Online Appendix

"Does entry remedy collusion? Evidence from the generic prescription drug cartel"

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A Data appendix

A.1 Sample construction

Table A.1 describes the construction of our sample.

Table A.1: *Sample construction*

Total number of generic drugs approved prior to 2008:	3722
Teva does not participate in the market just prior to hiring of NP (i.e., in 2013q1).	*-2966*
First generic launches during sample period.	*-138*
Complaint indicates KG and/or DR may have affected prior to NP joining Teva.	*-62*
Injectible, dental, shampoo, suppository, or aerosol.	*-60*
Exceptionally high price due to ongoing/potential litigation.	*-28*
Complaint is ambiguous with respect to alleged conduct.	*-28*
Complaint alleges two price increases.	*-23*
Particular strength not sold in any meaningful quantity.	*-1*
Total number of generic drug markets in the sample:	= 416

The drugs with "exceptionally high price due to ongoing/potential litigation" include (a) tretinoin/isotretinoin, which are Vitamin A derivatives including Accutane that were facing litigation due to certain birth defects, (b) methotrexate, and (c) immune system suppressants such as cyclosporine.)

Table A.2 lists cartel members and their "quality," as assigned by NP.

Table A.2: *Firm quality and cartel membership.*

Firm	Original quality (as of 2013q2)	Updated quality (as of 2014q2)	Is a cartel member (as of 2014q2)?
Actavis/Watson	3	3	Yes
Amneal	1	2	Yes
Apotex	-3	2	Yes
Breckenridge	1	2	Yes
Glenmark	3	2	Yes
Greenstone	0	1	Yes
Heritage	0	3	Yes
Lupin	2	3	Yes
Mylan	3	3	Yes
Par	1	2	Yes
Rising	1	2	No
Sandoz	3	3	Yes
Taro	3	3	Yes
Upsher Smith	2	2	Yes
Versapharm	-2	-2	No
Zydus	-3	2	Yes

The table is restricted to firms explicitly assigned a score greater than -3 by NP. The other firms include Accord, Acella, Aci Healthcare, Afaxys, Ajanta, Akorn, Akron, Alembic, Alkem, Almus, Alvogen, American Antibiotics, Amici, Ani, Apace Ky, Apnar, Arbor, Ascend, Aurobindo, Avpak, Banner, Bausch, Bayshore, Belcher, Biocon, Biomes, Bionpharma, Blu, Bristol, Burel, Cadista, Camber, Cambridge Therapeutic Tech, Cameron, Carlsbad Tech, Cipla, Citron, Clay Park Lab, Corepharma, Cosette, Daiichi, Dash, Dava, Edenbridge, Endo, Epic, Ethex, Excellium, Exelan, Eywa, Gavis, Gen Source Rx, Genbiopro, Glaxosmithkline, Granules, Granules India, Gw, Hi Tech, Hikma, Impax, Ingenus, Int Medication Systems, Invagen, Inwood Lab, Ipca Lab, Johnson Johnson, Jsj, Kremers Urban, Kvk Tech, Lannet, Lannett, Larken, Laurus Lab, Leading, Lineage Therapeutic, Macleods, Major, Mallinckrodt, Marathon, Mayne, Medimetriks, Medstone, Megalith, Metcure, Method, Micro Lab, New Horizon Rx Group, Nivagen, Nostrum, Novitium, Orchid, Osmotica, Pack, Patriot, Pernix Therapeutic, Perrigo, Pharm Assoc, Pharmacist, Polygen, Prasco, Precision Dose, Prinston, Puracap, Puracap Lab, Purdue, Quagen, Quinn, Reddy, Roxane, Sagent, Sanofi, Sciegen, Sigmapharm Lab, Silarx, Sky Packaging, Solco, Sti, Strides, Sun, Sunrise, Tagi, Time Cap Lab, Torrent, Tris, Trupharma, Unichem, Valeant, Vensun, Vertical, Vertical Trigen, Viona, Virtus, Vista, Warner Chilcott, Westminster, Wilshire, Winthrop, Wockhardt, Woodward Services, X Gen, Xiromed, and Yiling.

Figure A.1 presents a histogram of assigned qualities.

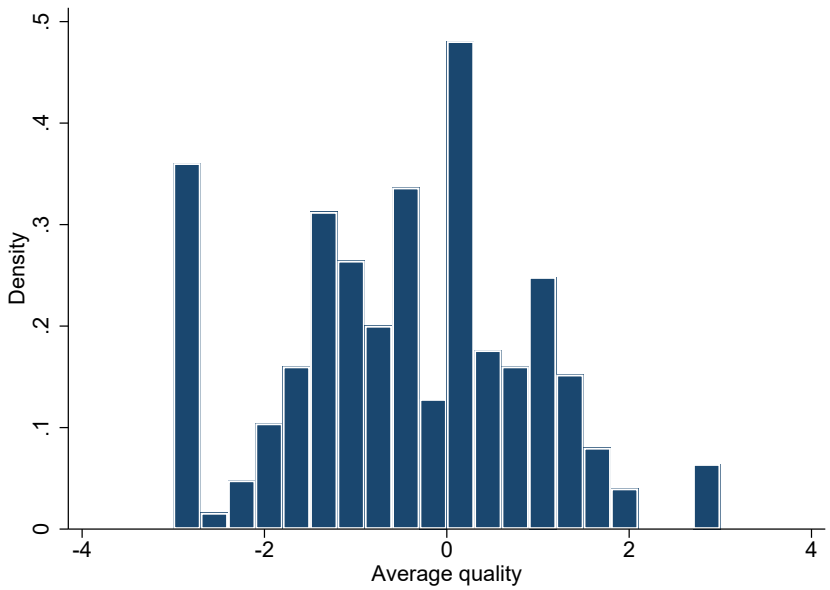

Figure A.1: *Histogram of average quality. The unit of observation is a drug market. (For instance, a "3" means NP was friends with all other rivals.)*

Table A.3 summarizes the differences between cartelized and uncartelized markets.

Table A.3: *Balance Table*

	Cartelized	Uncartelized	Difference	
Price	27.38	33.86	-6.49	1.00
	(1.15)	(0.91)	(0.74)	
Quantity (in thousands)	627.54	1572.71	-945.17	1.00
	(37.73)	(73.26)	(55.11)	
Expenditure (in millions)	12.05	26.96	-14.91	1.00
	(0.81)	(1.36)	(1.02)	
Number of ANDA filings	0.18	0.29	-0.11	1.00
	(0.02)	(0.02)	(0.01)	
Number of firms	3.76	4.36	-0.60	1.00
	(0.07)	(0.06)	(0.05)	

The unit of observation is drug-year across all observations between 2008 and 2012, inclusive. There are 113x5 observations for the cartelized drugs and 303x5 observations for the uncartelized drugs. Standard errors of the means are given in parentheses.

