A method for calculating the probability of collusion based on observed price patterns*

David Granlund†, Umeå University

Niklas Rudholm, The Institute of Retail Economics

Abstract: We present a method for calculating the probability of collusion based on observed price patterns. Given these probabilities, we can also estimate the impact of market characteristics on the probability of collusion, and price increases and total overcharge caused by collusion. These estimates are essential to inform collusion prevention policies. Applying our method to 28,863 auctions in the Swedish generic pharmaceuticals markets, we find that collusion increases average prices by 65% and that increasing the number of firms from two to four reduces the probability of collusion by approximately one-half. Nonetheless, collusion remains a concern with four or five firms.

Keywords: bid rigging; coordinated effects; collusion; competition; price coordination.

JEL codes: C57, D22, D44, I11, L41

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Legal disclaimer: We want to stress that we cannot with certainty know that any individual firm is part of a collusion, because also patterns for which the probability of collusion is rounded to 100% could have occurred by chance during competition. In addition, we find it likely that at least most of the collusions are tacit, and we do not mean to suggest that any individual firm has violated any laws. In addition, for the cases mentioned in the papers we cite, we make no claim of guilt for any entity or individual.

† Corresponding author: Department of Economics, Umeå University, SE-901 87 Umeå, Sweden. E-mail: david.granlund@umu.se. Phone: +46 90 786 99 40.

I. Introduction

Most markets involve repeated interactions which can enable firms to collude, tacitly or explicitly. Still, we lack information about how common collusion is. An ever-present problem is that outside observers never know with certainty which markets are affected by collusion. Thus, there is a need for a method that can be used to estimate the probability of collusion. To inform policy on how to best prevent collusion, the method should also enable estimation of total overcharges and how different market characteristics affect the likelihood of collusion.

Our method for calculating the probability of collusion has three steps. First, we identify price patterns consistent with collusion, for example, that two firms have the lowest price every other period for a specific duration. Second, for each pattern, we calculate the probability that it arises by chance during competition, accounting for–among else–firms' incentives to set higher prices when they face high demand from returning consumers or have low quantities in stock. Third, using these probabilities and observed frequencies of different price patterns, we use Bayes' theorem to calculate the probability that a given price pattern is the result of collusion. In short, long patterns consistent with bid rotation or parallel bidding are far more common in the data than predicted by the competitive model and, as a result, the probabilities that they are caused by collusion are high.

In addition, we use the resulting probabilities to estimate the effects the number of firms and other market characteristics have on the probability of collusion, the effect of collusion on prices, and the total overcharge due to collusion.

Our study is related to Byrne and de Roos (2019) in that we identify patterns consistent with tacit collusion. However, while Byrne and de Roos focused on describing collusion initiation in one city, we calculate collusion probabilities and analyze differences across several well-defined markets. Our research differs from the collusion detection literature (e.g., Baldwin et al., 1997; Bajari and Ye, 2003; Athey et al., 2011; Chassang and Ortner, 2019; Chassang et al., 2022; and Kawai and Nakabayashi, 2022)[1] by calculating the probability that each auction was part of a collusive price pattern rather than classifying markets as likely collusive or not depending on whether they divert from the predictions of a competitive model at, for example, the 90% or 95% significance level.

[1] These papers use data from markets with suspected collusions. A related literature use data on known cartels to construct collusion detection methods (e.g., Hendricks and Porter, 1988; Porter and Zona, 1993; 1999; Pesendorfer, 2000; Röller and Steen, 2006; Asker, 2010; Clark and Houde, 2013; Conley and Decarolis, 2016; Imhof et al., 2018; Imhof, 2019; and Kawai et al., 2023).

A similarity with Bajari and Ye (2003) is that we use Bayes' theorem. They elicited a prior distribution of the production cost from two industry experts, estimated the cost under the assumption of competition and collusion, and then used Bayes' theorem to decide between a competitive and two collusive models under the assumption that the same model explained the bidding in all auctions. With this approach, they calculated the posterior probability of competition to be 1. We instead use Bayes' theorem to calculate the probability of collusion for each combination of price pattern and number of bidders based on the observed frequency of price patterns and calculated probabilities of observing these patterns under competition. Our method does not require estimating production costs and allows the market regime to change between competition and collusion at any time and at different times in the different markets.

The main innovation in our research is our method for calculating the probability of collusion. Calculating the probability of collusion is important since it makes it possible to estimate total expected overcharges and how the number of firms and other market characteristics affects the probability of collusion, which is needed to understand how to best reform markets to prevent collusion. Preventing collusion is important since tacit collusion is not considered illegal in many jurisdictions but still incurs considerable costs for society, and the time and cost of prosecuting explicit collusion is considerable.

Studying the effect of the number of firms on the probability of collusion using market data is itself a major contribution since the existing knowledge about this effect primarily comes from classroom experiments. Information about the effect of the number of bidders on the probability of collusion is vital for competition authorities when accessing the risk for coordinated effects of mergers and for firms or government organizations when setting criteria for procurement auctions.

The method developed in this paper can be applied in diverse markets. For example, it could be used to investigate collusive pricing in many procurement markets, repeated auction markets, or online marketplaces such as Amazon.

The main results from our statistical analysis are as follows. The collusion probabilities are estimated to exceed 90% when F firms have sold the lowest-priced product every F^{th} period for at least nine periods and when there has been a tie between the same two or more firms for at least five periods. In addition, in auctions with at least four bidders, the probabilities of collusion exceed 60% already when the duration of the suspicious pattern weakly exceeds three periods.

The results also show that an increase in the predicted collusion probability increases prices and that market characteristics such as number of firms and multimarket contact affect this probability in line with theoretical predictions. This strengthens the conjecture that the method gives a relevant measure of the probability of collusion. However, the main value of these estimates is that they can inform on which measures are worth taking to prevent collusion. More precisely, we find that an increase in the predicted probability of collusion from 0 to 1 increases average prices by 65%. The price effects are larger than in most previous studies. For example, the meta-analyses by Connor and Bolotova (2006) and Connor (2014), with significant overlap in their samples, reported average price effects of cartels of 29% and 23%, respectively. Our findings are more consistent with the findings of Clark et al. (2022) and Starc and Wollmann (2022), who analyzed the impact of an alleged U.S. generic pharmaceuticals cartel. Starc and Wollmann reported average price increases of 45%–50% after two years, while Clark et al. reported increases ranging from 0%–166% for different pharmaceuticals.[2] Because the demand elasticity is low for pharmaceuticals at the market level (Kanavos and Costa-Font, 2005), it is unsurprising that the highest price effects of collusion have been found for pharmaceuticals.

We also confirm the qualitative predictions from theoretical analyses (Selten, 1973; Shapiro, 1989; Phlips, 1995; Ivaldi et al., 2003) and classroom experiments (see Huck et al. [2004], Fonseca and Normann [2012], Horstmann et al. [2018], and the literature therein) that the number of firms has a significant negative effect on the probability of collusion. More precisely, we find that increasing the number of bidders from two to four reduces the probability of collusion by half. This reduction is small compared to Huck et al. and Fonseca and Normann, who found quantities and prices to be close to competitive levels with four players who were not allowed to communicate.

Davies et al. (2011) analyzed merger decisions taken by the European Commission and concluded that the Commission held tacit collusion to rarely occur in markets with more than two firms. We are not aware of any similar analyses for other competition authorities. However, Bergman et al. (2019) found the U.S. Federal Trade Commission slightly more permissive regarding a closely related variable, the post-merger market share. Our results question the conjecture that tacit collusion rarely occurs in markets with more than two firms. Indeed, we find likely collusions with five participants in markets with up to seven firms. In addition, most collusions in the markets we study are likely tacit because they take the form of bid rotations

[2] It should be noted that these papers use samples from non-indicted U.S. generic drug markets as their competitive counterfactuals, which might be a strong assumption. If we use an estimation approach like those adopted in many previous studies by grouping observations with a probability of collusion <90% and treating them as competitive, we instead find a price effect of 13%. This indicates that the price effects can be underestimated if all markets without high certainty of being collusive are treated as competitive.

that, compared to parallel bidding, are less stable and, because of a price cap, yield lower profits but, arguably, should be easier to initiate without verbal communication.

The remainder of this paper is structured as follows. Sections II and III describe the Swedish generic pharmaceuticals markets and the data, respectively, while section IV describes competitive bid behavior in the markets. Section V presents the calculations of the probability of collusion given the observed price patterns, and Section VI shows that increases in the probability of collusion result in higher prices. Section VII estimates the effect of the number of bidders and other variables on the probability of collusion, while section VIII concludes the paper.

II. The markets

Pharmaceutical markets often have features that increase the likelihood of collusion. One is that many jurisdictions, including Sweden, many other European countries, and all American states, have generic substitution systems where consumers can switch to cheaper substitutes at the pharmacy and have economic incentives to do so (Vivian, 2008). These systems create markets which are nearly one-dimensional in prices and, therefore, firms need only to coordinate prices to achieve a collusion. Additionally, while pharmaceutical benefit schemes can maintain price sensitivity in choices between exchangeable products, they make consumers less price sensitive regarding the decision to buy a pharmaceutical at all, thus increasing the monopoly price and therefore the gain from collusion.

In Sweden, a government-funded benefit scheme covers 75%–80% of the cost of prescription drugs for consumers. The generic substitution law requires pharmacists to inform consumers whether less costly substitutes are available and to dispense the lowest-priced pharmaceutical unless: (i) the consumer chooses to pay the price difference themselves to get the prescribed product; (ii) the prescribing physician has prohibited an exchange for medical reasons; or (iii) the pharmacist has reason to believe that the consumer would be adversely affected by substitution, such as if the low-cost alternative has a package that would be difficult for the consumer to open.

Only products within narrowly defined exchange groups, which have the same combination of active ingredients, administration method, strength, and nearly identical packet size, are considered substitutes. When the physician or pharmacist prevents a switch, the entire prescription cost is included in the benefit scheme. Otherwise, only the cost of the cheapest available alternative—the product-of-the-month (PM)—will be reimbursed under the benefits scheme. Therefore, demand for off-patent drugs is steered towards the least costly alternative, and becoming the PM is associated with a 70-percentage-points larger market share, on average (Granlund, 2021).

To decide who becomes the PM, prices for off-patent pharmaceuticals are set in monthly sealed-bid first-price sell auctions for each exchange group, where the pharmaceutical providers place bids. For the product to be included in the pharmaceutical benefits scheme, the Dental and Pharmaceuticals Benefits Agency (DPBA) must approve the price. The DPBA ordinarily approves prices not exceeding a price cap equal to 35% of the pre-patent-expiration price and, otherwise, equal to the highest existing price of exchangeable products. The price cap is dynamic in the sense that it depends on existing and previous prices in the exchange group.

Pharmacies are not allowed to negotiate discounts from the national prices determined by the auctions or to give discounts to consumers. Pharmacies' retail margin is set in a regulatory process and can be expressed mathematically so that the wholesale prices offered by the providers also completely determine the retail prices.

The rules determining what information is available to the firms when setting the prices can be summarized as follows:

(i) At the end of Month 1, all firms that wish to sell a particular product during Month 3 submit a price bid to the DPBA.

(ii) During Month 2, the DPBA will announce the winner for Month 3. The winner's product is called the PM for that exchange group and month. For a product to be a PM, it must be the cheapest product within the exchange group (in terms of pharmacies' sales prices per smallest unit [e.g., per pill]) and, since November 2014, the pharmaceutical firm must have actively guaranteed it to be available across the entirety of Sweden throughout the month. If two or more firms submit identical bids, they will all be called PM.

(iii) Sales during Month 3 will be paid for according to the bids submitted in Month 1.

Note that when firms submit their bids for Month 3, the prices that will apply in Month 2 have already been announced. Consequently, if firms are colluding, deviations can be punished by others with only one month's delay, increasing the stability of collusions.

Several other market characteristics are also worth noting from a collusion perspective. First, only a few firms are bidding to become the PM. Second, the markets are transparent since the bidding process used to determine the PM provides firms with data on competitors' prices, while data on quantities sold are also easily obtainable. Third, most sellers of generics are active in several exchange groups (i.e., markets), making multimarket contact a prominent feature of these markets.

III. Data

This study is based on a panel dataset obtained by merging different datasets compiled by the DPBA. The dataset contains all products included in the PM system from March 2010 through September 2020. Most importantly, it includes information on which exchange groups products belong to and each product's price and PM status each month. It also lists each product's active ingredient(s), strength, administrative form, and package size, and it identifies its seller and the quantity sold for each month. We complemented the datasets compiled by the DPBA with datasets prepared by the company IQVIA (formerly IMS), which contains similar information. The IQVIA datasets are used to follow exchange groups over time (the DPBA has changed the numbering of exchange groups several times), check for consistency across the two data sources, and generate some control variables.

Because firms must guarantee availability for products to be eligible to be a PM since November 2014, we use data from November 2014 through September 2020. We include auctions (i.e., exchange group and month combinations) with positive sales and at least one product marketed by a potential bidder being declared a PM. Additionally, because we aim to study interactions between firms, we exclude auctions with just one potential bidder. In addition, 0.2% of the product-by-month observations are excluded because they may be affected by errors in the exchange group variable.

III.A. Definition of potential bidders and potential low-price bidders

Because colluding firms can choose not to bid when it is not their turn to win, we cannot restrict our focus solely to actual bidders but must define the potential bidders. In the primary analysis, we define a potential bidder in auction *et* as any firm that sold at least one package in exchange group *e* from month $t - 2$ to $t + 2$. In practice, including potential bidders does not matter a great deal. In the estimation sample, the mean number of potential ($nbid_{et}$) and active ($nbida_{et}$) bidders are 4.8 and 4.7 and the two variables have a correlation of 0.99.[3]

Some firms submit prices on more than one product per auction, for example, because they want to sell both blister packages and tins or both a 98-pill package and a 100-pill package. However, firms selling two products in an exchange group know that the more expensive product cannot become a PM. Therefore, submitting prices for several products per auction does not affect the likelihood that at least one of the firm's products will be a PM. Because of this, and given this paper's focus on studying collusion and not the choices of product portfolios, we aggregated observations to firm × exchange group × month combinations and defined the variable PM_{fem} to take the value 1 if at least one of firm *f*'s products in exchange group *e* is PM in year-month *m*. The number of unique firm × exchange group × month combinations equals 274,147.

