Squeezing the last drop out of your suppliers: an empirical study of market-based purchasing policies for generic pharmaceuticals

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Abstract: We study the effect of the degree of exclusivity for the lowest bidder on the average price of generic pharmaceuticals in the short and long terms. Our results indicate that a 1-percentage-point gain in market share of the lowest bidder reduces average costs by 0.3% in the short term and 0.8% in the long term, but also reduces the number of firms by 1%. We find that reducing the number of firms has a strong positive (and hence counteracting) effect on average prices, i.e., a 1% reduction raises prices by approximately 1%.

Keywords: Pharmaceutical industry, generic competition, generic drugs, brand-name drugs.

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1. Introduction

Most countries regulate patent-protected pharmaceuticals (Ellison and Wolfram, 2006; Kyle, 2007; Filson, 2012), the most obvious reason being that neither patients nor physicians have strong incentives to respond to price signals when all or most of the costs are borne by taxpayers or the insured collective. A notable exception is the USA, where cost containment, for both patent-protected and off-patent drugs, instead is managed by non-government buyers, such as health maintenance organizations (HMOs) or third-party payers (TPPs). Efforts are also made to reinstate patients' price sensitivity via higher coinsurance rates or tiered copayments (Duggan and Scott Morton, 2006; Berndt and Newhouse, 2012). Many European countries use reference prices and generic substitution to make demand for generics more elastic; typically, the coinsurance rate rises to 100% above the reference price (Pavcnik, 2002; Brekke et al., 2009). The reference price can be internal (e.g., the lowest-priced version on offer or an average of some set of low-price products) or external (e.g., the average price of the same drug in a group of comparison countries).

When cost containment is delegated to a non-government entity, two key mechanisms are used by the buyer to obtain price concessions from manufacturers (and more generally from health providers). First, the decision to extend coverage to a particular drug can be conditioned on the granting of a discount. Second, low-cost providers can be given preferential treatment, for example, by being slotted into the tier with the lowest copayment.

Exactly because price negotiations are delegated to third parties, there are limited possibilities for an outside observer to study the details of price formation and hence the optimal degree of exclusivity. However, due to a strictly formalized and highly transparent price-setting mechanism in combination with observable quantities, the Swedish market for generics offers a unique window into the relationship between the total cost to the buyer and the degree of exclusivity offered the lowest-cost provider. Our main finding is that whereas increasing the market share of the lowest-cost provider beyond about half of the market does yield significant short-term savings, these savings dissipate relatively quickly over time, due to exit and the associated reduction in price competition. We can also estimate what we argue is a causal relationship between the number of current market participants and the average price. Our estimates suggest that increasing the number of sellers from two to three reduces average prices by about one third.

In the market we study, each month the sellers bid for the right to be the nominal sole supplier of each narrowly defined generic product for a one-month period. Monthly observations of price bids for more than 800 distinct products, with average (per-month) revenues for the winner of approximately EUR 25,000, allow us to evaluate how average prices depend on the share awarded to the lowest bidder – in our setting, possibly a policy variable – and on the number of active bidders in the market. The average market has 2.5

generic manufacturers, the original brand is approximately 70% likely to be present, and there are, on average, 1.3 parallel importers of the branded product, although parallel importers cluster in periods soon after patent expiration and then tend to leave the market as generic competition intensifies.

With its well-defined rules, the Swedish generic drug market offers a laboratory-like setting in which price competition and price responses to preferential treatment can be observed. Our results can also shed light on the more general question of whether and how contracts should be split between the winner and the runners-up, a topic that has been the subject of considerable theoretical work but that has so far been little studied empirically. Theoretical analyses of share auctions (Wilson, 1979), multi-price auctions (Barut and Kovenock, 1998), and models with informed and uninformed consumers (Salop and Stiglitz, 1977; Varian, 1980; Baye and Morgan, 2001) suggest that when a higher fraction is allocated to the lowest bidder (when informed consumers account for a larger share of demand) competition will intensify. Some empirical evidence supports the claim that better information lowers prices. For example, prices tend to be lower for internet sales (Sengupta and Wiggins, 2014), which may, according to some studies, have spillover effects that reduce prices in traditional channels as well (Brown and Goolsbee, 2002).[1]

A relatively substantial theoretical literature on split-award contracting has elaborated on the standard setting and demonstrated that it need not always be optimal to source from a single supplier (Perry and Sákovics, 2003, with endogenous entry; Alcalde and Dahm, 2013, when costs are highly asymmetric; Gong et al., 2012, when in a first stage bidders can invest to reduce marginal costs). Although the practice of splitting contracts between two or more providers appears to be quite common for private as well as public buyers, few studies have empirically addressed the issue, at least using modern econometric tools.[2] Those that do exist further support the notion that split-award contracting can be advantageous for buyers (Lyon, 2006; Anton and Yao, 1989).

Turning to the empirical literature on rivalry in pharmaceutical markets under regulation, Danzon and Chao (2000), Ekelund and Persson (2003), Kyle (2006), Abbott and Vernon (2007), Ellison and Wolfram (2006, Filson and Masia (2007), Sood et al. (2009), and Filson (2012) all recognize a tradeoff between low pharmaceutical prices achieved by regulation today, and the potential long-term risk of having fewer pharmaceutical products with which to treat patients in the future. Their main concern is thus with the effects of regulation on pharmaceutical R&D and the introduction of new pharmaceutical substances, but

[1] The relationship between consumer information and pharmaceutical prices has been the subject of several recent studies. Sorensen (2000) finds that frequently purchased pharmaceuticals have lower markups and exhibit less price dispersion. Granlund and Rudholm (2011) find that increases in consumer information on average lower pharmaceutical prices by approximately 4%.

[2] For examples of split-award contracts used in practice, see, for example, Gong et al. (2012). In public procurement, split-award contracts have been used, notably, in defense procurement.

some studies also recognize that price regulations could adversely affect consumer welfare today through reduced competition in the generic drug market, and through the possibility that firms in that market may try to “game” the regulations (Sood et al., 2009).

The literature on entry into pharmaceutical markets is also relevant to this study. In early studies, the main findings were that pharmaceutical firms usually enter large or fast-growing markets (Yu, 1984; Bae, 1997; Scott-Morton, 1999) or more profitable markets (Grabowski and Vernon, 1992; Rudholm, 2001). More recent literature addresses how regulation affects pharmaceutical research and the entry of pharmaceuticals specifically (e.g., Danzon et al., 2005; Kyle, 2007; and many of the studies cited in the previous paragraph).

A substantial literature addresses how generic entry affects pricing in the pharmaceutical market. Caves et al. (1991), Frank and Salkever (1997), and Wiggins and Maness (2004) all report that increasing the number of actual generic suppliers from one to ten reduces prices by 45–50%, whereas Reiffen and Ward (2005) estimate the effect to be slightly smaller, at 30–40%. More recently, Berndt and Aitken (2011) report that the effect may be as large as 94%.

We believe a further contribution of our study is that the setup of the studied market makes it possible to evaluate the effect of supplier concentration on price in a way that avoids many problems that have plagued most previous studies. As pointed out by, i.a., Newmark (2006), one key concern is that firms may be engaged in non-price competition, i.e., a firm offering superior quality may charge high prices and still be the preferred choice of many consumers. If quality is not observed, the high price will erroneously be attributed to the resulting high concentration. Similarly, problems may arise if the definition and size of the market is unclear or if non-observable cost differences exist between markets. As explained below, none of these problems is a major concern in our study.

The purpose of this article is twofold: first, to empirically investigate whether and to what extent short- and long-term savings can be achieved by increasing the market share of the lowest bidder – i.e., by varying how the implicit contract is split between suppliers; second, to examine how the number of firms in the market affects the price in a setting with well-defined markets and few non-price competitive actions available to the firms. Advertising directed toward consumers, for example, is banned by law for prescription pharmaceuticals in Sweden and the physical and financial conditions for delivery and payment are fixed by the market regulator.

To identify the causal effects of the number of firms, we apply a dynamic model to monthly data and use the fact that the rules require that firms wanting to be active in the market must submit their price bids three months in advance. The monthly data and the bidding rules thus effectively solve the simultaneity problem that often troubles price–concentration studies and, under the assumption that firms cannot predict shocks in the average price three months ahead, allow us to identify causal effects.

We use a dataset provided by IMS Sweden that covers all off-patent prescription pharmaceuticals sold in the Swedish reimbursement system at Swedish pharmacies from 2006 through 2011. The dataset contains a total of 49,256 observations of actual transaction prices and total national sales related to 169 pharmaceutical substances and over 800 distinct product markets. Using these data, we estimate the effect of the market share of the lowest-priced product on the cost per defined daily dose (DDD), the effect of this market share on the number of firms in the market, and the effect of the number of firms on the average costs. Based on these estimations, we then calculate the short- and long-term effects on the cost per DDD of increasing the market share of the lowest-priced product.

A key finding is that a higher market share for the lowest-priced product results in significant short-term savings, whereas the long-term effect is insignificant. The latter is the sum of three effects, two of which are negative and one of which is positive. First, increasing the lowest bidder's market share results in a composition effect that immediately reduces the average price. Via this channel, a permanent 1-percentage-point increase reduces average costs by 0.2% in both the short and long terms. Second, for a given number of firms, a higher market share intensifies competition. We estimate this effect to be approximately 0.1% in the short term and approximately 0.6% in the long term.

Third, the number of active firms decreases with the lowest bidder's market share: a 1-percentage-point gain in market share is estimated to reduce the number of firms by approximately 1% and this will, in turn, increase average prices. The estimated sum of these three long-term effects is positive but insignificant.