The set of cartelized drugs include Amoxicillin Clavulanate Potassium tablet chewable oral in 2 strengths, Azithromycin for suspension oral in 2 strengths, Baclofen tablet oral in 2 strengths, Bethanechol Chloride tablet oral in 4 strengths, Bumetanide tablet oral in 3 strengths, Carbamazepine tablet chewable oral in one strength, Carbamazepine tablet oral in one strength, Cefdinir capsule oral in one strength, Cefdinir for suspension oral in 2 strengths, Cefprozil tablet oral in 2 strengths, Cephalexin for suspension oral in 2 strengths, Ciprofloxacin Hydrochloride tablet oral in 3 strengths, Clarithromycin ER tablet oral in one strength, Clotrimazole solution topical in one strength, Cyproheptadine Hydrochloride tablet oral in one strength, Desmopressin Acetate tablet oral in 2 strengths, Dicloxacillin Sodium capsule oral in 2 strengths, Diflunisal tablet oral in one strength, Disopyramide Phosphate capsule oral in 2 strengths, Doxazosin Mesylate tablet oral in 4 strengths, Estazolam tablet oral in 2 strengths, Estradiol tablet oral in 3 strengths, Ethosuximide capsule oral in one strength, Ethosuximide syrup oral in one strength, Etodolac tablet oral in 2 strengths, Etodolac ER tablet oral in 3 strengths, Fluconazole tablet oral in 4 strengths, Fluoxetine Hydrochloride tablet oral in one strength, Flurbiprofen tablet oral in one strength, Flutamide capsule oral in one strength, Glimepiride tablet oral in 3 strengths, Griseofulvin Microsize suspension oral in one strength, Hydroxyurea capsule oral in one strength, Hydroxyzine Pamoate capsule oral in 2 strengths, Isoniazid tablet oral in 2 strengths, Ketoconazole cream topical in one strength, Ketoconazole tablet oral in one strength, Loperamide Hydrochloride capsule oral in one strength, Medroxyprogesterone Acetate tablet oral in 3 strengths, Moexipril Hydrochloride tablet oral in 2 strengths, Nabumetone tablet oral in 2 strengths, Nadolol tablet oral in 3 strengths, Nortriptyline Hydrochloride capsule oral in 4 strengths, Nystatin tablet oral in one strength, Oxybutynin Chloride tablet oral in one strength, Penicillin V Potassium tablet oral in 2 strengths, Pentoxifylline ER tablet oral in one strength, Pravastatin Sodium tablet oral in 4 strengths, Prochlorperazine Maleate tablet oral in 2 strengths, Propranolol Hydrochloride tablet oral in 2 strengths, Ranitidine Hydrochloride tablet oral in 2 strengths, Sotalol Hydrochloride tablet oral in 3 strengths, Tamoxifen Citrate tablet oral in one strength, Theophylline ER tablet oral in one strength, and Warfarin Sodium tablet oral in 9 strengths .

The set of uncartelized drugs include Acetaminophen Codeine Phosphate tablet oral in 3 strengths, Acyclovir capsule oral in one strength, Acyclovir tablet oral in 2 strengths, Albuterol Sulfate syrup oral in one strength, Alendronate Sodium tablet oral in 4 strengths, Amiodarone Hydrochloride tablet oral in one strength, Amlodipine Besylate tablet oral in 3 strengths, Amoxicillin capsule oral in 2 strengths, Amoxicillin for suspension oral in 4 strengths, Amoxicillin tablet chewable oral in 2 strengths, Amoxicillin tablet oral in 2 strengths, Amoxicillin Clavulanate Potassium for suspension oral in one strength, Amoxicillin Clavulanate Potassium tablet oral in 2 strengths, Mixed Amphetamine Salt (long name) tablet oral in 7 strengths, Anagrelide Hydrochloride capsule oral in 2 strengths, Atenolol tablet oral in 3 strengths, Azithromycin tablet oral in 3 strengths, Benazepril Hydrochloride tablet oral in 4 strengths, Benzonatate capsule oral in one strength, Benztropine Mesylate tablet oral in 3 strengths, Bisoprolol Fumarate tablet oral in 2 strengths, Bupropion Hydrochloride ER tablet oral in one strength, Cabergoline tablet oral in one strength, Calcitriol capsule oral in 2 strengths, Carbidopa Levodopa tablet oral in 3 strengths, Carvedilol tablet oral in 4 strengths, Cefadroxil Cefadroxil Hemihydrate capsule oral in one strength, Cefadroxil Cefadroxil Hemihydrate tablet oral in one strength, Cephalexin capsule oral in 2 strengths, Cephalexin tablet oral in 2 strengths, Chlordiazepoxide Hydrochloride capsule oral in 3 strengths, Chlorzoxazone tablet oral in one strength, Ciclopirox solution topical in one strength, Cilostazol tablet oral in 2 strengths, Citalopram Hydrobromide tablet oral in 3 strengths, Clarithromycin tablet oral in 2 strengths, Clindamycin

Hydrochloride capsule oral in 2 strengths, Clomiphene Citrate tablet oral in one strength, Clonazepam tablet oral in 3 strengths, Clonazepam tablet orally disintegrating oral in 5 strengths, Clozapine tablet oral in 4 strengths, Cromolyn Sodium solution drops ophthalmic in one strength, Cromolyn Sodium solution inhalation in one strength, Cyclobenzaprine Hydrochloride tablet oral in one strength, Danazol capsule oral in 2 strengths, Dexmethylphenidate Hydrochloride tablet oral in 3 strengths, Dextroamphetamine Sulfate ER capsule oral in 3 strengths, Dextroamphetamine Sulfate tablet oral in 2 strengths, Diazepam tablet oral in 3 strengths, Diclofenac Sodium ER tablet oral in one strength, Dipyridamole tablet oral in 3 strengths, Disulfiram tablet oral in 2 strengths, Doxepin Hydrochloride concentrate oral in one strength, Doxycycline Hyclate tablet oral in one strength, Enalapril Maleate Hydrochlorothiazide tablet oral in 2 strengths, Ergocalciferol capsule oral in one strength, Estradiol Norgestimate tablet oral in one strength, Ethambutol Hydrochloride tablet oral in one strength, Ethinyl Estradiol Levonorgestrel tablet oral in 3 strengths, Ethinyl Estradiol Norgestimate tablet oral in 2 strengths, Etodolac capsule oral in one strength, Famotidine tablet oral in 2 strengths, Finasteride tablet oral in one strength, Fluconazole for suspension oral in one strength, Fludrocortisone Acetate tablet oral in one strength, Fluoxetine Hydrochloride capsule oral in 3 strengths, Fluoxetine Hydrochloride solution oral in one strength, Fluvoxamine Maleate tablet oral in 2 strengths, Fosinopril Sodium tablet oral in 3 strengths, Gabapentin tablet oral in 2 strengths, Gemfibrozil tablet oral in one strength, Glipizide tablet oral in 2 strengths, Glipizide Metformin Hydrochloride tablet oral in 3 strengths, Glyburide tablet oral in 6 strengths, Glyburide Metformin Hydrochloride tablet oral in 3 strengths, Haloperidol Lactate concentrate oral in one strength, Hydralazine Hydrochloride tablet oral in 4 strengths, Hydrochlorothiazide tablet oral in 2 strengths, Hydrochlorothiazide Lisinopril tablet oral in 3 strengths, Hydrocodone Bitartrate Ibuprofen tablet oral in one strength, Hydroxyzine Hydrochloride tablet oral in 3 strengths, Indomethacin capsule oral in 2 strengths, Lamotrigine tablet chewable oral in 2 strengths, Leflunomide tablet oral in 2 strengths, Lidocaine Hydrochloride jelly topical in one strength, Lisinopril tablet oral in 6 strengths, Lovastatin tablet oral in 3 strengths, Mefloquine Hydrochloride tablet oral in one strength, Megestrol Acetate tablet oral in 2 strengths, Meloxicam tablet oral in 2 strengths, Metformin Hydrochloride tablet oral in 3 strengths, Metformin Hydrochloride ER tablet oral in 2 strengths, Methyldopa tablet oral in 2 strengths, Metoclopramide Hydrochloride tablet oral in 2 strengths, Metoprolol Tartrate tablet oral in 2 strengths, Metronidazole capsule oral in one strength, Metronidazole cream topical in one strength, Metronidazole tablet oral in 2 strengths, Mexiletine Hydrochloride capsule oral in 3 strengths, Minocycline Hydrochloride capsule oral in 3 strengths, Mirtazapine tablet oral in 3 strengths, Mirtazapine tablet orally disintegrating oral in 3 strengths, Misoprostol tablet oral in one strength, Mometasone Furoate cream topical in one strength, Mometasone Furoate lotion topical in one strength, Mometasone Furoate ointment topical in one strength, Mupirocin ointment topical in one strength, Naltrexone Hydrochloride tablet oral in one strength, Naproxen tablet oral in 3 strengths, Naproxen DR tablet oral in 2 strengths, Naproxen Sodium tablet oral in one strength, Nefazodone Hydrochloride tablet oral in 5 strengths, Neomycin Sulfate tablet oral in one strength, Nifedipine ER tablet oral in 3 strengths, Oxaprozin tablet oral in one strength, Oxazepam capsule oral in 3 strengths, Oxybutynin Chloride ER tablet oral in 3 strengths, Pantoprazole Sodium DR tablet oral in 2 strengths, Paroxetine Hydrochloride tablet oral in 4 strengths, Penicillin V Potassium for solution oral in 2 strengths, Piroxicam capsule oral in 2 strengths, Prednisolone syrup oral in one strength, Protriptyline Hydrochloride tablet oral in one strength, Ramipril capsule oral in 3 strengths, Simvastatin tablet oral in 5 strengths, Sucralfate tablet oral in one strength, Terazosin Hydrochloride capsule oral in 4 strengths, Terbinafine Hydrochloride tablet oral in one strength, Tetracycline Hydrochloride capsule oral in one strength, Torsemide tablet oral in 4 strengths, Tramadol Hydrochloride tablet oral in