[3] Online Appendix A provides a list of definitions and additional descriptive statistics for all variables.

The dataset identifies three product categories. First, originators are products that have previously been patent-protected. Second, generics are copies that can be sold after patent expiration. Third, parallel imports are products sold by the producer at low prices in some countries within the European economic area and legally imported by traders without the producer’s permission. In contrast, originators and generics only refer to products intended for the Swedish market.

Most exchange groups are vertically separated in the sense that many sellers of originators and parallel imports (and some sellers of generics) consistently sell at prices exceeding the price of the cheapest product. Instead of aiming to become the PM, these sellers seem to focus on selling to consumers who are prepared to pay extra for their products.

When calculating the probability that the price pattern is caused by collusion in Section IV, we use the number of potential low-price bidders in each auction. We have classified firms as currently being a low-price bidder in an exchange group if (a) at least once in the current month, or in the preceding or following two months, one of its products was a PM, or (b) in the current month it offers a product that is declared to be available and has a price that is equal to or below the price of the PM in the last or the second-to-last month. Criterion (a) is primarily motivated by the notion that firms currently involved in collusion in the low-price segment should also be considered to belong to this segment. Some firms might fail to become a PM seller several months in a row, even when attempting. Therefore, criterion (b) was added.

Column 4 of Table 1 provides evidence of vertical separation by showing that the share that sells a PM is much lower for originators and parallel importers than for generics. We present descriptive statistics for the low-price segment classification in the last column. Two-thirds of the observations are classified as belonging to the low-price segment. As expected, the share is highest for generics and lowest for originators.

Table 1. Descriptive statistics for firm categories.

Category	Number of obs.	Share of obs.	Share of PM	Share of category that is PM	Share of category in low-price segment
Generics	212,634	77.56%	88.27%	29.13%	75.41%
Originators	38,102	13.90%	6.81%	12.54%	27.67%
Parallel imp.	23,411	8.54%	4.92%	14.75%	45.97%
All	274,147	100%	100%	25.60%	66.26%

Note: Firms are categorized by which category of products they market in each exchange group each month. Nine percent of originators and 3% of parallel imports are for firms that market both originators and generics and both parallel imports and generics, respectively, in the same auction. No firm marketed both originators and parallel imports in the same auction.

Figure 1 shows histograms of the number of low-price bidders and all bidders, respectively. According to our classification, there are at most nine low-price bidders, but there are only three auctions with eight or nine low-price bidders.

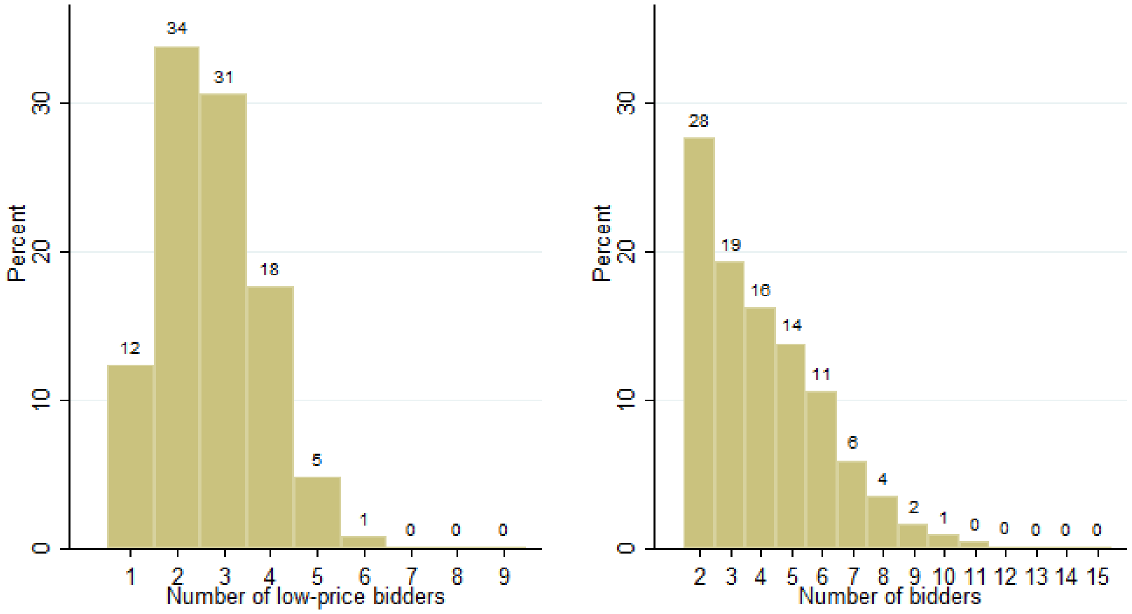

Figure 1. *Histogram of low-price (left panel) and all (right panel) bidders per auction. The number of auctions is 58,381.*

III.B. Price patterns consistent with collusion

Figures 2 and 3 show two empirical examples of firms' prices in exchange groups where one could suspect that the low-price bidders colluded during parts of the study period. In Figure 2, the low-price bidders' behavior is consistent with them starting bid rotating in the middle of 2016, with the price of the low-price bidders consistently increasing toward the price cap of 153 SEK. In Figure 3, we find a similar pattern suggesting a link between the number of firms and the likelihood of collusion.

Figure 3 shows an exchange group with a clear negative trend in the total number of packages sold and where some generics left the market before June 2016, the first month included in the figure. Generic C left the market in 2017, and the originator exited in 2018. The remaining two firms won every other month from October 2018 through April 2020. During the first part of this potentially collusive period, the winning firm set a price significantly lower than the losing bid, but in the end, the winning bids were also close to the price cap of 3,333 SEK. Moreover, when three generics firms were active in the market, Generic A set very high prices in some months, which can indicate a desire to establish a bid rotation. However, a stable bid-rotation pattern was first achieved over a year after Generic C left the market.

We would like to derive the probability that observed patterns like the ones in Figures 2 and 3 are the result of collusion. In Section IV, we describe the reasons why firms relatively frequently win every other or every third month also during competition, and we will account for this when we calculate the probability that collusion has occurred during the observed price pattern in Section V. For now, we simply state that *F* firms winning every F^{th} month are price patterns that are consistent with collusion using bid rotation, even though these patterns could also result from competition. Similarly, we classify patterns with the same two or more firms being shared winners for at least three months as consistent with collusion using parallel bidding.

We focus on bid rotation and parallel bidding since the experimental results of Fonseca and Normann (2012) showed that these were the two most common types of collusion. Also, Cletus (2016) documented the existence of bid-rotation- and parallel-bidding-like patterns for Swedish pharmaceutical markets and found these to be associated with significantly higher prices. In total, we define 24 different price patterns (*W*) that are consistent with collusion and Table 2 shows that 91% of the auctions are part of some of these patterns. In principle, collusions can take any form. Thus, we might miss some collusive patterns, but that 91% of the auctions are part of a pattern we classify as consistent with collusion indicates that we do not miss common collusive patterns. Also, we find it likely that firms can coordinate on the simple bid-rotation and parallel-bidding patterns we analyze without verbal communication. Because of this, that these patterns are quite effective in raising prices (Section VI), and given that tacit collusion is not prosecuted in Sweden, while explicit collusion is, we find it unlikely that firms choose to coordinate on more sophisticated patterns that require communication.

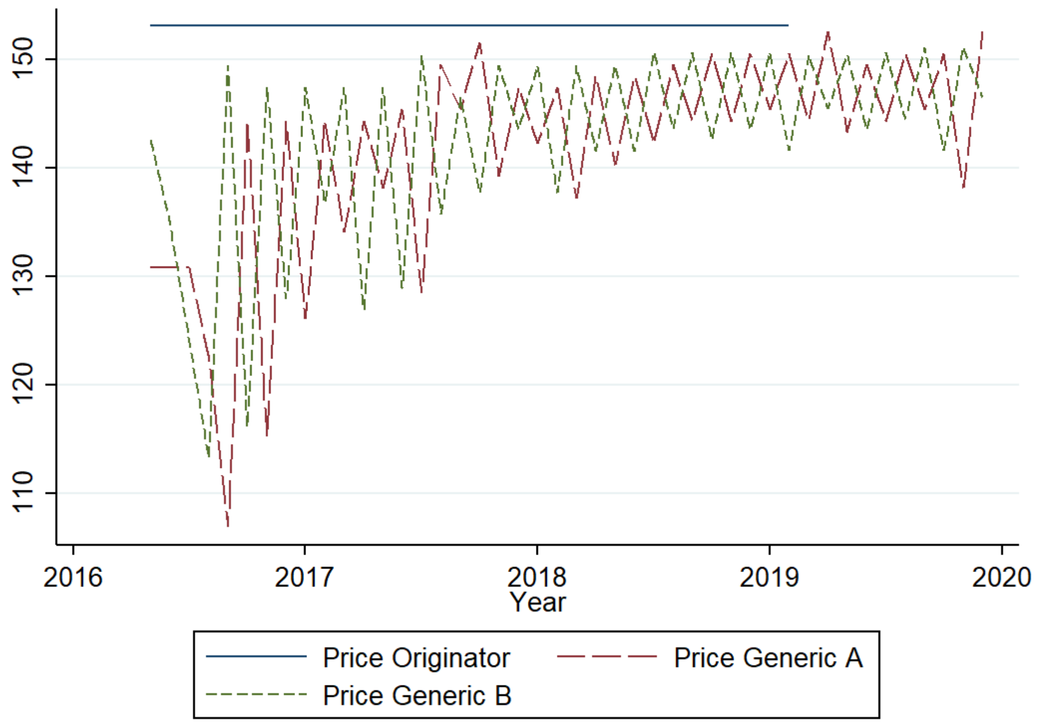

Figure 2. *Example of a two-firm bid-rotation-like pattern.*

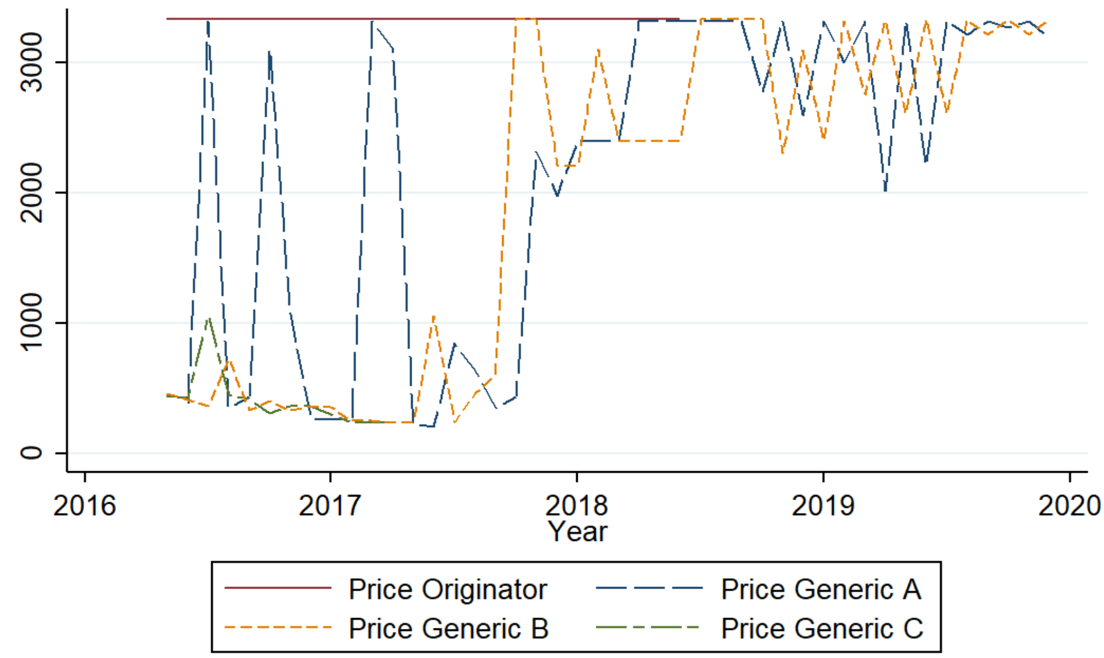

Figure 3. *Example of two-firm bid-rotation-like pattern.*

We note that these price patterns can only exist in auctions with at least two low price bidders and use ≥11 months as the longest duration. Therefore, Table 2 shows descriptive statistics for these price patterns for the 28,863 auctions with at least two low-price bidders for all months from *t – 10* to *t + 10*. These auctions are for 891 exchange groups observed for, on average, 32.4 months. All observations are from September 2015 to November 2019, and their sales account for 55% of all sales (measured in pharmacies' purchase prices) within the PM system during this period. Table 2 show that long pattern consistent with bid-rotation, like those in Figures 2 and 3, are common; 18.22% [= 3.44 + 14.78] of the auctions are part of such pattern lasting at least nine months. Table 2 also indicates that collusion seldom takes the form of parallel bidding.

Figure 4 shows the empirical distributions of low-price and all bidders separately for auctions that are and are not part of a bid-rotation or parallel-bidding-like patterns that lasted at least nine months. Our calculations described in the following sections suggest that 99% of bid-rotations- or parallel-bidding-like patterns that weakly exceed nine months are at least partially caused by collusion, while over a third of the shorter patterns arose during competition.

Figure 4 shows that the longer possible collusive patterns are highly over-represented in auctions with two low-price bidders, consistent with theoretical and experimental findings suggesting that collusion is most likely to occur when there are few bidders in a market (Selten, 1973; Huck et al., 2004; Fonseca and Normann, 2012; Horstmann et al., 2018). The right panel shows a large over-representation of suspicious patterns for auctions with three bidders. This finding is expected given the pattern shown in the left panel and the fact that the originator often sells branded products to loyal consumers at high prices.

Table 2. Share of auctions that are part of different possible collusive patterns.