As mentioned, our data also make it possible to estimate the relationship between the number of firms and average prices. We find that reducing the number of firms by 1% raises prices by approximately 1% in the long term. This corresponds, for example, to average prices being approximately 50% higher when there are two instead of three firms in the market and 100% higher when there is only one firm instead of two.

The article is organized as follows: Section 2 presents the Swedish pharmaceutical market and Section 3 provides the theoretical foundations underpinning our study. Section 4 discusses the data, Section 5 the empirical method, and Section 6 the results. Finally, Section 7 presents the conclusions of the study.

2. The Swedish market for generic pharmaceuticals

A government-funded insurance program covers 75–80% of the cost of prescription drugs for Swedish patients and, on the margin, a patient with high costs will pay nothing. To contain costs, since 2002 pharmacists have had to inform consumers whether less costly substitute products are available, as is normally the case for off-patent products. Only the cheapest *available* generic (chemically and medically identical) substitute or parallel imported product will be fully reimbursed.[3] Only products within narrowly defined exchange groups, which have the same combination of active substance, form of administration, strength, and packet size, are considered substitutes.[4]

Demand for off-patent drugs is hence steered toward the least costly generic alternative although, for several reasons, there will also be demand for more costly alternatives. First, patients can buy the prescribed product, rather than the cheapest alternative, if they pay the difference between the two prices themselves. Second, the prescribing physician can prohibit an exchange for medical reasons. Third, the pharmacist may waive the requirement to switch if switching would risk harming the consumer. When the physician or pharmacist prevents a switch for medical or safety reasons, the consumer is still fully reimbursed by the insurance system. Finally, there is no obligation to switch (and no financial consequences for the patient) if the least costly alternative is not available (Dental and Pharmaceutical Benefit Agency, 2009).

The suppliers of generic products are free to set their prices as long as they do not exceed the highest existing price within the exchange group. However, prices can be changed only once a month and only according to the rules set for the government-organized national marketplace for generics. In tightly regulated sealed-bid first-price sell auctions, the pharmaceutical providers place bids that, by regulatory fiat, are binding on the manufacturers and pharmacies. Hence, for off-patent pharmaceuticals, pharmacies are *not* allowed to negotiate discounts from the national prices. Furthermore, the pharmacies' retail margin is set in a regulatory process and can be expressed mathematically, so that the wholesale prices offered by the providers completely determine the retail prices as well.

The market rules determining what information is available to the firms when they bid can be summarized as follows:

[3] Other measures to contain costs are used for patent-protected products; for example, only products that pass a cost–benefit test will be subsidized.
[4] Packet size is allowed to vary slightly; for example, substitution will be made from a 30-pill package to a package in the 28–32-pill range.

- At the end of Month 1, all firms that wish to sell a particular product during Month 3 must submit a price bid to the Dental and Pharmaceuticals Benefits Agency (DPBA).

- During Month 2, the DPBA will announce the winner for Month 3. The winner's product is called "product of the month" for that particular exchange group and period. If two or more firms submit identical bids, they will all be called "product of the month."

- Sales during Month 3 will be paid according to the bids submitted in Month 1. Prices are national, pharmacies are not allowed to negotiate prices, and consumer (retail) prices are linked to wholesale prices via a formula.

Note that when the firms submit their bids in Month 1, the prices that will apply in Month 2 have already been announced. Consequently, the number of active firms in that period is also known, whereas sales data for Month 0 will only be available after the bids have been submitted. The informational structure is illustrated in Figure 1.

Figure 1 about here.

On October 1, 2009, as part of a liberalization of the pharmacy market, the interpretation of lowest-cost available generic was changed from the lowest-cost product *at the local pharmacy* to the lowest-cost product *in the market as a whole* (i.e., in Sweden). Because the cheapest alternative was often not available at a particular pharmacy, the cheapest alternative was sold in only approximately 45% of cases during the 2006–2009 period (Tillväxtanalys, 2012). This fraction increased to approximately 50% due to the revised interpretation, but possibly also due to the other reforms introduced at about the same time. Most significantly for the present study, on July 1, 2009, the prices of off-patent pharmaceuticals were capped at 35% of their prices 12 months before patent expiration.

In February 2010, the groups within which substitution should be made were unambiguously defined and in May the same year, following complaints that the manufacturer of the lowest-cost generic sometimes ran out of stock, pharmacies were allowed to dispense the second-lowest-cost generic if the DPBA declared a national stock-out of the first choice. The third-lowest-cost generic could be used if the second-cheapest went out of stock.

Furthermore, in February 2010 two thirds of Sweden's pharmacies were privatized, following an auction of previously state-owned pharmacies. As prices on prescription pharmaceuticals are still regulated, competition between pharmacies mainly concerns location and service quality, for example, opening hours and in-store availability of pharmaceuticals, but also concerns the pricing of OTC drugs and non-drug products. Before February 2010, substitution could be made for a packet that did not differ from the size of the prescribed alternative by more than 12%; since then, substitution can only be made within pre-defined groups.

To allow pharmacies to clear excess inventory, the previous month's nominated lowest-price product can be sold during the first 15 days of the coming month. However, from day 16 to the end of the month, pharmacies are not reimbursed at all if they sell the previous month's preferred product, being penalized more for selling this product than for selling other generic alternatives. In regressions not reported in this article, we find that a winner that fails to win the subsequent month achieves an average market share the first month after being ousted that is 6 percentage points higher than if it had not been the winner the previous month.

Although pharmacies are required to follow the rules and regulations, their economic incentives to do so are limited. The algorithm for the retail margin actually gives the pharmacy an incentive to steer customers toward high-cost alternatives and toward buying multiple small packets rather than a single large packet. To offset the consumers' adverse reaction to having to pay the price difference out of pocket, the pharmacy could in principle claim that substitution would cause harm. Consequently, the regulatory oversight of the market has been sharpened. There is at least a theoretical possibility of penalties or even loss of the license to sell pharmaceuticals if market rules are ignored.

3. Theoretical analysis

A higher market share for the least costly generic alternative can influence average costs through at least three mechanisms. First, at given price bids the average cost will fall due to a pure composition effect when a larger fraction is bought at the lowest price. Second, given the number of firms in the market, changes in the market share of the lowest bidder are likely to influence bidding. For example, a higher market share for the lowest bidder may induce more aggressive bidding, because this makes it relatively more attractive to be the lowest bidder. Third, lower aggregate profits resulting from lower average prices may induce exits from the market and this, in turn, may cause prices to increase again, e.g. by triggering a transition to a collusive equilibrium.

To characterize the three mechanisms more formally, let P be the average price. Then

$$P = s_w P_w(s_w, n(s_w)) + (1 - s_w) P_{-w}(s_w, n(s_w)) \qquad (1)$$

where s_w is the lowest bidder's market share, P_w the lowest price bid, P_{-w} the (weighted) average of the other prices, and n the number of firms. Assuming proportionally equal reductions of sales for non-low bidders, the total effect on the average price of changing s_w can then be written

$$\frac{dP}{ds_w} = \left(P_w - P_{-w}\right) + \left(s_w \frac{\partial P_w}{\partial s_w} + (1-s_w)\frac{\partial P_{-w}}{\partial s_w}\right) + \left(s_w \frac{\partial P_w}{\partial n}\frac{dn}{ds_w} + (1-s_w)\frac{\partial P_{-w}}{\partial n}\frac{dn}{ds_w}\right) \quad (2)$$

The first term corresponds to the composition effect, the second to the direct (weighted) price effect, and the third to an equilibrium effect via the number of firms.

The first effect follows immediately from the calculation of the average price. To address the second mechanism, we rely on the Barut and Kovenoch (1998) analysis (hereafter, BK). According to their Theorem 2B, in a multi-prize auction with n players and n prizes, $v_n \geq v_{n-1} \geq ... \geq v_1$, and in any equilibrium the expected payoff, u_i, of any player i is v_1. According to their Theorem 2A, in equilibrium, the players will randomize their bids over the interval $[0, v_n – v_1]$.[5]

In our setting, the payoff is total revenues minus total costs, or sales times the difference between price and per-unit cost. We assume that the lowest bidder meets fraction s_w of the market demand, that the original's market share is s_0, and that the rest, $(1 – s_w – s_0)$, is split equally between the $n – 1$ non-winning generic suppliers. Normalizing the per-unit cost to 0 and total demand to 1, following BK, in the equilibrium the firms will randomize bids over the interval $[P_{min}, P_0]$, where P_0 is the highest permissible price and P_{min} is defined by

$$P_0 \frac{\left(1 - s_w - s_0\right)}{n-1} = P_{\min} s_w \quad (3)$$

That is, a firm that bids P_{min} and wins – and hence gets to meet share s_w of the market demand – will make a profit just as large as that of a firm that bids P_0, the maximum price allowed, and meets share $(1 – s_w – s_0)/(n – 1)$ of the demand. Note that $P_{\min}$ is the lowest bid that a firm will consider offering in equilibrium, not necessarily the lowest bid actually observed.[6]

[5] Similar equilibria will arise in markets with informed and uninformed consumers (see, e.g., Varian, 1980). In particular, a firm's payoff from selling only to its own captive customers at the maximum (monopoly) price is the same as the payoff from selling to the captive customers and to all informed customers at the lowest price that is bid with positive probability.

[6] In practice, the bid rank will matter not only for the lowest bidder but also for higher bids. The effect of this is to reduce the profit of a firm that bids P_0 and this, in turn, will intensify competition and reduce P_{min} even further.