one strength, Trandolapril tablet oral in 3 strengths, Trazodone Hydrochloride tablet oral in 4 strengths, Ursodiol capsule oral in one strength, Valproic Acid capsule oral in one strength, Venlafaxine Hydrochloride tablet oral in 5 strengths, Verapamil Hydrochloride ER tablet oral in 2 strengths, and Zolpidem Tartrate tablet oral in 2 strengths .

A.2 Comparing data sources

The dataset we obtained from IQVIA (2022) reports the number of dispensed prescriptions nationally at the drug-month-year level but is subject to two minor limitations. First, it covers the first quarter of 2011 through the fourth quarter of 2017, inclusive. In other words, it does not span the period studied in the main text (i.e., 2008-2019 inclusive). We were limited by cost as well as historical availability, so we focused on acquiring data around cartel formation. Second, IQIVA aggregates tablets and capsules, which affects a small number of substance-release-strength combinations that are offered contemporaneously in both forms. When we compare the evolution of unit sales in IQVIA and Centers for Medicare & Medicaid (2022) (see Figure A.2, below), we require precise measurements, so we drop these drugs. Observing these distinctions would require more granular data, which was *much* more expensive, and since the omissions reflect random features of the sample, they will not affect the comparisons we derive from them. When all we require from IQVIA is market size (i.e., one number for each drug that scales up our Medicaid data), we compute total unit sales in IQVIA at the substance-release-strength level and then split sales up according to proportions implied by our Medicaid data. Related to this limitation, in an equally small number of cases, IQVIA does not distinguish between immediate and extended release forms of a substance-delivery-strength combination. Etodolac tablets are one example. We handle ambiguity arising from the drug's release the same way we handle ambiguity arising from drugs offered in both tablet and capsule form.

In terms of model predictions, the most influential feature of the quantity data is the mean change around cartel formation in cartelized markets relative to uncartelized ones. As a result, we compare the Medicaid and IQVIA datasets along this dimension. Specifically, we denote the log of the number of prescriptions of drug d consumed in quarter t as y_{dt}. We then estimate

$$y_{dt} = \sum_{\tau=-13}^{13} \beta^{\tau} x_{dt}^{\tau} + a_d + b_t + e_{dt}, \tag{1}$$

where a_d and b_t denote drug and quarter fixed effects, respectively, and x_{dt}^{τ} denotes an indicator variable that equals one if and only if d is a cartelized drug and t is τ periods from cartel formation. We $\beta^{-1} = 0$ to facilitate comparisons to the period just prior to cartel formation.

Figure A.2 plots β^{τ} estimated on each dataset. Despite how differently the underlying observations are collected, the sources present very similar graphs. We observe (a) a very slightly positive pre-event trend one to three years prior to cartel formation, (b) no appreciable pre-event trend just prior to cartel formation, and (c) a clear decline in quantity thereafter, (d) culminating in a statistically significant decrease of about 15%. By way of this comparison to the "gold standard" represented by IQVIA, we conclude that Medicaid utilization data accurately measures changes in prescription drug quantities and is well-suited for demand estimation.

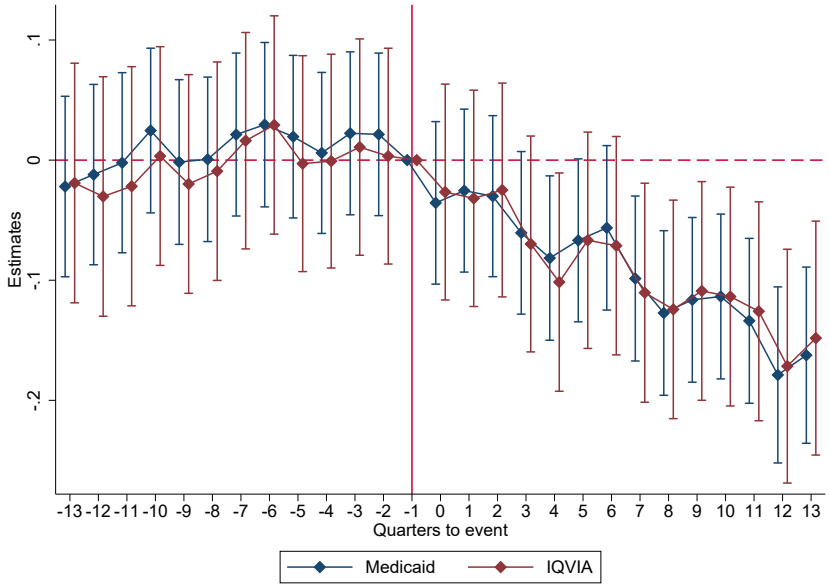

Figure A.2: *The quantity responses reported in IQVIA and Medicaid are very similar.*

This figure plots coefficients obtained by estimating equation 2 on the y-axis against event time on the x-axis. Log prescriptions are the outcome of interest, and the unit of observation is a drug-year. The vertical red line at event time -1 corresponds to the year just prior to cartel formation. Vertical bars around the point estimates show 95 percent confidence intervals, based upon standard errors that are clustered by drug. Notice that while the quantity decline in the Medicaid data following cartel formation lags the one evidenced by IQVIA data, the delayed response does not have a meaningful effect on our results; when we estimate demand, we omit observations from the year in which each cartel is formed.

A.3 Inferring filing dates

Figure A.3 shows that while there is no comprehensive correspondence between ANDA numbers and filing dates, the latter can be inferred without meaningful error.

To obtain filing dates, we downloaded all available approval letters from US Food & Drug Administration (2022) and parsed filing dates from the PDFs. We then supplemented the parsed dates with information from Feldman et al. (2016). Since 2000, the agency has issued three "waves" of ANDA numbers. Within each wave, numbers are assigned in chronological order. Specifically, the agency issued numbers in the 70,000s from 2000 to 2008, in the 90,000s from 2008 to 2010, and in the 200,000s thereafter.

In Panel A, we plot filing dates on the x-axis against ANDA numbers on the y-axis. The graph reflects 8,185 ANDAs for which we were able to obtain filing dates from parsed PDFs. The three waves are clearly visible. Putting aside a small number of very early ANDAs, which are filed years before our sample starts, there are only two obvious parsing errors.

