main independent variable) and joint index presence (our proposed IV) are not driven by a particular entry opportunity. These findings are consistent with the Durbin-Wu-Hausman tests which indicate that our OLS and IV estimates yield the same coefficient estimates, which is indeed what we would expect if both variables were exogenous. For the remaining analysis, we therefore refrain from using IV estimations and continue with more efficient estimation methods.

Non-linear effects. We now investigate whether greater levels of common ownership have a relatively larger impact, i.e., whether the relationship between common ownership and entry is non-linear. As explained in the previous section, we define natural cut-off values on the basis of the size-based measure δ_S, with $\delta_S > 0.5$ representing a "strong" common ownership link in that more than half of the total ownership in the pair is in the hands of the common investors, where Banal-Estañol et al. (2021) explain the features of this measure in more detail. To test the robustness of our results, we repeat this analysis using equivalent cut-offs, in terms of percentiles, for δ_κ.

[Insert Table 4 about here]

The results in Table 4 indicate that the effect of common ownership is greater the larger the level of common ownership. The coefficients on each categorical variable increase in magnitude (become more negative) with higher levels of common ownership. Furthermore, once δ_S or δ_κ is greater than 0.5, the coefficient is significant at the 1% level. A change from zero common ownership to common ownership δ_S greater than 0.5 reduces the entry probability of a generic by 1.7 percentage points on average. This is adecline in the unconditional probability of entry by more than a half.

These results indicate that common ownership levels have a non-linear impact on entry, where high levels have a much stronger impact than low levels. In particular, common ownership has its strongest and most significant effect when more than half

of the total ownership in the pair is in the hands of the common investors.[45] Given its intuitive interpretation and the strong results, we will use of the idea of strong links when constructing our main market-level measure of common ownership in Section 7.

Heterogeneous effects. In order to obtain further insights on what drives our average results, we explore the effects of common ownership for different market sizes and different types of potential entrants. The full analysis and results are presented in Appendix F and briefly summarized here. The key findings are: (i) common ownership has a stronger (more negative) marginal effect in markets where there is a larger profit at stake, as measured by brand-generated revenues prior to generic entry, and (ii) highly experienced generics with high common ownership are significantly less likely to enter than highly experienced generics with low common ownership. In contrast, common ownership with the brand does not significantly affect the entry rates of less experienced generics.

Robustness checks. Our main results are robust to a series of different specifications, as can be seen from the tables in Appendix C and Appendix G. Appendix C describes seven alternative measures of common ownership that have appeared in the literature in detail. The results using these measures are presented in Table C1. We find that across all measures, the effect of common ownership on entry is negative.

In Appendix G, Table G1 shows results where we add drug product fixed effects. The significance and magnitude of the coefficients stays virtually the same. Table G2 presents probit and logit regressions and Table G3 shows the respective marginal effects for the common ownership measures. Results show that our three common ownership measures negatively impact entry. The size of the OLS coefficients and marginal effects for the probit and logit models are similar in terms of magnitude.

Furthermore, in our main specification we use Medicaid reimbursements for outpatient prescription drugs as a proxy for market size. To check the robustness of our results to this measure, in Tables G4 and G5 we use a different proxy for market size based on the total sales volume for the drug in the US.[46] In Table G4 we substitute Medicare reimbursements with an indicator variable which takes the value 1 if the drug

[45] As a robustness check, we also run (non-reported) regressions with equally sized bins (quartiles). The relationship is also monotonic when using equally sized bins: The larger the common ownership, the more negative the impact on entry.

[46] To construct the measures we use publicly available sales data from drugs.com on the annual US sales figures for the top 200 drugs for the years 2003 - 2010 (Drugs.com, 2017b) and the top 100 drugs for the years 2011 - 2013 (Drugs.com, 2017a).

is in the top 100 in terms of sales in the year before the end of regulatory protection. In Table G5 we limit the sample to drugs where we have information on the annual US sales in the year before the market becomes open for entry and use logged total US brand sales in the year before the end of regulatory protection as our measure of market size. Our results are robust to both of these alternative measures of market size.

Another important dimension may be the set of potential entrants. In our main specification, the set of potential entrants is relatively narrowly defined. We exclude generic firms from the potential entrant set that have not previously launched a generic drug of the same form as the relevant brand drug. Doing so, however, means that we drop 51 *actual* entry observations (5% of all actual entry observations). To check the robustness of our results to a broader potential entrant set, we expand the set to also include generics without experience in the relevant drug form. Results in Table G6 show that the effects are qualitatively identical to our main results: for all common ownership measures, the effect is negative and significant at the 1% level.

We also test the robustness of our results to different time windows, as entry may be slower or faster than our chosen six-quarter window. In Table G7 we consider entry within any time period. Findings are qualitatively the same as in our main specification, i.e., entry is significantly negatively influenced by common ownership.[47]

Finally, we conduct a robustness check on the date we consider as the end of regulatory protection. In our main analysis, we consider a market to be open for generic entry at the earlier of either the date at which the *last* patent listed in the Orange Book for the drug expires or the date of first generic entry. To check the robustness of our results to an alternative date for end of regulatory protection, we use information, where available in the Orange Book, on the type of patent. In particular, we take the end of regulatory protection to be the earlier of either the date at which the *substance* patent expires and the date of first generic entry or the date at which the *product* patent expires and the date of first generic entry. Results stay qualitatively the same and are shown in Table G8.

7 Market outcomes

In the previous section we show how common ownership between a particular generic firm and the brand affects the entry probability of that generic. The next step is to

[47] We also considered alternative time windows such as entry within a two year time period. These results are available on request.

analyze how common ownership impacts market outcomes. In this section, we consider the effect of market level measures of common ownership (between all the potential generic entrants and the brand) on market level measures of generic entry.

We first present the main dependent and independent variables, i.e., the market level generic entry and common ownership variables. As market level controls we use the same variables as in the pairwise analysis. Subsequently, we describe the empirical implementation and results. Lastly, we discuss our results, making use of the analysis of the theory that is presented in Appendix B.

Market entry. Several outcome variables are used to assess entry at the market level: (i) the number of generic entrants within six quarters of the end of regulatory protection, (ii) the number of generic entrants within two years of the end of regulatory protection, (iii) the number of generic entrants ever, i.e., until the end of our dataset (iv) the probability that there is no generic entry at all, and (v) the duration of time (in quarters) until the first generic entry.[48]

Market level common ownership. We build on our preferred measure of common ownership, $I(\delta_S > 0.5)$, and construct the market level measure δ_Z, which captures the fraction of strong common ownership links in the same market. For each market, we count the number of strong common ownership links and divide this number by the number of potential generic entrants. Formally,

$$\delta_Z(\text{m}) \equiv \frac{\sum_{g \in S_m} I(\delta_S(g,b) > 0.5)}{S_m}, \tag{4}$$

where $I()$ is an indicator function which is equal to 1 if the argument is true, and to 0 otherwise, and S_m is the set of potential entrants in market m of the brand firm b.

Descriptive statistics. Table 5 presents summary statistics for the market outcomes and the market level measures of common ownership. The average level of common ownership at the market level, as measured by δ_Z, is 0.05, with a minimum of 0 and a maximum of 0.32. A maximum value of 0.32 indicates that in at least one market 32% of potential generic entrants have strong common ownership links with the brand. The average number of generic entrants within six quarters for our sample of drug markets is 2.4. This figure increases to 3.8 if we do not limit ourselves to a specific time window

[48] If there is no generic entry within the sample, the duration is calculated as the time between when the market becomes open for entry and the end date of the dataset.

and consider all occurrences of entry in the data. For 20% of our markets, there is no generic entry at all. In terms of the timing of entry, on average, the first generic enters six quarters after the market becomes open for entry.

[Insert Table 5 about here]

Empirical implementation. For each outcome variable we estimate the following model:

$$Y_m = \beta_0 + \beta\delta_Z(m) + \eta Z_m + A_m + \mu_t + \epsilon_m,$$

where Y_m is one of the outcome variables (i) - (v) mentioned above, δ_Z is our market level measure of common ownership, Z_m is the vector of drug market control variables, A_m is a vector of fixed effects for drug form/route, submission class and therapeutic field (ATC-2 level), and lastly μ_t is a fixed effect for the year of the end of regulatory protection. The model is estimated by a Poisson regression for the count outcomes (i) - (iii), as the number of entrants is a discrete positive number.[49] We estimate linear regression models for the outcomes (iv) and (v).

Results. Table 6 presents the coefficient estimates β for the market-wide measure of common ownership δ_Z. For the Poisson regressions, average marginal effects are reported alongside the estimated coefficients. Common ownership has a negative effect on the number of entrants within six quarters (column 1), a negative effect on the number of entrants within two years (column 3), a negative effect on the number of entrants ever (column 5), a positive impact on the probability that there is no entry at all in the market (column 7), and a positive impact on the time until the first generic entry (column 8). All the estimates are significant, which is a strong result, given the small number of observations (one per market, 395 markets in total). Thus, not only does common ownership result in fewer generic entrants, it also delays the onset of generic competition and makes it more likely that a brand firm will face zero competition from generic entrants.

[Insert Table 6 about here]

We now consider the economic magnitude of these effects. A one standard deviation increase in δ_Z leads to a 14% decrease in the number of entrants within six quarters, a 11% decrease in the number of entrants within two years and a 15% decrease in the

[49] We perform a robustness check using negative binomial regression. As we will show in the robustness checks section, both models yield similar results.

number of entrants within any time frame. A one standard deviation increase in the share of strong links increases the probability of no generic entry at all by $0.058 \times 0.927 = 5.4$ percentage points (column 7) which represents a 27% increase in the unconditional probability of zero entry. Finally, a one standard deviation increase in the share of strong links extends the time to first generic entry by 1 quarter, which is an 17% increase in the average time until generic entry (column 8).

We can use the estimated coefficients to compute the average number of entrants for each level of common ownership. For example, using the results of column 3, we find that when going from the minimum level of δ_Z, zero, to the maximum market level of 0.3, the average number of entrants in a market within two years would go down from about 2.8 to 1.6, keeping all else constant. This change is shown by the margins plot depicted by Figure 5. Thus, we find that common ownership has an economically significant effect on total generic entry as it may reduce the average number of total entrants by almost 50%.

[Insert Figure 5 about here]

We also find that the effects of the common ownership on the number of entrants differ depending on the market size. In top 100 drug markets in terms of sales, we find that when going from the minimum level of δ_Z, zero, to the maximum market level of 0.3, the average number of entrants in a market would go down from about 5.2 to 2.5. Conversely, in markets that are not in the top 100 drug markets in terms of sales, we find that when going from the minimum level of δ_Z, zero, to the maximum market level of 0.3, the average number of entrants in a market would go down from about 2.2 to 1 (see Figure 6). Thus, common ownership has a bigger impact in larger markets. For more details on potential welfare effects of common ownership, see Appendix H.

[Insert Figure 6 about here]

Robustness checks. We present two robustness checks. First, we compute a second market measure of common ownership, δ_W, defined as the average of δ_S for all S_m potential generic entrants of the relevant market. Results with this measure, presented in Appendix Table G9, are similar although less significant. This is in line with our earlier finding that higher levels of common ownership have a more pronounced impact.

Table G10 presents a second robustness check using, instead of the Poisson model, a negative binomial regression. Negative binomial regression can be used for modeling over-dispersed count data (where the variance is greater than the mean). In our case,

both models yield similar results.

Discussion. Section 6 shows that an increase in common ownership between a particular generic and the brand implies that this particular generic is less likely to enter. The results of this section show that this reduction in entry is not (entirely) filled by the entry of other generics. Indeed, an increase in market-level common ownership, which could for example be produced from an increase in the common ownership of a particular generic-brand pair, reduces overall entry. Due to the low number of observations at the market level, we cannot go beyond the average reported effects at the market level. However, we can make use our conceptual framework (see Appendix B) to propose a tentative explanation.

As we show in Appendix B, entry decisions between the pool of potential generic entrants may exhibit strategic complementarities in the presence of common ownership. In other words, a reduction in the likelihood of entry of a given generic may induce a rival generic, if it also has common ownership with the brand, to be less likely to enter the market as well. This happens because the entry of the first generic is more detrimental for the brand than that of additional entrants. Therefore, if a given generic's likelihood of entry goes down, a commonly owned rival generic could optimally respond by refraining from entering as well, as its entry may be especially harmful for the brand. This happens because common investors may then see their generic gains out-weighted by their brand losses.

This effect allows for an overarching explanation of our pairwise and market results. Following an increase in common ownership between a focal generic and the brand, the focal generic enters less. Rival generics (those with positive levels of common ownership with the brand) might enter less, in reaction. The remaining generics, such as the non-experienced generics, may be non-strategic or have a too high entry cost to fill the gap. This leads to an overall decrease in entry.

8 Conclusion

Ownership linkages between firms, typically due to the ownership holdings of large institutional investors, are a defining feature of ownership structures today. Consequently the question of whether firms' strategies are influenced by the presence of these investors and, correspondingly, whether common ownership has an effect on product market outcomes have attracted significant attention. This article considers the effect of common

ownership on market entry decisions in the pharmaceutical industry. Given that generic entry results in substantial revenue losses for the brand firm and relatively lower revenue gains for generic entrants, we argue that higher levels of common ownership may reduce generic entry as common owners have both the incentive and ability to push back entry.

Our empirical results lend robust support to this proposition: Higher common ownership between a potential generic entrant and the brand incumbent firm has a significant negative effect on generic entry. In terms of economic magnitude, a one-standard-deviation increase in pairwise common ownership decreases the probability of entry by 13-16%. Furthermore, our results indicate a non-linear impact, with high levels of common ownership having a much larger impact. A change from zero common ownership to a brand-generic pair having a "strong common ownership link," i.e., where common owners have the majority, leads to a decline in the unconditional probability of entry by more than a half. That being said, full common ownership still only has about half the impact of full direct ownership, a result, we believe is intuitive as parent companies most likely have a higher degree of control than common owners.

At the market level, higher common ownership leads to a lower number of entrants, delays generic entry and increases the probability that the brand will face zero generic competition. Our results further indicate that these effects depend on the market size. In particular, for the larger (top 100) markets in terms of sales, common ownership links have a much stronger impact on market-level entry than in smaller (outside top 100) markets. Given the importance of generic entry for reducing drug prices and therefore overall healthcare costs, common ownership in the pharmaceutical industry has the potential to raise costs to consumers and healthcare payers, especially in the largest markets.

While we believe our paper robustly shows that common ownership reduces entry, there is room for further research. One could explicitly model the effects of entry decisions of competitors in a structural model. Such a structural model could help determine which specific generics respond to a change in common ownership between a specific brand-generic pair (or subset of pairs), shedding further light on what drives the average market effects shown in this paper and uncovering strategic interactions between generic entrants.

Moreover, more can be done to understand the corporate governance of common ownership, namely how investors holdings translate into influence and control. While shareholdings in a brand company provide common investors with financial incentives to

steer decisions towards joint profits, shareholdings in the generic provide investors with the ability to influence such decisions via the control afforded to those shares. Future research that leverages asymmetric shareholdings can help determine the respective importance of incentives and ability in the decision-making process.