The equilibrium expected profit of a generic pharmaceutical firm is defined by the left-hand side of equation (3). Solving for P_{min}, we have

$$P_{\min} = P_0 \frac{(1 - s_w - s_0)}{s_w (n-1)} \tag{4}$$

Assuming that $n > 1$, it follows that a higher market share for the lowest bidder, s_w, will lower the lowest price, P_{min}, therefore reducing the expected per-firm profit. As the sum of the bidders' expected profits is the buyer's expected cost, it follows that when the number of firms is fixed, the expected cost (or the average price) will fall as well.

Turning to the third mechanism, note first that from equation (4) the minimum price, P_{min}, is falling in n (for a given s_w) and that, from equation (3), so is the per-firm profit. Holding all other parameters fixed while increasing the number of firms from n to $n + 1$ will change average price by a factor of $(n + 1)(n - 1)/n^2 < 1$.[7]

Assume now that the number of generic pharmaceutical firms, n, is endogenous and that each firm that wants to participate in the market must incur a per-period fixed cost, f. The number of firms will then be determined by the entry condition

$$P_o \frac{(1 - s_w - s_o)}{n-1} \geq f \geq P_o \frac{(1 - s_w - s_o)}{n} \tag{5}$$

The market share of the lowest bidder is the policy variable – i.e., it is no longer assumed to be constant. As argued above, a higher market share for the lowest bidder reduces the per-firm profit and hence the expected average cost for a given n. However, for the same reason, fewer firms will be viable when s_w increases. When one of the firms exits, the equilibrium prices and profits will increase discontinuously.

Let $\hat{s}_w$ be the market share of the winning bid that makes the first weak inequality of equation (5) hold with equality. As the first term is the expected per-firm profit with n generic pharmaceutical firms (i.e., one low-bidding firm and $n - 1$ non-low bidders), this is the threshold market share for the low bidder that allows a total of n generic pharmaceutical firms to earn a profit that is just sufficient to cover the fixed cost, f. If s_w increases slightly, the generic pharmaceutical firms will be unprofitable and we predict that one of them will exit. With fewer firms, expected net profit again becomes non-negative.

[7] To see this, divide $P_{min}(n + 1)$ by $P_{min}(n)$ to obtain the change in per-firm profit; to obtain the change in industry profit, multiply this value by $(n + 1)/n$.

As s_w increases, fewer and fewer generic pharmaceutical firms will be viable. However, and as illustrated in the lower part of Figure 2, expected per-firm (gross) profit cannot (in equilibrium) fall below *f*. As illustrated in the upper part of Figure 2, total profit will fall as s_w increases. As we assume constant and equal marginal costs and a fixed total quantity, the total sales value is the sum of total costs and total firm profit. It follows that the total-profit graph also illustrates the average cost and that the critical levels at which exit occurs are associated with successively lower prices. That is, $P_{\min}(n, \hat{s}_w^1) < P_{\min}(n, \hat{s}_w^2)$ if $\hat{s}_w^1 > \hat{s}_w^2$.

This could possibly continue until only one firm remains, but then that firm would presumably set the maximum price, P_0. However, the firms may be able to coordinate on a collusive equilibrium and set high prices even before the market is monopolized. Hence, raising s_w above some critical threshold may actually result in *higher* average prices. Assume that collusion is possible for $n \leq n^*$ firms. An increase of s_w that causes the number of firms in the non-collusive equilibrium to fall from $n^* + 1$ to n^* will then change the nature of the equilibrium, resulting in higher prices.

Figure 2 illustrates expected per-firm and total profit (cost) as a function of the market share of the lowest bidder. As s_w increases (to the left), per-firm gross profit falls until it equals the fixed cost. As compliance increases further, the equilibrium number of firms drops by one and per-firm profit increases discontinuously. Total costs will generally decline with increasing s_w, though rising discontinuously at the thresholds at which exit is induced. When a threshold market share, c^*, is exceeded, the number of firms falls to n^* and the nature of the equilibrium changes, such that total costs increase more drastically. In the graph, n^* is assumed to be 2.

Figure 2 about here.

Total costs in excess of the marginal costs, equal to the sum of the firms' profit gross of the fixed cost, reach a minimum when the market share of the lowest bidder is c^*. For higher market shares of the lowest bidder, one of the three firms will exit and the per-firm profit will increase to π_D, i.e., the collusive duopoly profit, here assumed to be half of the monopoly profit. In practice, the influence of collusion may of course increase more gradually as the number of firms falls.

To summarize, we predict that increasing the lowest bidder's market share will initially reduce average costs through two mechanisms. First, the average costs given certain bids will fall due to a composition effect and, second, a higher market share for the lowest bidder will (at least when the number of firms is relatively large) induce more aggressive bidding, as it becomes relatively more attractive to be the low bidder. However, as the average cost falls, so does the per-firm (gross) profit. Given the existence of some fixed costs, the number of active firms will therefore fall as the market share of the lowest bidder increases. At some point (or perhaps more gradually), the nature of the rivalry between the firms will change: they will start to collude. This is a third mechanism through which an increased market share of the lowest bidder can affect the average market price. The transition to a collusive equilibrium implies that further cost reductions cannot be achieved by increasing the market share of the lowest bidder.

4. Data

The dataset used here has been compiled by IMS Sweden and covers prescription pharmaceuticals sold at Swedish pharmacies from 2006 through 2011. Due to the regulatory regime, the observed list prices are also the effective transaction prices and the observed quantities correspond to virtually the entire sales to the Swedish market. Only products included in the reimbursement system with active substances no longer protected by patents are included. We aggregate the data to one observation per exchange group and month, an exchange group being defined as a unique active substance-strength-form-package size combination. To be precise, the exchange group will include a range of packet sizes, for example, 90–105 tablets or capsules. Our definition of an exchange group therefore combines the Swedish Medical Products Agency’s exchange groups and the DPBA’s package-size groups.

We exclude 3.5% of the observations because they are not assigned to any exchange group by the Swedish Medical Product Agency and therefore are not exchangeable. Of the exchange group-month observations, 1% are excluded due to missing data on DDDs and 27% are excluded because, throughout the study period, only a single firm sells positive quantities within the exchange group. This leaves us with 49,256 observations covering 826 exchange groups, 406 drugs, and 169 active substances. Each “drug” is a unique combination of active substance, strength, and form, so that for each drug there can be several exchange groups differing only in package size. As will be explained below, nearly half of these observations cannot be used to identify the direct effect of the lowest bidder’s market share, but they are still included in the regressions and help identify other parameters.

Table 1 presents the mean, standard deviation, minimum, maximum, and quantiles for variables used in the estimations as well as for some other variables. Observations are weighted by total sales within the exchange group during the study period (2006–2011), using pharmacies’ purchase prices to calculate the weights.

Table 1 about here.

CDDD is the cost per defined daily dose, measured in pharmacies’ purchase prices, and *lnCDDD* is the natural logarithm of this variable. The next two variables are the mean of *CDDD* per exchange group relative to the overall mean and the difference between the maximum and minimum values of *CDDD* for each exchange group relative to the group's overall mean. These two variables are not used in the estimation but indicate that there is large variation in *CDDD*, across as well as within exchange groups.

Sw is defined as the cheapest product's (or products') share of the number of DDDs sold within the exchange group during a month. Sometimes, however, the value of *Sw* might not reflect the efforts pharmacy personnel make to sell the cheapest version. Because it is this effort, as perceived by the pharmaceutical firms, that will affect their pricing and entry decisions, we created two additional variables.

First, the indicator variable *NotPolicy* takes the value of 1 if *i*) *Sw* is below 0.1, *ii*) *Sw* is above 0.9, or *iii*) the cheapest product is parallel imported. Very low values are likely explained by the firm running out of stock. Very high values can result from only one firm selling the product or of two or more firms setting equal prices, so that both or all of them are nominated "product of the month." In neither of these situations does the variable *Sw* reflect the efforts of pharmacies and of the regulator to concentrate sales to the lowest-price bidder. Similarly, when the lowest bidder is a parallel importer, available quantities are likely too small to meet all of the demand. Finally, coding *NotPolicy* as 1 when *Sw* is below 0.1 or above 0.9 will reduce the effect of potential errors in the data, for example, sales coded in the wrong month.

NotPolicy equals 1 for 23,493 observations, corresponding to a weighted share of 53%. Of these 53%, 15 percentage points are explained by *Sw* being equal to 1, 4 percentage points by *Sw* exceeding 0.9 but being strictly below 1, 29 percentage points by the cheapest product being parallel imported, and 6 percentage points by *Sw* being below 0.1.[8] When *Sw* = 1, in two instances out of three this is because only one firm sells a product in that exchange group in that month. In nearly one third of the cases, two firms bid identical prices for their products, whereas in just above 1% of the cases is this done by three to five firms.

The second variable created to capture the pharmacies' efforts to promote the lowest-price product is *SwP*, defined as *Sw**(1 – *NotPolicy*). For the most part, we will use *SwP* in the regressions to identify the effect of the lowest bidder's market share on average prices. Figure 3 shows the distribution of *SwP* conditioned on *NotPolicy* being zero.

Winners, a variable not used in the estimation, indicates that on average there are 1.14 firms selling the cheapest products, i.e., ties are relatively rare. Data, not presented in the tables, indicate that a winner has a 56% chance of being a winner in the subsequent month as well, conditional on submitting a bid. This is

[8] *Sw* is below 0.1 for a weighted share of 20% of the observations, but for two thirds of this share the criterion that the cheapest product is parallel imported is also met. When a parallel-imported product is the cheapest one, *Sw* is only 0.14 on average.

twice the average probability of being a winner, which amounts to 25%. On average, 96% of firms selling a product one month sell this product the next month as well. For winners, the corresponding figure is 95%.