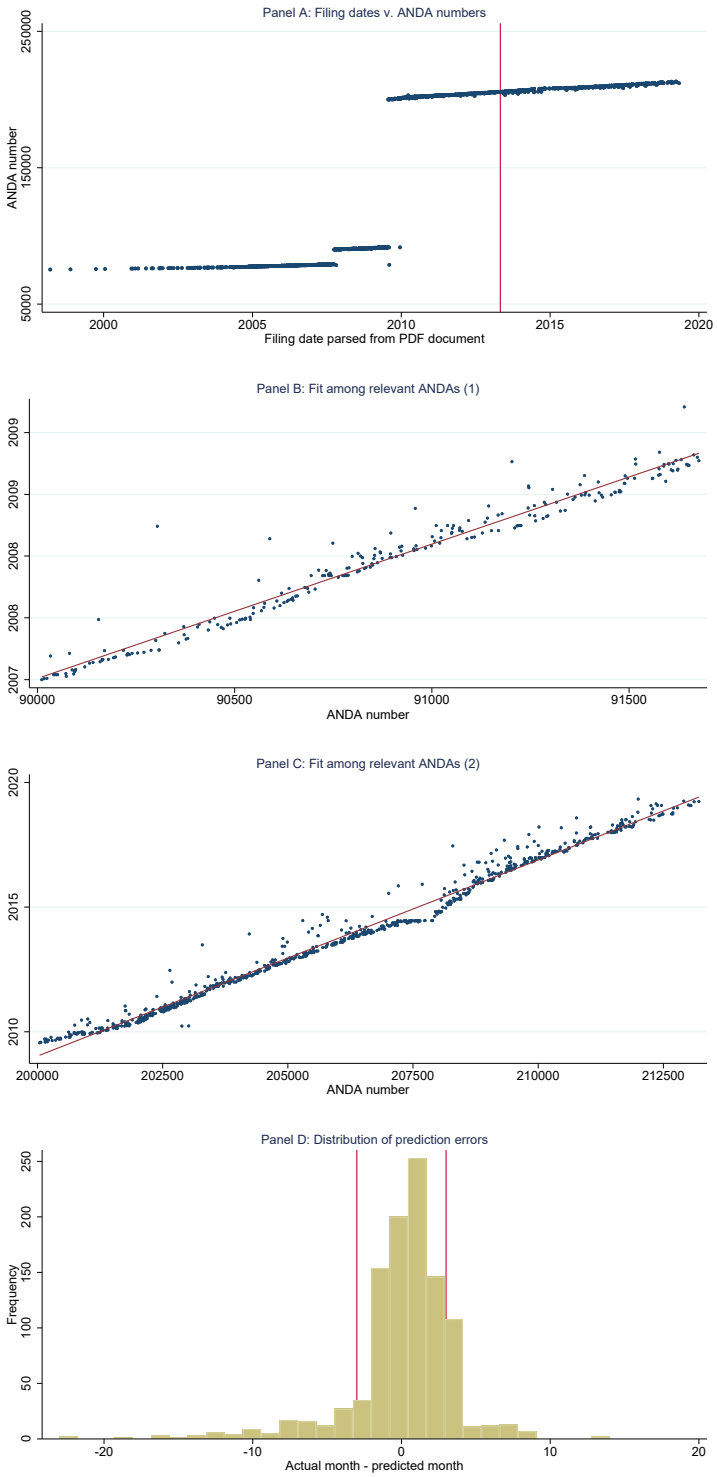

Figure A.3: *Filing dates are inferred without meaningful error.*

Panel A plots parsed ANDA filing dates on the x-axis and ANDA numbers on the y-axis. Panels B and C plot ANDA numbers on the x-axis and parsed filing dates on the y-axis for the relevant "waves" of ANDAs. Panel D plots the difference between the actual and predicted filing months.

Panel A shows that the sample period corresponds to the second and third wave of ANDA numbers. Thus, in Panels B and C, we isolate the waves separately. Panel B depicts ANDA numbers in the 90,000s, while Panel C depicts them in the 200,000s. In each panel, we plot ANDA numbers on the x-axis and filing dates on the y-axis. Both graphs illustrate the linearity of this relationship.

Given the aforementioned linearity, we regress ANDA numbers on filing dates within each wave and then predict filing dates for the remaining ANDA numbers. To assess overall fit, we compute the difference between actual and predicted dates measured in months and plot the density in Panel D. Substantially all of the parsed dates fall within 3 months of the predicted dates. Especially given that we aggregate ANDAs to the annual level, we conclude that ANDAs filing dates are measured accurately.

B Tables/figures related to descriptive results

B.1 Tables and figures related to Section 4.1

We compare the price of cartelized drugs before and after cartel formation, using uncartelized drug prices to control for any time-varying factors affecting all generic markets. The unit of analysis is a drug-quarter, and the estimating equation is given by

$$y_{dt} = \sum_{\tau=-21}^{24} \beta^{\tau} x_{dt}^{\tau} + a_d + b_t + e_{dt}. \tag{2}$$

y_{dt} represents the log of average price of drug d in calendar-quarter t. a_d and b_t represent drug- and quarter-specific fixed effects, while x_{dt}^{τ} is an indicator variable that equals one if and only if d is a cartelized drug and t is τ periods from cartel formation. Given the timing of the price increases and the time period covered by our data, τ can take a value between -21 and 24. We set $\beta^{-1} = 0$, so the coefficients on x^{τ} terms represent differences in prices relative to the period immediately preceding cartel formation. Figure B.1 reports estimates of β^{τ}.

Figure B.1 replicates Figure 1 in the body of the main text with an exception: instead of employing two-way fixed effects, we follow Sun and Abraham (2020), whose approach accounts for potential contamination of leading and lagging coefficients. (See their paper for details.) We obtain similar coefficients.

Figure B.3 replicates Figure 1 in the body of the main text with an exception: rather than distinguish between cartelized and uncartelized markets, we distinguish between *markets we predict are cartelized and uncartelized*. Our predictions are based on scores assigned by NP, which reflect the strength of her personal relationships.

Figure B.4 replicates Figure 1 in the body of the main text with an exception. We add a third price series, which tracks the average log price of markets in which Teva is a monopolist (as of the first quarter of 2013). Figure B.4 reports this result.

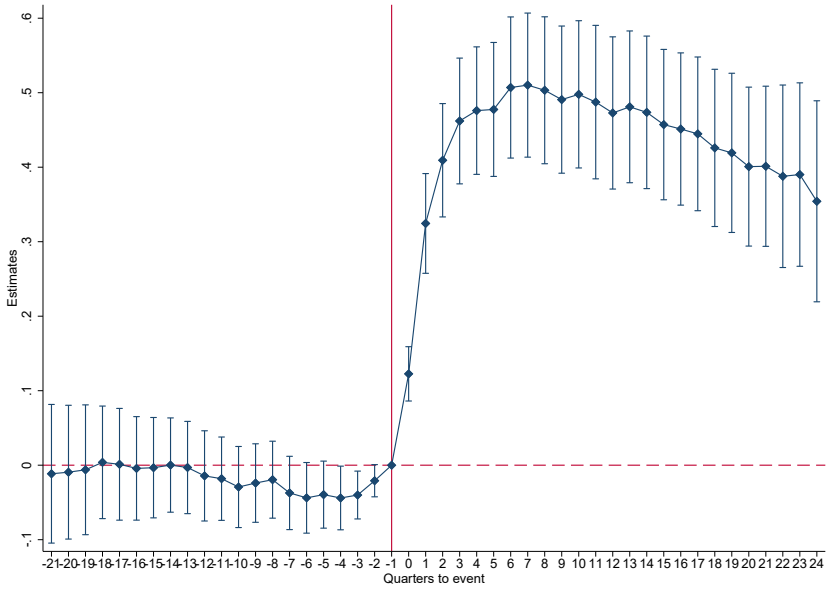

Figure B.1: *Prices in event time (two-way fixed effects)*

This figure plots β^{τ}, which is obtained by estimating equation 2, on the y-axis against event time on the x-axis. The unit of observation is a drug-year. The outcome variable is log average price. The vertical red line at event time -1 corresponds to the year the cartel is formed. Vertical bars around the point estimates show 95 percent confidence intervals for those coefficients. Standard errors are clustered by substance-delivery-release.