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9 Tables

Table 1: Top 5 largest shareholders (2013)

Brand		Generic	
Johnson & Johnson		**Mylan**	
State Street Global	6%	Vanguard Group	7%
BlackRock	6%	BlackRock	6%
Vanguard Group	5%	State Street Global	4%
Royal Bank of Canada	2%	Wellington Mgmt.	4%
Wellington Mgmt.	2%	John Paulson	4%

Notes: Percentage of shares as reported in Thomson Global Ownership Database

Table 2: Summary statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Entry	34,144	0.0278	0.164	0	1
δ_S	34,144	0.0846	0.160	0	0.946
δ_R	34,144	0.0537	0.137	0	1
δ_κ	34,144	0.0665	0.164	0	1.613
Subsidiary	34,144	0.00246	0.0495	0	1
Experience Route	34,144	2.124	3.633	0.100	29.90
Experience ATC2	34,144	0.0969	0.261	0	3.200
Experience New Drug	34,144	0.220	0.466	0	2.800
Breadth (ATC2)	34,144	1.373	1.243	0.100	6.100
Market Size (ln)	34,144	16.12	3.285	0	21.49
Authorized Generic	34,144	0.280	0.449	0	1
New Chemical Entity	34,144	0.527	0.499	0	1
Orphan Drug	34,144	0.0917	0.289	0	1
Pediatric Drug	34,144	0.318	0.466	0	1
Substitutes on Patent	34,144	2.498	1.732	0	7.300
Substitutes off Patent	34,144	1.714	1.268	0	6.100

Table 3: Main specification - Pairwise analysis

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
δ_S	-0.0248			-0.0258		
	(0.00668)			(0.0148)		
δ_R		-0.0269			-0.0300	
		(0.00723)			(0.0174)	
δ_κ			-0.0284			-0.0241
			(0.00548)			(0.0139)
Subsidiary	-0.0552	-0.0544	-0.0544	-0.0554	-0.0547	-0.0540
	(0.0150)	(0.0150)	(0.0150)	(0.0150)	(0.0149)	(0.0149)
Experience Route	0.00835	0.00832	0.00839	0.00835	0.00832	0.00838
	(0.000854)	(0.000853)	(0.000856)	(0.000853)	(0.000851)	(0.000854)
Experience ATC2	0.0609	0.0610	0.0608	0.0608	0.0610	0.0608
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
Experience New Drug	0.00424	0.00361	0.00463	0.00435	0.00385	0.00415
	(0.00284)	(0.00282)	(0.00287)	(0.00309)	(0.00296)	(0.00303)
Breadth (ATC2)	0.000855	0.000575	0.000786	0.000892	0.000644	0.000660
	(0.00231)	(0.00230)	(0.00228)	(0.00235)	(0.00231)	(0.00231)
Market Size (ln)	0.00496	0.00496	0.00494	0.00496	0.00496	0.00495
	(0.000705)	(0.000705)	(0.000705)	(0.000703)	(0.000702)	(0.000703)
Authorized Generic	0.00366	0.00364	0.00363	0.00366	0.00363	0.00365
	(0.00387)	(0.00389)	(0.00388)	(0.00386)	(0.00387)	(0.00387)
New Chemical Entity	-0.00963	-0.00971	-0.00965	-0.00962	-0.00970	-0.00967
	(0.00404)	(0.00405)	(0.00404)	(0.00404)	(0.00404)	(0.00404)
Orphan Drug	-0.00484	-0.00486	-0.00487	-0.00483	-0.00484	-0.00491
	(0.00728)	(0.00727)	(0.00727)	(0.00728)	(0.00728)	(0.00726)
Pediatric Drug	0.00623	0.00610	0.00620	0.00625	0.00615	0.00612
	(0.00457)	(0.00459)	(0.00457)	(0.00454)	(0.00455)	(0.00454)
Substitutes on Patent	-0.00606	-0.00589	-0.00602	-0.00606	-0.00587	-0.00602
	(0.00611)	(0.00610)	(0.00609)	(0.00609)	(0.00610)	(0.00608)
Substitutes off Patent	-0.00875	-0.00888	-0.00875	-0.00874	-0.00887	-0.00878
	(0.00489)	(0.00489)	(0.00488)	(0.00487)	(0.00488)	(0.00487)
Observations	34144	34144	34144	34144	34144	34144
R-squared	0.0877	0.0877	0.0879			
Therapeutic field	Yes	Yes	Yes	Yes	Yes	Yes
Drug form	Yes	Yes	Yes	Yes	Yes	Yes
Submission type	Yes	Yes	Yes	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes	Yes	Yes	Yes
Drug markets	395	395	395	395	395	395

Notes: Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within 6 quarters. The constant term is estimated but not reported. The instrument is an indicator equal to 1 if both firms are listed on the Dow Jones US Select Pharmaceutical Index.

Table 4: Categorical specification

VARIABLES	(1)	(2)
$I(0 < \delta_S \leq 0.3)$	0.00112	
	(0.00302)	
$I(0.3 < \delta_S \leq 0.5)$	-0.00545	
	(0.00425)	
$I(\delta_S > 0.5)$	-0.0168	
	(0.00470)	
$I(0 < \delta_\kappa \leq 0.2)$		0.00330
		(0.00310)
$I(0.2 < \delta_\kappa \leq 0.5)$		-0.0127
		(0.00398)
$I(\delta_\kappa > 0.5)$		-0.0147
		(0.00393)
Observations	34144	34144
R-squared	0.0877	0.0880
All controls	Yes	Yes
All fixed effects	Yes	Yes
Drug markets	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within 6 quarters. The constant term and control variables are estimated but not reported. The numerical cutoffs correspond to the 65th and 87th percentile respectively, and this for both δ_S and δ_κ.

Table 5: Summary statistics of market-level common ownership and market outcomes

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
δ_Z	395	0.0458	0.0584	0	0.318
No. entrants within 6 quarters	395	2.400	2.978	0	17
No. entrants within 2 years	395	2.610	3.214	0	17
No. entrants ever	395	3.838	4.070	0	23
No entry	395	0.197	0.399	0	1
Time until first entry (in quarters)	395	5.954	11.93	0	55

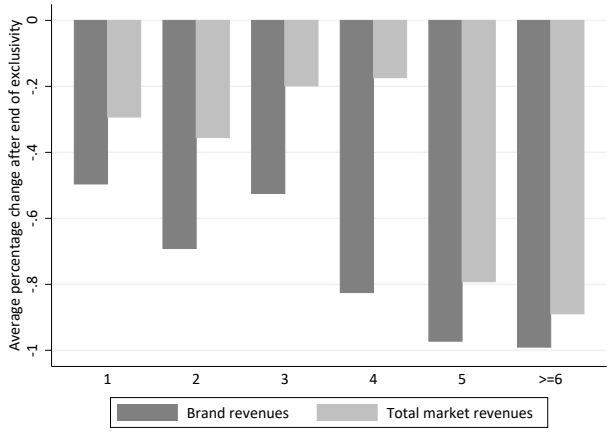
Table 6: Market outcomes

VARIABLES	(1) N-6q	(2) $\partial y/\partial x$	(3) N-2y	(4) $\partial y/\partial x$	(5) N-ever	(6) $\partial y/\partial x$	(7) No entry	(8) Time
δ_Z	-2.326	-5.583	-1.872	-4.885	-2.521	-9.675	0.927	17.23
	(1.155)	(2.771)	(1.083)	(2.828)	(0.959)	(3.695)	(0.428)	(11.06)
Market Size (ln)	0.201	0.483	0.205	0.536	0.200	0.766	-0.0444	-1.327
	(0.0271)	(0.0697)	(0.0261)	(0.0732)	(0.0217)	(0.0866)	(0.0102)	(0.292)
Authorized Generic	0.158	0.380	0.144	0.376	0.186	0.715	-0.0969	-2.105
	(0.114)	(0.276)	(0.112)	(0.295)	(0.0860)	(0.334)	(0.0405)	(1.307)
New Chemical Entity	-0.305	-0.733	-0.343	-0.895	-0.197	-0.754	0.0244	0.384
	(0.138)	(0.329)	(0.135)	(0.352)	(0.111)	(0.421)	(0.0496)	(1.584)
Orphan Drug	-0.278	-0.668	-0.304	-0.794	-0.0561	-0.215	0.0881	1.763
	(0.209)	(0.502)	(0.204)	(0.534)	(0.166)	(0.637)	(0.0863)	(2.492)
Pediatric Drug	0.0701	0.168	0.0812	0.212	0.0715	0.275	-0.0130	-1.175
	(0.138)	(0.329)	(0.136)	(0.353)	(0.112)	(0.429)	(0.0505)	(1.544)
Substitutes on Patent	-0.179	-0.429	-0.183	-0.476	-0.0648	-0.249	-0.00332	0.721
	(0.161)	(0.386)	(0.155)	(0.402)	(0.132)	(0.506)	(0.0566)	(1.796)
Substitutes off Patent	-0.0987	-0.237	-0.0877	-0.229	-0.150	-0.577	-0.00479	0.00599
	(0.136)	(0.327)	(0.134)	(0.349)	(0.112)	(0.426)	(0.0592)	(2.057)
Observations	395		395		395		395	395
Therapeutic field	Yes		Yes		Yes		Yes	Yes
Drug form	Yes		Yes		Yes		Yes	Yes
Submission type	Yes		Yes		Yes		Yes	Yes
Year end of exclusivity	Yes		Yes		Yes		Yes	Yes
(Pseudo) R-squared	0.298		0.319		0.348		0.394	0.366

Notes: Poisson regression in col. 1, 3 and 5. Average marginal effects reported alongside estimated coefficients. OLS regression in col. 7 and 8. Standard errors in parentheses are robust. The constant term is estimated but not reported. Pseudo R-squared reported for Poisson regressions.

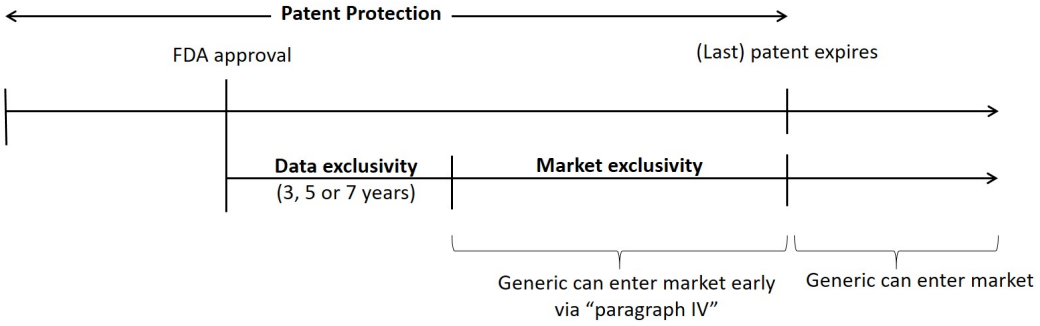
10 Figures

Figure 1: Decline in brand and total revenues with number of generic entrants



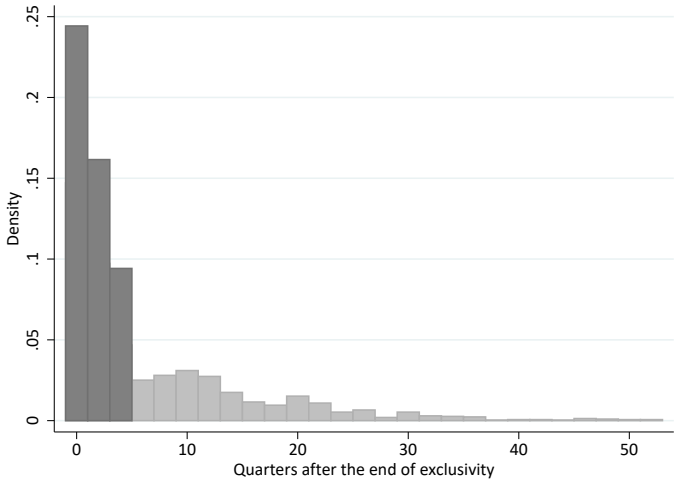
Notes: This figure illustrates the average decline in brand revenues and total market revenues, defined as the sum of brand and generic revenues, two years after the end of regulatory protection relative to two years before, by the number of generic entrants in the market. The declines reported are relative to the average revenue change when there are no entrants. Note that one outlier where total market revenues increased by over 1500% after the end of exclusivity has been removed from the sample when creating this figure.

Figure 2: Exclusivities and patent protection in pharmaceuticals



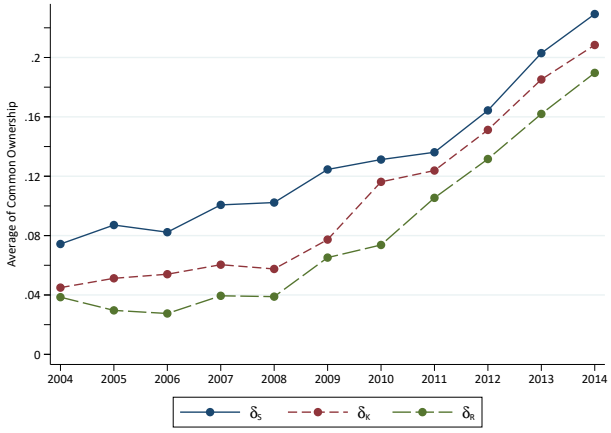
Notes: This figure illustrates the two types of protection awarded to new drugs. Data exclusivity protects the underlying clinical data and runs concurrently with patent protection. At the end of data exclusivity, a drug is protected only by its patents until they expire, a period termed "market exclusivity."

Figure 3: Histogram of entry



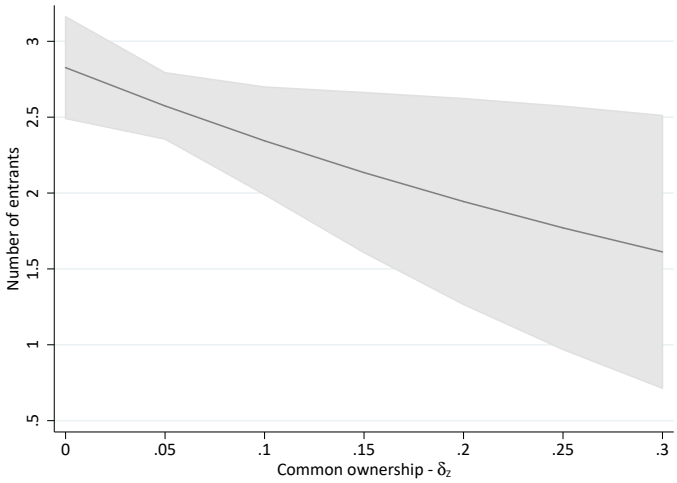
Notes: This figure depicts the histogram of relative frequencies of entry, on a bi-quarterly basis, after the end of regulatory protection. The dark gray area shows the share of entry that occurs within six quarters after the end of regulatory protection.

Figure 4: Evolution of common ownership



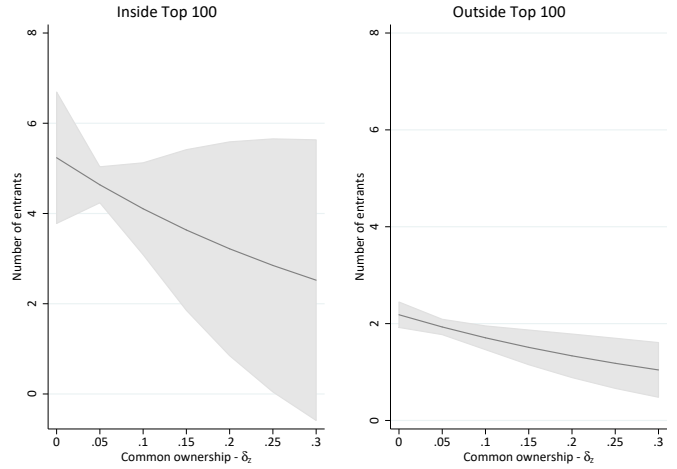
Notes: This figure illustrates the evolution of common ownership over time for our measures. We only include the company-pairs that are observed for the entire period, as this provides a clearer overview of how the degree of connectedness between brand and generic pairs has changed over time.

Figure 5: Number of generic entrants by common ownership level - All drugs



Notes: The margins plot displays the predicted count of generic entrants within two years, with 95% confidence intervals, at different levels of market-level common ownership holding all other covariates at their average values. The plot uses the Poisson model estimated in Table 6 column 3.

Figure 6: Number of generic entrants by common ownership level split by market size



Notes: The margins plot displays the predicted count of generic entrants within two years for drugs in the top 100 in terms of sales (left) and drugs outside of the top 100 (right), with 95% confidence intervals, at different levels of market-level common ownership holding all other covariates at their average values.