Firms is the number of pharmaceutical companies selling locally sourced (i.e., excluding parallel imported but including the original) products, by exchange group and month, with *lnFirms* being the natural logarithm of this variable. For 853 observations, *Firms* equals 0 (and *lnFirms* is missing) because only parallel-imported products are sold. Parallel-imported products are sold mainly while the original brand is patent protected and in the interval between patent expiration and generic entry. In our sample, there are on average 1.29 firms selling parallel-imported products and the data (not shown in the tables) reveal that for 87% (60%) of the observations (weighted observations) there is no parallel-imported product. *All_Firms* is the sum of *Firms* and *PIfirms*. *All_Firms* and *PIfirms* are not used in the final estimations presented here.

Figure 3 about here.

Orig is a dummy variable signaling the presence of the original product, i.e., that the former patent holder sells a locally sourced product.

Since July 2009, there has been a price cap at 35% of the pre-patent-expiration price, conditional on generics having been sold at a price less than 30% of that price, with at least one of the generics at that time accounting for a market share of at least 10%, on generics having been sold in the Swedish market for more than four months, *and* on at least six months having passed since patent expiration. *2009PriceCap* is an indicator variable equal to 1 for pharmaceutical substances and months after June 2009 when at least six months have passed since patent expiration. That is, *2009PriceCap* equals 1 for observations that could be affected by the price cap. We choose not to condition on whether the price cap is actually in effect, because this depends on generic entry and generic prices and is therefore endogenous. *PatentExp6m* is an indicator variable that takes the value of 1 six months or more after patent expiration, both before and after July 2009.

In line with Brekke et al. (2009) and Pavcnik (2002), *ThAlt* is defined as the number of other pharmaceutical substances with the same five-digit ATC code. *ThGenAlt* is defined as the number of therapeutic alternatives for which generic versions exist. *PackageSize* is defined as the average package size within the exchange group, relative to the (unweighted) average package size within the drug, and thus describes a key difference across exchange groups within each drug.[9] The variable *lnDDD* is the natural logarithm of the number of DDDs sold.

[9] Our fixed effects are defined at the drug level; hence, *PackageSize* allows the cost per DDD to differ when average package size varies across exchange groups within the same drug.

Finally, we report descriptive statistics for the sales value for each exchange group and month. This variable is not used in the statistical analysis and, contrary to all other variables, the observations for this last variable are not weighted.

5. Empirical specifications

In this article, we study two related issues: 1) how the share of the lowest bidder, *Sw*, directly and indirectly affects the average price and 2) the effect of the number of firms on the average price. The two issues are linked via a feedback mechanism extending from the lowest bidder's share to pricing and profitability through the number of firms, and then back to pricing and profitability.

We estimate three sets of specifications. In the first, we estimate the partial effect of *Sw* and *SwP* on *CDDD*, conditional on the number of firms and on whether or not the original is sold.[10] In this specification, we also estimate the effects of the number of firms and of the indicator variable for the original being sold. In the second and third sets of specifications, we estimate the total effect of *Sw* and *SwP* on the number of firms and on the probability that the original is sold, respectively. Based on the preferred specification from each set, we then calculate the total long-term effect of *SwP* on *CDDD*, using a derivative that, in short form, can be written as in equation (2) except that it also includes a term reflecting that *SwP* might affect the probability that the original is present.

We believe that our estimates of the relationship between number of firms and pricing are of independent value. In contrast to most studies of the relationship between price and concentration, we have panel data, so we can identify effects from variations over time rather than across markets. In addition, there are few ways in which suppliers of generic pharmaceuticals are allowed to engage in non-price competition in Sweden. As mentioned, advertising of prescription pharmaceuticals to consumers is not allowed. Even though some types of non-price competition are possible, such as establishing brand recognition among physicians or holding larger inventories so as to be consistently able to meet the demand throughout months, we believe that the effect of these measures is relatively small.

As for the scope of the market, it is very precisely defined by the rules for the monthly auctions. The pharmaceutical firms bid to be the cheapest product in an exchange group defined as a unique active substance-strength-form-package size combination, the geographical market is always all of Sweden, and the time period bid for is always one month. In addition, the bidding firms are usually well informed about the current size of each market, which can also be observed by us. Furthermore, cost differences between

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[10] Remember that *SwP* is an interaction of *Sw* with a dummy variable that excludes values of *Sw* that are likely not driven by intentional policies of the regulator or by activities of the pharmacy staff.

suppliers of pharmaceutical products should be small compared with those in many other markets and our independent variables should be able to capture most of the differences between markets. Thus, our setting is relatively advantageous for evaluating the effect of the number of firms on prices.

Specifications for cost per DDD

There are reasons to believe that prices, and hence cost per DDD, do not adjust instantaneously to the new long-term equilibrium when market conditions change. For example, the full price effect of an additional competitor entering the market might not come immediately, as some firms might wait and observe the pricing strategy of the entrant firm before adjusting their own prices. Because of this and because we are interested in distinguishing between the immediate and long-term effects of *Sw* (or *SwP*) on the cost per DDD, we use a partial-adjustment model that includes the lag of the dependent variable. An interpretation of the immediate effect is that this corresponds to what we call a composition effect.

Let $Y_t^* = \delta X_t + \epsilon_t$ describe the long-term equilibrium relationship between *Y* and *X*, and let $Y_t - Y_{t-1} = (1-\theta)(Y_t^* - Y_{t-1})$ describe the adjustment, with index *t* representing time. Substituting for Y_t^* gives the equation to be estimated: $Y_t = \theta Y_{t-1} + \beta X_t + \varepsilon_t$, where $\beta = (1-\theta)\delta$ and $\varepsilon_t = (1-\theta)\epsilon_t$. Hence, the long-term effect can be obtained by dividing the estimated parameters by the estimated speed of adjustment, $(1-\theta)$. In Section 3, we discussed the time structure of the firms' access to information. As explained below, we utilize this to estimate the effects.

The baseline specification to be estimated is written

$$\begin{aligned} lnCddd_{e,t} = {} & \theta_0 lnCDDD_{e,t-1} + \beta_1 SwP_{e,t} + \theta_1 SwP_{e,t-1} + \beta_2 SwP_{e,t-3,t-8} + \beta_3 lnFirms_{e,t-1} \\ & + \beta_4 Orig_{e,t-1} + \beta_5 PatentExp6m_{e,t} + \beta_6 2009PriceCap_{e,t} + \beta_7 ThAlt_{e,t-1} \\ & + \beta_8 ThGenAlt_{e,t-1} + \beta_9 PackageSize_e + \beta_{10} Trend_t + \beta_{11} NotPolicy_{e,t} \\ & + \theta_2 NotPolicy_{e,t-1} + \beta_{12} NotPolicy_{e,t-3,t-8} + \sum_{m=2}^{12} \vartheta_{m,t} + \mu_d + \varepsilon_{e,t}, \end{aligned} \tag{7}$$

where the basic partial-adjustment parameter is represented by θ_0, whereas the other θ terms allow for the possibility that some variables may have no long-term effects, and indices *e* and *t* represent exchange group and time, respectively.

The lag structure is chosen based on the institutional characteristics of the market and, in particular, the information available to the firms. First, $SwP_{e,t}$ is included to capture the composition effect, i.e., that a higher share for the cheapest product, at given prices, will reduce the average cost per DDD. Note that this effect does not depend on what the firms can observe, but arises as a direct consequence of buyer behavior.

Unlike what we believe to be true for the other variables of the baseline specification, there are no strong reasons to expect $SwP_{e,t}$ to have any remaining long-term effect. The long-term effect should instead come through the time-lagged price variable that the firms can observe when they bid for period *t*, i.e., $SwP_{e,t-3,t-8}$. To offset the effect of including the lagged dependent variable for the effect of $SwP_{e,t}$, we include $SwP_{Pe,t-1}$ with the coefficient θ_1. If $\theta_1 = -\theta_0\beta_1$, a contemporaneous increase in *SwP* indeed has no lasting effects.[11]

The variable $SwP_{e,t-3,t-8}$ is included to capture the effect of the lowest bidder's market share on firms' price bids. As mentioned previously, price bids for month *t* must be given to the DPBA at the end of month *t* – 2. At this time, firms can observe $SwP_{e,t-3}$. They have the theoretical possibility of observing Sw_e (and perhaps SwP_e) for a small part of month *t* – 2 at this time by purchasing weekly sales data from IMS. However, according to IMS, firms in the generics market very rarely do this. If firms to some extent can already predict $SwP_{e,t}$ in *t* – 2, the parameter for $SwP_{e,t}$ (i.e., β_1) would capture part of the price-bid effect and we would get $\theta_1 \neq -\theta_0\beta_1$.

We use a six-month average because we believe (and find supporting evidence) that $SwP_{e,t-3,t-8}$ better captures firms' expectations of $SwP_{e,t}$ than does $SwP_{e,t-3}$. The variable $SwP_{e,t-3,t-8}$ is defined as the average of strictly positive values of $SwP_{e,t-3}$ through $SwP_{e,t-8}$, but $SwP_{e,t-3,t-8}$ takes the value of 0 if none of these six values is strictly positive. In this case, the indicator variable $NotPolicy_{e,t-3,t-8}$ takes the value of 1 and does not contribute to the estimation of the parameter β_2.

We do not expect to be able to fully separate the composition and price-bid effects. Instead, the main motivation for using different lags of SwP is to capture the full effect of this variable, and to allow this effect to be partly temporal and partly persistent. The composition effect should not, however, affect the parameter estimate for $SwP_{e,t-3,t-8}$.