	3–4 months	5–6 months	7–8 months	9–10 months	≥11 months	**≥3 months**
2-firm bid rotation	8.12%	4.19%	1.74%	1.45%	9.06%	24.56%
3-firm bid rotation	21.99%	9.91%	3.30%	1.65%	3.82%	40.67%
4-firm bid rotation	9.16%	7.71%	1.36%	0.26%	0.07%	18.56%
5-firm bid rotation	–	4.38%	0.53%	0.01%	0%	4.92%
2-firm parallel bidding	0.10%	0.07%	0.06%	0.07%	1.83%	2.13%
SUM	39.38%	26.26%	7.00%	3.44%	14.78%	90.85%

Note: *F*-firm bid rotations (F = 2, 3, 4, 5) are defined as the same *F* firms win every *F*:th month for the specified number of months. The definitions for 2-firm parallel bidding are that the same two firms are shared winner for the specified number of months. The entry of 0% indicates that no auction (i.e., exchange group × month combination) is part of a five-firm bid rotation weakly exceeding eleven months. There is no bid rotation among more than five firms (lasting more than five months) and no parallel bidding involving more than two firms (lasting at least three months). The number of auctions is 28,863.

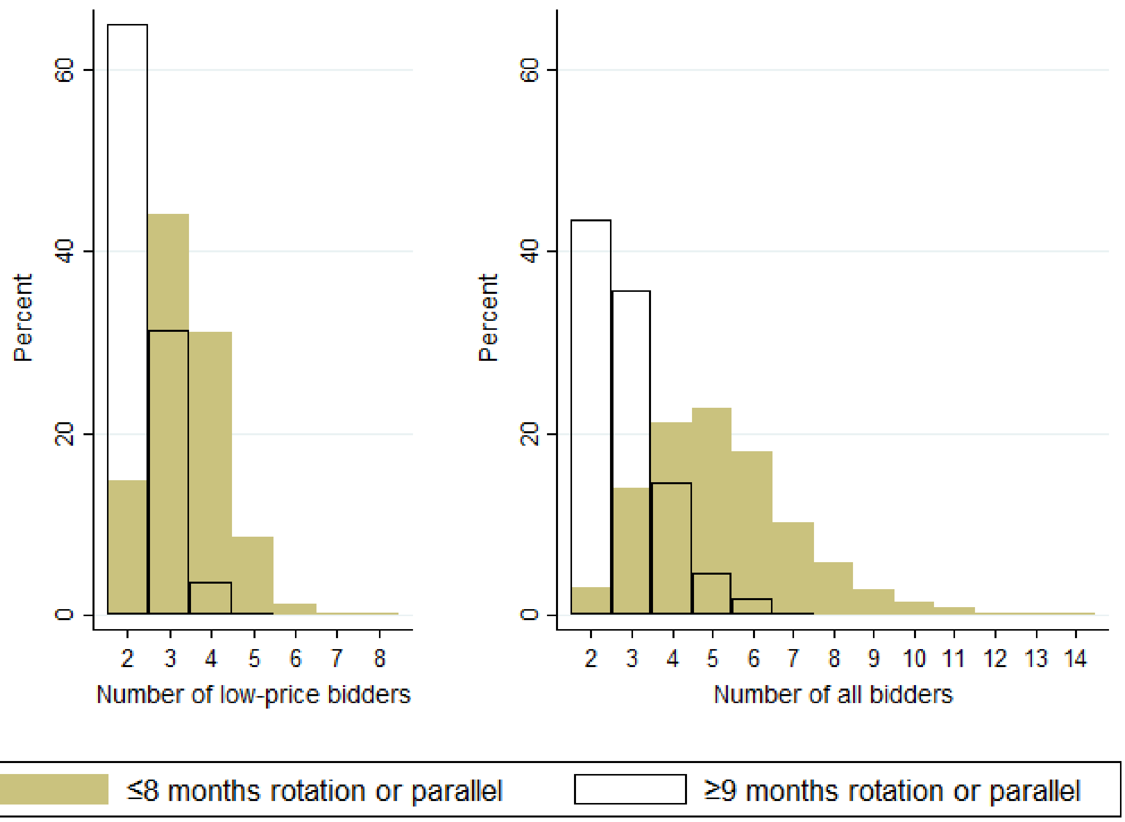

Figure 4. *Histogram of low-price (left panel) and all (right panel) bidders per auction, separate for auctions that are and are not part of any pattern consistent with bid rotations or parallel bidding weakly exceeding nine months. The number of auctions is 28,863.*

IV. Competitive bid behavior

IV.A. Frequent price changes

The basic price-setting incentives for competing low-price bidders can be understood using the model by Varian (1980). This model shows that when some consumers' choices are unaffected by relative prices, price changes will be common and large even if production costs are fixed. As a result, variation in marginal cost will explain only a minor share of the variation in prices.

The model implies that the probability of having the lowest price is simply $1/n$ for each of the *n* low-price bidders in each auction (Bergman et al., 2017). We take this as a starting point, but allow for ties (Subsection IV.B) and account for the fact that firms have an incentive to set higher prices when they face high demand for returning consumers or have low quantities in stock (Subsection IV.C).

With marginal costs normalized to zero, low-price bidders in a generics market will submit bids over the interval $[P_{min}, P_O]$, where

$$P_{min} = P_O \frac{1 - S_w - S_H}{S_w(n-1)} \qquad (1)$$

and P_O is the maximum price permitted within the benefits scheme (Bergman et al., 2017). In this equation, S_w is the market share of the winner, S_H is the joint market share of all high-price bidders. The logic here is that a firm can secure a revenue of $P_O \frac{1-S_w-S_H}{n-1}$ by setting the highest permissible price and that $P_{min}S_w$ must be equally large. We will use the relationship between the bid interval and *n* from the model when calibrating the probabilities of ties in the next subsection.

IV.B. Probability of ties during competition

One simplifying assumption in Varian's (1980) model is that prices are continuous. In practice, prices are discrete because only two decimal places are allowed when they are submitted to the DPBA. More importantly, 42% of the price bids are in whole crowns, further increasing the possibility of ties (defined as several firms being shared winners) when firms compete using mixed pricing strategies. The data reveals that there are ties in 6% of the auctions.

The probability of ties during competition should depend on the number of discrete prices within the interval over which firms randomize their bids, the bid distribution functions, and the number of bidders. The latter can be formalized as the probability of a single winner should equal x^{n-1}, where $x \in (0,1)$. The logic of this function is that since (at least) one firm must have the lowest price, the number of trials for a tie is $n - 1$. The function x^{n-1} reveals that the probability of a single winner should fall in n for a given width of the bid interval and given bid distribution functions.

The parameter x should be a function of $1-1/w$, where w is the width of the bid interval, e.g., $w = P_O\left(1-\frac{1-S_W-S_H}{S_W(n-1)}\right)$ if firms bid according to the model described in section IV.A. Indeed, x should equal $1-1/\left[P_O\left(1-\frac{1-S_W-S_H}{S_W(n-1)}\right)\right]$ if P_O is equal to the number of possible prices above the marginal cost, and the firms have uniform bid distributions. We do not assume this but instead assume that $x = 1-1/\left[P_p\left(1-\frac{1-S_W-S_H}{S_W(n-1)}\right)\right]$ and set the parameter P_p to equalize the predicted share of single winners with the observed share among auctions not part of a possible collusive pattern lasting at least three months.[4]

We let $1-x^{n-1}$ be the probability of a tie between two or more firms and denote it by PT_{et}. With the values $S_W = 0.794$ and $S_H = 0.095$, which are the means in the estimation sample, we obtain $P_P = 12.531$, x ranging from 0.907 to 0.919, and the predicted share of ties between two or more firms as 17.6%. Specifically, the share of ties is predicted to increase from 9.3% when the number of potential low-price bidders in auction *et* (n_{et}) is equal to 2 to 16.4%, 23.1%, and 29.2% when n_{et} increases to 3, 4, and 5, respectively.

IV.C. Autocorrelation in probability of winning during competition

We identify three reasons why, during competition, the probability of a product becoming a PM in the current month could depend on the PM status of the product in previous months. The first is that the winner(s) will be the same as the previous month if all firms in an exchange group submit the same bid, there is no entry, and the last month's winner(s) did not exit. This scenario is particularly important when calculating the probability of repeated ties between the same firms. The second reason relates to state dependence (i.e., that some consumers are prepared to pay extra to get the same brand they bought last time), and the third relates to the effect of previous winnings on the quantity in stock. Zona (1986) and Lang and Rosenthal (1991) showed that bid-rotation-like price patterns can arise under competition if the firms are capacity-constrained, and a naïve model would then overestimate the likelihood of collusion for a given price pattern.

We begin by addressing the issue that the winner(s) will be the same as in the previous month if all firms in an exchange group submit the same bid, there is no entry, and the last month's winner(s) did not exit. We estimate the probability that a low-price bidder will submit the same bid as in the previous month (U) using observed frequencies for products from

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[4] If we instead assumed that firms randomize over half of the bid interval, P_p would just obtain twice as high value, but the values of x, which we use when calculating the probabilities of collusion, would remain unchanged.

auctions with at least three low-price bidders which are not part of a possible collusive price pattern weakly exceeding three months. In line with the theoretical expectation, we find price changes to be common and large with $U = 0.2838$ and the average absolute value of the price changes equals 97.75% of the previous price. We estimate the probability that all bids by low-price bidders are the same in months *t +1* and *t* as $U^{n_{et}}E^{n_{et}}S1_{et}$, where $E = 0.9366$ is the probability that a low-price bidder month *t* was this also month *t – 1*, so that $E^{n_{et}}$ is the probability that there was no entry into the low-price segment, and $S1_{et}$, which equals 0.9676 when $n_{et} = 3$, is the probability that a winner will continue to be a low-price bidder in the next month. Therefore, when $n_{et} = 3$, $U^{n_{et}}E^{n_{et}}S1_{et} = (0.2838^3 \times 0.9366^3 \times 0.9676) \approx 0.018$. The values of E and $S1_{et}$ are the observed frequencies in the sample. One reason why $S1_{et} < 1$ is that the winner is sometimes bought by, or merges with, another pharmaceutical company.

To address the remaining two issues, we calculate autocorrelation in winning probabilities related to state dependence and stock quantity by first estimating models that include some variables related to these mechanisms that depend on whether the firm has won in previous months. Then, we calculate the contribution of state dependence and variation in stock quantity to autocorrelation in winning probabilities during competition based on the estimation results and the correlation between relevant variables and previous winnings. We cannot simply estimate autocorrelation coefficients for PM_{fet} (i.e., an indicator for firm *f*'s product in exchange group *e* to be a PM month *t*) because they would also capture autocorrelation caused by collusive behavior. For these estimations, we restrict the sample to low-price bidders from exchange groups that have existed for at least six months and current months with at least two low-price bidders and a single PM. To be able to sum all sources of autocorrelation during competition without double counting, we include only exchange group × month observations where the winner can differ from the previous month, either because of entry, the changed bid of at least one low-price bidder, or due to the exit of the previous month's winner.

State dependence implies that firms can partly predict month-to-month variation in demand for their products. For example, if a firm's product containing three months of pills was sold in large quantities in January because it was a PM, the demand for that product will increase in April when many consumers return for a refill. Therefore, it is profitable for the firms to harvest this increased demand by setting a higher price in April. Consequently, we expect PM_{fet} to correlate negatively with $PM_{fe,t-3}$ if consumers buy the drug every third month.

The time between drug fills differs across exchange groups due to differences in package sizes and drug types (e.g., whether the drug is for a chronic or acute condition) and across consumers within an exchange group. Therefore, to account for the autocorrelation caused by state dependence and repeated purchases, we create variables for the time between purchases using the 1.9 million drug fills that occur after the first six months of the data set described in

Granlund (2021). Specifically, we generate $Harv_{fet} = \sum_{\mathrm{m=t-1}}^{t-6} Share_e^m \, PM_{fem}/nPM_{em}$, where $Share_e^m$ equals the proportion that made their most recent filling t – m months before their current filling in exchange group e. The variable PM_{fem} is an indicator that firm f in exchange group e sold a PM in month m and is divided by the number of products (usually one) that were a PM in that exchange group and month (nPM_{em}). It is the difference in $Harv_{fet}$ between firm f and competing firms that affect the probability of firm f selling a PM. Therefore, we define $DiffHarv_{fet} = Harv_{fet} - \overline{Harv_{et}}$, where $\overline{Harv_{et}}$ is the mean of $Harv_{fet}$ for low-price bidders in exchange group e in month t.

A high value of $Harv_{fet}$, and thus $DiffHarv_{fet}$, means that a high proportion of the consumers making purchases in exchange group e in month t made their most recent purchase in that exchange group when firm f's product was a PM. Given the large effect of being a PM on a product's market share, most of these consumers likely bought firm f's product, and some of them are prepared to pay extra to secure firm f's product again. To harvest this increased demand, firm f is expected to set a higher-than-average price in month t. Therefore, we expect $DiffHarv_{fet}$ to negatively affect the probability of selling a PM.[5] The variable $DiffHarv_{fet}$ has a mean of 0 by definition and ranges from −0.50 to 0.80.

As stated above, stock quantities can also lead to autocorrelation in the probability of a product being a PM because the drugs have limited durability, meaning that firms holding excessively large quantities in stock will risk having to dispose of them or price very aggressively when their expiration date approaches. However, firms must hold some quantities in stock because the delivery time of drugs is often a few months. Therefore, some optimal stock quantity should exist. When a firm's stock falls below this level, perhaps because its product has recently been a PM for more months than expected, we expect it to raise its price, reducing the probability that its product becomes a PM and the product's expected sales. To capture this effect, we create

$$PrevPM_{fet} = \sum_{m=t-6}^{t-1} \delta^{t-m} \left(PM_{fem}/nPM_{em} - 1/n_{em} \right). \tag{2}$$

For products that are a PM in month m, the parenthetical term is intended to capture higher-than-average sales that month, and it will take higher values for exchange groups with a high number of low-price bidders since the probability of becoming a PM is lower in them. The parameter $\delta \in (0,1)$ is included so that there is room for higher-than-expected sales in the more

[5] We lacked data on drug fills for 12% of the firm × exchange group × month observations (e.g., because the exchange group only existed at the beginning or end of the study period, which the filling data do not cover). For these, we assume that the distribution of months between fillings equals the mean for all drug fillings.

distant past to matter less. The product's PM status over six months ago is assumed to not matter because firms should be able to restore their stock to the optimal level within six months by adjusting their orders or production. For all values of δ, $PrevPM_{fet}$ has a mean close to 0 (not identical because it is based on past values and some firms exit). For example, when $\delta = 0.298$ (which we estimate it to be below), $PrevPM_{fet}$ ranges from −0.42 to 0.34.