Appendices

A Common ownership in pharma: Anecdotal evidence

In this appendix we provide anecdotal evidence of common investors' influence in the pharma industry (see also Banal-Estanol et al., 2021). In 2016, a group of representatives of major US mutual funds (Fidelity Investments, T. Rowe Price Group Inc., Wellington Management Co., among others) met up with top biotechnology and pharmaceutical executives and lobbyists to discuss the pricing conditions of the market and the possible steps that could be taken in order to avoid future regulations. This example also illustrates that investor interactions need not be addressed to a particular company but can be extended to a specific industry.[50]

In 2019, BlackRock stated in their annual report that they engaged with a number of pharmaceutical companies including Abbott, Abbvie, Bristol-Myers Squibb, Pfizer, Novartis, Merck, GlaxoSmithKline, Johnson Johnson, Sanofi, Biogen, Allergan, Teva Pharmaceutical and Takeda.[51] Similarly, State Street reported in their 2019 annual report that they engaged with 64 pharmaceutical companies.[52] The head of corporate governance at State Street Global Advisors stated that "Our size, experience, and long term outlook provide us with corporate access and allow us to establish and maintain an open and constructive dialogue with company management and boards."[53]

More recently, in relation to the COVID-19 crisis, institutional investors have pushed for firms to collaborate with rivals and share information. In April 2020, a number of asset managers, including BlackRock and Fidelity, announced that "they want drug companies to put aside any qualms about collaborating with rivals." BlackRock held talks with pharma companies to discuss ways to develop and deploy treatments by "working with industry competitors." Separately, a group of 50 investors with over $2.5 trillion in assets requested that companies share their findings related to the vaccine and agree not to enforce the relevant patents. Since then a number of alliances have

[50]See Caroline Chen, Mutual Fund Industry to Drugmakers: Stand Up and Defend Yourself, Bloomberg News, 2016, available at https://www.bloomberg.com/news/articles/2016-05-09/ top-funds-said-to-tell-pharma-leaders-to-defend-drug-pricing.

[51]See Investment Stewardship Annual Report, BlackRock, 2019, available at https://www.blackrock.com/corporate/literature/publication/blk-annual-stewardship-report-2019.pdf.

[52]See Stewardship Report, State Street, 2019 available at https://www.ssga.com/library-content/products/esg/annual-asset-stewardship-report-2018-19.pdf

[53]See Rakhi Kumar, Passive investment, active ownership, State Street, 2014, available at https://www.ft.com/content/7c5f8d60-ba91-11e3-b391-00144feabdc0

formed to collaborate on treatments and vaccines for COVID-19.[54]

Institutional investors have also been involved in merger decisions. BlackRock is reported to have actively pushed for a merger between the pharmaceutical firms AstraZeneca and Pfizer. The largest institutional shareholder in AstraZeneca and also a top five shareholder in Pfizer at the time, "urged the British pharma giant's board to eventually re-engage in talks with Pfizer Inc. over a possible deal."[55]

[54]See Attracta Mooney and Donato Mancini, Drugmakers urged to collaborate on coronavirus vaccine, Finanicial Times, April, 2020, available at https://www.ft.com/content/ b452ceb9-765a-4c25-9876-fb73d736f92a; Matt Levine, Investors Want a Cure, Not a Winner, Bloomberg, April, 2020, available at https: //www.bloomberg.com/opinion/articles/2020-04-24/investors-want-a-cure-not-a-winner

[55]See Hester Plumridge, AstraZeneca Shareholder Backs Board Rejection of Pfizer Bid, Wall Street Journal, 2014, available at https://www.wsj.com/articles/ astrazeneca-shareholder-blackrock-sides-with-board-on-rejecting-pfizer-bid-1400791061; Phil Serafin Mary Childs, BlackRock Is Said to Encourage Pfizer-AstraZeneca Talks, BLOOMBERG, 2014, available at https://www.bloomberg.com/news/articles/2014-05-22/blackrock-is-said-to-encourage-pfizer-astrazeneca-talks

B Simple model of strategic interaction

In this appendix, we characterize the simultaneous entry decisions of a set of *strategic* entrants, i.e., firms that take the entry decisions of other firms into account, making use of the setting of the conceptual framework, described in Section 3. We first use the case of two potential generic entrants to illustrate the type of strategic effects that may appear in this setting. Thereafter we characterize the equilibrium entry decisions of N symmetric generics as a function of their individual (and market) level of common ownership with the brand, δ. All the proofs can be found in the last subsection of this appendix.

Let us make the following additional assumptions. To make the problem interesting, let us assume that generic profits increase with entry, $\pi_g^k > 0$. This is consistent with the evidence in Figure 1. We also assume that generic competition reduces individual generic profits, i.e. π_g^k is decreasing in k, and that the change in the brand firm's profit loss decreases with the number of entrants, i.e. $\left|\Delta\pi_b^k\right|$ is decreasing in k. This is also consistent with the evidence in Figure 1: brand revenues decline steadily with the number of entrants, but the marginal loss for an additional entrant is smaller for larger number of entrants.

Strategic effects: complements or substitutes?

For ease of illustration, let us restrict ourselves in this subsection to the case of $N = 2$ potential generic entrants. Neither the analysis nor the notation of this subsection uses the symmetry assumption. This assumption, though, simplifies the notation and the equilibrium analysis of the following subsection.

We investigate if focal generic g is less (or equally) likely to enter as the probability p_1 of having a competing generic increases, and the probability p_0 of having none declines ("strategic substitutes"); or alternatively, if g is more (or equally) likely to enter as p_1 increases ("strategic complements"). Substituting $p_0 = 1 - p_1$ and deriving Π_g in (1) with respect to p_1,

$$\partial\Pi_g(p_0, p_1, \delta)/\partial p_1 = (\pi_g^1 - \pi_g^0) + \delta(\Delta\pi_b^1 - \Delta\pi_b^0),$$

we can identify two effects. The first term is negative, as $\pi_g^0 > \pi_g^1$, and therefore the gains from entry of g are lower if the other is more likely to enter. This is the traditional business stealing effect from competition of other generics. The second term, though, is positive, as $|\Delta\pi_b^0| > |\Delta\pi_b^1|$. As the other generic is more likely to enter, the effect

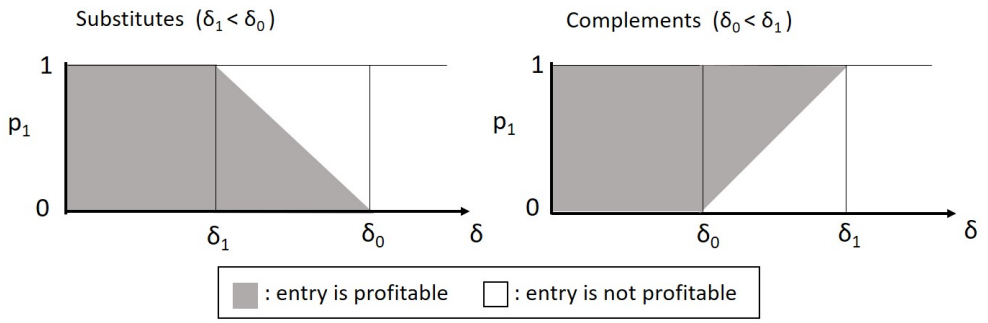
of focal generic entry on the brand firm is less detrimental, as the reduction of brand profits in the presence of another competing generic is smaller.

The overall effect depends on which of the two effects, proxied by the profits of generic entrant π_g^k and the loss in profits of the brand $\left|\Delta\pi_b^k\right|$, decreases faster with the entry of others, and thus how the ratio $\bar{\delta}_k \equiv \pi_g^k / \left|\Delta\pi_b^k\right|$ changes with k. If the generic profits decrease faster, and thus the ratios are such that $\bar{\delta}_1 < \bar{\delta}_0$, others entering is more detrimental and entry decisions exhibit strategic substutabilities. Instead, if the brand losses decrease faster, and thus $\bar{\delta}_0 < \bar{\delta}_1$, others entering is less detrimental and entry decisions exhibit strategic complementarities. The results are summarized in the following proposition.

Proposition 1. *(a) If $\bar{\delta}_1 < \bar{\delta}_0$, the generic firm g is less (or equally) likely to enter if the other generic firm is more likely to enter (strategic substitutability).*
(b) If $\bar{\delta}_0 < \bar{\delta}_1$, the generic firm g is more (or equally) likely to enter if the other generic is more likely to enter (strategic complementarity).

Figure B1 depicts the combinations of g's common ownership with the brand, δ, and probability of the other entering, p_1, for which g's entry is profitable (marked in the darker shade in the figure); where the left panel shows the case of strategic substitutes and the right panel the case for strategic complements. Clearly, for a given p_1, common ownership reduces entry profitability. But the effect of the probability of the other entering, p_1, for a given level of common ownership δ has non-trivial effects on the profitability of entering. An increase in p_1 may mean that entry switches from profitable to unprofitable in the intermediate region of δ in the case of substitutes (the left-hand panel) whereas it may switch from unprofitable to profitable in the intermediate region of δ in the case of complements (the right-hand panel). Still, in both cases, entry is profitable for any p_1 if δ is sufficiently low, i.e. entering is a dominant strategy, whereas entry is unprofitable for any p_1 if δ is sufficiently high, i.e. not entering is a dominant strategy.

Figure B1: Profitable entry of g as a function of δ and p_1



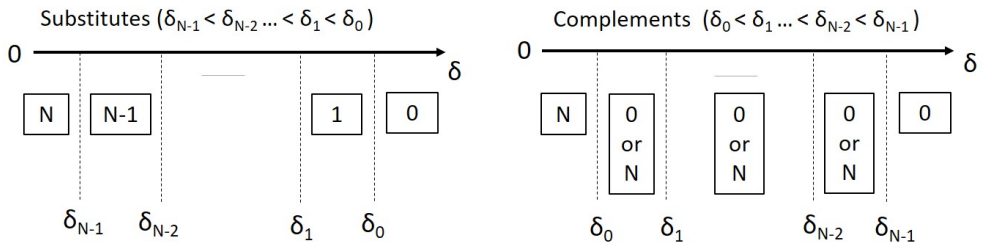
Equilibrium entry decisions

Now let us consider the pure-strategy equilibrium decisions in the general case of N potential entrants as a function of their symmetric level of common ownership with the brand, δ. Note that δ is both the individual and market levels of common ownership of the generics with the brand in this symmetric setting. Considering and distinguishing between the two cases identified in the previous proposition, the next proposition summarizes the overall number of entrants in equilibrium.

Proposition 2. *(a) In the case of strategic substitutes ($\bar{\delta}_{N-1} < \bar{\delta}_{N-2} < ... < \bar{\delta}_0$), the number of entrants in equilibrium is: N if $\delta \leq \bar{\delta}_{N-1}$; $N-k$ if $\bar{\delta}_{N-k} < \delta \leq \bar{\delta}_{N-k-1}$ for $k = 1, ..., N-1$; and 0 if $\bar{\delta}_0 < \delta$.*
(b) In the case of strategic complements ($\bar{\delta}_0 < \bar{\delta}_1 < ... < \bar{\delta}_{N-1}$), the number of entrants in equilibrium is: N if $\delta \leq \bar{\delta}_0$; N or 0 if $\bar{\delta}_0 < \delta \leq \bar{\delta}_{N-1}$; and 0 if $\bar{\delta}_{N-1} < \delta$.

Figure B2 depicts the number of entrants in equilibrium as a function of their symmetric level of common ownership with the brand, δ. In both cases, there exists multiple equilibria in all the intermediate regions. But in the case of strategic substitutes, the equilibrium difference is between the identity of entrants and not how many of the entrants enter. In the case of complementarities, the equilibrium number of entrants is extreme, either none or all of them shall enter. This is because, in the case of substitutes, the entry of another generic makes generic entry less profitable, whereas in the case of complements, it makes it more profitable.

Figure B2: Number of entrants in equilibrium as a function of δ



Still, in both cases, the equilibrium number of entrants decreases with the level of common ownership, as long as we assign a fixed probability of selecting one equilibrium over another.

Proof of Proposition 1

We determine the optimal entry decision of focal generic firm g for a given probability of entry of the other generic, p_1, i.e. the best response function.

We first note that whether profits of the focal generic increase if the other is more likely to enter depends on the level of common ownership. Indeed, in the case where $N = 2$, we can write the profits as a function of just p_1,

$$\Pi_g(p_1, \delta) = (1 - p_1)(\pi_g^0 + \delta\Delta\pi_b^0) + p_1(\pi_g^1 + \delta\Delta\pi_b^1)$$

and, as displayed in the text,

$$\partial\Pi_g(p_1, \delta)/\partial p_1 = (\pi_g^1 - \pi_g^0) + \delta(\Delta\pi_b^1 - \Delta\pi_b^0).$$

As this function is strictly increasing in δ ($\partial^2\Pi_g(p_1, \delta)/\partial p_1\partial\delta = \Delta\pi_b^1 - \Delta\pi_b^0 > 0$), and it has a negative intercept ($\partial\Pi_g(p_1, 0)/\partial p_1 = \pi_g^1 - \pi_g^0 < 0$), there exists δ^* such that, if $\delta \leq \delta^*$, profits are decreasing in p_1 ($\partial\Pi_g(p_1, \delta)/\partial p_1 \leq 0$) whereas, if $\delta > \delta^*$, profits are increasing in p_1 ($\partial\Pi_g(p_1, \delta)/\partial p_1 > 0$), where

$$\delta^* \equiv -(\pi_g^1 - \pi_g^0)/(\Delta\pi_b^1 - \Delta\pi_b^0).$$

Second, we determine the optimal decision in cases where the other generic uses pure-strategies:

- If $p_1 = 0$ (i.e., it does not enter for sure), g shall it find it optimal to enter if

$\delta \leq \bar{\delta}_0$ as $\Pi_g(0,\delta) = \pi_g^0 + \delta\Delta\pi_b^0 \geq 0$ if and only if

$$\delta \leq \pi_g^0 / \left|\Delta\pi_b^0\right| \equiv \bar{\delta}_0.$$

- Similarly, if $p_1 = 1$ (i.e., it does enter for sure), g shall it find it optimal to enter if $\delta \leq \bar{\delta}_1$ as $\Pi_g(1,\delta) = \pi_g^1 + \delta\Delta\pi_b^1 \geq 0$ if and only if

$$\delta \leq \pi_g^1 / \left|\Delta\pi_b^1\right| \equiv \bar{\delta}_1.$$

Simple algebra shows that if $\bar{\delta}_1 < \bar{\delta}_0$ then $\bar{\delta}_0 < \delta^*$ whereas if $\bar{\delta}_0 < \bar{\delta}_1$ then $\delta^* < \bar{\delta}_0$. These two cases affect the strategic interaction.

Let us now consider the best response function for different levels of common ownership, δ. We first show that, if $\bar{\delta}_1 < \bar{\delta}_0$ and thus $\bar{\delta}_1 < \bar{\delta}_0 < \delta^*$, focal generic g is less (or equally) likely to enter if p_1 is greater (termed "strategic substitutes"). Still, it may be that the generic's profits increase with the entry of the other, as long as it does not affect the decision.

- If $\delta \leq \bar{\delta}_1$ then entering is a dominant strategy. Indeed, we have that $\delta < \delta^*$ and g is less likely to enter if the probability of entering of the other is greater ($\partial\Pi_g(p_1,\delta)/\partial p_1 < 0$). As $\delta \leq \bar{\delta}_1$, g should enter for any p_1 as $\Pi_g \geq 0$ even in the most adverse case, in which the other does enter for sure, $p_1 = 1$.