The variable *NotPolicy* is included with the same lags as SwP. As discussed in the previous section, the aim is to remove the influence of the variable *Sw* for those observations for which we have reason to believe that it does not reflect the efforts of pharmacies and the regulator, but rather the outcome of seller-side actions or particular situations.

[11] To see this, note, for example, that $\frac{dlnCddd_{e,t+1}}{dSwP_{e,t}} = \frac{\partial lnCddd_{e,t+1}}{\partial lnCddd_{e,t}}\frac{\partial lnCddd_{e,t}}{\partial SwP_{e,t}} + \frac{\partial lnCddd_{e,t+1}}{\partial SwP_{e,t}} = \theta_0\beta_1 + \theta_1$. For the same reason, we include $SwP_{e,t-1}lnFirms_{e,t-2}$ in the specification with $SwP_{e,t}lnFirms_{e,t-1}$. This specification is discussed below.

We use one-month lags for the number of firms and for the indicator variable for (at least) one brand-name firm selling products in the market, as well as for the variables $ThAlt$ and $ThGenAlt$. This is because firms, when they set their prices for period *t* at the end of *t* – 2, can observe the price bids of other firms that will be valid during period *t* – 1. Hence, when the prices for month *t* are set, firms have good information about the number of competitors they will face in month *t* – 1, but lack this information for month *t*. We assume that firms in *t* – 3, when they choose whether or not to bid for *t* – 1, cannot predict $\varepsilon_{e,t}$. The main motivation for this assumption, which allows us to rule out the possibility that reversed causality biases the estimators for these variables, is the inclusion of the lagged dependent variable.[12]

We use the natural logarithm of the number of firms because it is reasonable to think that the effect of an additional firm becomes smaller as the number of firms increases. In Section 6, "Estimation results," we demonstrate that using indicator variables for the number of firms gives similar results to using *lnFirms.* The number of firms selling parallel-imported products is not included because this variable was found to be insignificant and because the small market share of such products and their inability to compete with the prices of generics make it reasonable to assume that they do not have any significant effect in this sample.

No lag is used for *2009PriceCap* as, by definition, it can affect the prices for month *t*. As the purpose of including $PatentExp6m$ is to prevent effects related to the time elapsed since patent expiration from being falsely attributed to the price cap, we use no lag for this variable either. (Although this variable could, of course, itself be considered a six-month lag.)

Finally, *Trend* is a linear time trend, $\vartheta_{m,t}$ represents eleven calendar-month fixed effects, and μ_d indicates drug-specific fixed effects. For obvious reasons, no lags are needed when these are estimated.

There is a potential endogeneity problem because the error term $\varepsilon_{e,t}$ can be correlated with price differences between the lowest bidder and other products. High price differences might in turn affect $Sw_{e,t}$ positively, by making it more expensive for consumers to buy another alternative, or negatively, because pharmacies tend to be more inclined to sell expensive products the more they earn by doing so (Brekke et al., 2013; Granlund, 2015). To address the potential endogeneity of $Sw_{e,t}$, we estimate a specification using *Sw*, instead of *SwP* and *NotPolicy*, with 2SLS and using OLS as a comparison. (No strong instruments are found for $SwP_{e,t}$ so IV estimates are not reported for this variable.) The 2SLS regressions were conducted using the ivreg2 command and using $Sw_{e,t-2}$ and the indicator variables *October2009* and *February2010* as instruments for $Sw_{e,t}$. The first indicator variable takes the value of 1 from October 2009, when the

[12] Without the lagged dependent variable and given serial correlation, bidders would be able to predict part of what, in such a model, would be future error terms. With the current setup, predicting future error terms effectively amounts to predicting future *changes* – rather than future levels – which is typically much more difficult.

interpretation of "available generics" was changed. The second variable takes the value of 1 from February 2010, when private firms assumed management responsibility for most of the pharmacies and when exchange groups were defined more precisely. We expect the main consequence of instrumenting $Sw_{e,t}$ to be that (a larger) part of the price-bid effect will be captured by the estimate of $Sw_{e,t}$ and less by $Sw_{e,t-3,t-8}$, as part of the variation in $Sw_{e,t}$ that the instruments can predict also can be predicted by firms when setting their prices.

Endogeneity problems might also arise when the lagged dependent variables are included at the same time as the fixed effects. As Baltagi (2001) explains, the endogeneity problem decreases with the number of observations per fixed-effect unit. In this case, the average number of observations per drug is 107, implying that the problem should not be too severe. We have obtained similar results when, instead of drug indicators, we used exchange-group fixed effects, with an average of 47 observations per fixed-effects unit, which should increase the bias. This indicates that the bias is already small with 47 observations per fixed-effects unit.

Descriptive statistics (not presented) indicate that the price of the lowest bidder relative to the average price of the other products is falling in $Firms_{e,t-1}$. This likely means that the effect of $SwP_{e,t}$ falls in $Firms_{e,t-1}$. In an alternative specification, we therefore include the interaction term $SwP_{e,t}lnFirms_{e,t-1}$ and, to allow this variable to have no lasting effect, $SwP_{e,t-1}lnFirms_{e,t-2}$. In all estimations, the error terms are allowed to be correlated within substances and, except for the IV estimations, all estimations are done with OLS using the areg command in Stata 12.

Specifications for the number of firms

The number of firms that bid for the right to sell will likely be affected by the market share of the lowest bidder. In particular, if a higher *SwP* causes prices and profits to fall, it is likely that fewer firms will actively bid for the right to be the nominal sole supplier for an exchange group. We estimate the following equation with OLS, using the areg command in Stata 12.1, and allowing the error terms to be correlated within substances:

$$\begin{aligned} lnFirms_{e,t} = \theta_{20} lnFirms_{e,t-1} &+ \beta_{21} SwP_{e,t-3,t-8} + \beta_{22} lnDDD_{e,t-3,t-8} + \beta_{23} PatentExp6m_{e,t} \\ &+ \beta_{24} 2009PriceCap_{e,t} + \beta_{25} ThAlt_{e,t-1} + \beta_{26} ThGenAlt_{e,t-1} + \beta_{27} PackageSize_{e} \\ &+ \beta_{28} Trend_{t} + \beta_{29} NotPolicy_{e,t-3,t-8} + \sum_{m=2}^{12} \Theta_{m,t} + M_d + E_{e,t}. \end{aligned} \quad (8)$$

We again use lagged values of SwP, with the minimum lag (three months) determined by the information available to the firms when they decide whether or not to participate in month *t*. The variable

$lnDDD_{e,t-3,t-8}$ is included to capture the effect of variations in the size of the market on the number of firms.[13] We use the six-month average because we believe (and find supporting evidence) that firms base their participation decisions on permanent changes in the size of the market rather than on monthly variations. The motivations for the other variables and the choice of lag structure for these follow the discussion in the previous subsection.

We also estimate a specification with $Sw_{e,t-3,t-8}$ instead of $SwP_{e,t-3,t-8}$ and $NotPolicy_{e,t-3,t-8}$ and, as a sensitivity analysis, we use $Firms_{e,t}$ as the dependent variable and rely on a negative binomial estimator. Similar specifications are used to estimate the probability of the original being sold, with $Orig_{e,t}$ and $Orig_{e,t-1}$ taking the places of $lnFirms_{e,t}$ and $lnFirms_{e,t-1}$. These specifications are estimated using logit.

6. Estimation results

In the estimates presented below, we first exploit the time structure of the firms' information to treat the number of firms as exogenous. Then, in the subsection "*Results for the number of firms*", we treat the number of firms (and the presence or absence of the original) as the dependent variable.

Price effects of the lowest bidder's market share and of the number of firms

The parameter estimate corresponding to $SwP_{e,t}$ in our preferred model, denoted OLS on S_wP in Table 2, suggests that an increase in $SwP_{e,t}$ by 1 percentage point reduces the average cost by 0.23%. Evaluating the derivative $\frac{dlnCDDD_{e,t+1}}{dSwP_{e,t}} = \frac{\partial lnCDDD_{e,t+1}}{\partial lnCDDD_{e,t}}\frac{\partial lnCDDD_{e,t}}{\partial SwP_{e,t}} + \frac{\partial lnCDDD_{e,t+1}}{\partial SwP_{e,t}}$ yields the point estimate –0.016 for the persistent effect and, consequently, an estimated transient composition effect of approximately –0.21. As the cheapest product on (weighted) average is 34% cheaper than the other products, the estimated composition effect suggests that the additional sales of the least expensive product come mainly at the expense of other relatively cheap products and to a smaller extent from the more expensive alternatives. Conversely, if increases in $SwP_{e,t}$ were to a larger extent explained by decreases in the market share of the original, we would expect the estimate composition effect to be more negative.

For the preferred model, the estimates of $SwP_{e,t-3,t-8}$ and the lag of the dependent variable indicate that an increase in $SwP_{e,t-3,t-8}$ of 1 percentage point, through the effects on the price bids, reduces the average cost by 0.48% in the long term. If we add the (insignificant) long-term component of the contemporaneous price-bid effect, derived in the previous paragraph, the total long-term effect through the price bids amounts to –0.57%, i.e., (–0.078 – 0.016)/(1 – 0.836) = –0.573. This estimate of the long-term effect through price bids

[13] Defined as the natural logarithm of the average of $DDD_{e,t-3}$, $DDD_{e,t-4}$, $DDD_{e,t-5}$, $DDD_{e,t-6}$, $DDD_{e,t-7}$, and $DDD_{e,t-8}$.

can be compared with estimates of the long-term effects of *SwP* on the prices of individual products (not shown), which amounts to –0.54%.[14] The derivative d*lnCDDD**/dSw*P**, presented at the bottom of Table 2, captures the estimated long-term effect of a permanent increase in *SwP* for a given number of firms. Except for rounding errors, it is the sum of –0.21% and –0.57%.