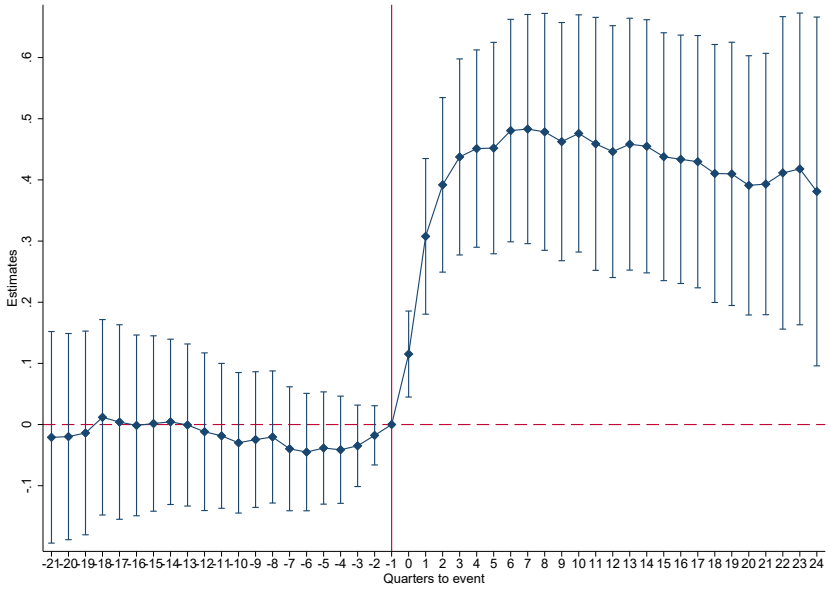

Figure B.2: *Prices in event time (Sun and Abraham (2020) approach)*

This figure plots β^{τ}, which is obtained by estimating equation 2, on the y-axis against event time on the x-axis. The unit of observation is a drug-quarter. Vertical bars around the point estimates show 95 percent confidence intervals for those coefficients. Standard errors are clustered by drug.

Figure B.3: *Prices in markets where NP does/does not have strong personal relationships*

This figure replicates Figure 1 in the body of the main text with one exception: rather than compare cartelized and uncartelized markets, we compare markets where NP does and does not have especially strong relationships. To do so, we obtain the "quality" of each Teva competitor from the Complaint (i.e., a score assigned by NP to reflect the strength of her personal relationships with the key sales and marketing persons at each firm). To approximate the process that NP actually used to determine what markets to cartelize, we compute each drug's weighted average competitor quality. We define "high quality" markets as ones in which the average competitor quality is greater than or equal to two, and we call the remaining markets "low quality."

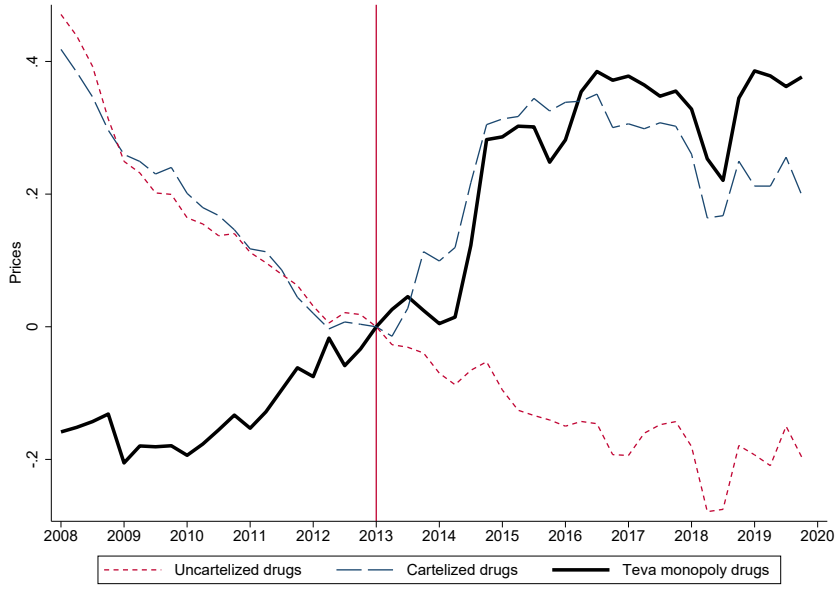

Figure B.4: *Prices in markets where Teva has a monopoly*

Unlike cartelized drugs, prices in markets where Teva was a monopolist did not rise discontinuously when NP joined; although there is a slight jump late in 2014, the fact is that they were increasing and continued increasing at roughly the same pace.

B.2 Tables and figures related to Section 4.2

Firms with dormant ANDAs—ones that were once associated with positive production but no longer are—might re-enter the market when cartels form. To study this possibility, we plot re-entry in calendar time for cartelized and uncartelized drugs. Figure B.5 reports the result. (The format of the graph is identical to the format of Figure 2 in the body of the main text except that the y-axis measures the average number of (re-)entrants per drug and year rather than per substance-delivery-release combination and year. Cartel formation clearly induces re-entry.

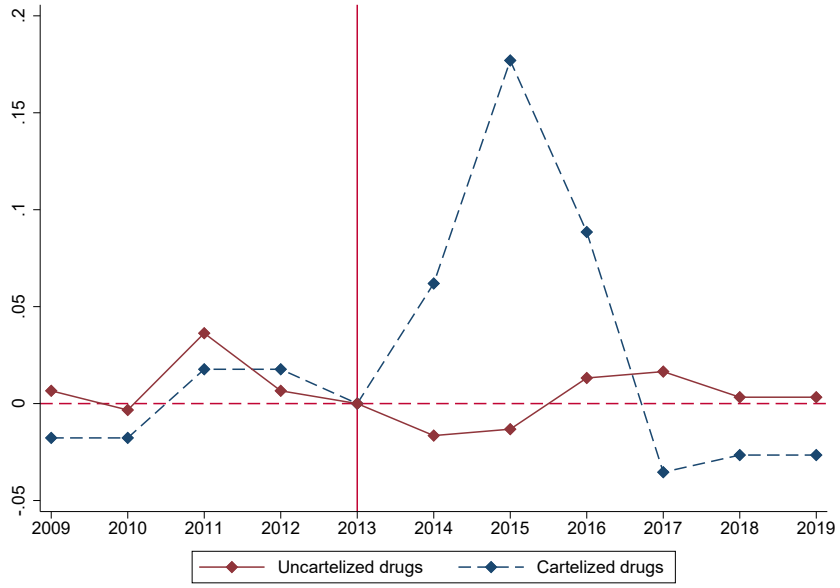

Figure B.5: *Reentry in calendar time*

This figure plots average number of re-entrants per drug on the y-axis against calendar year on the x-axis. The vertical red line corresponds to the first quarter of 2013—the period in which NP joined Teva. The number of entrants are normalized to zero in that quarter.

We also compare entry into cartelized markets before and after cartel formation, using uncartelized drug prices to control for any time-varying factors affecting all generic markets. We denote the number of ANDA filings for a substance-delivery-release combination j in year t by y_{jt}, and we estimate

$$y_{jt} = \sum_{\tau=-5}^{5} \beta^{\tau} x_{jt}^{\tau} + a_j + b_t + e_{jt}. \tag{3}$$

a_j and b_t represent drug- and year-specific fixed effects, respectively, while x_{jt}^{τ} is an indicator variable that equals one if and only if j is a cartelized substance-delivery-release combination and t is τ periods from cartel formation. We set $\beta^{-1} = 0$, so the coefficients on x^{τ} terms represent differences in prices relative to the period immediately preceding cartel formation. We plot estimates of β^{τ} in event-time. Panel A of Figure B.6 reports this result. We then replicate this procedure but replace ANDA filings with ANDA approvals, again, plot estimates of β^{τ} in event time. Panel B of Figure B.6 reports this result. We also replicate this procedure but replace ANDA filings or approvals with re-entry, and we plot estimates of β^{τ} in event time. Figure B.6 reports this result.