We estimate the following equation:

$$P\left(PM_{fet} = 1\right) = F\left(\alpha_1 DiffHarv_{fet} + \alpha_2 PrevPM_{fet}(\delta) + \alpha_3 \frac{1}{n_{et}} + \mu_{fe} + \varepsilon_{fet}\right), \qquad (3)$$

where μ_{fe} is firm × exchange group fixed effects. This model is estimated using observations from exchange groups that three (five) months earlier were not part of any pattern consistent with bid rotation or parallel bidding weakly exceeding three (five) months. This implies that we restrict the sample to observations where the winner's identity in month *t* should not be a function of preexisting collusive behavior. Consequently, the parameters are identified almost exclusively using observations from competitive regimes.

In the larger sample, which includes observations with up to four months of possible bid rotations, we also include three dummy variables (PM_ll_{fet}) that for l = 2, 3, and 4 take the value 1 if $PM_{fe,t-l} = 1$ and $n_{fe,t-l} = 1$. That is, PM_22_{fet} takes the value 1 for firm *f* if it sold a PM two months ago and there were two low-price bidders in the exchange group that month. These dummy variables are included to control for the dynamics caused by bid rotations among 2–4 firms that could otherwise bias the estimators.

We assume that the parameters α_1, α_2, and δ are identical across competitive observations included and excluded from these estimations. Since the model is nonlinear because of only one parameter (δ), estimating Equation (3) using a grid-search estimation strategy is convenient. We use this method by setting δ to values from 0 to 1 and estimating the other parameters using *xtreg* (Specifications 1 and 2) and *xtlogit* (Specifications 3–4) in STATA 14. Finally, likelihood values are used to discriminate between the different values of δ.

Specification 1 is preferred because it is estimated on the smaller sample, reducing the risk of estimates being affected by collusions, and is a linear probability model. We consider the latter an advantage because $1/n_{et}$ should have a linear effect on the probability of winning.[6]

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[6] In a model without any other explanatory variables, the effect of $1/n_{et}$ on the probability of winning should equal 1. A linear model also guarantees that $DiffHarv_{fet}$ has a symmetric effect on the probability of winning. For example, for an exchange group with two low-price bidders (*f* = *A*, *B*), it holds by construction that $DiffHarv_{Aet} = -DiffHarv_{Bet}$, and because the average probability of winning in this sample must be $1/n_{et}$, the marginal effect of $DiffHarv_{fet}$ must be equal for all values of the variable within the exchange group in the current month. In exchange groups with no entry and exit, the same holds for $PrevPM_{fet}$.

Table 3. Estimations of the probability of winning during competition.

Specification Estimator	1 OLS	2 OLS	3 Logistic	3 Logistic marginal effects	4 Logistic	4 Logistic marginal effects
$DiffHarv_{fet}$ (α_1)	−0.052*	−0.032**	−0.266**	−0.037*	−0.135*	−0.018*
	(0.025)	(0.013)	(0.119)	(0.017)	(0.073)	(0.010)
$PrevPM_{fet}$ (α_2)	−1.156***	−0.720***	−5.329***	−0.740***	−4.214***	−0.565***
	(0.025)	(0.008)	(0.125)	(0.034)	(0.051)	(0.011)
$PrevPM_{fet}$ (δ)	0.298***	0.460***	0.300***		0.434***	
	(0.021)	(0.009)	(0.024)		(0.010)	
$1/n_{et}$ (α_3)	0.881***	0.925***	4.149***	0.576***	4.791***	0.642***
	(0.050)	(0.025)	(0.237)	(0.007)	(0.119)	(0.004)
$PM\_22_{fe,t-l}$		0.150***			0.652***	0.087***
		(0.007)			(0.030)	(0.005)
$PM\_33_{fe,t-l}$		0.068***			0.318***	0.043***
		(0.005)			(0.026)	(0.004)
$PM\_44_{fe,t-l}$		0.033***			0.168***	0.023***
		(0.007)			(0.037)	(0.005)
Within R^2	0.133	0.130				
Log-l	−12,706.950	−49,883.216	−8,498.840		−40,087.184	
Observations	24,395	90,111	21,525		88,537	

Note: Standard errors are reported in parentheses. The standard errors are robust to correlation within exchange group × firm combinations for the linear probability specifications. *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% level with one-sided tests. Table A1 in Online Appendix A provides descriptive statistics and repeats variable definitions.

The signs of all parameter estimates reported in Table 3 align with our expectations, meaning they support the hypotheses that a firm sets a higher price, reducing the probability its product will become the PM, the larger the expected demand caused by state dependence, and the more it has recently sold. The effects of $DiffHarv_{fet}$ and $PrevPM_{fet}$ are larger in Specification 1 than in Specification 2. Because the sample used to estimate Specification 2 includes some short possible collusive patterns, this difference suggests that $DiffHarv_{fet}$ and $PrevPM_{fet}$ have no (or smaller) effects during collusions. The estimates for $PM\_ll_{fe,t-l}$ (l = 2, 3, 4) indicate that the identity of the PM in the larger sample is, in some cases, affected by bid rotations among 2–4 firms.

We use the estimates from Specification 1 to calculate values for al_{et} (l = 2, 3, 4, 5). These parameters describe the likelihood of selling a PM in auction *et* for a seller that sold a PM l months ago and has not sold a PM in the exchange group between that month and month t, relative to the average probability for selling a PM for a low-price bidder in auction *et*. We calculate separate values for each pair of l and $\breve{n}_{et}$, where $\breve{n}_{et} = n_{et}$ for $n_{et} \leq 5$ and $\breve{n}_{et} = 6$ for $n_{et} \geq 6$. Specifically, for each $\breve{n}$, we first replace the values of $DiffHarv_{fet}$ and

$PrevPM_{fet}$ with the mean values for all low-price bidders and predict the probability of $PM_{fet} = 1$, called $p\_\breve{n}_{fet}$. Next, we replace the values of $DiffHarv_{fet}$ and $PrevPM_{fet}$ with their mean values for each $\breve{n}$ and l and predict the probability of $PM_{fet} = 1$, called $p\_\breve{n}\mathrm{l}_{fet}$. Lastly, for each pair of $\breve{n}$ and *l*, we divide the mean of $p\_\breve{n}\mathrm{l}_{fet}$ by the mean of $p\_\breve{n}_{fet}$ and define al_{et} as the maximum of this quotient and $1/\breve{n}_{et}$. al_{et} is restricted to never fall below $1/\breve{n}_{et}$ primarily to avoid negative values, which otherwise could follow from a linear probability model, and we set the lower bound to $1/\breve{n}_{et}$ because the correct adjustment factor can be expected to be decreasing in $\breve{n}_{et}$. However, this restriction is only binding for $a1_{et}$ with $\breve{n}_{et} \geq 4$. The combined effect of $PrevPM_{fet}$ and $DiffHarv_{fet}$ gives the values of al_{et} reported in Table 4. The values for $a1_{et}$ reported in Table 4 show that the seller of a PM last month is less likely than other low-price bidders to sell a PM this month, and especially so in auctions with many low-price bidders. If this is not accounted for, the probability of a firm winning every n^{th} month during a competitive regime will be underestimated. Table 4 also show that the longer the time was since a low-price bidder sold a PM, the more likely is it—relative to its competitors—to sell a PM the current month. This effect is mainly driven by the variable $PrevPM_{fet}$.

Table 4. The relative probability during competition of selling a PM for a firm that sold a PM *l* months ago and has not sold a PM between that month and month *t*.

$al_{et} \backslash \breve{n}_{et}$	2	3	4	5	6
$a1_{et}$	0.682	0.365	0.250	0.200	0.167
$a2_{et}$	1.242	1.141	1.038	0.944	0.853
$a3_{et}$	1.400	1.383	1.329	1.269	1.203
$a4_{et}$	1.459	1.452	1.411	1.373	1.341
$a5_{et}$	1.500	1.490	1.463	1.436	1.409

Note: These parameter values only vary by $\breve{n}_{et}$.

Lastly, in addition to $S1_{et}$ defined above and for each value of $\breve{n}_{et}$, we define Sl_{et} for l = 2, 3, 4, and 5 as the probability of a firm marketing a low-price product in exchange group *e* in month *t* for those with $PM_{fe,t-l} = 1$ and no product being a PM between $t - l$ and *t*. These survival probabilities are provided in Table 5.

Table 5. Probability of selling a PM again after *l* months during competition.

$Sl_{et} \backslash \breve{n}_{et}$	2	3	4	5	6
$S1_{et}$	0.9390	0.9676	0.9712	0.9754	0.9803
$S2_{et}$	0.8511	0.9300	0.9408	0.9499	0.9571
$S3_{et}$	0.2674	0.6515	0.6891	0.7286	0.7840
$S4_{et}$	0.1302	0.4815	0.6261	0.6890	0.7319
$S5_{et}$	0.0605	0.3716	0.5598	0.6447	0.6716

Note: These parameter values only vary by $\breve{n}_{et}$.

IV.D. The competitive model in a nutshell

Because the cheapest product does not capture the entire market, price changes should be common, and firms should be unlikely to set the same price even if they have the same marginal costs. Therefore, it will be unlikely that the same firms end up being shared winners several months in a row during competition.

On average, the probability of being a single winner equals $(1 - PT_{et})/n_{et}$ for a low-price bidder, where PT_{et} is a probability of a tie. However, because of state dependence and stock quantity, a firm's probability of winning will depend on when it won last time. Therefore, we define $Al_{et} = al_{et}(1 - PT_{et})/n_{et}$ as the probability of being a single winner, conditional on marketing a low-price product, for a firm that last won *l* months ago.

In the next section, we use the parameters defined above (PT_{et}, Al_{et}, Sl_{et}, etc.) to calculate $P(W_{et}|K, \check{n}_{et})$, defined as the probability of observing the price pattern W_{et} conditioned on competition (*K*) and the truncated number of low-price bidders ($\check{n}_{et}$). That is, we calculate how common price patterns that are consistent with collusion would be under competition according to our competitive model.

V. Calculating probabilities of collusion based on price patterns

V.A. A method based on Bayes' theorem

Probability theory tells us that the probability of collusion (*S*) given an observed price pattern (W_{et}) can be calculated using Bayes' theorem:

$$P(K|W_{et}, \check{n}_{et}) = \frac{P(W_{et}|K, \check{n}_{et})P(K|\check{n}_{et})}{P(W_{et}|\check{n}_{et})}, \tag{4}$$

where and $P(S|W_{et}, \check{n}_{et}) \equiv 1 - P(K|W_{et}, \check{n}_{et})$. Recall that we focus on collusions involving each auction's winner(s). Therefore, the identity follows from the fact that there will or will not be a collusion involving the winner; no third possibility exists. To prevent the frequencies from being heavily influenced by just a few observations, the probabilities are conditioned on $\check{n}_{et}$ (recall that $\check{n}_{et} = n_{et}$ for $n_{et} \leq 5$ and $\check{n}_{et} = 6$ for $n_{et} \geq 6$), instead of n_{et}.

We proxy the denominator of Equation (4), $P(W_{et}|\check{n}_{et})$, with the observed frequencies in the data. We set $P(K|W_{et}, \check{n}_{et}) = 1$ for the 9% of the observations that are not part of any possible collusion patterns in Table 2. Then, note that $P(K|\check{n}_{et})$ is the weighted probability of competition for all price patterns. That is:

$$P(K|\check{n}_{et}) = \sum_{W=1}^{\bar{W}} P(K|W_{et}, \check{n}_{et})P(W_{et}|\check{n}_{et}) + 1 - \sum_{W=1}^{\bar{W}} P(W_{et}|\check{n}_{et}), \tag{5}$$

where $\bar{W}$ is the number of patterns consistent with collusion, so $1 - \sum_{W=1}^{\bar{W}} P(W_{et})$ is the share of observations with $P(K|W_{et}, \check{n}_{et}) = 1$ by definition. By substituting $(K|W_{et}, \check{n}_{et})$ using equation (4) and rearranging, we obtain Equation (6):

$$P(K|\check{n}_{et}) = \frac{1 - \sum_{W=1}^{\bar{W}} P(W_{et}|\check{n}_{et})}{1 - \sum_{W=1}^{\bar{W}} P(W_{et}|K, \check{n}_{et})}. \qquad (6)$$

What remains to be determined is $P(W_{et}|K, \check{n}_{et})$. As an example, let us start by explaining how $P(W_{et}|K, \check{n}_{et})$ is calculated for two firms winning every other month for at least 11 months (denoted $W_{et} = b2m11$)[7], when $\check{n}_{et}$ = 2 for all relevant months and under the hypothetical assumption that the probability of being a single winner is constant at 0.5 for each firm. In this hypothetical case, $P(b2m11|K, 2) = 1 - (1 - 2 \times 0.5^{11})^{11} \approx 0.01$. The first exponent is explained by the fact that the bid-rotation-like pattern must last 11 months, and the multiplication by two is because a pattern can start with either of the two firms winning. Note that 2×0.5^{11} = 1/1024 is the probability of observing an 11-month bid-rotation-like pattern in each 11-month window. Because we use moving windows so that $W_{et} = b2m11$ regardless of whether the pattern is observed from *t – 10* through *t*, or from *t – 9* through *t + 1*, and so on up to *t* through *t + 10*, $P(b2m11|K, 2)$ equals one minus the probability that exactly zero 11-month bid-rotation-like patterns have occurred during the eleven possible periods, which explains the rest of the formula. Also, note that $P(W_{et}|K, \check{n}_{et})$ is the probability of observing W_{et} if firms compete during all relevant months. Therefore, $P(S|W_{et}, \check{n}_{et})$ is the probability that there was collusion during at least one month during the price pattern.