Table 2 about here.

Comparing the first two specifications in Table 2, we see that the estimate of $Sw_{e,t}$ is significantly lower than that of $SwP_{e,t}$, possibly because $Sw_{e,t}$ takes the value of 1 if all firms collude by setting the same price. The estimate of $Sw_{e,t\text{-}3,t\text{-}8}$, however, is not significantly different from that of $SwP_{e,t\text{-}3,t\text{-}8}$. In the IV specification, we find a more negative estimate of $Sw_{e,t}$, whereas the estimate of $Sw_{e,t\text{-}3,t\text{-}8}$ is close to zero. Contrary to the other specification, we can reject the null hypothesis that $Sw_{e,t}$ has no lasting effect under the IV specification, indicating that the predicted variation in $Sw_{e,t,}$ also captures the price-bid effect. The results with the interaction variables (last column in Table 4) indicate, as expected, that the effect of $SwP_{e,t}$ is not significantly different from zero when $lnFirms_{e,t\text{-}1}$ is 0, i.e., when the number of firms selling locally sourced products is 1, and that the effect of $SwP_{e,t}$ becomes more negative when the number of firms increases.

A 1% increase in the number of firms is found to reduce the cost per DDD the next month by approximately 0.16%. Expressed differently, an increase from two to three firms reduces the cost by approximately 6%.[15] However, the long-term effect of an increase from two to three firms is a cost decrease of 33%, according to our preferred model.[16] The effect of a brand-name drug being sold is approximately equal, in absolute value, to the effect of the number of firms increasing from two to three, but has the opposite sign. This indicates that if the brand-name firm leaves a market with two generic suppliers, this has no effect on the intensity of price competition.

The effect of the number of firms is quite large and it is perhaps surprising that a 50% increase in the number of firms reduces the average cost by 6% in the short term and 33% in the long term, even when the number of firms is quite large, for example, increasing from four to six. Figure 4 below indicates that this is not

[14] This regression used the same control variables as in specification 1P. To prevent *SwP* from capturing composition effects, all products that belong to the same exchange group were assigned the same weight. The joint long-term effect on prices of $SwP_{e,t}$, $SwP_{e,t-1}$, and $SwP_{e,t-3,t-8}$ was –0.538 (standard error, 0.169).

[15] This is obtained by taking 100*[exp[(ln3-ln2)*-0.164]-1], given our estimate of β_3. In general, the formula 100*[exp(β)-1] can be used to calculate the percentage effect of a unit increase in an explanatory variable. For small effects, however, the parameter estimates approximately equal the percentage effect.

[16] This is obtained by taking 100*[exp[((ln3-ln2)*-0.164)/(1-0.836)]-1], given our estimates of β_3 and θ_0.

caused by our choice of functional form. Quite similar effects are obtained when we use indicator variables for the number of firms.

Figure 4 about here.

Regarding the other results, before July 2009 we find, at the 5% level, no significant effect of a dummy variable indicating that more than six months have passed since patent expiration. However, after this date, when *2009PriceCap* takes the value of 1 for these exchange groups, we find a long-term cost-reducing effect of approximately 25%. This is consistent with the rule, effective since that date, that the price of the brand-name drug can be reduced by up to 65%.

The presence of therapeutic alternatives are found to reduce the cost per DDD, but only significantly so if generic versions of the alternative are sold. Finally, the average cost per DDD is found to be lower in exchange groups with larger package sizes, but no significant time trend is found.

Results for the number of firms

In Table 3 we report the estimation results for number of firms. We find a significant negative effect of $SwP_{e,t\text{-}3,t\text{-}8}$, but not of $Sw_{e,t\text{-}3,t\text{-}8}$. The long-term effect of $SwP_{e,t\text{-}3,t\text{-}8}$ amounts to –0.96 when OLS is used and –1.10 when a negative binomial estimator is used, i.e., *SwP* increases by 1% when the number of firms decreases by approximately 1% in the long term.

We have also estimated models including $SwP_{e,t\text{-}3,t\text{-}8}$ raised to the powers 2 and 3, but the estimates of these variables were not significant, indicating that the marginal effect of $SwP_{e,t\text{-}3,t\text{-}8}$ does not significantly depend on the value of this variable.

We find, as expected, that the number of firms increases with the total quantity sold on the market. More specifically, a 1% increase in the number of DDDs increases the number of firms by approximately 0.2% in the long term. The price cap introduced in 2009 is found to decrease the number of firms. Controlling for DDD and the other variables, *Firms* is also found to be smaller in exchange groups with larger package sizes. This is consistent with the estimates of this variable reported in Table 2 that indicated that the cost per DDD was lower in exchange groups with larger package sizes. We find a significantly positive time trend, likely reflecting the fact that the number of firms increases with the time elapsed since patent expiration.

The logit estimation results for the probability that the original is sold are presented in Table 4. Due to the inclusion of drug fixed effects, these estimations are only made for the drugs that display variations in $Orig_{e,t}$. Here, we find no significant effect of $SwP_{e,t\text{-}3,t\text{-}8}$. The probability that the original is sold increases with the quantity sold in the exchange group, and the estimates of $PatentExp6m_{e.t}$ and $Trend_t$ indicate that the probability of the original being sold decreases with the time elapsed since patent expiration.

Combining estimation results from Tables 2, 4, and 5 allows us to calculate the total long-term effect of an increased market share for the lowest bidder on the average price. Using results from the first estimations in Tables 2 and 3, we find an insignificant total long-term effect with a point estimate of 0.15. This estimate is quite close to zero, indicating that increasing the market share by as much as 20 percentage points would only increase the price by 3%. Including the statistically and economically insignificant effect of *SwP* on the probability of the original being sold has only a minor effect, changing the point estimate to 0.14 and 0.17 depending on the specification used.

Tables 3 and 4 about here.

7. Summary and conclusions

Rising pharmaceutical costs are recognized as a worldwide phenomenon, and measures are being taken in most countries to curb the growth in pharmaceutical expenditures (Sood et al., 2009). In Sweden, for example, monthly auctions are held for the nominal right to be the sole provider of each substance-strength-form-package size combination in the Swedish generic pharmaceutical market. This nominal right is given to the lowest bidder, whereas in practice this bidder achieves a market share of only approximately 50%. The purpose of this article is to use the detailed and unique data generated in that process to shed light on two issues of general relevance.

First, we study how average prices respond to increases in the lowest bidder's market share, in the short as well as long terms. We are aware of no empirical work that directly addresses this question, which is relevant when market rules are designed.

Second, we investigate how changes in the number of actively bidding firms affect pricing. Although the price–concentration relationship has been the subject of a large amount of empirical research, relatively few of these studies exploit within-market variations over time.

We use a dataset that covers all off-patent prescription pharmaceuticals sold at Swedish pharmacies from 2006 through 2011 to identify the effects of increasing the market share of the lowest bidder on the average cost. Our strategy for identifying the effect is to use the time structure of the information available to the bidders. When they submit a bid for period t they know the number of rivals in period t – 1, whereas the rivals' sales and hence market shares are known only for period t – 3 and earlier. This helps us deal with the endogeneity concerns.

Our results indicate that increasing the lowest-priced product's market share results in significant short-term savings, whereas the long-term effect is statistically insignificant and close to zero. The long-term effect is the sum of three effects. First, increasing the lowest bidder's market share results in a composition effect, which immediately reduces average prices. Through the composition effect, a 1-percentage-point increase in the market share of the lowest bidder reduces average costs by 0.2% in both the short and long terms. Second, a higher market share intensifies competition, and we estimate the effect to be a reduction in costs of approximately 0.1% in the short term and of nearly 0.6% in the long term. The third and perhaps most important finding is that the number of active firms decreases with the lowest bidder's market share. We find that a 1-percentage-point market-share gain for the lowest bidder reduces the number of firms by approximately 1% and that this, in turn, causes an increase in costs. The estimated sum of these three long-term effects is to increase pharmaceutical prices, but the estimate is insignificant at conventional levels.

Concerning the relationship between number of firms and prices, we estimate that a 1% reduction in the number of firms raises prices by approximately 1% in the long term. This corresponds, for example, to prices falling by approximately 33% when the number of firms rises from two to three. The effect appears to be fairly smooth over the range of our predictions, from two to twelve firms, relative to markets with a single (generic) firm. In contrast to most studies within the price–concentration literature, we identify this result from examining within-market variation over time, whereas our detailed data and the tightly regulated studied environment give us reasonable control over sources of bias that are likely to plague most research in this tradition. The policy implications of these results are potentially important. Increasing the market share of the lowest bidder does reduce costs, but only in the short term.

In the context of generic pharmaceuticals, instead of focusing on a more efficient system for pharmaceutical substitution at pharmacies and increasing the lowest bidder's market share, more attention should perhaps be directed toward lowering barriers to entry. This could, for example, be accomplished by reducing the fees for being active on the market and would, according to our results, probably be a more efficient way to achieve low pharmaceutical costs for consumers and the government in the long term. In addition, it appears that the concerns articulated before the Swedish reforms, i.e., that purchases should not be exclusively directed toward the lowest bidder, were well founded. Whereas purchase costs will be minimized in the short term by giving the winner full market exclusivity, this strategy will boomerang, because the market's equilibrium response is to reduce the number of bidders, perhaps to the point at which costs actually increase.