- In the case in which $\bar{\delta}_1 < \delta \leq \bar{\delta}_0$, the decision to enter depends on p_1: g should enter if the probability of the other entering is low. In formal terms, $\Pi_g > 0$ if and only if $p_1 < p_1^*$ where p_1^* is such that $\Pi_g(p_1^*,\delta) = 0$. Notice that p_1^* is well defined, as $\Pi_g(0,\delta) > 0$ (as $\delta < \bar{\delta}_0$), $\partial\Pi_g(p_1,\delta)/\partial p_1 < 0$ (as $\delta < \delta^*$) and $\Pi_g(1,\delta) < 0$ (as $\delta > \bar{\delta}_1$). In addition, note that the threshold level of p_1^* is decreasing in the level of common ownership,

$$\partial p_1^*/\partial\delta = -[\partial\Pi_g(p_1,\delta)/\partial\delta]/[\partial\Pi_g(p_1,\delta)/\partial p_1] < 0.$$

- If $\bar{\delta}_0 < \delta \leq \delta^*$, then not entering is a dominant strategy. Indeed, g should not enter for any p_1 as $\Pi_g < 0$ even in the most favorable case, in which the other does not enter for sure, $p_1 = 0$.

- In case the levels of common ownership δ are such that $\delta > \delta^*$ then not entering is dominant. In that case g is more likely to enter if the probability of entering

of the other is greater ($\partial\Pi_g(p_1,\delta)/\partial p_1 > 0$), but g should not enter for any p_1 as $\Pi_g < 0$ even in the most favorable case, in which the other enters for sure, $p_1 = 1$ as $\delta > \bar{\delta}_1$.

Second, we show that, if $\bar{\delta}_0 < \bar{\delta}_1$ and thus $\delta^* \leq \bar{\delta}_0 < \bar{\delta}_1$, focal generic g is more (or equally as) likely to enter if p_1 is greater (labeled as "strategic complements").

- In case the levels of common ownership δ are such that $\delta < \delta^*$ then entering is dominant. In that case g is less likely to enter if the probability of entering of the other is greater ($\partial\Pi_g(p_1,\delta)/\partial p_1 < 0$) but g should p_1 as $\Pi_g > 0$ even in the most adverse case, in which the other enters for sure, $p_1 = 1$ as $\delta < \bar{\delta}_1$.

- In the case in which $\delta^* < \delta \leq \bar{\delta}_0$, entering is dominant. Indeed as $\delta > \delta^*$ g is more likely to enter if the probability of entering of the other is greater $\partial\Pi_g(p_1,\delta)/\partial p_1 > 0$). As $\delta < \bar{\delta}_0$ g should enter for any p_1 as $\Pi_g > 0$ even in the most adverse case, in which the other does not enter for sure, $p_1 = 0$.

- In the case in which $\bar{\delta}_0 < \delta \leq \bar{\delta}_1$, the decision to enter depends on p_1: g should enter if the probability of the other entering is high. In formal terms, $\Pi_g > 0$ if and only if $p_1 > p_1^*$ where p_1^* is such that $\Pi_g(p_1^*,\delta) = 0$. Notice that p_1^* is well defined, as $\Pi_g(0,\delta) < 0$ (as $\delta > \bar{\delta}_0$), $\partial\Pi_g(p_1,\delta)/\partial p_1 > 0$ (as $\delta > \delta^*$) and $\Pi_g(1,\delta) > 0$ (as $\delta < \bar{\delta}_1$). In addition, note that the threshold level of p_1^* is decreasing in the level of common ownership,

$$\partial p_1^*/\partial\delta = -[\partial\Pi_g(p_1,\delta)/\partial\delta]/[\partial\Pi_g(p_1,\delta)/\partial p_1] > 0.$$

- If $\delta^* > \bar{\delta}_1$ g then not entering is dominant. Indeed g should not enter for any p_1 as $\Pi_g < 0$ even in the most favorable case, in which the other does enter for sure, $p_1 = 1$.

Proof of Proposition 2

We proceed in two steps. We first determine the optimal entry decision of focal generic firm g for each entry decision of the other $N-1$ generics. That is, we compute, as in the previous proposition, the best response function (which depends again on the level of common ownership). But here, although allowing for N generics, we concentrate on pure strategies. As we assume generics to be symmetric, the key is how many,

but not which one, of the others decide to enter. In a second step, we compute the (pure-strategy) Nash equilibria.

As in the previous proposition, in case k of the other entrants enter ($k = 0, ...N-1$, $p_k = 1$ and, for any $j \neq k$, $p_j = 0$), g shall it find it optimal to enter if and only if $\delta \leq \bar{\delta}_k$ as $\Pi_g = \pi_g^k + \delta \Delta \pi_b^k \geq 0$ if and only if

$$\delta \leq \pi_g^k / \left| \Delta \pi_b^k \right| \equiv \bar{\delta}_k.$$

In the case of a single potential entrant ($N = 1$ and $k = 0$), this is the optimal decision: enter if $\delta \leq \bar{\delta}_0$ and do not if $\delta > \bar{\delta}_0$. In this case, parts (a) and (b) in the statement of the proposition are the same. From now on we consider $N > 1$.

Now let us consider the two cases of the statement of the proposition. Suppose first that $\bar{\delta}_{N-1} < \bar{\delta}_{N-2} < ... < \bar{\delta}_0$ ("strategic substitutes"). The best response function of g with respect to the number of other entrants depends, as in the previous proposition, on the level of common ownership.

- If $\delta \leq \bar{\delta}_{N-1}$ entering is a dominant strategy for g, independent of the number of other entrants, as $\delta \leq \bar{\delta}_k$ for any k.
- If $\bar{\delta}_{N-k} < \delta \leq \bar{\delta}_{N-k-1}$ for any $k = 1, ..., N-1$, g shall enter if $N-k-1$ other generics, or less, enter, as $\delta \leq \bar{\delta}_{N-k-1} < ... < \bar{\delta}_0$, but it shall not enter if $N-k$ other generics, or more, do enter, as $\bar{\delta}_{N-1} < ... < \bar{\delta}_{N-k} \leq \delta$.
- Finally, if $\delta > \bar{\delta}_0$ not entering is a dominant strategy, as $\delta > \bar{\delta}_k$ for any k.

For instance in the case of two potential entrants ($N = 2$), g should enter if $\delta \leq \bar{\delta}_1$, enter if and only if the other does not enter if $\bar{\delta}_1 < \delta \leq \bar{\delta}_0$ (as $N = 2$, $k = 1$, $N-k-1 = 0$ and $N-k = 1$) and not enter if $\delta > \bar{\delta}_0$.

The equilibrium number of entrants also depends on the (symmetric) level of common ownership with the brand.

- If $\delta \leq \bar{\delta}_{N-1}$ all should enter in equilibrium, as entering is a dominant strategy.
- If $\bar{\delta}_{N-k} < \delta \leq \bar{\delta}_{N-k-1}$ for any $k = 1, ..., N-1$, $N-k$ generics should enter in equilibrium, as entering is optimal if $N-k-1$ other generics enter and not entering is optimal if $N-k$ do so.
- Finally, if $\delta > \bar{\delta}_0$ none of them should enter as not entering is a dominant strategy.

For instance in the case of two potential entrants ($N = 2$, which implies $k = 1$), the two generics should enter if $\delta \leq \bar{\delta}_1$, one of them should enter if $\bar{\delta}_1 < \delta \leq \bar{\delta}_0$ (as $N = 2$, $k = 1$ and $N - k = 1$) and none of them should enter if $\delta > \bar{\delta}_0$.

Suppose now that $\bar{\delta}_0 < \bar{\delta}_1 < ... < \bar{\delta}_{N-1}$ ("strategic complements"). The best response function of g with respect to the number of other entrants is now as follows:

- If $\delta \leq \bar{\delta}_0$ entering is again a dominant strategy for g, as $\delta < \bar{\delta}_k$ for any k.
- But now, if $\bar{\delta}_{N-k-1} < \delta \leq \bar{\delta}_{N-k}$ for any $k = 1, ..., N-1$, g shall enter if $N - k$ other generics, or more, enter, as $\delta \leq \bar{\delta}_{N-k} < ... < \bar{\delta}_{N-1}$, but it shall not enter if $N - k - 1$ other generics, or less, do enter, as $\delta_0 < ... < \bar{\delta}_{N-k-1} < \delta$.
- Similarly, if $\delta > \bar{\delta}_{N-1}$ not entering is again a dominant strategy, as $\delta > \bar{\delta}_k$ for any k.

For instance in the case of two potential entrants ($N = 2$), g should enter if $\delta \leq \bar{\delta}_0$, enter if and only if the other does enter if $\bar{\delta}_0 < \delta \leq \bar{\delta}_1$ and not enter if $\delta > \bar{\delta}_2$.

The equilibrium number of entrants also depends on the (symmetric) level of common ownership with the brand.

- As before, if $\delta \leq \bar{\delta}_0$ all should enter in equilibrium, as entering is a dominant strategy.
- But the equilibria in the intermediate cases $\bar{\delta}_0 < \delta \leq \bar{\delta}_{N-1}$ are different: either all the N generics enter or none of them does. Indeed, if $N - 1$ generics enter, it is optimal to enter, as $\delta \leq \bar{\delta}_{N-1}$, and if 0 of them does, it is optimal not to enter either, as $\delta > \bar{\delta}_0$. Moreover, there is no equilibrium within $\bar{\delta}_0 < \delta \leq \bar{\delta}_{N-1}$ in which k generics enter, for k is such that $0 < k < N$. Indeed, if an entrant finds it profitable to enter then it should also be profitable for those that do not enter (and if one of the non-entrants find it profitable not to enter then it should also be non-profitable for one of the entrants).
- Finally, if $\delta > \bar{\delta}_{N-1}$ none of them should enter as not entering is a dominant strategy.

In the case of two potential entrants ($N = 2$, which implies $k = 1$), the two generics should enter if $\delta \leq \bar{\delta}_0$, the two or none of them should enter if $\bar{\delta}_0 < \delta \leq \bar{\delta}_1$ and none of them should enter if $\delta > \bar{\delta}_1$.

C Alternative common ownership measures

The main text provides three pairwise measures of common ownership that capture different channels of investor influence. In this appendix we show that our pairwise results are robust to the use of alternative measures of common ownership.

First, while our size-based measure δ_S assumes that the marginal effect of an increase in incentives does not depend on the level of ability, and vice versa, the following measure, which we label "complements" assumes that incentives require ability, and vice versa:

$$\delta_C(g,b) \equiv \textstyle\sum_i \min\{\gamma_{ig}, \gamma_{ib}\}. \tag{5}$$

The measure δ_S does not penalize unequal shareholdings in the two firms, whereas δ_C does. For instance, a shareholder that owns 5% of the shares of one firm and 15% of the other would have the same value for δ_S as someone that owns 10% in both firms, but only half of that value when applying the complements measure δ_C. Of course, both measures are similar if the relative holdings of all common investors in the brand and generic are roughly equal.

Second, we consider an alternative rank-based measure on the basis of the top 10 investors, which we call δ_{R10}, instead of the top 5 investors, δ_R, that we use in the main text:

$$\delta_{R10}(g,b) \equiv \textstyle\sum_i I(\gamma_{ig} \geq \gamma_{(10)g} \text{ and } \gamma_{ib} \geq \gamma_{(10)b})/10,$$

where $\gamma_{(10)g}$ and $\gamma_{(10)b}$ are the 10-th largest shareholding in the generic and brand firm.

Third, we construct all the relevant bilateral measures from Boller and Scott Morton (2020). Note that they also include δ_κ, which we discuss and employ in the main text.[56] We also include a short discussion of how two of these measures, the "Fraction of Capitalization" (FCAP) and the "Percentage of common funds" (PCF), compare with our size-based pairwise measure of common ownership, δ_S.

- **Cosine similarity** between the vectors of shareholdings of the brand and generic firms, formally defined as

[56] Boller and Scott Morton (2020) further employ a measure that reflects the weight that the brand should conceptually place on the generic firm. This does not fit well in our setup, as it is the generic rather than the brand that takes the entry decision. Furthermore, they include a measure for the "Density of firm pairs" (DFP), defined as the number of firm-pairs that are connected in an industry. In our setting, it is not obvious how to construct industry measures such as the DFP or the Modified Herfindahl-Hirschman Index (MHHI), as the generic firms are not yet in the market at the time of deciding whether to enter, and thus information on "market shares" does not exist at that moment.

$$\delta_{cossim} = \frac{M*N}{||M||||N||},$$

where we define M and N as the ownership vectors for the generic and brand firms, respectively. Components of M and N correspond to ownership stakes. As shown in Backus et al. (2021), δ_{cossim} is one of the components of δ_{κ}.[57]

- **Bray-Curtis similarity** measure, derived in Deza and Deza (2009), and defined as

$$\delta_{braycurtis} = 1 - \frac{\sum_i |M_i - N_i|}{\sum_i M_i + N_i)}.$$

A similarity of 1 indicates perfect shareholder overlap, whereas a similarity of 0 indicate orthogonal ownership vectors. This similarity measure gives an equal weight to shifts in ownership regardless of the size of the owners' stake.

- **Capitalist Conspiracy (CC)** measure, which adds up the ownership stakes of the "Big Three" funds (BlackRock, State Street, and Vanguard) in each pair. This measure increases if the shares of the top funds increase, independently of whether they are common owners in the particular pair.

- **Fraction of Capitalization (FCAP)** measure due to Anton and Polk (2014), defined as the total ownership value held by all common owners of the two firms over the total market capitalization of the two firms. This measure is similar to our size-based measure δ_S, defined as the total number of shareholdings held by all common owners of the two firms over the total number of shareholdings held by all (common and non-common) owners in our database. An increase in both measures reflects an increase in shareholdings of existing common owners relative to non-common owners. The difference between the two measures lies in the fact that δ_S is based on shareholdings, whereas FCAP is based on the value of these shareholdings. FCAP takes therefore into account that firms may be different in size, and attribute more weight to the larger firm. Thus, an increase in the size of the shareholdings of common investors in the smaller firm will count less than an increase in the size of the shareholdings in the larger firm. δ_S, instead, considers both equally.

[57] Note that for this measure private firms are treated as having one (non-common) investor with shareholding equal to 1 and with market capitalisation equal to 1; this in order to prevent having 0 values in denominators.

- **Percentage of common funds' (PCF)** measure, due to Koch et al. (2019), which, despite being originally an industry-based measure, can be adjusted to a bilateral measure. Koch et al. (2019) define a "common investor" as an investor that is a blockholder in at least two of the firms of the industry, and consider the importance of the common blockholders relative to all blockholders. In our δ_S measure, a common investor is a blockholder in two firms, the generic and the brand. Further, δ_S is slightly different from PCF in two respects. First, PCF measures the importance of the common blockholders by computing the number of common blockholders relative to the total number of blockholders (common and not common). Instead, we use the number of shares. In this sense we take into account not only the number but also the size of the blockholders. Second, PCF defines a blockholder as an investor that owns at least 5% of the shares of the firm, whereas in our case we use the 1% threshold. Their measure, therefore, puts relatively higher weight on large owners than ours. We have checked and confirmed that our results are robust to the use of a 3% or 5% threshold to define blockholders.

All the above-described measures are used in the same pair-wise regression as we employed in Section 6: δ_S (column 1), δ_{R10} (column 2), δ_{cossim} (column 3), $\delta_{braycurtis}$ (column 4), δ_{CC} (column 5), δ_{fcap} (column 6), and δ_{pcf} (column 7). The results are displayed in Table C1. Results, while changing in magnitude of effect, are robust: common ownership has a negative impact on entry.