Figure B.8 plots the distribution of total and regulatory-specific delays.

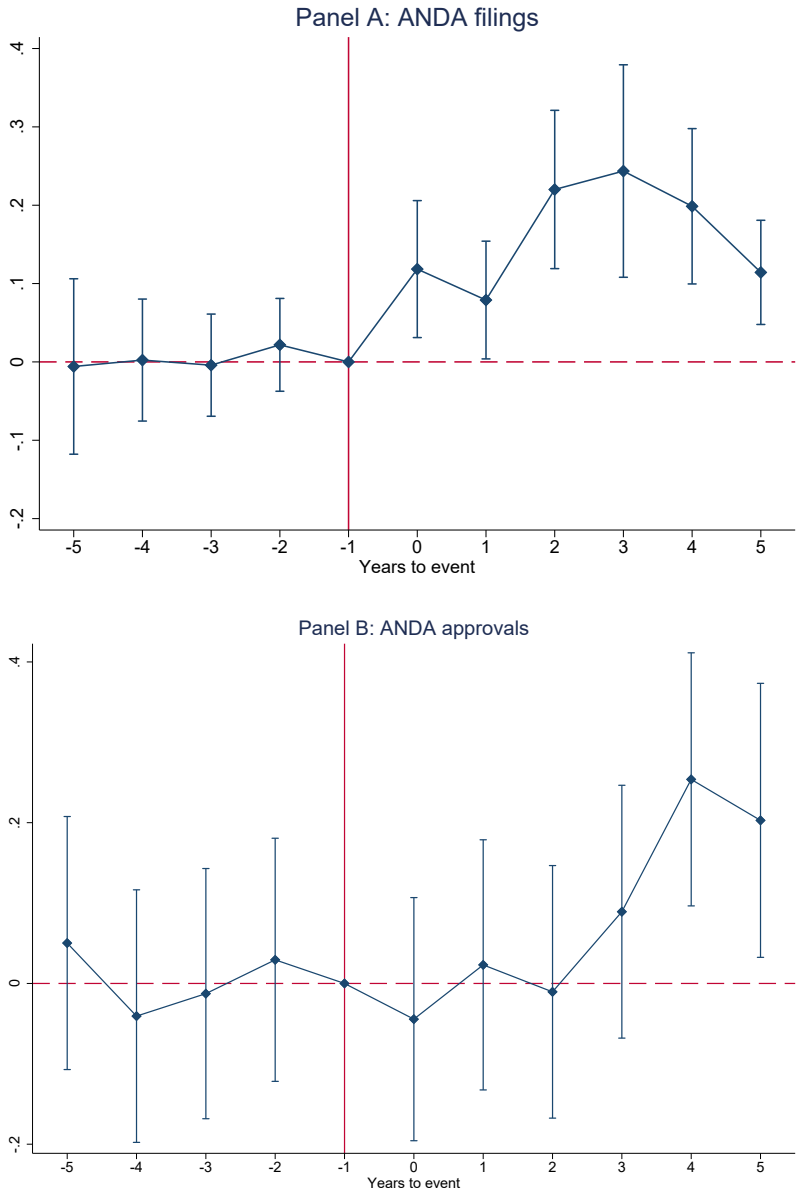

Figure B.6: *Entry in event time*

This figure plots β^{τ}, which is obtained by estimating equation 2, on the y-axis against event time on the x-axis. The unit of observation is a substance-delivery-release-year. In Panel A, ANDA filings are the outcome of interest. In Panel B, ANDA launches are the outcome of interest. The vertical red line at event time -1 corresponds to the year immediately prior to cartel formation, as described in the Complaint. Vertical bars around the point estimates show 95 percent confidence intervals for those coefficients. Standard errors are clustered by drug.

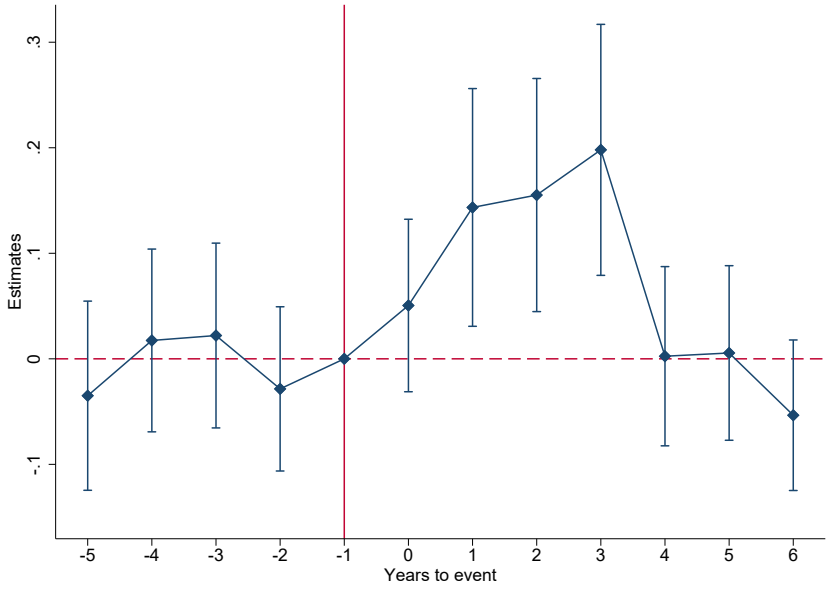

Figure B.7: *Reentry in event time*

In the body of the main text, we find that cartel formation attracts new entrants (i.e., ANDA filings). However, re-entry is also possible. Firms with dormant ANDAs—ones that were once associated with positive production but no longer are—might re-enter the market when cartels form. To study this possibility, we plot re-entry in event time for cartelized and uncartelized drugs. There is an economically and statistically increase in entry, and that re-entry occurs very soon after collusion begins. The stark contrast of this figure and the one that reports ANDA launches highlights the effect of approval delays. This figure plots coefficients obtained by estimating equation 2 on the y-axis against event time on the x-axis. The unit of observation is a drug-year, and the outcome of interest is a ANDA re-entry. Re-entering ANDAs are those where the ANDA was associated with some output, then went at least one year without being associated with output, and then re-entered (i.e., was once again associated with output). The vertical red line at event time zero corresponds to the year in which Teva hired NP. Vertical bars around the point estimates show 95 percent confidence intervals for those coefficients, based upon standard errors that are clustered by drug.