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Table 1. Descriptive statistics

	n	Mean	S.D.	Min	.25	Mdn	.75	Max
CDDD (SEK/DDD)	49256	13.11	26.04	0.04	1.15	4.38	14.39	674.18
lnCDDD	49256	1.42	1.63	–3.17	0.14	1.48	2.67	6.51
RelCDDD (ratio)	826	1.00	1.89	0.00	0.12	0.38	1.06	48.61
RelSpreadCDDD (ratio)	826	0.92	1.49	0.00	0.09	0.36	1.00	18.83
Sw (fraction)	49256	0.47	0.34	0.00	0.18	0.45	0.74	1.00
SwP (fraction)	49256	0.23	0.28	0.00	0.00	0.00	0.48	0.90
NotPolicy (fraction)	49256	0.53	0.50	0.00	0.00	1.00	1.00	1.00
SwP if *NotPolicy*=0	25763	0.50	0.19	0.10	0.36	0.50	0.63	0.90
Winners	49256	1.14	0.41	1.00	1.00	1.00	1.00	7.00
Firms (number)	49256	3.22	2.76	0.00	1.00	2.00	5.00	12.00
lnFirms	48403	0.83	0.81	0.00	0.00	0.69	1.61	2.48
PIfirms (number)	49256	1.29	2.02	0.00	0.00	0.00	2.00	8.00
All_Firms (number)	49256	4.51	2.74	1.00	2.00	4.00	7.00	13.00
Orig (dummy)	49256	0.72	0.45	0.00	0.00	1.00	1.00	1.00
2009PriceCap (dummy)	49256	0.31	0.46	0.00	0.00	0.00	1.00	1.00
PatentExp6m (dummy)	49256	0.61	0.49	0.00	0.00	1.00	1.00	1.00
ThAlt (number)	49256	1.33	1.05	0.00	0.00	1.00	2.00	4.00
ThGenAlt (number)	49256	0.92	1.00	0.00	0.00	1.00	1.00	4.00
PackageSize (ratio)	45549	1.20	0.53	0.06	0.76	1.26	1.56	6.64
lnDDD (log of number)	49256	12.71	1.84	–0.69	11.67	12.96	13.99	17.63
Value (100 kSEK)	49256	4.72	13.03	0.00	0.26	1.02	3.55	173.25

Table 2. Estimation results, cost per DDD

	OLS on *SwP*	OLS on *Sw*	IV on *Sw*	OLS on *SwP*, *SwP*ln*Firms*
$lnCDDD_{e,t\text{-}1}$	0.836***	0.832***	0.831***	0.842***
	(0.022)	(0.023)	(0.022)	(0.021)
$Sw_{e,t}$ or $SwP_{e,t}$	–0.229***	–0.128***	–0.302***	0.018
	(0.027)	(0.015)	(0.056)	(0.110)
$Sw_{e,t\text{-}1}$ or $SwP_{e,t\text{-}1}$	0.175***	0.094***	0.163***	–0.049
	(0.027)	(0.013)	(0.028)	(0.079)
$SwP_{e,t}lnFirms_{e,t\text{-}1}$				–0.167**
				(0.072)
$SwP_{e,t\text{-}1}lnFirms_{e,t\text{-}2}$				0.143**
				(0.058)
$Sw_{e,t\text{-}3,t\text{-}8}$ or $SwP_{e,t\text{-}3,t\text{-}8}$	–0.078***	–0.057***	–0.006	–0.068**
	(0.028)	(0.018)	(0.022)	(0.027)
$lnFirms_{e,t\text{-}1}$	–0.164***	–0.164***	–0.171***	–0.139***
	(0.019)	(0.019)	(0.019)	(0.026)
$Orig_{e,t\text{-}1}$	0.064***	0.061***	0.053***	0.061***
	(0.019)	(0.019)	(0.019)	(0.018)
$PatentExp6m_{e,t}$	–0.052	–0.031	–0.028	–0.053*
	(0.032)	(0.029)	(0.028)	(0.029)
$2009PriceCap_{e,t}$	–0.044***	–0.045***	–0.038***	–0.042***
	(0.013)	(0.014)	(0.014)	(0.013)
$ThAlt_{e,t\text{-}1}$	–0.004	–0.007	–0.013	–0.003
	(0.014)	(0.012)	(0.012)	(0.013)
$ThGenAlt_{e,t\text{-}1}$	–0.027**	–0.028**	–0.025*	–0.026**
	(0.012)	(0.014)	(0.014)	(0.011)
$PackageSize_{e}$	–0.018***	–0.022***	–0.022***	–0.017***
	(0.006)	(0.007)	(0.008)	(0.006)
$Trend_{t}$	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
d*lnCDDD**/dSw*		–0.542***	–0.856***	
		(0.082)	(0.118)	
d*lnCDDD**/dSw*P**	–0.803***			–0.837***
	(0.164)			(0.158)
Observations	41652	41652	41628	41592
R^2	0.989	0.989	0.989	0.989

Eleven indicator variables for month in year are included as well as drug-specific indicators. d*lnCDDD*/dSw** (d*lnCDDD**/d*SwP**) captures the long-term effect of an increase in *Sw* (*SwP*), holding the number of firms constant. For the IV specification, the Kleibergen-Paap rk Wald statistic, which indicates the strength of the instruments, is 50.485. The last two specifications include three indicator variables for *NotPolicy* with different lags, and the last specification also indicates two interactions between such indicators and lags of *lnFirms*.

Table 3. Estimation results, number of firms

	OLS on *SwP*	Nbreg on *SwP*	OLS on *Sw*
$lnFirms_{e,t\text{-}1}$	0.944***	0.925***	0.939***
	(0.021)	(0.019)	(0.022)
$SwP_{e,t\text{-}3,t\text{-}8}$	–0.054**	–0.082**	
	(0.023)	(0.032)	
$Sw_{e,t\text{-}3,t\text{-}8}$			0.009
			(0.014)
$lnDDD_{e,t\text{-}3,t\text{-}8}$	0.014***	0.016***	0.012**
	(0.005)	(0.004)	(0.005)
$PatentExp6m_{e,t}$	0.085	0.064	0.076
	(0.057)	(0.049)	(0.057)
$\text{2009PriceCap}_{\text{e,t}}$	–0.029*	–0.031**	–0.030**
	(0.015)	(0.013)	(0.015)
$ThAlt_{e,t\text{-}1}$	0.022	0.044**	0.023
	(0.019)	(0.019)	(0.019)
$ThGenAlt_{e,t\text{-}1}$	–0.017	–0.028***	–0.016
	(0.011)	(0.009)	(0.010)
$PackageSize_{e}$	–0.024***	–0.028***	–0.020**
	(0.009)	(0.009)	(0.008)
$Trend_{t}$	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
$NotPolicy_{e,t\text{-}3,t\text{-}8}$	0.005	0.001	
	(0.011)	(0.012)	
d*lnFirms**/d*SwP**	–0.955*	–1.101***	
	(0.503)	(0.369)	
d*lnFirms**/d*Sw**			0.150
			(0.238)
Observations	41615	41652	41615
R^2	0.971		0.971
Log pseudo likelihood		–1.998e+12	

Eleven indicator variables for month in year are included as well as drug-specific indicators. d*lnFirms**/d*SwP** (d*lnFirms**/d*Sw**) captures the long-term effect of an increase in *SwP* (*Sw*). OLS estimation of $lnFirms_{e,t}$ is used in the first and last specifications, whereas negative binomial regression on $Firms_{e,t}$ is used in the second specification. Thirty-seven more observations are used in the nbreg estimations because the dependent variable equals zero in these cases without the one-month lag of firms being zero.

Table 4. Estimation results for the original being sold

	SwP		Sw	
	Coeff	Marginal effect	Coeff	Marginal effect
$Org_{e,t\text{-}1}$	6.010***	0.596***	5.968***	0.590***
	(0.475)	(0.012)	(0.469)	(0.049)
$SwP_{e,t\text{-}3,t\text{-}8}$	0.641	0.012		
	(1.029)	(0.020)		
$Sw_{e,t\text{-}3,t\text{-}8}$			–0.830	–0.016
			(0.665)	(0.013)
$lnDDD_{e,t\text{-}3,t\text{-}5}$	0.456***	0.009***	0.479***	0.009***
	(0.127)	(0.003)	(0.115)	(0.003)
$PatentExp6m_{e,t}$	–2.802**	–0.101	–2.647**	–0.091
	(1.200)	(0.068)	(1.199)	(0.065)
$2009PriceCap_{e,t}$	0.344	0.007	0.402	0.008
	(0.509)	(0.010)	(0.518)	(0.010)
$ThAlt_{e,t\text{-}1}$	0.519	0.010	0.484	0.009
	(0.727)	(0.014)	(0.724)	(0.014)
$ThGenAlt_{e,t\text{-}1}$	–0.641	–0.012	–0.713	–0.014
	(0.566)	(0.011)	(0.559)	(0.011)
$PackageSize_{e}$	–0.329	–0.006	–0.404	–0.008
	(0.267)	(0.005)	(0.246)	(0.005)
$Trend_{t}$	–0.048***	–0.001***	–0.045***	–0.001***
	(0.015)	(0.000)	(0.014)	(0.000)
$NotPolicy_{e,t\text{-}3,t\text{-}5}$	–0.407	–0.008		
	(0.573)	(0.011)		
d*Org**/dSwP*		0.031		–0.039
		(0.050)		(0.031)
d*Org**/dSw*				
Pseudo R^2	0.853		0.852	
Observations	24388		24388	

Eleven indicator variables for month in year are included as well as drug-specific indicators. d*Org*/*d*SwP** (d*Org*/*d*Sw**) captures the long-term effect of an increase in *Swp* (*Sw*). The logit estimator is used, marginal effects are calculated using the command margins in Stata 12.1, and the standard errors of the marginal effects are calculated using the delta method.