Table C1: Alternative common ownership measures

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ_C	-0.0459						
	(0.0111)						
δ_{R10}		-0.0322					
		(0.00791)					
δ_{cossim}			-0.0283				
			(0.00654)				
$\delta_{braycurtis}$				-0.0381			
				(0.00888)			
δ_{cc}					-0.0367		
					(0.0132)		
δ_{fcap}						-0.0186	
						(0.00612)	
δ_{pcf5}							-0.0345
							(0.00891)
Subsidiary	-0.0550	-0.0553	-0.0546	-0.0551	-0.0495	-0.0543	-0.0538
	(0.0150)	(0.0151)	(0.0150)	(0.0150)	(0.0151)	(0.0150)	(0.0149)
Experience Route	0.00835	0.00835	0.00836	0.00835	0.00833	0.00834	0.00832
	(0.000854)	(0.000855)	(0.000855)	(0.000854)	(0.000852)	(0.000854)	(0.000853)
Experience ATC2	0.0609	0.0609	0.0608	0.0609	0.0610	0.0609	0.0609
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
Experience New Drug	0.00433	0.00429	0.00425	0.00441	0.00314	0.00363	0.00320
	(0.00284)	(0.00285)	(0.00284)	(0.00285)	(0.00276)	(0.00282)	(0.00281)
Breadth (ATC2)	0.000952	0.000905	0.000758	0.000909	0.000482	0.000814	0.000371
	(0.00231)	(0.00231)	(0.00230)	(0.00231)	(0.00228)	(0.00233)	(0.00228)
Market Size (ln)	0.00496	0.00497	0.00495	0.00496	0.00492	0.00496	0.00498
	(0.000705)	(0.000707)	(0.000705)	(0.000704)	(0.000707)	(0.000706)	(0.000704)
Authorized Generic	0.00366	0.00362	0.00370	0.00369	0.00372	0.00370	0.00373
	(0.00387)	(0.00388)	(0.00388)	(0.00387)	(0.00387)	(0.00388)	(0.00388)
New Chemical Entity	-0.00962	-0.00972	-0.00969	-0.00963	-0.00915	-0.00966	-0.00970
	(0.00404)	(0.00405)	(0.00405)	(0.00404)	(0.00409)	(0.00404)	(0.00405)
Orphan Drug	-0.00472	-0.00494	-0.00484	-0.00480	-0.00384	-0.00486	-0.00483
	(0.00728)	(0.00729)	(0.00727)	(0.00728)	(0.00737)	(0.00729)	(0.00726)
Pediatric Drug	0.00626	0.00625	0.00623	0.00625	0.00735	0.00615	0.00599
	(0.00457)	(0.00458)	(0.00456)	(0.00457)	(0.00461)	(0.00458)	(0.00457)
Substitutes on Patent	-0.00609	-0.00599	-0.00598	-0.00600	-0.00598	-0.00606	-0.00581
	(0.00610)	(0.00611)	(0.00611)	(0.00611)	(0.00616)	(0.00610)	(0.00610)
Substitutes off Patent	-0.00878	-0.00872	-0.00879	-0.00878	-0.00872	-0.00877	-0.00896
	(0.00489)	(0.00490)	(0.00488)	(0.00489)	(0.00487)	(0.00489)	(0.00489)
Observations	34144	34144	34144	34144	34144	34144	34144
R-squared	0.0878	0.0878	0.0878	0.0878	0.0877	0.0876	0.0877
Therapeutic field	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug form	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Submission type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug markets	395	395	395	395	395	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported.

D Dataset construction

This appendix contains a detailed description of how the data used for the analysis in this article was constructed. The Orange Book has been downloaded from the FDA website for each year (2001q4, 2002q4,..., 2017q4) using Internet Archive. In the current version of the Orange Book online the names of companies have been partially back-dated to display the current manufacturer of a drug. To establish the company name and drug status at the time of approval, we merged information from multiple versions of the FDA Orange Book.

Duplicate applications in the FDA Orange Book were identified and removed. Where duplicate applications had different approval dates, the earlier date was taken. Thereafter the products in the dataset were merged with historical patent data from the FDA based on the FDA drug application number and product number. The patent data provides a complete list of which patents are associated with the product and their corresponding expiration dates.

In the FDA Orange Book, a drug product can be identified as a unique ingredient-form-strength combination. For example, Cetirizine Hydrochloride in syrup form with a strength of 5mg/5ml. Initially, the FDA Orange Book reports 3964 products at the ingredient-form-strength level that were launched from 1982q1 until 2017q2. For our purposes we restricted the data in multiple ways. First, we consider only drug products that faced generic entry or patent expiry in the time frame 2004q1 to 2014q4 (this is the range where we have data on all variables). This results in a sample of 1080 unique drug products. We then drop drug products which are not linked to any patent (as this study focuses on market entry in markets that are initially protected by patents). This results in 666 unique drug products. Thereafter we drop OTC drugs, keeping only prescription drugs. This results in 640 unique drug products.

On the basis of information contained in the Orange Book we seek to remove drug products where the original brand drug was withdrawn for safety reasons. We identify these products as cases where the original brand has been discontinued, and there is no note in the Orange Book that the discontinuation was not for safety reasons. Dropping these brand products results in 554 unique drug products. We drop two further drug products where generic applications (ANDAs) were approved before the NDA application for the same ingredient-form-strength. This results in 552 drug products.

We then aggregate these drug products to the ingredient-form level. We take the first strength that was approved by the FDA at the ingredient-form level as the relevant brand product. We then identify subsequent ANDAs that were approved at the same

ingredient-form level. In cases where a generic enters with multiple strengths, we keep only the earliest entry. This results in 457 unique drug product markets, or brand products, at the ingredient-form level.

A variable is constructed that takes the earlier of either generic entry or the date of the last expiring patent for the relevant product market at the ingredient-form level; called "end of exclusivity."

Each product is linked through exact text matching, based on compound-name, with the ATC/DDD Index 2015.[58] The ATC/DDD Index 2015 is used to identify relevant therapeutic markets and chemical classes for different levels of the ATC classification system. Whereas the ATC3 level is most in line with market definition in M&A approval procedures in Europe and the United States, through the matching process one drug may be linked with numerous therapeutic classes at the ATC3 level. To ensure that we obtain a unique therapeutic class for each drug, we use the broader market definition of ATC2.

For each drug product market, we identify if the brand firm has launched its own generic in the market (an "authorized generic") using the FDA list of authorized generics. The merge was conducted on the basis of trade name and form. Additional information, such as submission class, is merged in using the FDA application number.[59] We recode the FDA form/route variable to construct five form/route classes namely oral, injection, topical, ophthalmic and inhalation.

The data on firms and their product launches from the FDA Orange book is then matched with the Thomson Reuters ownership dataset based on the name of the pharmaceutical company. We correct for the fact that firms may change their name over the course of the sample period and undergo mergers, on the basis of public information. We record the year-quarters in which each firm is either publicly listed or not. For example, some companies in the sample start out being publicly listed, and then are taken off the stock exchange (e.g., if they experience a leveraged buyout) and then are later made public again. It can occur that a company that is known to have been public in a specific year-quarter, has no ownership information in this year-quarter in

[58]The ATC/DDD Index 2015 categorizes all chemical compounds used in any therapeutic field according to a five-level hierarchical system, called the Anatomical Therapeutic Chemical (ATC) Classification System. The highest level (ATC1) consist of 14 anatomical main groups (e.g. Alimentray Tract and Metabolism (A) or Cardiovascular System (C)). The next lower level (ATC2) describes 88 therapeutic main groups (e.g. Drugs used in Diabetes (A10) or Diuretics (C03)). Lower levels make even finer distinctions between products. The lowest level (ATC5) indicates 3709 chemical substances.

[59]The main submission classes include Type 1 New Molecular Entity, Type 2 New Active Ingredient, Type 3 New Dosage Form, Type 4 New Combination, Type 5 New Formulation or Other Differences (e.g., new indication, new applicant, new manufacturer).

the Thomson Reuters dataset. Where we have a public firm in the pair that has missing ownership data we remove this pair from the analysis. A total 6 markets are dropped due to missing ownership data, resulting in 451 drug markets.

We then match the brand drug products in our sample with Medicaid reimbursement data, publicly available from medicaid.gov, at the national level using National Drugs Codes (NDC) which are unique product identifiers for drugs in the US. A drug product in our sample may be matched with multiple NDC codes due to the fact we define drug products at the ingredient-form level, whereas NDC codes are defined at the finest level taking drug strength and package size into account. We aggregate information on the total amount reimbursed per year by summing over NDC codes for a drug product. Due to that fact that some drugs cannot be matched with Medicaid reimbursements, we are left with 395 unique drug product markets.

Subsidiary firms are assigned the ownership structure of the parent firm under the assumption that they are fully controlled by the parent. However in recognition of the fact that the subsidiary is a separate entity from the parent with its own previous experience, we determine all experience variables at the subsidiary level. That is, we do not assign the experience of the parent to the subsidiary.

In the final dataset, there are 93 unique brand companies and 189 unique generic companies operating within the relevant markets and time period. Given that the focus of the article is on links between brand and generic companies, we then make our dataset pairwise; creating brand-generic pairs. There are 10,453 unique pairs.

The common ownership measures are constructed at the pair level using data from Thomson Reuters Global Ownership Database from 2003 to 2014. We calculate common ownership measures in the year of the end of exclusivity (lag 0), one year prior (lag 1) and two years prior (lag 2). When constructing measures of common ownership, we restrict ourselves to the investor holdings that represent at least one percent in the equity of the firms. Investor acquisitions during this period and ultimate owners are identified on the basis of public sources.

Table D1 gives an example of the structure of our pairwise data using the drug Natrecor which was launched by Johnson & Johnson. The relevant market is defined by the ingredients (nestiritide recombinant) and drug form/route (solution; intravenous). The patent associated with Natrecor expired in 2014q2. All pharmaceutical firms in the Table had previous experience in launching generic drugs of the same form/route (solution; intravenous). Entry is defined within 6 quarters of the end of market exclusivity, in this case between 2014q2 and 2015q4. None of the generics in the Table

entered the market. The common ownership measures of the generic firms, one of which is Mylan (see Table 1), with the brand, Johnson & Johnson, correspond to those of the year 2013.

Table D1: Example data structure

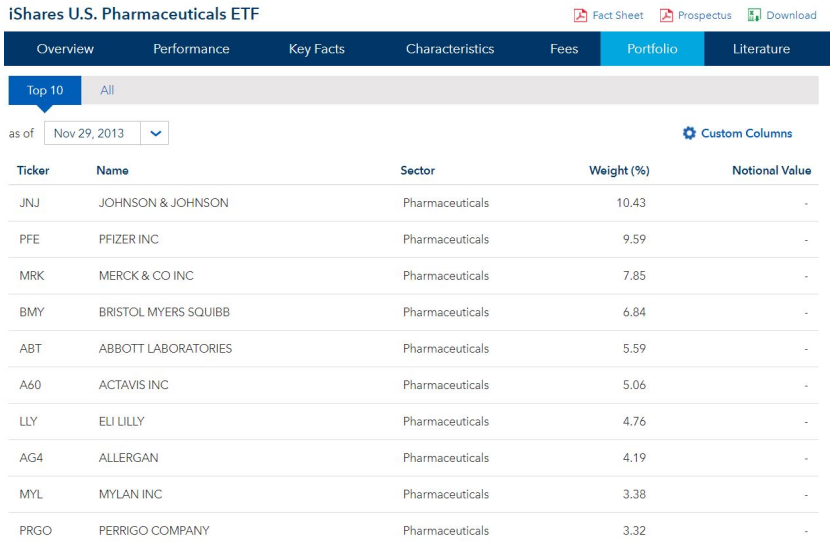
obs.	trade name	brand	generic entrant	entry	δ_S	δ_R	δ_κ
1	natrecor	JOHNSON & JOHNSON	MYLAN	0	0.64	0.8	0.91
2	natrecor	JOHNSON & JOHNSON	BARR	0	0.51	0.4	0.21
3	natrecor	JOHNSON & JOHNSON	SANDOZ	0	0.44	0.2	0.29
4	natrecor	JOHNSON & JOHNSON	AMNEAL	0	0	0	0
5	natrecor	JOHNSON & JOHNSON	APOTEX	0	0	0	0
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.

E Identification

To investigate the concern of potential endogeneity we perform IV estimations and instrument for common ownership with financial index membership at the pair level. This appendix provides a more in-depth discussion of identification and undertakes further analysis to bolster the identification arguments made in the paper.

Figure E1 provides a snapshot of the top 10 investments of the iShares U.S. Pharmaceutical ETF as of November 2013. As can be seen, both generic and brand firms are present; e.g., Mylan primarily produces generic drugs whereas Johnson & Johnson is a brand company. On average, the fund has been comprised of 39 pharma holdings over time.[60] Since May 2006, each listed company has been included in the ETF for an average of four years. The fund has been marked by various periods of high entrance and exit – for instance, more than six companies dropped out and entered the fund in the last quarter of 2013 and the third quarter of 2015, respectively – and periods of no change.

Figure E1: iShares U.S. Pharmaceutical ETF (IHE) - Snapshot of Holdings



Ticker	Name	Sector	Weight (%)	Notional Value
JNJ	JOHNSON & JOHNSON	Pharmaceuticals	10.43	-
PFE	PFIZER INC	Pharmaceuticals	9.59	-
MRK	MERCK & CO INC	Pharmaceuticals	7.85	-
BMY	BRISTOL MYERS SQUIBB	Pharmaceuticals	6.84	-
ABT	ABBOTT LABORATORIES	Pharmaceuticals	5.59	-
A60	ACTAVIS INC	Pharmaceuticals	5.06	-
LLY	ELI LILLY	Pharmaceuticals	4.76	-
AG4	ALLERGAN	Pharmaceuticals	4.19	-
MYL	MYLAN INC	Pharmaceuticals	3.38	-
PRGO	PERRIGO COMPANY	Pharmaceuticals	3.32	-

Our instrument, *Index Presence* is an indicator equal to 1 if both firms are listed on the Dow Jones US Select Pharmaceutical Index at the point in time when common ownership is measured. We expect that if both companies in the pair appear in the

[60] A detailed description of how the Dow Jones US Select Pharmaceutical Index is constructed can be found at: https://www.spglobal.com/spdji/en/documents/methodologies/methodology-dj-us-select-sector-specialty.pdf

Index, common ownership will increase by virtue of the fact that investors who track the index, so-called *index investors*, will hold shares in both companies.

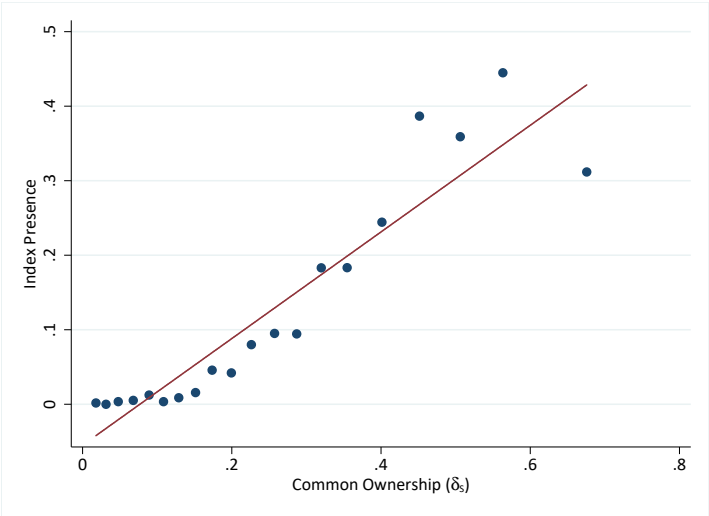
Summary statistics for our instrument show that firms which appear jointly on the index are more likely to be commonly owned. As can be seen from the first line of Table **??**, which focuses on our first measure of common ownership δ_S, 11,728 of our observations have common ownership links different from zero ($\delta_S > 0$). Of these 11,728 observations, 12% are also jointly present in the index (our IV), as the mean of 0.12 shows. On the other hand, as one can see from the second line, 22,416 observations have no common ownership. Of those, only 0.1%, are jointly in the index, as the mean of 0.001 shows.

Table E1: Summary statistics for our instrument

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Index Presence $\delta_S > 0$	11,422	0.126	0.332	0	1
Index Presence $\delta_S = 0$	22,722	0.000924	0.0304	0	1
Index Presence All	34,144	0.0428	0.202	0	1

We further illustrate this with a binned scatter plot. The binned scatter plot shows that the IV neatly corresponds with common ownership levels, especially for high values. This provides support for our IV in terms of instrument relevance: broadly, it correctly identifies which brand-generic pairs are connected through common ownership.