When applying this method to the data, we must account for the fact that n_{et} varies over time. We do this by defining $P(W_{et}|K, \check{n}_{et})$ as the mean value of $P(W_{et}|K, \boldsymbol{n_{et}})$ for each value of $\check{n}_{et}$, where, $\boldsymbol{n_{et}}$ denotes a vector of n_{et} values affecting the probability of observing the pattern during competition. For example, for $b2m11$, $\boldsymbol{n_{et}}$ includes the values $n_{e,t-10}$ through $n_{e,t+10}$.

We must also account for autocorrelation in winning probabilities during competition and, for the patterns with an upper limit of the duration of the pattern, we must subtract the probability that a winning sequence exceeds this limit. All this complicates the calculation of $P(W_{et}|K,\boldsymbol{n_{et}})$. Equation (7) shows the formula for calculating $P(b2m11|K,\boldsymbol{n_{et}})$ when accounting for this:

$$P(b2m11_{et}|K, \boldsymbol{n_{et}}) = 1 - \prod_{T=t}^{t+10}(1 - Pb2m11_{eT}), \qquad (7)$$

where

[7] *b* indicates bid rotation, *2* indicates the number of firms involved in the pattern, and *m11* indicates that the duration is at least 11 months. Parallel-bidding-like patterns are denoted with an initial *p* instead of an initial *b*.

$$Pb2m11_{eT} = PS1_{e,T-10} PS2_{e,T-9} \prod_{m=T-8}^{T} C2_{em}. \quad (8)$$

For $b2m11$, the variable T denotes the 11th or later month with two alternating winners during at least 11 months, while $Pb2m11_{eT}$ denotes the probability during competition of observing two alternating winners from month $T-10$ (or earlier) to month T (or later). A difference between this and the case with constant $n_{et} = 2$ is that the probabilities vary across months and, therefore, we must multiply different probabilities instead of raising one probability to a power.

We define $PS1_{et} = (1 - PT_{et})$; that is, the probability that any firm is the single winner in month *t* equals one minus the probability of a tie. For the first observation in a price pattern (i.e., in $T-10$ in eq. [7]), the winning probabilities are not conditioned on any price pattern in other months. However, the winner in the second month in a bid rotation must differ from the winner in the first month. Therefore, we define $PS2_{et} = (1 - PT_{et} - C1_{et})$ as the probability that a firm other than the winner in month $t-1$ is the single winner in month *t*, where $C1_{et} = S1_{et}[U^{n_{et}} E^{n_{et}} + (1 - U^{n_{et}} E^{n_{et}}) A1_{et}]$ is the probability that the winner in the previous month is also the winner in this month. The equation reveals that $C1_{et}$ depends on the probability that the winner in the previous month markets a low-price product this month ($S1_{et}$), the probability that all low-price bidders submit the same bid as they did in the previous month ($U^{n_{et}}$) and were also low-price bidders in the exchange group in the previous month ($E^{n_{et}}$), and the probability that a firm has entered or changed their bid ($1 - U^{n_{et}} E^{n_{et}}$), so that there could be a new winner, and the probability that the winner in the previous month is the single winner this month conditional on it being a low-price bidder ($A1_{et}$) and there being a possibility for another winner to emerge. Recall from Section IV that $A1_{et} = a1_{et}(1 - PT_{et})/n_{et}$, where $a1_{et}$ corrects for autocorrelation caused by state dependence and stock quantity. We also define $C2_{et} = (1 - S1_{et} U^{n_{et}} E^{n_{et}}) S2_{et} A2_{et}$ as the probability that a firm that sold a PM two months earlier but not one month earlier is a single winner in month *t*.

The number of possible collusive participants can differ from the current number of potential low-price bidders (n_{et}). Consequently, the observed frequencies for some combinations of price patterns and $\check{n}_{et}$ are very low and, therefore, heavily influenced by just a few observations. To prevent this from causing imprecise estimates of $P(K|W_{et}, \check{n}_{et})$ when applying Bayes' theorem (eq. [4]), we group bid-rotation-like patterns with the same duration (e.g., ≥ 11 months) together, regardless of the number of firms involved. For example, we group $b2m11$, $b3m11$, $b4m11$, and $b5m11$ together in the price pattern b_m11 and calculate the following:

$$P(b\_m11_{et}|K,\boldsymbol{n}_{et}) = 1 - \prod_{T=t}^{t+10}\left(1 - \sum_{F=2}^{5} PbFm11_{eT}\right). \tag{9}$$

The probabilities $PbFm11_{eT}$ for 3–5 firms participating in the possible collusion (F = 3, 4, and 5) are defined in Equations (B.25)–(B.27) in Online Appendix B. A description of how $P(W_{et}|K,\check{n}_{et})$ is calculated for the other price patterns is also provided in Online Appendix B. As detailed in the following section, we also group the price patterns of different durations together when $P(W_{et}|\,\check{n}_{et})$ would otherwise take the value 0. In addition, we impose the restriction $P(W_{et}|K,\check{n}_{et}) \leq \frac{P(W_{et}|\check{n}_{et})}{P(K|\check{n}_{et})}$, which ensures that $P(K|W_{et},\check{n}_{et})$ never exceeds 1.

V.B. Predicted collusion probabilities

The results for $\check{n}_{et} = 2$ reported at the top of Table 6 indicate that most patterns consistent with bid rotations lasting 3–6 months arose in competitive regimes. However, 92.3% (99.7%) of bid-rotation-like patterns lasting 9–10 (≥11) months arose, at least partly, during collusive regimes. Table 6 shows that $P(W_{et}|K,\check{n}_{et})$ takes values close to 0 also for short parallel-bidding-like patterns. It also shows that parallel-bidding-like patterns are far more frequent than would be expected under competition for all durations when $\check{n}_{et} = 2$, resulting in high values of $P(S|W_{et},\check{n}_{et})$. Note also that $P(S|W_{et},\check{n}_{et})$ is always strictly less than 100%, and that $P(W_{et}|K,\check{n}_{et})$ is always strictly positive.

Figure 5 and Table 6 show that $P(W|S,\check{n}_{et})$ already exceeds 90% for bid-rotation-like patterns lasting 7–8 months when n_{et} equals 3 or 4 and for patterns lasting 5–6 months when $n_{et} \geq 5$ compared to 9–10 months for $n_{et} = 2$. Figure 5 also shows that for both bid rotation and parallel bidding and for all values of $\check{n}_{et}$, the probability of collusion increases with the duration of the pattern.

Table 6 also reports standard errors for $P(S|W_{et},\check{n}_{et})$, reflecting the uncertainty caused by sampling variability in the share of auctions belonging to each pattern. The large standard error for parallel-bidding-like patterns lasting 3–4 months when $n_{et} = 2$ is caused by the square of the derivative $dP(S|W_{et},\check{n}_{et})/d\,P(W_{et}|\check{n}_{et})$, by which the variance in $P(W_{et}|\check{n}_{et})$ is multiplied when calculating the variance in $P(S|W_{et},\check{n}_{et})$, takes a high value.[8]

[8] For bid-rotation-like patterns lasting 3–4 months when $\check{n}_{et} = 2$, $P(S|W_{et},\check{n}_{et})$ would remain 0 unless the share of observations with this price pattern increases from 18.73% to 20.82% since $P(W_{et}|K,\check{n}_{et})$ = 46.89% if the restriction $P(W_{et}|K,\check{n}_{et}) \leq \frac{P(W_{et}|\check{n}_{et})}{P(K|\check{n}_{et})}$ is not imposed. Similarly, for parallel-bidding-like patterns lasting 3–4 months, $P(S|W_{et},\check{n}_{et})$ would remain 0 unless the share of the observations in this category increases to 0.14% when $\check{n}_{et} = 3$ and to 0.10% as when $\check{n}_{et} = 4$ since $P(W_{et}|K,\check{n}_{et})$ equals 0.32% and 0.42%, respectively, if the restriction $P(W_{et}|K,\check{n}_{et}) \leq \frac{P(W_{et}|\check{n}_{et})}{P(K|\check{n}_{et})}$ is not imposed.

Table 6. Percentage probabilities of collusion conditioned on $\breve{n}_{et}$ and W_{et} for bid-rotation- and parallel-bidding-like patterns by duration.

Price pattern	Variable	Duration (months) 3–4	5–6	7–8	9–10	≥11	Sum
		Two low-price bidders					
Bid rotation	$P(S\|W_{et},\breve{n}_{et})$	0	28.19	66.08	92.25	99.67	
	S.e.	-	2.89	1.92	0.44	9.09×10^{-3}	
	$P(W_{et}\|K,\breve{n}_{et})$	42.17	15.26	3.84	0.92	0.27	62.45
	% of obs.	18.73	9.44	5.02	5.25	36.27	74.70
Parallel bidding	$P(S\|W_{et},\breve{n}_{et})$	62.93	99.34	99.99	100	100	
	S.e.	7.93	0.15	2.41×10^{-3}	1.94×10^{-5}	1.74×10^{-9}	
	$P(W_{et}\|K,\breve{n}_{et})$	0.27	4.06×10^{-3}	5.00×10^{-5}	5.62×10^{-7}	6.08×10^{-9}	0.27
	% of obs.	0.32	0.27	0.23	0.29	7.63	8.74
		Three low-price bidders					
Bid rotation	$P(S\|W_{et},\breve{n}_{et})$	46.45	67.08	92.18	98.46	99.92	
	S.e.	0.77	0.77	0.29	0.08	2.70×10^{-3}	
	$P(W_{et}\|K,\breve{n}_{et})$	62.36	16.47	1.49	0.14	1.85×10^{-2}	80.44
	% of obs.	49.16	21.12	7.82	3.83	9.79	91.71
Parallel bidding	$P(S\|W_{et},\breve{n}_{et})$	0	90.66	99.91	-	-	
	S.e.	-	6.60	6.47×10^{-2}	-	-	
	$P(W_{et}\|K,\breve{n}_{et})$	0.12	3.67×10^{-3}	3.60×10^{-5}	-	-	0.12
	% of obs.	0.05	0.02	0.02	-	-	0.08
		Four low-price bidders					
Bid rotation	$P(S\|W_{et},\breve{n}_{et})$	71.61	88.08	96.62	99.40	99.90	
	S.e.	0.85	0.40	0.19	5.53×10^{-2}	1.46×10^{-2}	
	$P(W_{et}\|K,\breve{n}_{et})$	57.48	19.41	0.95	4.67×10^{-2}	3.18×10^{-3}	77.90
	% of obs.	47.48	38.22	6.57	1.83	0.72	94.82
Parallel bidding	$P(S\|W_{et},\breve{n}_{et})$	0	-	-	-	-	
	S.e.	-	-	-	-	-	
	$P(W_{et}\|K,\breve{n}_{et})$	5.65×10^{-2}	-	-	-	-	5.65×10^{-2}
	% of obs.	1.33×10^{-2}	-	-	-	-	1.33×10^{-2}
		Five low-price bidders					
Bid rotation	$P(S\|W_{et},\breve{n}_{et})$	61.31	94.24	98.63	99.12	-	
	S.e.	3.23	0.40	0.15	0.28	-	
	$P(W_{et}\|K,\breve{n}_{et})$	50.79	20.95	0.77	2.77×10^{-2}	-	72.54
	% of obs.	22.54	62.48	9.72	0.54	-	95.28
		Six or more low-price bidders					
Bid rotation	$P(S\|W_{et},\breve{n}_{et})$	63.73	93.25	97.63	-	-	
	S.e.	6.68	1.02	0.70	-	-	
	$P(W_{et}\|K,\breve{n}_{et})$	44.79	20.73	0.66	-	-	66.18
	% of obs.	25.07	62.39	5.67	-	-	93.13

Note: $P(S|\breve{n}_{et} = 2) = 55.59\%$, $P(S|\breve{n}_{et} = 3) = 57.78\%$, $P(S|\breve{n}_{et} = 4) = 76.55\%$, $P(S|\breve{n}_{et} = 5) = 82.83\%$, and $P(S|\breve{n}_{et} = 6) = 79.70\%$. The number of observations for which the probabilities of collusion are calculated when $\breve{n}_{et}$ equals 2, 3, 4, 5, and ≥6 is 6,910; 12,038; 7,544; 2,036; and 335, respectively. S.e. denotes analytic standard errors for $P(S|W_{et},\breve{n}_{et})$; see also Footnote 11. Parallel-bidding-like patterns exceeding seven and three months when $\breve{n}_{et}$ equals 3 and 4, respectively, are grouped together. There were no parallel-bidding patterns lasting ≥3 months when $n_{et} > 4$. Bid-rotation-like patterns exceeding nine and seven months when $\breve{n}_{et}$ equals 5 and 6, respectively, are grouped together.