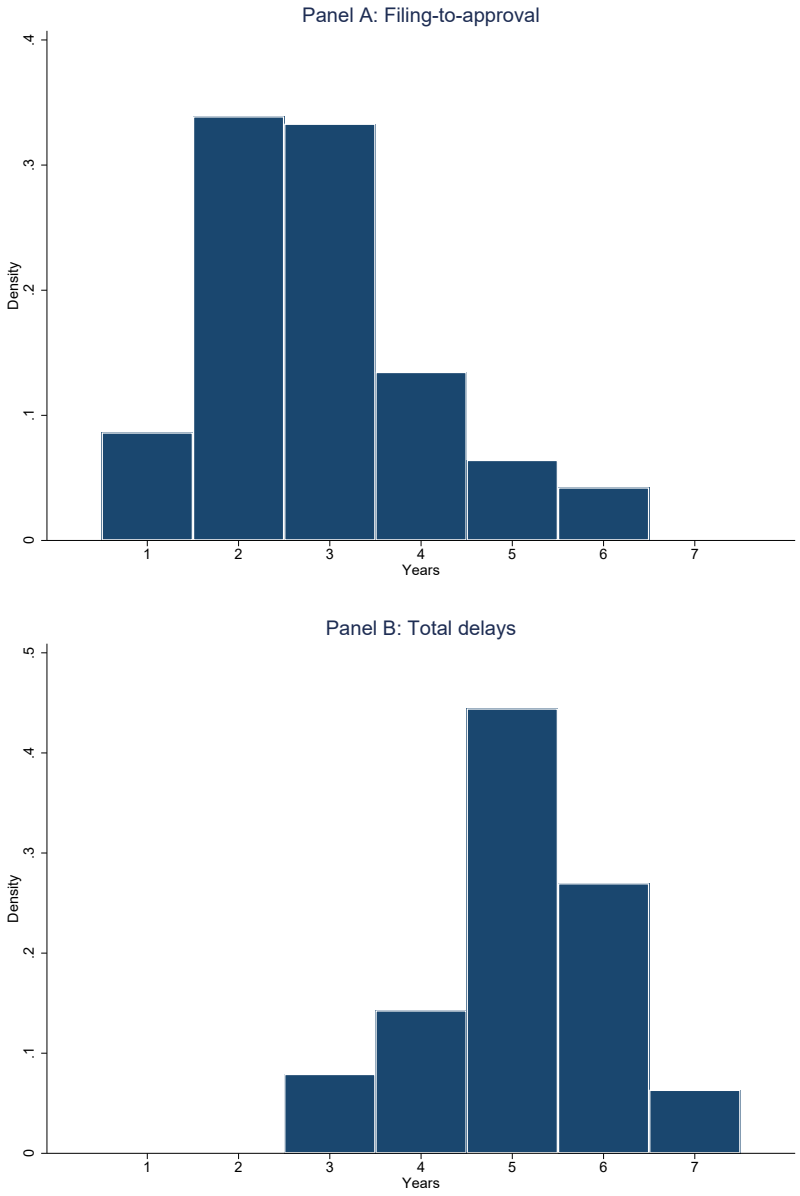

Figure B.8: *Distributions of delays*

This figure plots the distribution of delays. The unit of observation is an ANDA. Panel A reports the distribution of regulatory delays (i.e., the time between ANDA filing and approval), whereas Panel B reports the distribution of total delays (i.e., the time between cartel formation and sales). In the underlying data, there are a very, very small number of ANDAs with a total delay of just under three years. So that certain figures, such as those reporting slack in the ICCs, more accurately represent reality, we set the mass of total delays at two years exactly equal to zero.

B.3 Tables and figures related to Section 4.3

Figure B.9 examines the relationship between market size and entry in cartelized markets. For the purposes of this figure, we proxy for market size using each drug's total revenue in the quarter just prior to NP joining Teva. In Panel A, we measure entry as the probability that each cartelized market experiences entry following cartel formation. In Panel B, we measure entry as the average number of firms entering each cartelized market following cartel formation. The graph shows that regardless of how we measure it, entry is closely related to market size. Only about 8% of drugs with around $1 million in revenue attract any entry at all. However, drugs with over $1 billion in revenue almost always attract entry, with an average of three firms filing ANDAs following cartel formation.

As we state in the body of the main text, comparing the paths of prices in large and small markets is complicated in this setting by antitrust risk. Large markets may be more "visible" than small ones, and the earliest entry events roughly coincide with the government's investigation, so cartel members may have reduced prices in large markets in an effort to reduce scrutiny of their behavior. In other words, prices in large cartelized might have fallen regardless of entry. To investigate this issue, we trace the investigation back to its origin, obtain the list of drugs whose price changes triggered the inquiry, and plot the size distribution of these drugs to the size distribution of the full sample in Figure B.10. The array of lawsuits faced by the firms all trace back to the Connecticut AG's office, which launched its initial inquiry based on July 8, 2014, *New York Times* article, which in turn described price changes first reported by Adam Fein of Pembrooke Consulting and the Drug Channels Institute. Fein's report, which appears as a November 19, 2013 article titled "Retail Generic Drug Costs Go Up, Up, and Away," simply orders the drugs in terms of year-over-year percentage increases in NADAC prices. The report cites increases in the price of doxycycline, clomapramine, albuterol sulfate, captopril, tetracycline, digoxin, and benazepril. Figure B.10 shows that the distribution of market size for the drugs that prompted the government's investigation is very similar to the distribution of market size for the full sample.

One-third of entrants into cartelized markets are cartel members. Of the remaining entrants, which are nonmembers, the vast majority (68%) were in existence prior to cartel formation. Figure B.11 plots entry into cartelized and uncartelized drug markets over time separately for members and nonmembers, and we observe similar patterns across the two groups. The distribution of member and nonmember entrants into cartelized markets does not change around the time NP is hired by Teva.

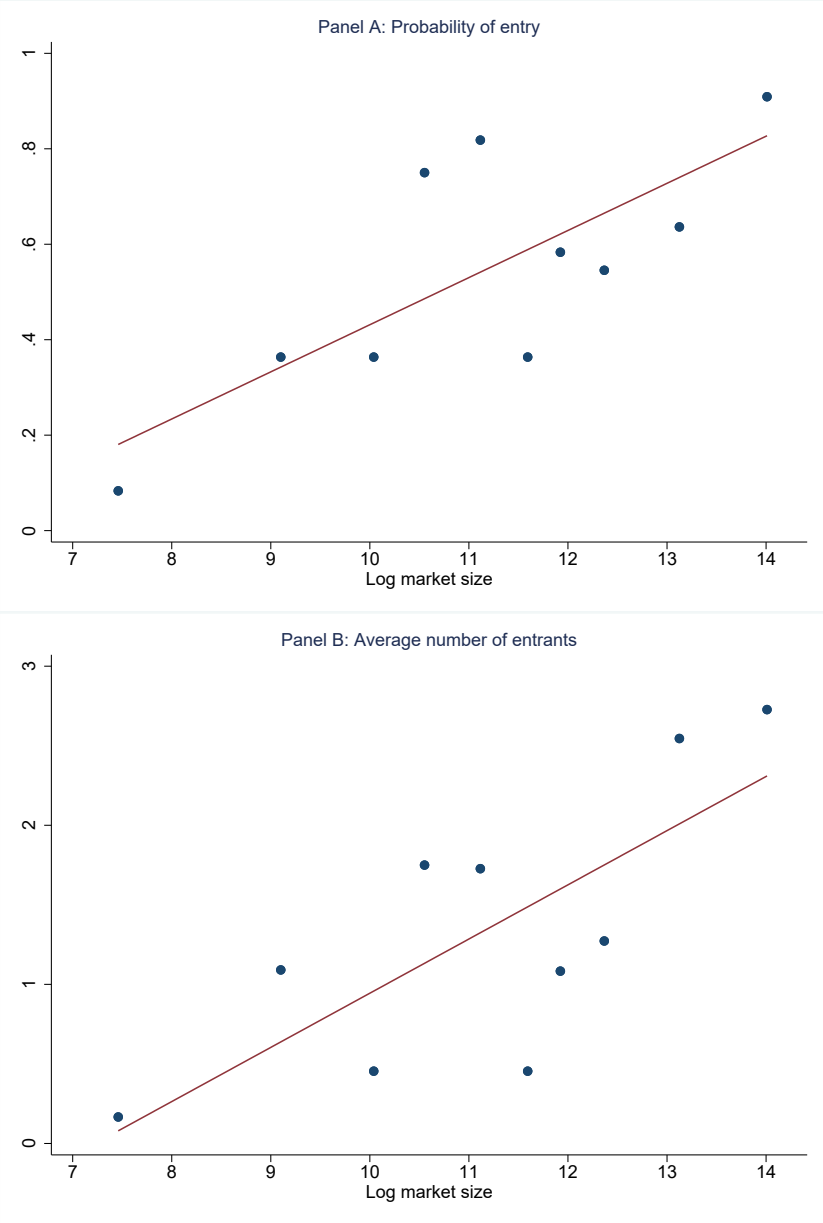

Figure B.9: *Larger markets attract more entry*

This figure plots log market size on the x-axis against the number of entrants in the post-collusion period. The unit of observation is a drug. Market size is measured in total revenue in 2012, the year immediately prior to NP joining Teva. Data are binned according to x-axis values, so averages within the bin are plotted (i.e., the graph represents a "binscatter").