Figure E2: Binned scatter plot of our instrument vs. common ownership



Notes: The binned scatter plot groups the x-axis variable (δ_S) into 20 equally sized bins in terms of number of observations (pairs) where we consider values of δ_S greater than zero. It then computes the mean of the x-axis variable (δ_S) and y-axis variable (*Index Presence*) within each bin, and creates a scatter plot of these data points.

The first-stage results, reported in Table E2, further indicate that the instrument is highly relevant and positively correlated with all measures of δ (see the F-stats of excluded instruments).

Table E2: First-stage IV regressions

VARIABLES	(1) δ_S	(2) δ_R	(3) δ_κ
Index Presence	0.329	0.283	0.353
	(0.00890)	(0.0142)	(0.0145)
Constant	0.0162	-0.0105	0.0286
	(0.0388)	(0.0342)	(0.0332)
Observations	34144	34144	34144
R-squared	0.406	0.358	0.380
All controls	Yes	Yes	Yes
All fixed effects	Yes	Yes	Yes
Drug markets	395	395	395
F-stat excl. instruments	1365	400.1	591.2
Endogeneity test (p-val)	0.935	0.846	0.718

Notes: For simplicity only the coefficient associated with the excluded instrument is reported.

A valid instrument must be both relevant and exogenous. The identifying assumption is that inclusion in the pharmaceutical index, is exogenous to a particular market entry, except through its effect on common ownership. This is the case provided that the index is not created with potential entry opportunities in mind and that, controlling for other factors, addition to the index does not directly affect entry decisions except through common ownership.

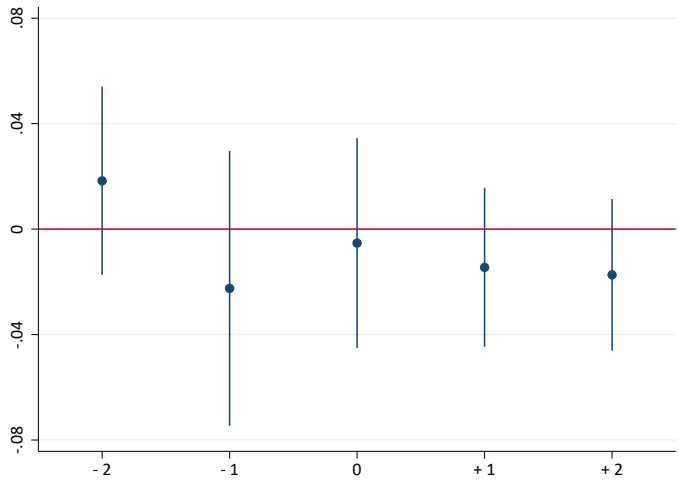
This exclusion restriction cannot be directly tested and has to be assumed. Nonetheless, to bolster this claim, we check if there is empirical evidence that pairwise index presence is driven by potential entry opportunities. To test for this possibility, we examine whether our instrument varies around the time when a market becomes open for entry. To this end, we adapt the event-study framework of Schmalz and Xie (2022) to our setting. We construct a panel of pairs observed throughout the sample period (2004-2014) and regress joint index presence for the pair on dummy variables, indicating the ith year relative to the end of regulatory protection for a specific drug market, i.e., we consider a window of time around the entry opportunity, where we take the ith year such that -2 $\leq i \leq$ 2. We further include time varying measures of experience, brand, generic and year fixed effects. Thus, we estimate the following equation:

$$Index_{gbt} = \beta_0 + \sum_{i=-2}^{i=+2} \beta_i \times End\,of\,Reg\,Protection(i)_{gbt} + \gamma X_{gt} + A_b + A_g + \mu_t + \epsilon_{gbt},$$

where the dependent variable $Index$ captures joint index presence between the generic firm g and the brand b at time t. $End\,of\,Reg\,Protection(i)_{gbt}$ are dummy variables indicating the i^{th} year prior or following an entry opportunity (-2 $\leq i \leq$ 2). X_{gt} captures time-varying generic experience in new drugs and generic drugs. Fixed effects for the brand and generic in the pair are represented by A_b and A_g respectively, μ_t captures year fixed effects, and ϵ_{gbt} is the error term. Standard errors are robust and clustered at the year level.

The figure below plots the estimated coefficients β_i and 95% confidence intervals. As can be seen, in a $[-2, +2]$ year window around the entry opportunity, there is no systematic impact on joint index presence. These results are consistent with the reasoning that index inclusion is not caused by an entry opportunity.[61]

Figure E3: Coefficient plot - Evolution of index presence around the end of regulatory protection



In a similar manner, one can also test whether common ownership itself varies around

[61]To provide an explanation for why this is the case, one could follow Boller and Scott-Morton (2020), who provide convincing arguments that inclusion into the S&P 500 index is an exogenous event. First, there is no clear "threshold" of firm size that guarantees entry into the index. Second, qualitative evidence from market participants points to the choice of new S&P entrants being random. Third, the S&P committee does not seem to be picking companies from "growing" markets, which indicates that index inclusion is not related to market performance. Following Boller and Scott's (2020) reasoning, we could argue that a company's inclusion in the Dow Jones US Select Pharmaceutical Index is to some extent random and, therefore, does not depend on its size/value, nor on the (future) attractiveness of a particular pharmaceutial market.

the date at which a market becomes open for entry as this dynamic is what would create the endogeneity concern in the first place. The concern is that if common ownership creates the incentive and ability to affect entry decisions, then there is also an incentive to increase common ownership between brands and generics around the period that drugs are coming off patent, i.e., around entry opportunities. For example, investors may anticipate entry opportunities, and as a consequence, either invest or dis-invest in the relevant brand and potential generic entrants.

To test for this possibility, we also examine whether common ownership varies around the time when a market becomes open for entry. Using the same panel of pairs observed throughout the sample period, we regress common ownership for the pair on dummy variables indicating the ith year relative to the end of regulatory protection, time-varying measures of experience, brand, generic and year fixed effects. The equation we estimate is as follows:

$$\delta_{gbt} = \beta_0 + \sum_{i=-2}^{i=+2} \beta_i \times End\,of\ Reg\ Protection(i)_{gbt} + \gamma X_{gt} + A_b + A_g + \mu_t + \epsilon_{gbt},$$

where the dependent variable δ is a measure of common ownership between the generic firm g and the brand b at time t. $End\,of\ Reg\ Protection(i)_{gbt}$ are dummy variables indicating the i^{th} (-2 $\leq i \leq$ 2) year prior or following an entry opportunity. X_{gt} captures time-varying generic experience in new drugs and generic drugs. Fixed effects for the brand and generic in the pair as represented by A_b and A_g respectively, μ_t captures year fixed effects, and ϵ_{gbt} is the error term. Standard errors are robust and clustered at the year level.

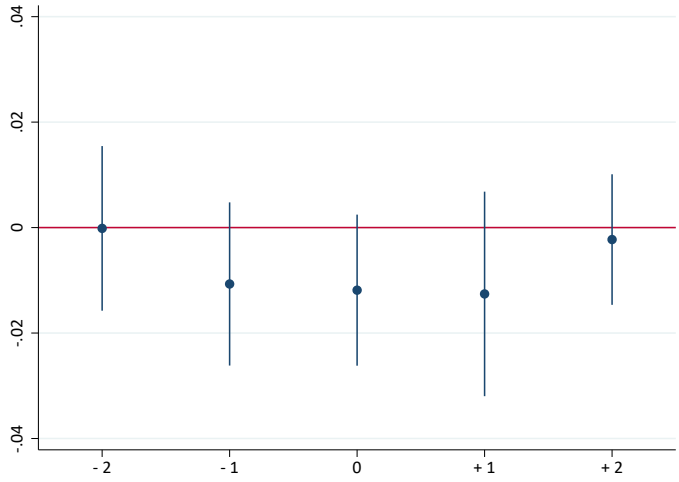
Figure E4 plots the estimated coefficients β_i and 95% confidence intervals using the measure δ_S.[62] As can be seen in the figure, we fail to detect any significant changes in common ownership before or after an entry opportunity.[63,64]

[62]Results are similar if we use δ_R or δ_κ.

[63]To square a passive investment strategy with an active owner strategy, one can cite papers on the topic that find that passive investors often have more incentives to be activist, as they have less ability to "vote with their feet" (i.e., sell their stakes) than other investors. For example, Appel et al. (2016, p111) state that "Our findings suggest that passive mutual funds influence firms' governance choices [...]. Passive investors appear to exert influence [...], and consistent with the observed governance differences increasing firm value, passive ownership is associated with improvements in firms' longer-term performance."

[64]Passive investors themselves also consider themselves to be active owners. As reported in an article by the Financial Times (2014), John Wilcox, chairman of Sodali, a New York-based investment consultancy, and former head of corporate governance at TIAA-CREF, one of the world's largest pension funds, states: "Having a passive investment strategy has nothing to do with your behavior as an owner. Being a "permanent" owner is not an excuse not to engage, it is a reason to engage, Mr Wilcox adds. "If you are a permanent owner, you want to make sure those assets per-

Figure E4: Coefficient plot - Evolution of δ_S around the end of regulatory protection



In sum, we find empirical evidence that common ownership in our setting is not driven by having potential entry opportunities in mind, as there are no major spikes in common ownership around an entry opportunity. One tentative explanation could be that the majority of our common owners have a passive, long-term investment strategy, but (or, therefore,) actively influence firms' strategies.

Thus, both common ownership (our main independent variable) and joint index presence (our proposed IV) are not driven by a particular entry opportunity. Note that the above findings are also in line with the endogeneity tests in the paper, where we find that our OLS and IV estimates yield the same coefficient estimates, which is indeed consistent with the hypothesis that our original and instrumental variable are both exogenous.

form well." See Mike Scott, Passive investment, active ownership, Financial Times, 2014, available at https://www.ft.com/content/7c5f8d60-ba91-11e3-b391-00144feabdc0

F Heterogeneous effects

F.1 Heterogeneous effects by market size

In order to obtain further insights on what drives our average results, we explore the effects of common ownership for different market sizes. Conceptually, the effect of common ownership on market entry can be stronger or weaker in larger markets. On the one hand, the loss in profits of the brand should be larger in larger markets and therefore the effect of common ownership may be stronger. On the other hand, the gain in profits of the generic is also larger and therefore the effect of common ownership may also be weaker.

Empirically, we can compare the regression results of our full sample (395 markets) with those of the top 100 markets, i.e., the markets with the highest sales in our sample. The regression results of the latter are presented in Table F1 below. The coefficients of the two tables can be compared while taking into account the potentially different distributions of common ownership in each of the samples. On average, the level of common ownership is similar across the two samples (0.084 vs. 0.086), and is distributed with the same variance (0.16). But the estimated coefficient of the effect of δ_S on entry is higher in the top 100 markets. Still, the unconditional entry rate is also higher. To compare, we compute the effect of a one standard deviation increase in δ_S on the probability of entry as a share of the unconditional entry rate. While the size of the effect is a decrease of 14% overall, it is a decrease of 33% in the top 100 markets. We interpret this as common ownership having a higher marginal effect in markets where there is a larger profit at stake.

Table F1: Sample of top 100 drugs

VARIABLES	(1)	(2)	(3)
δ_S	-0.0954		
	(0.0149)		
δ_R		-0.102	
		(0.0183)	
δ_κ			-0.0895
			(0.0134)
Subsidiary	-0.118	-0.113	-0.113
	(0.0374)	(0.0370)	(0.0374)
Experience Route	0.0144	0.0143	0.0145
	(0.00220)	(0.00220)	(0.00222)
Experience ATC2	0.0667	0.0679	0.0671
	(0.0265)	(0.0267)	(0.0267)
Experience New Drug	0.0274	0.0241	0.0267
	(0.00790)	(0.00786)	(0.00806)
Breadth (ATC2)	-0.00633	-0.00717	-0.00688
	(0.00572)	(0.00571)	(0.00569)
Market Size (ln)	0.00731	0.00736	0.00717
	(0.00266)	(0.00266)	(0.00267)
Authorized Generic	0.00588	0.00612	0.00589
	(0.00904)	(0.00922)	(0.00913)
New Chemical Entity	-0.0150	-0.0128	-0.0143
	(0.0104)	(0.0105)	(0.0104)
Orphan Drug	0.00408	0.00488	0.00429
	(0.0128)	(0.0129)	(0.0128)
Pediatric Drug	0.0182	0.0198	0.0191
	(0.0134)	(0.0137)	(0.0135)
Substitutes on Patent	0.0131	0.0135	0.0127
	(0.00966)	(0.00979)	(0.00977)
Substitutes off Patent	0.0123	0.0127	0.0130
	(0.0211)	(0.0217)	(0.0214)
Observations	8600	8600	8600
R-squared	0.153	0.153	0.153
Therapeutic field	Yes	Yes	Yes
Drug form	Yes	Yes	Yes
Submission type	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes
Drug markets	395	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term and control variables are estimated but not reported.

F.2 Heterogeneous effects by level of experience

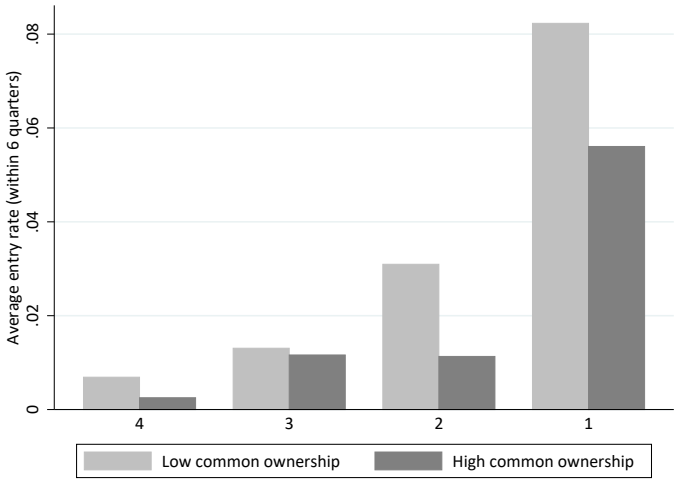
Our main results indicate that more experienced generic entrants are significantly more likely to enter (see Table 3). We explore, therefore, the heterogeneous effects of common ownership along this dimension. We use the variable *Experience Route*, and this for several reasons. First, entry relies on the manufacturing capabilities, which differ depending on the drug form (e.g., being able to manufacture injections vs. tablets). Second, this variable provides a measure of experience tailored to the focal market. Third, there is enough variation across generics, and it is thus suited to explore heterogeneous effects.

Figure F1 displays average generic entry rates, split by this measure of experience (in quartiles, with quartile 1 being the most and quartile 4 being the least experienced set of generics) and by level of common ownership with the brand. Given that our main analysis reveals that strong common ownership links are associated with the strongest effects on entry, we separate generic entrants of each quartile of experience into the following two groups: those with a strong common ownership link with the brand, i.e., where $\delta_S > 0.5$ (labeled as "high common ownership") and those without a strong link with the brand, i.e., where $\delta_S \leq 0.5$ ("low common ownership").

We first note that more experienced generics are more likely to enter the market, independently of their level of common ownership. Especially for the most experienced (quartile 1), entry rates are much higher than for the rest (other quartiles). Secondly, highly experienced generics with high common ownership are significantly less likely to enter than highly experienced generics with low common ownership. In contrast, the existence of a strong common ownership link with the brand does not affect significantly the entry rates of less experienced generics.[65]

[65] We perform tests of difference of means. For the most experienced generics, the difference is significantly different from zero at the 5% level. For the most second most experienced generics, the difference is significantly different from zero at the 10% level. For the other quartiles, the difference is insignificant.

Figure F1: Entry rate over level of experience and pairwise common ownership



Notes: High common ownership is defined at the pair level as $\delta_S > 0.5$, whereas low common ownership occurs if $\delta_S \leq 0.5$. Levels of experience are displayed in quartiles, with quartile 1 being the most experienced entrants and quartile 4 being the least experienced set of generics.