Figure 1. Firms’ informational structure when bidding for Period 3

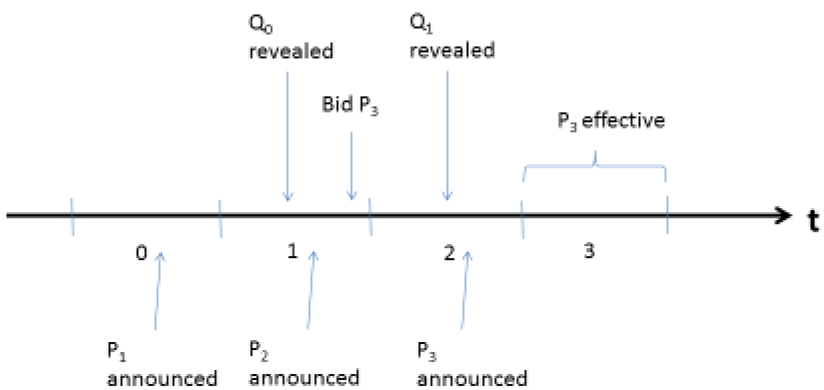


Figure 2. The market share of the lowest bidder and per-firm and total profit

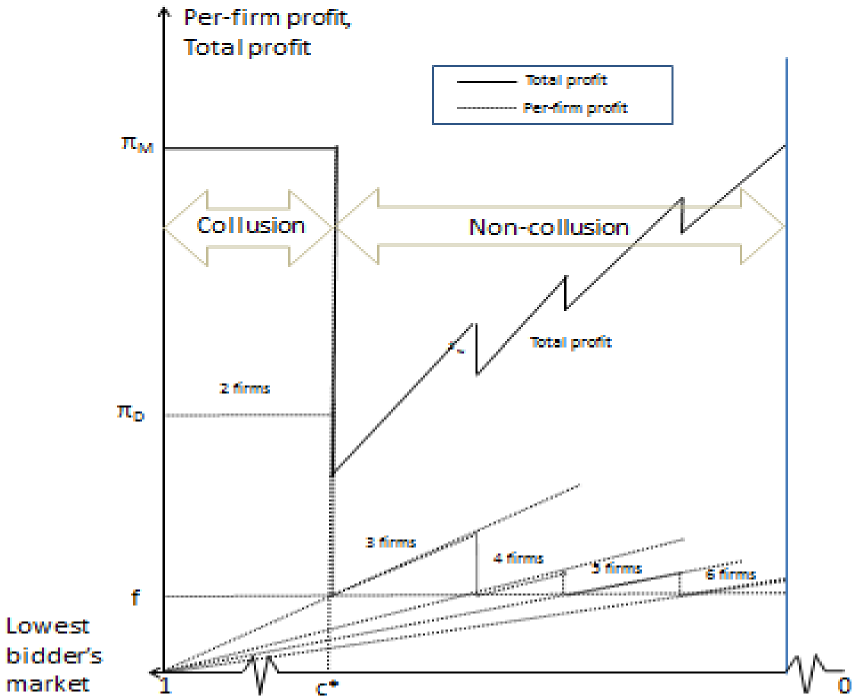
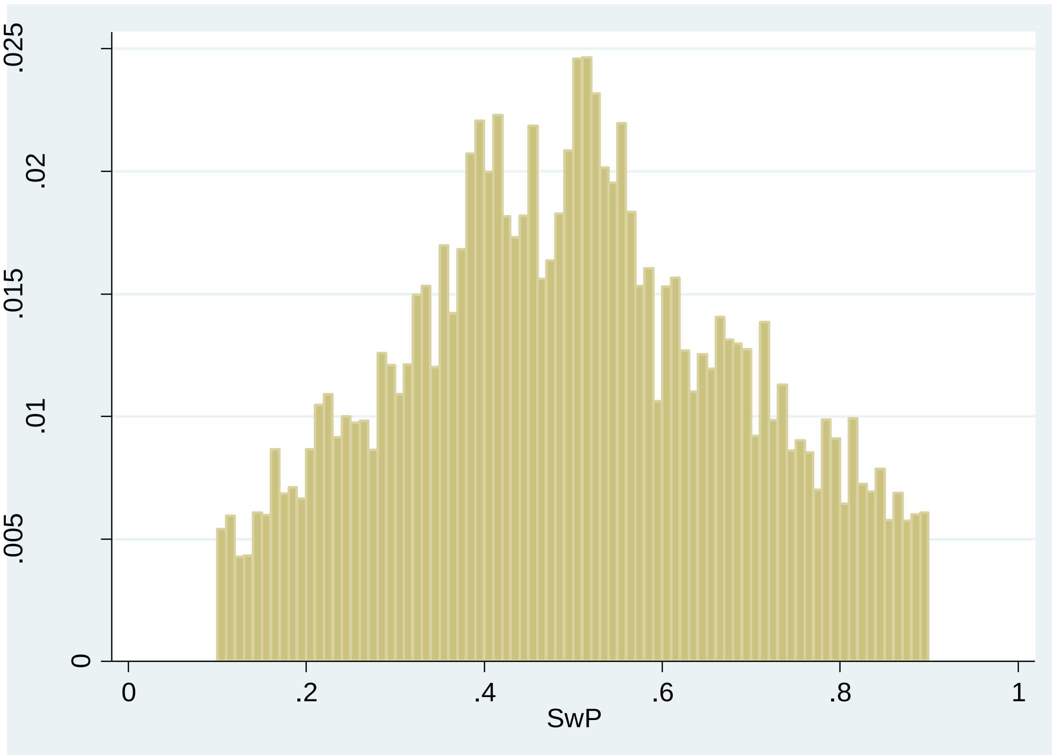
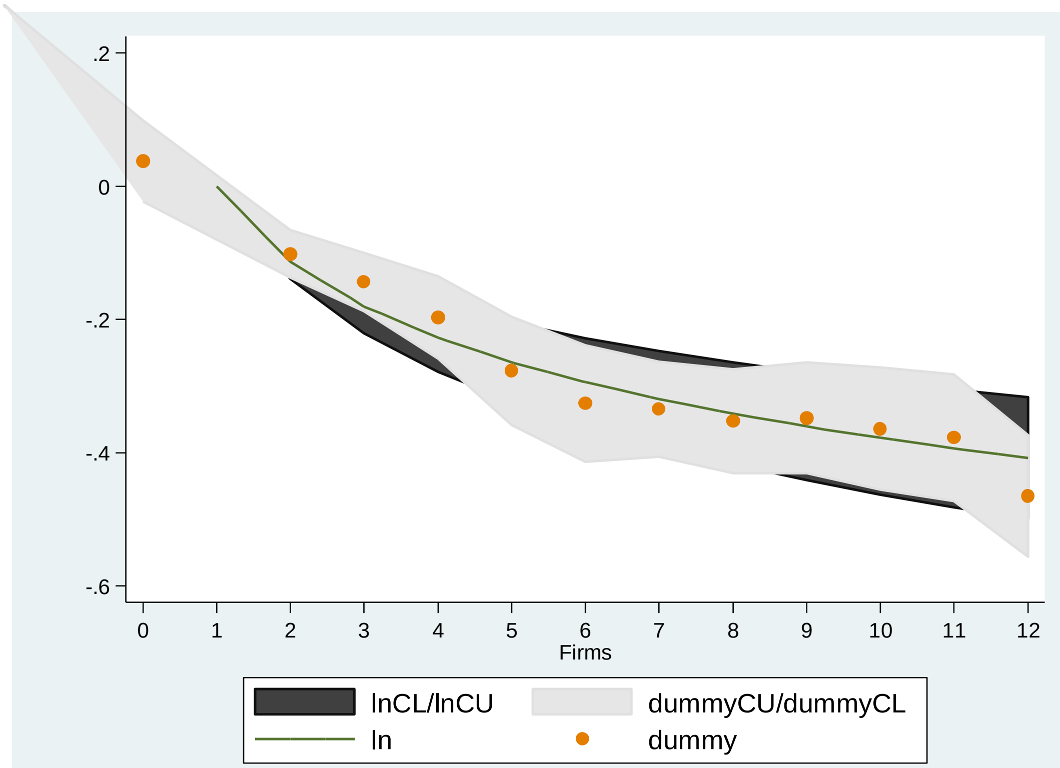


Figure 3. Empirical distribution of the low bidder's market share (*SwP*)



Note: The width of the bins is 0.01. The minimum value is 0.1 and the maximum value is 0.9 because the histogram includes only observations for which *NotPolicy* is zero.

Figure 4. Estimated short-term effect of $Firms_{t-1}$ on $lnCDDD_t$; comparison of functional-form and flexible-form estimates



Note: The smooth line is the effect of $lnFirms_{t-1}$ predicted from specification 1p and the black (partly hidden) area shows the associated 95% confidence interval. The dots are the point estimates of indicator variables for $Firms_{t-1}$, where $Firms_{t-1} = 1$ is the omitted category, and the grey area shows the associated 95% confidence interval. When indicator variables are used, the 2% of the observations for which $Firms_{t-1} = 0$, due to only parallel-imported products being sold, are also included. When indicator variables are used, the coefficient of $lnCDDD_{e,t-1}$ is 0.829 (0.021), compared with 0.836 (0.022) when $lnFirms_{t-1}$ is used, implying that the long-term effects of $Firms_{t-1}$ are also nearly identical.