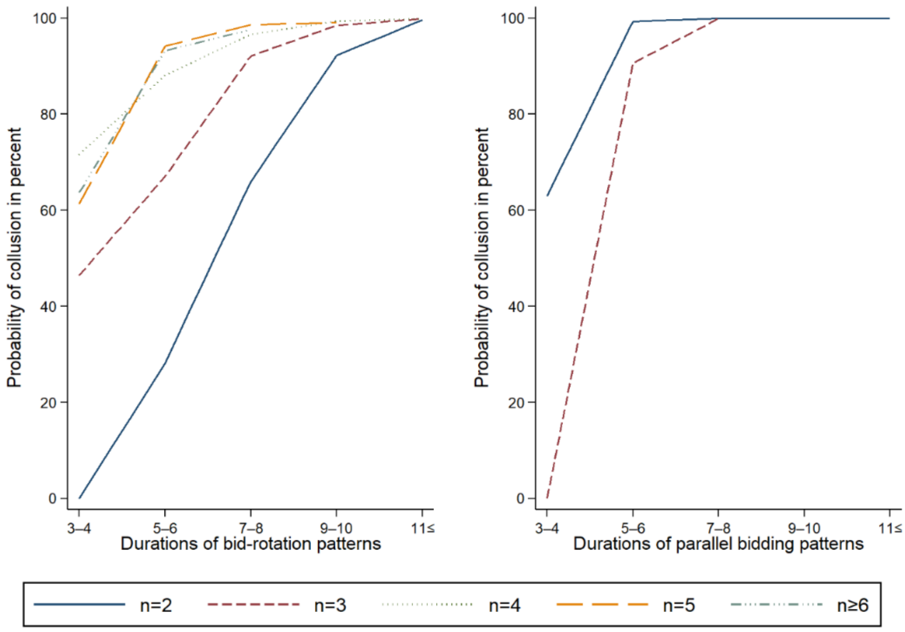

Figure 5. *Probability of collusion for patterns consistent with bid-rotation (left panel) and parallel-bidding (right panel) of different durations and for different numbers of low-price bidders (n).*

Together, the estimates of $P(S|W_{et},\breve{n}_{et})$ reported in Table 6 and the number of observations for each pattern suggest that 2% of the 28,863 studied auctions are part of parallel-bidding patterns that are at least partly caused by collusion. In contrast, 62% of the studied auctions are part of bid-rotation patterns that are at least partly caused by collusion. Of the 64% of the studied auctions expected to be part of collusive patterns, 56% have a value of $P(S|W_{et},\breve{n}_{et})$ below 0.90, while 70% have a value of $P(S|W_{et},\breve{n}_{et})$ below 0.95. This finding implies that 19% (= 64% × [1 – 0.70]) of the auctions are part of patterns that significantly deviate from competition at the 5% level. Therefore, while the number of auctions expected to be part of collusive patterns is high, the proportion of auctions that are part of patterns significantly deviating from competitive behavior falls short of the 37% estimate obtained by Kawai and Nakabayashi (2022) for construction contracts in Japan.

Note that the method presented in this section does not require production costs to be estimated, and neither rests on assumptions of rationality being common knowledge or that firms never make mistakes. We consider this an advantage since imposing inaccurate assumptions can give biased estimates of the prevalence of collusion. However, since the estimated probabilities depend on the parameter values derived in Section IV, we investigate how sensitive the results are to these values. First, we make naïve calculations where the effects of state dependence and stock balance on the probability of selling the cheapest product are ignored—that is, we set $a_{let} = 1$ for l = 1–5. These naïve calculations produce considerably higher values of $P(S|W_{et},\breve{n}_{et})$, especially for short bid-rotation-like patterns. For example, for $n_{et} = 2$ and bid-rotation-like patterns lasting 3–4 and 5–6 months, $P(S|W_{et},\breve{n}_{et})$ increased by

37 and 48 percentage points (pps), respectively, and the mean value of $P(S|W_{et},\check{n}_{et})$ over all 28,863 auctions increased from 64% to 80%. These findings demonstrate that accounting for the autocorrelation in the probability of selling the cheapest product that arises under competition is important.

If, in addition to setting $al_{et} = 1$ for l = 1–5, we also ignore the propensity to leave prices unchanged by setting U = 0, we obtain a similar mean for $P(S|W_{et},\check{n}_{et})$ of 79%. Furthermore, by disregarding changes in the identity of the low-price bidders by setting E = 1 and $Sl_{et} = 1$ for l = 1–5, we again obtain a mean for $P(S|W_{et},\check{n}_{et})$ of 80%. That is, when $al_{et} = 1$, the values of U, E, and Sl_{et} only have minor effects on the mean of $P(S|W_{et},\check{n}_{et})$. If we instead set al_{et} to the preferred values, setting U = 0, E = 1, and $Sl_{et} = 1$ for l = 1– 5, the mean of $P(S|W_{et},\check{n}_{et})$ reduces from 64% in the main analyses to 61%, indicating an interaction between the effect of the different parameters. In Online Appendix C, we also show that we obtained similar results, with the same mean for the probability of collusion, when using active instead of potential low-price bidders in the calculations.

VI. A higher probability of collusion leads to higher prices

In this section, we first present a simple specification (5) to demonstrate that prices are positively associated with the probability of collusion. Then, we add control and interaction variables to obtain estimates of the causal effect of collusion on prices. In all specifications, we use the natural logarithm of the average price per unit (e.g., pill or gram), weighted by the number of units sold within an exchange group and month (lnP_{et}) as the dependent variable.

In Specification 5, we only control for fixed effects for each active ingredient and year × month fixed effects. Because the estimation sample is restricted to exchange groups with generic alternatives that have had at least two low-price bidders for at least ten months, this simple regression can provide us with some idea of the price effect of collusion. However, we identify four potentially important drawbacks with this model, which we then address in turn. The first concern is that prices are correlated with the number of bidders because of the effect of prices on entry and exit and the causal price effects of the number of bidders, and that, at the same time, the number of bidders is correlated with the probability of collusion. We address this by controlling for the number of active bidders ($lnnbida_{et}$) and the number of active bidders in the low-price segment ($lnna_{et}$).[9] We also control for the natural logarithm of the

[9] The correlation between the number of potential bidders ($nbid_{et}$) and the number of active bidders ($nbida_{et}$) is high (0.99), and the correlation between the number of active low-price bidders (na_{et}) and the number of potential low-price bidders (n_{et}) is also high (0.98). We control for active bidders because this should affect the expected minimum price even if all firms randomize prices from the same distribution and we find stronger instruments for

number of available different active ingredients within the same therapeutic group (*$lnThAlt_{et}$*). More therapeutic alternatives can increase price competition across drugs with different active ingredients because recommendations to physicians regarding which drug to consider first for different patient groups are partly determined by relative prices. Moreover, given the finding of Granlund and Bergman (2018) that prices fall faster the shorter the time from patent expiration, we control for *$lnMonths\_PatG_{et}$*, defined as the natural logarithm of the number of months since patent expiration or, when this data is missing, from generic entry in Sweden.

The second concern is that prices vary across exchange groups due to the differences in administrative forms, strengths, and package sizes. We address this in two ways: i) by including 20 indicator variables for administrative form (*$form_e$*) and the natural logarithms of the strength (*$lnStrength_e$*) and the package size (*$lnSize_{et}$*);[10] ii) by replacing the fixed effects for active ingredients with exchange group fixed effects, exploiting the fact that we have variation over time in $P(S|W_{et}, \check{n}_{et})$ for exchange groups accounting for 97% of the auctions, and that the mean spread in $P(S|W_{et}, \check{n}_{et})$ within these exchange groups is as high as 0.88. With fixed effects for exchange groups and year × month combinations, we thus study differences in price changes across exchange groups with different changes in the probability of collusion.

The third concern is that prices do not adjust immediately to new competitive environments. One reason is that firms' expectations regarding competitors' future bids can depend on past bids. Another reason is that the dynamic price cap gives firms selling the most expensive alternative within an exchange group an incentive to adjust prices gradually to new market environments,[11] and the price of the most expensive alternative can affect the prices of cheaper alternatives. For the specifications with fixed effects for active ingredients, we address this autocorrelation simply by allowing the error term to be correlated across observations with the same active ingredient. We do not include lags of the dependent variable in these specifications since their estimators would be biased by unexplained time-invariant variation across exchange groups. In specifications with exchange group fixed effects, the parameters of interest are only

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$lnnbida_{et}$ and $lnna_{et}$ among those that should be valid according to logic and tests. We obtain similar results for the OLS specifications when using potential bidders.

[10] Examples of administrative forms are ordinary tablets and capsules, tablets and capsules with extended release, solutions, eye preparations, and powders. *$Strength_e$* is the amount of active ingredient per unit (e.g., milligram per pill). *$Size_{et}$* is defined as the average size of packages sold (e.g., number of pills per package) in exchange group *e* in month *t*, weighted by the number of packages of each product sold.

[11] If a seller of the most expensive alternative is uncertain about how much its optimal price is reduced when, for example, a new firm enters the exchange group, it is because the price cap better off starting with a small price reduction and then complementing it with an additional price cut if the first is found to be too small. If it instead starts with a price cut that, in retrospect, is too large, it cannot be reversed because of the dynamic price cap, which is described in greater detail in Section II. Consequently, dynamic specifications have been used before when analyzing determinants of prices in this market (Bergman et al., 2017; Granlund and Bergman, 2018).

identified using variation over time. Therefore, it is important to model price dynamics to prevent the parameters from describing something in between the variables' short- and long-term effects.[12] We use the Akaike information criterion (AIC) to determine how many lags of the dependent variable should be included. The AIC is minimized by including four lags for both ordinary least squares (OLS) and instrumental variable (IV) specifications. That more than one lag should be included is expected since the value of P_{et} is influenced by price randomization during competition and temporary variations in how market shares relate to the relative prices.[13]

The fourth concern is that the variables $lnnbida_{et}$ and $lnna_{et}$ can be endogenous because high prices can increase entry and decrease exit. However, it is also possible that $lnnbida_{et}$ and $lnna_{et}$ are exogenous because the decision to be an active bidder in month *t*—that is, having a price for this month—must be taken at the latest in month *t – 2* when prices must be submitted. If there is no autocorrelation in the error term, firms are unlikely to be able to predict the value of ε_{et} when they make the entry and exit decisions that affect the values of $lnnbida_{et}$ and $lnna_{et}$. Therefore, we test for autocorrelation in the true regression error using the test proposed by Cumby and Huizinga (1992), which allows for some regressors (e.g., lags of the dependent variable) to be only weakly exogenous. This test, implemented in STATA by Baum and Schaffer (2013), rejected the null hypothesis of no autocorrelation of order two at the 5% level for the first dynamic OLS specification. Therefore, we also estimated a model accounting for first- and second-order serial correlation using generalized least squares, which indicated that the estimated correlation is −0.17 between ε_{et} and $\varepsilon_{e,t-1}$ and −0.12 between ε_{et} and $\varepsilon_{e,t-2}$. The low absolute value for the correlation between ε_{et} and $\varepsilon_{e,t-2}$ suggests that the endogeneity problem is largely resolved by the fact that the entry and exit decisions affecting $lnnbida_{et}$ and $lnna_{et}$ must be made in month *t – 2* instead of month *t*. Nonetheless, we also estimate IV specifications using $lnnbida_{e,t-1}$, $lnn_{e,t-1}$, and $lnQ_{e,t-3}$ as instruments, and we discuss the relevance and validity of these instruments in Online Appendix D. Using predicted values for $lnnbida_{et}$ and $lnna_{et}$ to resemble the IV estimation, we cannot reject any of the null hypotheses of no autocorrelation of order one to four at the 5% level.

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[12] In an extreme case with an explanatory indicator variable alternating between 0 and 1 each month, the estimator would only capture the short-term effect in a static model with exchange group fixed effects. In general, the more persistent the explanatory variable is, the closer the estimate from such a model will be to the long-run effect.

[13] Simultaneously including lagged dependent variables and fixed effects can cause Nickell bias, but as we have many time periods per exchange group, this bias is expected to be small. According to Nickell (1981), the limit of the bias for the parameter θ as N̰ approaches infinity can be approximated by –(1 + θ)/(T − 1), where N̰ and T are the number of fixed effects and time periods, respectively. With T averaging 32.4 and the estimates for the lagged dependent variable, we expect biases of approximately −0.03 to −0.04.

Lastly, we include interaction terms between $P(S|W_{et},\check{n}_{et})$ and $lnnbida_{et}$ and $lnna_{et}$ to allow the effect of collusion to differ by the number of bidders and prices to fall with the number of bidders at different speeds in competitive and collusive regimes. The equation with interactions is written as follows:

$$lnP_{et} = \sum_{l=1}^{4} \theta_l lnP_{e,t-l} + \beta_1 P(S|W_{et},\check{n}_{et}) + \beta_2 P(S|W_{et},\check{n}_{et}) lnnbida_{et} + \beta_3 P(S|W_{et},\check{n}_{et}) lnna_{et} + \beta_4 lnnbida_{et} + \beta_5 lnna_{et} + \beta_6 lnThAlt_{et} + \beta_7 lnMonths\_PatG_{et} + \eta_t + \mu_e + \varepsilon_{et}, \quad (10)$$

where η_t and μ_e are year × month and exchange group fixed effects, respectively, and ε_{it} is the error term, which is allowed to be correlated among observations for products with the same active ingredient. We estimate Equation (10) with OLS (spec. 9) and IV (spec. 10), where $lnnbida_{et}$ and $lnna_{et}$ and their two interactions are treated as endogenous and $P(S|W_{et},\check{n}_{et})lnnbida_{e,t-1}$ and $P(S|W_{et},\check{n}_{et})lnna_{e,t-1}$ are used as additional instruments.

The derivative $dlnP_e^*/dP(S|W_e^*,\check{n}_e^*)$ reported in Table 7 shows the long-term effect of collusion on logarithmic prices, which for the specifications with interactions (9 and 10) are calculated at within-sample means for $lnnbida_{et}$, and $lnna_{et}$. This derivative is translated into percentage effects on prices of going from competition to collusion $(dP_e^*/dP(S|W_e^*,\check{n}_e^*)\%)$ using the formula $100 \times [\exp(dlnP_e^*/dP(S|W_e^*,\check{n}_e^*)) - 1]$. In addition, calculations not reported in the tables show that, on average, 67%–68% of the long-term effect is realized within three months and 87% within six months for Specifications 9 and 10.

All specifications show that an increase in the predicted collusion probability increases prices significantly. According to the static Specifications 5 and 6, collusion increases prices by 30%–31% (95% confidence interval: 17%–43% and 19%–42%, respectively). However, since they do not differentiate between short- and long-term effects, this is likely an overestimation of the short-term effect and an underestimation of the long-term effect.

Interestingly, adding control variables has negligible effects on the estimated effect. Adding exchange group fixed effects and lags of the dependent variable is more important, as we do in Specifications 7–10. According to these specifications, collusions increase prices by 49%–65% in the long term.