We confirm the intuition of the previous figure by performing regressions on split samples (by the four quartiles of generic experience). The specification is the same as for the pairwise regression that we run in Table 3. We repeat this procedure for all three of our continuous pairwise common ownership variables. The results are shown in Tables F2, F3 and F4.

Across all three measures, the results show that common ownership reduces the likelihood of entry for the most experienced generics (quartile 1 and 2) more negatively than for less experienced generics (quartile 3 and 4), both in terms of size and significance.

Table F2: Split by Experience Level - δ_S

VARIABLES	(1) all	(2) quartile 1	(3) quartile 2	(4) quartile 3	(5) quartile 4
δ_S	-0.0248	-0.0252	-0.0391	-0.000985	0.00816
	(0.00668)	(0.0138)	(0.0123)	(0.0141)	(0.00476)
Subsidiary	-0.0552	-0.0743	-0.0667	-0.00186	-0.00555
	(0.0150)	(0.0323)	(0.0207)	(0.0142)	(0.00932)
Experience Route	0.00835	0.00844	0.00754	0.00632	0.0267
	(0.000854)	(0.00116)	(0.00447)	(0.00681)	(0.0214)
Experience ATC2	0.0609	0.0675	0.0499	0.00876	0.0173
	(0.0104)	(0.0141)	(0.0180)	(0.00645)	(0.0125)
Experience New Drug	0.00424	0.0154	-0.00327	-0.00941	0.00116
	(0.00284)	(0.00742)	(0.00440)	(0.00531)	(0.00197)
Breadth (ATC2)	0.000855	0.0247	-0.00658	-0.00222	-0.00682
	(0.00231)	(0.00683)	(0.00640)	(0.00490)	(0.00342)
Market Size (ln)	0.00496	0.0121	0.00456	0.00242	0.000481
	(0.000705)	(0.00176)	(0.00105)	(0.000545)	(0.000365)
Authorized Generic	0.00366	0.0123	0.000657	-0.00113	0.00268
	(0.00387)	(0.00932)	(0.00555)	(0.00310)	(0.00195)
New Chemical Entity	-0.00963	-0.0171	-0.0104	-0.00681	-0.00334
	(0.00404)	(0.0104)	(0.00552)	(0.00315)	(0.00204)
Orphan Drug	-0.00484	-0.0164	0.00421	-0.00486	-0.00164
	(0.00728)	(0.0152)	(0.0129)	(0.00701)	(0.00387)
Pediatric Drug	0.00623	0.0187	0.00584	-0.00149	0.00174
	(0.00457)	(0.0113)	(0.00610)	(0.00375)	(0.00297)
Substitutes on Patent	-0.00606	-0.00447	-0.0126	-0.00756	0.00187
	(0.00611)	(0.0151)	(0.00848)	(0.00625)	(0.00209)
Substitutes off Patent	-0.00875	-0.0200	-0.00426	-0.00583	-0.00405
	(0.00489)	(0.0113)	(0.00680)	(0.00419)	(0.00285)
Observations	34144	8676	8489	8589	8390
R-squared	0.0877	0.120	0.0382	0.0348	0.0434
All controls	Yes	Yes	Yes	Yes	Yes
All fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term and control variables are estimated but not reported.

Table F3: Split by Experience Level - δ_R

VARIABLES	(1) all	(2) quartile 1	(3) quartile 2	(4) quartile 3	(5) quartile 4
δ_R	-0.0269	-0.0253	-0.0284	-0.00444	0.00485
	(0.00723)	(0.0148)	(0.0135)	(0.0133)	(0.00514)
Subsidiary	-0.0544	-0.0730	-0.0634	-0.00261	-0.00619
	(0.0150)	(0.0322)	(0.0203)	(0.0133)	(0.00932)
Experience Route	0.00832	0.00842	0.00677	0.00620	0.0257
	(0.000853)	(0.00116)	(0.00445)	(0.00689)	(0.0215)
Experience ATC2	0.0610	0.0677	0.0499	0.00872	0.0173
	(0.0104)	(0.0141)	(0.0181)	(0.00646)	(0.0125)
Experience New Drug	0.00361	0.0146	-0.00553	-0.00908	0.00168
	(0.00282)	(0.00737)	(0.00421)	(0.00488)	(0.00191)
Breadth (ATC2)	0.000575	0.0250	-0.00605	-0.00206	-0.00642
	(0.00230)	(0.00680)	(0.00638)	(0.00482)	(0.00336)
Market Size (ln)	0.00496	0.0121	0.00455	0.00242	0.000476
	(0.000705)	(0.00176)	(0.00105)	(0.000545)	(0.000366)
Authorized Generic	0.00364	0.0122	0.000673	-0.00114	0.00266
	(0.00389)	(0.00934)	(0.00557)	(0.00310)	(0.00195)
New Chemical Entity	-0.00971	-0.0172	-0.0105	-0.00680	-0.00331
	(0.00405)	(0.0104)	(0.00553)	(0.00316)	(0.00204)
Orphan Drug	-0.00486	-0.0165	0.00407	-0.00484	-0.00161
	(0.00727)	(0.0152)	(0.0129)	(0.00702)	(0.00388)
Pediatric Drug	0.00610	0.0184	0.00543	-0.00145	0.00182
	(0.00459)	(0.0113)	(0.00611)	(0.00377)	(0.00298)
Substitutes on Patent	-0.00589	-0.00424	-0.0125	-0.00752	0.00180
	(0.00610)	(0.0151)	(0.00847)	(0.00624)	(0.00208)
Substitutes off Patent	-0.00888	-0.0203	-0.00452	-0.00582	-0.00402
	(0.00489)	(0.0113)	(0.00684)	(0.00419)	(0.00284)
Observations	34144	8676	8489	8589	8390
R-squared	0.0877	0.120	0.0376	0.0348	0.0432
All controls	Yes	Yes	Yes	Yes	Yes
All fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term and control variables are estimated but not reported.

Table F4: Split by Experience Level - δ_κ

VARIABLES	(1) all	(2) quartile 1	(3) quartile 2	(4) quartile 3	(5) quartile 4
δ_κ	-0.0284	-0.0287	-0.0194	-0.00564	0.00707
	(0.00548)	(0.0110)	(0.00974)	(0.00925)	(0.00543)
Subsidiary	-0.0544	-0.0736	-0.0621	-0.00318	-0.00625
	(0.0150)	(0.0320)	(0.0203)	(0.0133)	(0.00928)
Experience Route	0.00839	0.00844	0.00674	0.00627	0.0270
	(0.000856)	(0.00116)	(0.00447)	(0.00689)	(0.0215)
Experience ATC2	0.0608	0.0676	0.0499	0.00871	0.0173
	(0.0104)	(0.0141)	(0.0181)	(0.00645)	(0.0125)
Experience New Drug	0.00463	0.0159	-0.00571	-0.00868	0.00114
	(0.00287)	(0.00745)	(0.00423)	(0.00509)	(0.00197)
Breadth (ATC2)	0.000786	0.0245	-0.00626	-0.00202	-0.00661
	(0.00228)	(0.00685)	(0.00641)	(0.00478)	(0.00336)
Market Size (ln)	0.00494	0.0121	0.00456	0.00241	0.000481
	(0.000705)	(0.00176)	(0.00105)	(0.000544)	(0.000366)
Authorized Generic	0.00363	0.0122	0.000697	-0.00115	0.00267
	(0.00388)	(0.00933)	(0.00558)	(0.00310)	(0.00195)
New Chemical Entity	-0.00965	-0.0171	-0.0105	-0.00680	-0.00332
	(0.00404)	(0.0104)	(0.00553)	(0.00315)	(0.00204)
Orphan Drug	-0.00487	-0.0163	0.00398	-0.00486	-0.00163
	(0.00727)	(0.0152)	(0.0129)	(0.00701)	(0.00388)
Pediatric Drug	0.00620	0.0187	0.00538	-0.00145	0.00179
	(0.00457)	(0.0113)	(0.00610)	(0.00374)	(0.00298)
Substitutes on Patent	-0.00602	-0.00457	-0.0127	-0.00751	0.00182
	(0.00609)	(0.0151)	(0.00847)	(0.00625)	(0.00208)
Substitutes off Patent	-0.00875	-0.0199	-0.00440	-0.00583	-0.00403
	(0.00488)	(0.0113)	(0.00684)	(0.00419)	(0.00284)
Observations	34144	8676	8489	8589	8390
R-squared	0.0879	0.121	0.0375	0.0348	0.0433
All controls	Yes	Yes	Yes	Yes	Yes
All fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term and control variables are estimated but not reported.

G Robustness checks

Table G1: Robustness - Drug market fixed effects

VARIABLES	(1)	(2)	(3)
δ_S	-0.0222		
	(0.00617)		
δ_R		-0.0253	
		(0.00727)	
δ_κ			-0.0269
			(0.00531)
Subsidiary	-0.0483	-0.0477	-0.0478
	(0.0142)	(0.0142)	(0.0142)
Experience Route	0.00825	0.00823	0.00828
	(0.000680)	(0.000680)	(0.000681)
Experience ATC2	0.0629	0.0631	0.0628
	(0.00810)	(0.00809)	(0.00810)
Experience New Drug	0.00412	0.00370	0.00460
	(0.00296)	(0.00290)	(0.00293)
Breadth (ATC2)	0.00196	0.00183	0.00188
	(0.00150)	(0.00150)	(0.00149)
Observations	34144	34144	34144
R-squared	0.121	0.121	0.121
Generic region of origin	Yes	Yes	Yes
Drug product fixed effect	Yes	Yes	Yes
Drug markets	395	395	395

Notes: OLS regression. Standard errors in parentheses are robust. The dependent variable is entry within 6 quarters. The constant term is estimated but not reported.

Table G2: Robustness - Logit and Probit

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
δ_S	-0.809			-0.393		
	(0.264)			(0.126)		
δ_R		-0.779			-0.361	
		(0.306)			(0.147)	
δ_κ			-1.007			-0.435
			(0.270)			(0.127)
Subsidiary	-2.378	-2.305	-2.335	-0.815	-0.784	-0.795
	(1.137)	(1.136)	(1.135)	(0.556)	(0.554)	(0.554)
Experience Route	0.151	0.151	0.151	0.0749	0.0747	0.0749
	(0.0121)	(0.0122)	(0.0123)	(0.00595)	(0.00598)	(0.00601)
Experience ATC2	0.680	0.686	0.678	0.385	0.387	0.384
	(0.119)	(0.119)	(0.119)	(0.0578)	(0.0575)	(0.0576)
Experience New Drug	-0.199	-0.220	-0.187	-0.0963	-0.108	-0.0932
	(0.0823)	(0.0813)	(0.0815)	(0.0381)	(0.0374)	(0.0377)
Breadth (ATC2)	0.529	0.520	0.522	0.220	0.215	0.217
	(0.0589)	(0.0589)	(0.0589)	(0.0279)	(0.0278)	(0.0277)
Market Size (ln)	0.231	0.229	0.229	0.103	0.102	0.102
	(0.0314)	(0.0313)	(0.0313)	(0.0140)	(0.0139)	(0.0140)
Authorized Generic	0.188	0.185	0.186	0.0907	0.0901	0.0902
	(0.133)	(0.133)	(0.133)	(0.0613)	(0.0616)	(0.0615)
New Chemical Entity	-0.347	-0.347	-0.346	-0.165	-0.167	-0.166
	(0.158)	(0.159)	(0.158)	(0.0707)	(0.0712)	(0.0709)
Orphan Drug	-0.251	-0.256	-0.250	-0.124	-0.127	-0.126
	(0.238)	(0.239)	(0.238)	(0.111)	(0.111)	(0.111)
Pediatric Drug	0.123	0.119	0.124	0.0470	0.0445	0.0459
	(0.168)	(0.170)	(0.168)	(0.0765)	(0.0773)	(0.0767)
Substitutes on Patent	-0.215	-0.211	-0.217	-0.0977	-0.0956	-0.0984
	(0.181)	(0.180)	(0.181)	(0.0825)	(0.0821)	(0.0822)
Substitutes off Patent	-0.236	-0.243	-0.235	-0.0966	-0.0996	-0.0967
	(0.166)	(0.166)	(0.166)	(0.0735)	(0.0737)	(0.0735)
Observations	32994	32994	32994	32994	32994	32994
Therapeutic field	Yes	Yes	Yes	Yes	Yes	Yes
Drug form	Yes	Yes	Yes	Yes	Yes	Yes
Submission type	Yes	Yes	Yes	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes	Yes	Yes	Yes
Drug markets	395	395	395	395	395	395

Notes: Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported.

Table G3: Robustness - Logit and Probit Average Marginal Effects

VARIABLES	(1) $\partial y/\partial x$	(2) $\partial y/\partial x$	(3) $\partial y/\partial x$	(4) $\partial y/\partial x$	(5) $\partial y/\partial x$	(6) $\partial y/\partial x$
δ_S	-0.0195			-0.0201		
	(0.00652)			(0.00655)		
δ_R		-0.0188			-0.0184	
		(0.00742)			(0.00754)	
δ_κ			-0.0243			-0.0222
			(0.00663)			(0.00657)

Notes: Average marginal effects and standard errors computed from the logit and probit regressions in Table G2.

Table G4: Robustness - Indicator for top 100 sales

VARIABLES	(1)	(2)	(3)
δ_S	-0.0270		
	(0.00686)		
δ_R		-0.0289	
		(0.00738)	
δ_κ			-0.0304
			(0.00562)
Subsidiary	-0.0550	-0.0540	-0.0541
	(0.0145)	(0.0145)	(0.0145)
Experience Route	0.00837	0.00834	0.00841
	(0.000855)	(0.000854)	(0.000857)
Experience ATC2	0.0608	0.0610	0.0608
	(0.0104)	(0.0104)	(0.0104)
Experience New Drug	0.00450	0.00378	0.00487
	(0.00285)	(0.00282)	(0.00287)
Experience in Generic Launches	2.74e-05	3.29e-05	2.55e-05
	(6.87e-05)	(6.87e-05)	(6.86e-05)
Breadth (ATC2)	0.000921	0.000607	0.000831
	(0.00231)	(0.00230)	(0.00228)
Top 100 in Sales (0/1)	0.0210	0.0208	0.0209
	(0.00557)	(0.00558)	(0.00557)
Authorized Generic	0.00260	0.00259	0.00258
	(0.00399)	(0.00400)	(0.00399)
New Chemical Entity	-0.0108	-0.0109	-0.0108
	(0.00408)	(0.00409)	(0.00408)
Orphan Drug	-0.0105	-0.0105	-0.0105
	(0.00723)	(0.00723)	(0.00721)
Pediatric Drug	0.00907	0.00896	0.00902
	(0.00490)	(0.00492)	(0.00490)
Substitutes on Patent	-0.00824	-0.00803	-0.00818
	(0.00612)	(0.00612)	(0.00611)
Substitutes off Patent	-0.00450	-0.00468	-0.00453
	(0.00496)	(0.00497)	(0.00495)
Observations	34144	34144	34144
R-squared	0.0859	0.0858	0.0861
Therapeutic field	Yes	Yes	Yes
Drug form	Yes	Yes	Yes
Submission type	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes
Drug markets	395	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported.