The results show that the collusion effect increases with $lnnbida_{et}$ and, according to the estimates for $P(S|W_{et},\check{n}_{et})lnna_{et}$, possibly at a lower rate when increases in this variable are caused by more low-price bidders rather than by more high-price bidders. With one high-price bidder so that $nbida_{et} = na_{et} + 1$, the estimated coefficients for Specification 10 imply that, in the long term, collusion increases prices by 37%, 57%, and 75% when the number of low-price bidders equals 2, 3, and 4, respectively. Therefore, in relative terms, price increases caused by collusion increase with the number of bidders, given that the bidders manage to form and maintain a collusion. However, the price effect of collusion in SEK is relatively stable because the competitive prices fall fast with $nbida_{et}$ and na_{et}. In addition, note that the collusive prices fall with $nbida_{et}$ since the sum of the coefficients for $P(S|W_{et}, \breve{n}_{et}) lnnbida_{et}$ and $lnnbida_{et}$ is negative.

Price effects reported for suspected collusion are below 20% (Baldwin et al., 1997; Price, 2008; Athey et al., 2011; Byrne and de Roos, 2019; Schurter, 2020), while the meta-analyses of Connor and Bolotova (2006) and Connor (2014) reported average price effects in convicted cartels of 29% and 23%, respectively. Our findings are more in line with those of Barkley (2023) who documented price reductions of 78% following the collapse of a collusion among insulin sellers in Mexico and those of Clark et al. (2022) and Starc and Wollmann (2022) concerning the impact of the alleged U.S. generic pharmaceuticals cartel. Starc and Wollmann observed average price increases of 45%–50%, while Clark et al. reported increases of 0%–166%, depending on the pharmaceutical compound.

In addition to the specifications presented in Table 7, we also estimated a version of Specification 6 where $P(S|W_{et}, \breve{n}_{et})$ is replaced by an indicator variable that takes the value 1 when $P(S|W_{et}, \breve{n}_{et})$ exceeds 0.90. This indicator variable increases the price by 13% (standard error [s.e.] = 3%), indicating that the price effects of collusions can be significantly underestimated if all the observations not considered collusive with 90% certainty are treated as competitive. A key reason for this, of course, is that many observations with $P(S|W_{et}, \breve{n}_{et}) < 0.90$ are likely to be affected by collusions, also raising prices in this group. Indeed, 56% of the observations predicted to be affected by collusion, and an equally large share of the sales, have a value of $P(S|W_{et}, \breve{n}_{et})$ below 0.90.[14]

We also simulate what the prices would have been if $P(S|W_{et}, \breve{n}_{et})$ had equaled 0 from September 2015 onwards using Specification 10. The simulations indicate that the weighted average price increase caused by collusion during the estimation period is 51% (s.e. = 4%).[15] In the estimation sample, the pharmacies' total purchase costs for the drugs amounted to 10,182 million SEK during the 51 months studied—on average, 2,396 million SEK (233 million USD) per year. Without the price increases of 51% due to collusion, the cost for these would have been 29%[16] (s.e. = 1%), or 694 (s.e. = 28) million SEK, lower per year.

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[14] Granlund and Rudholm (2023) reported in section 7.2 that an increase in $P(S|W_{et}, \breve{n}_{et})$ reduces the variation in prices of low-price bidders over time within a price pattern and variation in prices across products within a given auction. That paper also reports some additional robustness analyses and discusses estimates for controls.

[15] The standard error is obtained by making 1000 draws from the distribution of the parameter estimates for the three variables including $P(S|W_{et}, \breve{n}_{et})$ and the four lags of the dependent variable, and for each draw simulating the weighted average price increase during the estimation period.

[16] Note that this is not identical to $1-1/1.51$ because this expression is a non-linear function of the denominator, which varies across observations.

Table 7. Estimation results for the effect of $P(S|W_{et}, n_{et})$ on lnP_{et}.

Specification	5	6	7	8	9	10
Estimator	OLS	OLS	OLS	IV	OLS	IV
$lnP_{e,t-1}$			0.366***	0.363***	0.364***	0.360***
			(0.019)	(0.019)	(0.019)	(0.018)
$lnP_{e,t-2}$			0.206***	0.204***	0.206***	0.205***
			(0.013)	(0.013)	(0.013)	(0.013)
$lnP_{e,t-3}$			0.096***	0.095***	0.096***	0.095***
			(0.013)	(0.013)	(0.013)	(0.013)
$lnP_{e,t-4}$			0.062***	0.061***	0.062***	0.061***
			(0.013)	(0.013)	(0.013)	(0.013)
$P(S\|W_{et}, \breve{n}_{et})$	0.264***	0.268***	0.108***	0.122***	−0.061*	−0.094*
	(0.051)	(0.045)	(0.012)	(0.018)	(0.027)	(0.037)
$P(S\|W_{et}, \breve{n}_{et})lnnbida_{et}$					0.178***	0.196***
					(0.028)	(0.034)
$P(S\|W_{et}, \breve{n}_{et})lnna_{et}$					−0.071*	−0.047
					(0.034)	(0.051)
$lnnbida_{et}$		−0.724***	−0.210***	−0.247***	−0.304***	−0.352***
		(0.078)	(0.030)	(0.039)	(0.036)	(0.044)
$lnna_{et}$		−0.099	−0.099***	−0.140***	−0.095***	−0.156*
		(0.065)	(0.017)	(0.040)	(0.027)	(0.061)
$lnThAlt_{at}$		−0.064	−0.039	−0.039	−0.036	−0.034
		(0.089)	(0.026)	(0.026)	(0.026)	(0.026)
$lnMonths\_PatG_{at}$		−0.499*	−0.094	−0.102	−0.085	−0.092
		(0.226)	(0.060)	(0.059)	(0.058)	(0.057)
$lnStrength_e$		0.239*				
		(0.094)				
$lnSize_{et}$		−0.199***				
		(0.033)				
$dlnP_e^*/dP(S\|W_e^*, \breve{n}_e^*)$	0.264***	0.268***	0.399***	0.441***	0.444***	0.503***
	(0.051)	(0.045)	(0.053)	(0.077)	(0.054)	(0.088)
$dP_e^*/dP(S\|W_e^*, \breve{n}_e^*)\%$	30.150***	30.676***	49.076***	55.459***	55.879***	65.344***
	(6.584)	(5.853)	(7.945)	(11.974)	(8.480)	(14.608)
Active Ingre. FE	yes	yes	no	no	no	no
Form FE	no	yes	no	no	no	no
Exchange group FE	no	no	yes	yes	yes	yes
Year × month FE	yes	yes	yes	yes	yes	yes
R^2	0.803	0.866	0.458	0.457	0.460	0.459
Log-*l*	−27,917	−22,358	−3,328	−3,352	−3,280	−3,303
N	28,863	28,863	28,851	28,851	28,851	28,851
K-P rk LM				96.229		89.790
K-P rk LM, p-v.				0.000		0.000
Hansen J, p-v.				0.084		0.080

Note: Standard errors robust to correlation across observations for products with the same active ingredient are reported in parentheses. The derivative $dlnP_e^*/dP(S|W_e^*, \breve{n}_e^*)$ shows the long-term effect of collusion on logarithmic prices calculated at within-sample means for $lnnbida_{et}$, and $lnna_{et}$, when all auctions are weighted equally, and $dP_e^*/dP(S|W_e^*, \breve{n}_e^*)\%$ equals $100\times\left(exp\left(dlnP_e^*/dP(S|W_e^*, \breve{n}_e^*)\right) - 1\right)$. Twelve exchange groups have only one observation each and are, therefore, dropped in Specifications 7–10. For specifications with exchange group fixed effects, within R^2 values are reported. K-P rk LM refers to the Kleibergen-Paap rk LM statistic, which indicates the strength of the instruments. The null hypothesis in the K-P test is that the model is under-identified. The null hypothesis for the Hansen J test is that the instruments are valid (i.e., uncorrelated with the error term). *, **, and *** indicate a statistically significant difference from 0 at the 5%, 1%, and 0.1% significance level, respectively. Table A1 in Online Appendix A provides descriptive statistics and repeats variable definitions.

VII. Market characteristics and the probability of collusion

This section aims to estimate the effect of the number of bidders, multimarket contact, and other variables on the probability of collusion ($P(S|W_{et}, \check{n}_{et})$).

We start by estimating a simple specification (11) with the number of bidders as the only explanatory variable and no fixed effects. In Specification 12, we add indicator variables for year × month combinations and other explanatory variables, as described below, and in Specification 13, we also add fixed effects for exchange groups. Thus, in Specification 13, we study differences in changes in the probability of collusions across exchange groups with different changes in the number of bidders.

If firms have been able to coordinate on a collusive behavior and maintain it until at least month $t-1$, they will likely collude also in month t. Therefore, we add $P(S|W_{e,t-1}, \check{n}_{e,t-1})$ as an explanatory variable in Specifications 14–16.[17]

We use two bidders as our reference category and include indicator variables for three, four, or five or more active bidders (I$\{nbida_{et} = m\}, for\ m = 3, 4, or \geq 5$) and the continuous variable $nbida6_{et} = max\{0, nbida_{et} - 5\}$. In the estimation sample, $nbida_{et}$ equals 6 for 14% of the auctions and ≥7 for 16%. We use a continuous variable to capture this variation instead of indicator variables to reduce the number of endogenous variables and because estimation results (not reported in the tables) suggest that the additional effect of an additional bidder is already small at $nbida_{et} = 6$. We use $nbida6_{et}$ instead of $nbida_{et}$ because otherwise estimates for $nbida_{et}$ must also be included when interpreting what the results say about the effect of, for example, a third bidder.

The three dummy variables, I$\{nbida_{et} = m\}\ for\ m = 3, 4, or \geq 5$, and $nbida6_{et}$ can all be endogenous because higher prices caused by collusion can increase entry and decrease exit (Starc and Wollmann, 2022). In Specifications 14–16, we address this by using the possibly endogenous variables' three-month lags and $lnQ_{e,t-3}$ as an instrument, but for the static specifications (11–13) we find no strong and valid instruments and therefore present only OLS results. The relevance and validity of the instruments are discussed in Online Appendix D.

As Bernheim and Whinston (1990) and Spagnolo (1999) observed, multimarket contact pools the incentive constraints from all the markets served by the firms and can, therefore, increase the probability of collusion. We defined MMC_low_{et} as the average over each pair of low-price bidders in an exchange group of the total number of exchange groups (E) the bidders currently have contact in as low-price bidders. This definition follows the definition of Evans

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[17] We have estimated models with up to four lags, and Akaike's Information Criterion is minimized when including only one lag. Also, the coefficient estimates for the second to fourth lags are below 0.02 in absolute value.

and Kessides (1994), except that we only look at contact between low-price bidders since we are studying collusion involving low-price bidders. To be exact, we define

$$alow_{klt} = \sum_{e=1}^{E} Dlow_{ket} Dlow_{let} \qquad k = 1, 2, \ldots \underline{F} - 1; l = k + 1, k + 2, \ldots \underline{F}, \qquad (11)$$

where $Dlow_{fet}$ for $f = k$, l denotes dummy variables taking the value 1 if low-price bidder f marketed a product in exchange group e in month t, and $\underline{F}$ is the number of low-price bidders marketing products within the PM system during month t. Then,

$$MMC\_low_{et} = \frac{1}{[n_{et}(n_{et} - 1)/2]} \sum_{k=1}^{\underline{F}-1} \sum_{l=k+1}^{\underline{F}} alow_{klt} Dlow_{ket} Dlow_{let}. \qquad (12)$$

As described by Ciliberto and Williams (2014), measures of multimarket contact depend on the identity of bidders in a market and can also correlate with unobservables affecting prices and, therefore, be endogenous. In our setting, the dependent variable is not prices but rather the probability of collusion, and we are primarily concerned that firms active in more markets might be more able to collude purely because of experience. To prevent this from being captured by the multimarket variables, we include $Markets\_low_{et}$, which is the average over low-price bidders in auction *et* of the number of auctions the bidders participate in as a low-price bidder. Following Ciliberto and Williams, we include the squares and cubes of the multimarket contact variables because we expect the marginal effect of multimarket contact to decline, and we also include squares and cubes of $Markets\_low_{et}$.

We also include proxies for entry barriers, cost and quality differences, heterogeneity, capacity, and variation in demand since theory predicts that these should affect the probability of collusion. Online Appendix E describes these proxies and presents their estimation results, OLS results for Specifications 14–16, and IV results for Specification 14 when one-month or six-month lags of the endogenous variables are used as instruments instead of three-month lags.

Specification 14 is written as follows:

$$P(S|W_{et}, \breve{n}_{et}) = \Theta P(S|W_{e,t-1}, \breve{n}_{e,t-1}) + \sum_{m=3}^{\geq 5} \gamma_m I\{nbida_{et} = m\} + \zeta nbida6_{et} + \sum_{d=1}^{3} \eta_m MMC\_low_{et}^{d} + \sum_{d=1}^{3} \vartheta_m Markets\_low_{et}^{d} + \boldsymbol{X_{et}\kappa} + \lambda_t + \nu_e + \epsilon_{et}, \qquad (13)$$

where $\boldsymbol{X_{et}}$ consists of the proxies defined in Online Appendix E; Θ, γ, ζ, η, ϑ, and $\boldsymbol{\kappa}$ are parameters to be estimated; λ_t and ν_e are year × month and exchange group fixed effects; and ϵ_{et} is the error term, which is allowed to be correlated among observations for products with the same active ingredient.

Specification 15 differs from Specification 14 in that it uses potential instead of active bidders. To determine whether the different types of bidders affect the probability of collusion differently, Specification 16 also includes indicator variables for the number of bidders marketing locally sourced generics ($nlsGena_{et}$) and uses their third lags as instruments.