Table G5: Robustness - Using total US sales for top drugs

VARIABLES	(1)	(2)	(3)
δ_S	-0.0959		
	(0.0145)		
δ_R		-0.102	
		(0.0181)	
δ_κ			-0.0898
			(0.0133)
Subsidiary	-0.120	-0.114	-0.114
	(0.0375)	(0.0371)	(0.0375)
Experience Route	0.0143	0.0143	0.0145
	(0.00219)	(0.00219)	(0.00221)
Experience ATC2	0.0667	0.0679	0.0671
	(0.0265)	(0.0267)	(0.0267)
Experience New Drug	0.0275	0.0242	0.0267
	(0.00791)	(0.00787)	(0.00808)
Experience in Generic Launches	0.000356	0.000350	0.000332
	(0.000214)	(0.000216)	(0.000217)
Breadth (ATC2)	-0.00633	-0.00717	-0.00689
	(0.00572)	(0.00571)	(0.00568)
Brand Sales USD (ln)	0.0200	0.0201	0.0196
	(0.00589)	(0.00601)	(0.00594)
Authorized Generic	0.00899	0.00925	0.00894
	(0.00861)	(0.00869)	(0.00869)
New Chemical Entity	-0.0257	-0.0235	-0.0248
	(0.00990)	(0.0101)	(0.00993)
Orphan Drug	-0.0154	-0.0147	-0.0148
	(0.0137)	(0.0137)	(0.0137)
Pediatric Drug	0.0128	0.0144	0.0138
	(0.0131)	(0.0135)	(0.0133)
Substitutes on Patent	-0.0118	-0.0116	-0.0118
	(0.0106)	(0.0108)	(0.0107)
Substitutes off Patent	0.0251	0.0256	0.0256
	(0.0202)	(0.0208)	(0.0206)
Observations	8600	8600	8600
R-squared	0.154	0.153	0.153
Therapeutic field	Yes	Yes	Yes
Drug form	Yes	Yes	Yes
Submission type	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes
Drug markets	93	93	93

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported.

Table G6: Robustness - Broader entrant set

VARIABLES	(1)	(2)	(3)
δ_S	-0.0136		
	(0.00432)		
δ_R		-0.0183	
		(0.00490)	
δ_κ			-0.0186
			(0.00379)
Subsidiary	-0.0337	-0.0336	-0.0336
	(0.00910)	(0.00911)	(0.00909)
Experience Route	0.00836	0.00835	0.00839
	(0.000791)	(0.000790)	(0.000792)
Experience ATC2	0.0558	0.0558	0.0557
	(0.00950)	(0.00950)	(0.00949)
Experience New Drug	0.00441	0.00433	0.00484
	(0.00201)	(0.00197)	(0.00200)
Breadth (ATC2)	-4.67e-05	-0.000117	2.45e-05
	(0.00169)	(0.00169)	(0.00168)
Market Size (ln)	0.00306	0.00305	0.00305
	(0.000447)	(0.000446)	(0.000446)
Authorized Generic	0.00258	0.00258	0.00256
	(0.00248)	(0.00248)	(0.00248)
New Chemical Entity	-0.00547	-0.00549	-0.00547
	(0.00256)	(0.00257)	(0.00256)
Orphan Drug	-0.00549	-0.00551	-0.00549
	(0.00458)	(0.00458)	(0.00458)
Pediatric Drug	0.00466	0.00465	0.00469
	(0.00287)	(0.00288)	(0.00287)
Substitutes on Patent	-0.00336	-0.00327	-0.00335
	(0.00335)	(0.00335)	(0.00334)
Substitutes off Patent	-0.00318	-0.00323	-0.00319
	(0.00253)	(0.00253)	(0.00253)
Observations	55769	55769	55769
R-squared	0.0825	0.0825	0.0826
Therapeutic field	Yes	Yes	Yes
Drug form	Yes	Yes	Yes
Submission type	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes
Drug markets	395	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported. The sample of potential generic entrants includes all pharmaceutical companies that launched at least one generic product in our drug markets.

Table G7: Robustness - Entry ever

VARIABLES	(1)	(2)	(3)
δ_S	-0.0392		
	(0.00818)		
δ_R		-0.0409	
		(0.00843)	
δ_κ			-0.0406
			(0.00680)
Subsidiary	-0.0783	-0.0767	-0.0765
	(0.0171)	(0.0170)	(0.0171)
Experience Route	0.00996	0.00991	0.0100
	(0.00101)	(0.00101)	(0.00101)
Experience ATC2	0.0837	0.0839	0.0837
	(0.0118)	(0.0118)	(0.0118)
Experience New Drug	0.00750	0.00637	0.00764
	(0.00329)	(0.00327)	(0.00330)
Breadth (ATC2)	0.00527	0.00479	0.00504
	(0.00255)	(0.00253)	(0.00252)
Market Size (ln)	0.00821	0.00820	0.00818
	(0.000865)	(0.000866)	(0.000867)
Authorized Generic	0.00723	0.00721	0.00720
	(0.00453)	(0.00454)	(0.00454)
New Chemical Entity	-0.0111	-0.0112	-0.0111
	(0.00468)	(0.00469)	(0.00468)
Orphan Drug	-0.000182	-0.000237	-0.000267
	(0.00912)	(0.00911)	(0.00909)
Pediatric Drug	0.00825	0.00803	0.00812
	(0.00560)	(0.00562)	(0.00560)
Substitutes on Patent	-0.00354	-0.00328	-0.00348
	(0.00772)	(0.00772)	(0.00771)
Substitutes off Patent	-0.0181	-0.0183	-0.0181
	(0.00564)	(0.00564)	(0.00563)
Observations	34144	34144	34144
R-squared	0.106	0.106	0.107
Therapeutic field	Yes	Yes	Yes
Drug form	Yes	Yes	Yes
Submission type	Yes	Yes	Yes
Generic region of origin	Yes	Yes	Yes
Year end of exclusivity	Yes	Yes	Yes
Drug markets	395	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry (within any time period). The constant term is estimated but not reported.

Table G8: Robustness - Patent expiry

VARIABLES	(1) Substance expiry	(2) Product expiry
δ_S	-0.0236	-0.0227
	(0.00654)	(0.00662)
Subsidiary	-0.0512	-0.0498
	(0.0145)	(0.0145)
Experience Route	0.00776	0.00783
	(0.000828)	(0.000825)
Experience ATC2	0.0608	0.0577
	(0.0104)	(0.0103)
Experience New Drug	0.00486	0.00454
	(0.00279)	(0.00278)
Breadth (ATC2)	0.00206	0.00166
	(0.00227)	(0.00225)
Market Size (ln)	0.00449	0.00458
	(0.000710)	(0.000725)
Authorized Generic	0.00152	0.00218
	(0.00392)	(0.00390)
New Chemical Entity	-0.0111	-0.0123
	(0.00419)	(0.00411)
Orphan Drug	-0.00435	-0.00348
	(0.00732)	(0.00742)
Pediatric Drug	0.00729	0.00495
	(0.00472)	(0.00483)
Substitutes on Patent	-0.00472	-0.00458
	(0.00617)	(0.00630)
Substitutes off Patent	-0.00762	-0.00591
	(0.00487)	(0.00483)
Observations	34144	34144
R-squared	0.0820	0.0807
Therapeutic field	Yes	Yes
Drug form	Yes	Yes
Submission type	Yes	Yes
Generic region of origin	Yes	Yes
Year end of exclusivity	Yes	Yes
Drug markets	395	395

Notes: OLS regression. Standard errors in parentheses are clustered at the drug market level. The dependent variable is entry within six quarters. The constant term is estimated but not reported.

Table G9: Robustness - Market outcomes δ_W

VARIABLES	(1) N-6q	(2) $\partial y/\partial x$	(3) N-2y	(4) $\partial y/\partial x$	(5) N-ever	(6) $\partial y/\partial x$	(7) No entry	(8) Time
δ_W	-2.567	-6.160	-2.199	-5.739	-3.032	-11.64	0.843	17.27
	(1.239)	(2.998)	(1.171)	(3.072)	(1.011)	(3.945)	(0.454)	(14.03)
Market Size (ln)	0.199	0.478	0.204	0.533	0.198	0.761	-0.0436	-1.311
	(0.0273)	(0.0704)	(0.0263)	(0.0738)	(0.0217)	(0.0867)	(0.0103)	(0.296)
Authorized Generic	0.136	0.326	0.125	0.328	0.166	0.636	-0.0869	-1.905
	(0.111)	(0.269)	(0.110)	(0.288)	(0.0831)	(0.322)	(0.0404)	(1.310)
New Chemical Entity	-0.306	-0.735	-0.341	-0.891	-0.201	-0.771	0.0243	0.373
	(0.136)	(0.325)	(0.133)	(0.347)	(0.108)	(0.411)	(0.0500)	(1.581)
Orphan Drug	-0.269	-0.646	-0.295	-0.769	-0.0528	-0.203	0.0879	1.755
	(0.206)	(0.496)	(0.202)	(0.531)	(0.165)	(0.635)	(0.0860)	(2.493)
Pediatric Drug	0.0925	0.222	0.100	0.262	0.0954	0.366	-0.0183	-1.306
	(0.137)	(0.327)	(0.134)	(0.348)	(0.111)	(0.424)	(0.0516)	(1.567)
Substitutes on Patent	-0.194	-0.466	-0.194	-0.507	-0.0833	-0.320	0.00664	0.912
	(0.155)	(0.372)	(0.150)	(0.391)	(0.129)	(0.493)	(0.0571)	(1.779)
Substitutes off Patent	-0.0641	-0.154	-0.0574	-0.150	-0.119	-0.456	-0.00985	-0.0938
	(0.140)	(0.335)	(0.137)	(0.358)	(0.112)	(0.428)	(0.0592)	(2.050)
Observations	395		395		395		395	395
Therapeutic field	Yes		Yes		Yes		Yes	Yes
Drug form	Yes		Yes		Yes		Yes	Yes
Submission type	Yes		Yes		Yes		Yes	Yes
Year end of exclusivity	Yes		Yes		Yes		Yes	Yes
(Pseudo) R-squared	0.298		0.319		0.350		0.390	0.365

Notes: Poisson regression. Standard errors in parentheses are robust. Average marginal effects reported alongside estimated coefficients. The constant term is estimated but not reported.

Table G10: Robustness - Negative binomial regression

VARIABLES	(1) N-6q	(2) $\partial y/\partial x$	(3) N-2y	(4) $\partial y/\partial x$	(5) N-ever	(6) $\partial y/\partial x$
δ_Z	-2.335	-5.612	-2.147	-5.616	-2.740	-10.62
	(1.040)	(2.510)	(0.999)	(2.630)	(0.928)	(3.645)
Market Size (ln)	0.208	0.500	0.213	0.558	0.212	0.824
	(0.0267)	(0.0713)	(0.0258)	(0.0758)	(0.0226)	(0.0954)
Authorized Generic	0.203	0.488	0.184	0.480	0.245	0.949
	(0.119)	(0.291)	(0.120)	(0.318)	(0.0959)	(0.380)
New Chemical Entity	-0.299	-0.718	-0.328	-0.857	-0.208	-0.806
	(0.130)	(0.312)	(0.127)	(0.332)	(0.105)	(0.405)
Orphan Drug	-0.298	-0.717	-0.311	-0.813	-0.115	-0.447
	(0.216)	(0.521)	(0.216)	(0.566)	(0.179)	(0.697)
Pediatric Drug	0.0449	0.108	0.0396	0.103	0.0498	0.193
	(0.132)	(0.316)	(0.129)	(0.338)	(0.112)	(0.433)
Substitutes on Patent	-0.152	-0.365	-0.144	-0.376	-0.0252	-0.0977
	(0.159)	(0.382)	(0.157)	(0.409)	(0.135)	(0.523)
Substitutes off Patent	-0.0459	-0.110	-0.0329	-0.0860	-0.0936	-0.363
	(0.136)	(0.326)	(0.134)	(0.349)	(0.118)	(0.456)
Observations	395		395		395	
Therapeutic field	Yes		Yes		Yes	
Drug form	Yes		Yes		Yes	
Submission type	Yes		Yes		Yes	
Year end of exclusivity	Yes		Yes		Yes	
Pseudo R-squared	0.157		0.163		0.163	
Squared correlation	0.467		0.452		0.384	

Notes: Negative binomial regression. Standard errors in parentheses are robust. Average marginal effects reported alongside estimated coefficients. The constant term is estimated but not reported.

H Medicaid data and tentative welfare implications

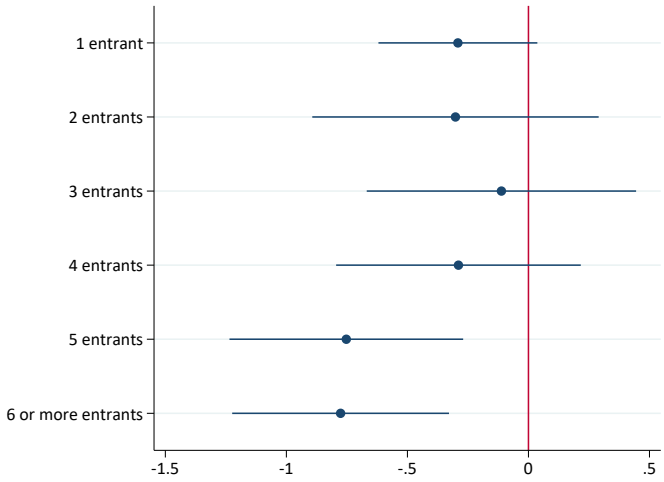
In this appendix we expand on the potential welfare effects of common ownership by first linking changes in the number of generic entrants to average drug prices, and secondly by linking the number of entrants to changes in common ownership.

To obtain a proxy measure for average prices for our data we match the brand drug products in our sample with Medicaid data (available from www.medicaid.gov) using National Drugs Codes (NDC) which are unique product identifiers for drugs in the US. A drug product in our sample may be matched with multiple NDC codes due to the fact we define drug products at the ingredient-form level, whereas NDC codes are defined at the finest level taking drug strength and package size into account.[66] We aggregate information on the total amount reimbursed per year by summing over NDC codes for a drug product.

The Medicaid data provides us with reimbursement information in dollar values and quantities, at the yearly level. We can, therefore, calculate the reimbursement per unit, which might be considered a proxy for the average price. We construct a variable which measures the percentage change in average reimbursement per unit, at the market-level, two years after entry vs. two years before the end of regulatory protection. We regress this proxy for the change in prices on the number of entrants, captured by binary indicator variables, two years after the end of regulatory protection and our full set of market level controls. Our sample consists of markets with complete reimbursement data for the relevant periods (374 markets). The figure below presents the estimated coefficients and 95% confidence intervals.

[66] Medicaid is a joint federal and state program that helps with medical costs for people with limited income and resources in the US. Drug utilization data is available at the state and national level for covered outpatient drugs that are paid for by state Medicaid agencies since the start of the Medicaid Drug Rebate Program in 1990. The data includes state, year, drug name, National Drug Code, number of prescriptions, dollars reimbursed and units reimbursed.

Figure H1: Coefficient plot - Effect of number of entrants on the percentage change in average reimbursement per unit



Notes: The plot displays the estimated coefficients with 95% confidence intervals from an OLS regression of the number of generic entrants within two years, captured by indicator variables, on the percentage change in average reimbursement per unit two years after the market becomes open for entry relative to two years before. The constant term is zero entrants hence the coefficient represents the percentage point change relative to the case with zero entrants. The regression includes all market-level controls and fixed effects.

As can be seen from the figure, relative to no entry, average prices are only significantly lower for five or more entrants. Therefore, having more than four entrants might make price reductions more likely on average and, hence, would meaningfully improve consumer welfare. Note that the above figure is also in line with Figure 1, which suggests a large decline in average total market revenues (in light gray) with five or more entrants vs. four entrants.

We can use our market-level regressions in the paper to compute the predicted count of entrants within two years for different levels of common ownership, as we show in the paper for all our markets in Figure 5. If we focus on the top 100 drug markets, where a higher level of entrants can be expected due to larger market sizes, a change of common ownership from zero to the maximum of 0.3, leads the predicted number of entrants (within two-years) to change from 5.2 to 2.5 (see the left panel of Figure 6). Thus, reducing common ownership could help to bring more competition into large/blockbuster drug markets, to the extent where we can expect prices to drop (> 4 entrants). Conversely, in markets that are not in the top 100 drug markets in terms of sales, we find that when going from the minimum level of δ_Z, zero, to the maximum

market level of 0.3, the average number of entrants in a market with two years would go down from about 2.2 to 1 (see the right panel of Figure 6). Thus, for the top drug markets, common ownership might have a large impact on consumer welfare; whereas for smaller drug markets, common ownership might not have that much impact.

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