Table 8 Estimation results for the determinants of the probability of collusion

Specification	11	12	13	14	15	16
Estimator	OLS	OLS	OLS	IV	IV	IV
$P(S \mid W_{e,t-1}, \check{n}_{e,t-1})$				0.595***	0.594***	0.593***
				(0.009)	(0.009)	(0.009)
$nbida_{et} = 3$	−0.169***	−0.219***	−0.150***	−0.104***	−0.091**	−0.089*
	(0.029)	(0.029)	(0.034)	(0.031)	(0.029)	(0.039)
$nbida_{et} = 4$	−0.192***	−0.266***	−0.194***	−0.159***	−0.142***	−0.125**
	(0.025)	(0.028)	(0.041)	(0.034)	(0.033)	(0.040)
$nbida_{et} \geq 5$	−0.182***	−0.278***	−0.195***	−0.187***	−0.176***	−0.130**
	(0.026)	(0.028)	(0.038)	(0.032)	(0.030)	(0.043)
$nbida6_{et}$	0.017**	0.011*	0.003	−0.011	−0.008	−0.008
	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.006)
$nlsGena_{et} = 2$						−0.196***
						(0.054)
$nlsGena_{et} = 3$						−0.184**
						(0.061)
$nlsGena_{et} = 4$						−0.235***
						(0.062)
$nlsGena_{et} \geq 5$						−0.243***
						(0.065)
MMC_low_{et}		0.014***	0.019***	0.013***	0.013***	0.013***
		(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$MMC\_low^2_{et}$ ($\times 10^{-4}$)		−1.654***	−2.108***	−1.415***	−1.419***	−1.403***
		(0.339)	(0.373)	(0.233)	(0.234)	(0.227)
$MMC\_low^3_{et}$ ($\times 10^{-7}$)		5.367***	6.598***	4.424***	4.476***	4.384***
		(1.486)	(1.417)	(0.916)	(0.923)	(0.894)
$Markets\_low_{et}$ ($\times 10^{-3}$)		1.109	2.055	1.728	1.677	2.211*
		(1.878)	(1.667)	(0.926)	(0.939)	(0.955)
$Markets\_low^2_{et}$ ($\times 10^{-5}$)		−1.895	−3.452*	−2.636**	−2.595**	−2.848**
		(1.932)	(1.633)	(0.877)	(0.889)	(0.881)
$Markets\_low^3_{et}$ ($\times 10^{-8}$)		5.112	8.171	6.073**	5.975**	6.366**
		(5.009)	(4.247)	(2.272)	(2.297)	(2.271)
Exchange group FE	no	no	yes	yes	yes	yes
Year × month FE	no	yes	yes	yes	yes	yes
Other controls	no	yes	yes	yes	yes	yes
R^2	0.031	0.077	0.056	0.399	0.399	0.399
Log-l	−7,899	−7,193	−2,685	3,759	3,743	3,763
N	28,863	28,863	28,851	27,888	27,888	27,888
K-P rk LM				51.696	54.054	58.363
K-P rk LM, p-v.				0.000	0.000	0.000
Hansen J, p-v.				0.718	0.767	0.669

Note: Results for other control variables are presented in Online Appendix E. Specification 15 includes variables for potential bidders instead of corresponding variables for active bidders. Standard errors robust to correlation among products with the same active ingredient are reported in parentheses. *, **, and *** indicate a statistically significant difference from 0 at the 5%, 1%, and 0.1% significance level, respectively. See also the notes for Table 7.

The estimation results show that a third bidder significantly reduces the probability of collusion in all specifications. According to the point estimates for the IV specifications, the incremental effect of a fourth bidder—that is, the difference between the point estimates for the fourth and the third bidder—is approximately half as large as the effect of the third bidder. For Specifications 14 and 15, it also holds that the incremental effect of the fifth bidder is around half as large as the incremental effect of the fourth bidder, but it is only for Specification 15 that the incremental effect of the fifth bidder differs significantly from 0. For the other specifications, the incremental effects of the fourth and fifth bidders are smaller, and we do not find a significant reduction in the probability of collusion when the number of bidders increases above five (i.e., the effect of $nbida6_{et}$ is not significantly negative) for any specification. Thus, the results indicate that the effects of additional bidders decline rapidly.

How strong, then, is the effect of the number of bidders on the likelihood of collusion? According to Specification 14, a third bidder reduces the probability of collusion by 10.4 pps in the short term and by 26 pps $[\approx (-0.104)/(1-0.595)]$ in the long term (s.e. = 7.7 pps). The effect is similar for Specifications 15 and 16, and, despite endogeneity, the estimate for the static OLS Specification 12 of –22 pps is comparable to the long-term estimates of the dynamic IV specifications. Comparing the long-term estimates of Specification 14 for four or five or more bidders (–39 and –46 pps, respectively) with the corresponding estimates for Specification 12 (–27 and –28 pps, respectively) indicates that variations in a higher number of bidders might be more endogenous, which is supported by the significant positive estimate for $nbida6_{et}$ for two of the OLS specifications.

The estimated effects can be compared with that the average probability of collusion is estimated to 79% for the 11% of the estimation sample with only two bidders. Therefore, according to Specification 14, the probability of collusion is half as large with four bidders as with two bidders. Then, the probability falls by an additional 6.8 pps $[\approx (-0.187+0.159)/(1-0.595)]$ when a fifth bidder enters and by 2.7 pps $[\approx (-0.011)/(1-0.595)]$ for each additional bidder thereafter. However, the latter effect is not significantly different from 0.

The similarities between the estimates of Specifications 11 and 12 indicate that correlations between the number of bidders and the other explanatory variables are relatively weak. That the estimates for the number of bidders are closer to 0 in Specification 13 than in Specification 12 is expected since introducing exchange group fixed effects should move the estimates towards the short-term effects. Comparing Specifications 14 and 15 reveals that the number of actual and potential bidders has a similar effect on the probability of collusion, even though the point estimates for potential bidders generally is a half to a third standard error closer to 0 than the corresponding estimate for active bidders. These similarities are expected because of the high correlation between these two variables.

Specification 16 shows significant negative effects for the indicator variables for two, three, four, or five or more bidders marketing locally sourced generics, implying that all else being equal, additional bidders reduce the probability of collusion more if they market locally sourced generics. Specifically, compared to a situation with two bidders—of which only one markets a locally sourced generic—adding two additional bidders reduces the probability of collusion by 76 pps $[\approx (-0.125 - 0.184)/(1 - 0.593)]$ (s.e. = 16 pps) if both market locally sourced generics but only by 31 pps $[\approx -0.125/(1 - 0.593)]$ (s.e. = 10 pps) if neither do this. These estimates are obtained when keeping all other variables constant. While the number of generic bidders may change independent of the other variables, it is positively correlated with, for example, $MultiM\_low_{et}$, which positively affects the probability of collusion. When including changes in the other explanatory variables, except market and year × month fixed effects, adding two bidders reduces the probability of collusion by 51 pps (s.e. = 16 pps) if both market generics and by 43 pps (s.e. = 10 pps) if neither do this.

Our results confirm previous findings that multimarket contact increases the probability of collusion, and like Ciliberto and Williams (2014), we find that this matters most for low and moderate levels. Figure 6 shows the empirical distribution of MMC_low_{et} and its short-term marginal effects obtained from Specification 14; that is, we evaluate the derivative of $P(S|W_{et}, \breve{n}_{et})$ relative to MMC_low_{et} at different values of MMC_low_{et} while keeping the lag of $P(S|W_{et}, \breve{n}_{et})$ constant. Specifically, Figure 6 shows that an increase in MMC_low_{et} from 1 to 2 increases the probability of collusion by 1.2 pp in the short term, but the marginal effect then decreases and becomes indistinguishable from 0 according to the confidence interval when MMC_low_{et} reaches 56. Similar effects are obtained with Specifications 13, 15, and 16, and those from Specification 12 are also close to these short-term effects.

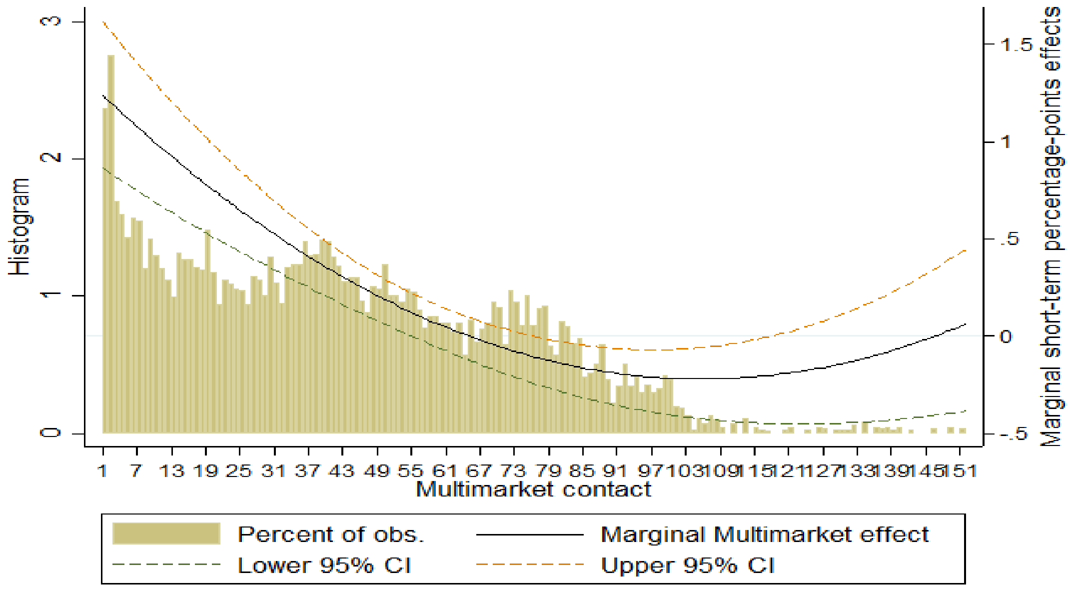

Figure 6. *Histogram and marginal short-term percentage-point effects of multimarket contact on the probability of collusion according to Specification 14.*

Regarding the cumulative effect, increasing multimarket contact by one standard deviation (28.90 units) increases the probability of collusion in the short term by 26 pps when increased from its lowest value of 1 but by only 4 pps when increased from its median value. The total effect of multimarket contact reaches its maximum at MMC_low_{et} = 65, when it increases the probability of collusion by 35 pps in the short term. Comparing the estimates for multimarket contact with those for different numbers of bidders reveals that reducing multimarket contact from its third quartile of 75 to its minimum of 1 reduces the probability of collusion as much as increasing the number of bidders from 2 to 4.

The control variables for the average number of markets in which the low-price bidders market their low-price products ($Markets\_low_{et}$, $Markets\_low^2_{et}$, and $Markets\_low^3_{et}$) have the same signs as the multimarket polynomials and estimations not presented in the tables reveal that not including them leads to an underestimation of the multimarket-contact effects. The latter is expected since firms active in many markets will, on average, have more multimarket contacts.

The estimation results for the proxies presented in Online Appendix E indicate that low entry costs and large quality differences reduce the probability of collusion, while sufficient capacity to punish deviators increases the probability of collusion. All of this is consistent with theory. However, only 1 in 20 estimates for the effect of heterogeneity among products and demand variation differs significantly from 0.

VIII. Discussion

In this study, we develop a method for calculating the probability that observed price patterns are caused by collusion. Such a method is needed to estimate the overcharges and determinants of collusion, and hence to inform policy on how to best prevent collusion. We apply the method to the Swedish generics markets and estimate how changes in the number of bidders and other market characteristics affect the probability of collusion and how collusion affects prices.

Our method has three steps. First, we identify price patterns consistent with collusion (e.g., three firms win every third month for 9–10 months). Second, we calculate the probability that each pattern arises during competition. When doing this, we account for short-term quantity constraints, firms' incentives to set higher prices when they face high demand from returning consumers, and for entry, exit, ties, and the probability of leaving prices unchanged. The last step is to use Bayes' theorem to calculate the probability that observed price patterns emanate from collusive behavior.

Zona (1986) and Lang and Rosenthal (1991) showed that bid-rotation-like patterns could also emanate from purely competitive behavior, such as when firms have short-term quantity constraints. Our results confirm this, indicating that a third of the actions that are part of bid-rotation-like patterns are competitive. Still, our estimates suggest that 62% of the auctions are part of bid-rotation patterns caused by collusion, and an additional 2% are part of parallel-bidding patterns caused by collusion.

Having estimated the probability of collusion for many markets and months enables us to empirically estimate how the number of bidders affects the probability of collusion. This estimation is important because knowledge on this is needed to assess coordinated effects of mergers and the existing knowledge primarily stems from classroom experiments. We confirm the qualitative predictions from theoretical and experimental research that the number of bidders has a significant negative effect on the probability of collusion. Specifically, we find that increasing the number of bidders from two to four reduces the probability of collusion by one-half. Nonetheless, we also observe suspicious price patterns lasting over nine months in markets with seven bidders, five of whom were low-price bidders (Section III.B, Figure 4), and the average probability that such patterns are caused by collusion is estimated to be 99%. This demonstrates that Huck et al.'s (2004) finding that four bidders are sufficient to avoid collusion does not necessarily hold for professional price setters in the field. Our results are more consistent with Selten's (1973) theoretical prediction that four bidders are sufficiently few for collusion to occur while six are unlikely to collude. However, this is qualified by the suggestion that the six bidders must belong to the same price segment in narrowly defined markets to avoid collusion.

There is also the question of how harmful collusion is for the consumers and society. Therefore, we also estimate how the prices are affected by collusion. The results indicate that an increase in the probability of collusion from 0 to 1 raises the average prices by 65%.

Estimates of overcharges and the effects of market characteristics on the probability of collusion are needed to make informed decisions about how best to reform markets to reduce the frequency of collusions. However, estimates of the costs of possible policies are also needed to provide specific policy suggestions, which is beyond the scope of this paper. Nonetheless, the high overcharges and large effect of the number of bidders on the probability of collusion provide a much stronger case for policies that stimulate entries and reduce exits (e.g., by lowering entry and annual fees) than would be the case without collusion. In addition, the multimarket contact results argue for facilitating small firms' participation in markets since they usually have fewer multimarket contacts. The results are also an argument for considering the effect on the probability of collusion in merger decisions even when the number of firms in the relevant price segment of the market would be three to five rather than two post-merger.

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