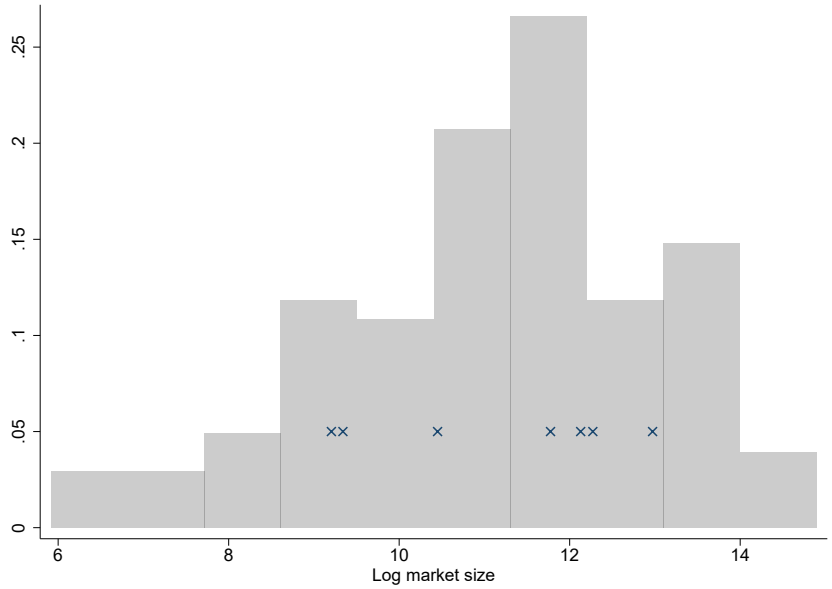

Figure B.10: *Size distribution of drugs that triggered the government's investigation*

This figure reports the distribution of (logged) size, measured by 2012 revenue. The drugs identified by Fein are marked with a blue "x."

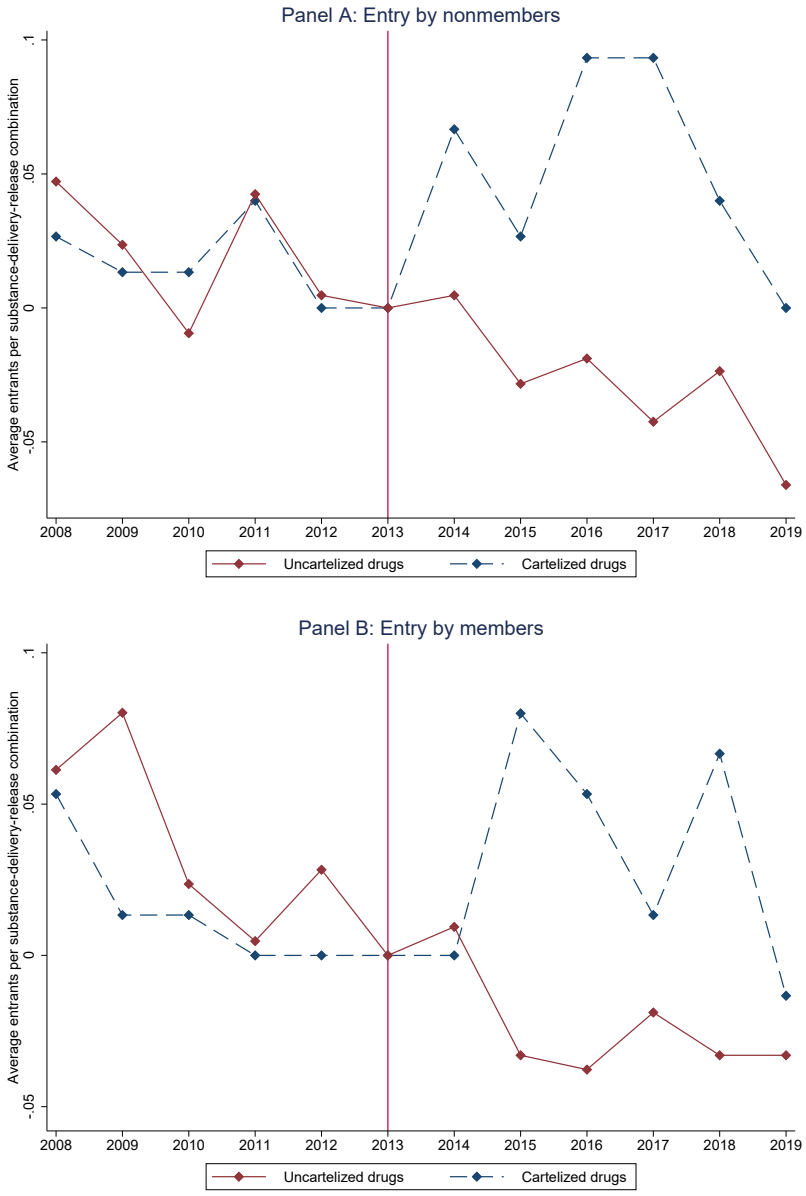

Figure B.11: *Entry in calendar time by cartel membership*

In the body of the main text, we find that cartel formation attracts new entrants (i.e., ANDA filings). Here, we plot the relationship separately for cartel nonmembers (left panel) and cartel members (right panel).

C Tables/figures rel. to structural estimation

C.1 Price elasticity of demand

To better understand heterogeneity in the price elasticity of demand, we plot inverse price coefficients (i.e., $1/\alpha$) against corresponding drug classes. Figure C.1 reports the result. Buyers of two classes of

drugs—other antiepileptics and β-blockers—are especially inelastic.

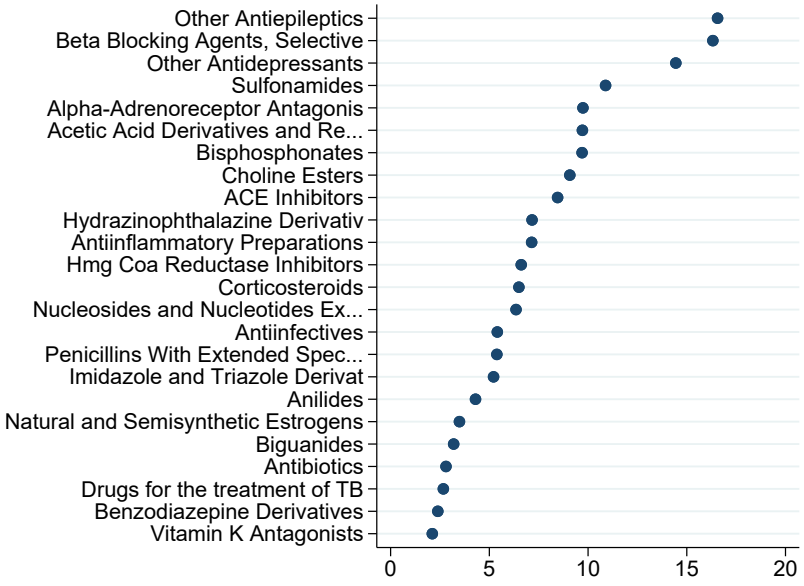

Figure C.1: *Patients consuming antiepileptics and β-blockers are inelastic.*

This figure plots inverse price coefficients (i.e., $1/\alpha$) on the x-axis against corresponding drug classes on the y-axis. Buyers of two classes of drugs—other antiepileptics and β-blockers—are especially inelastic, so we incorporate this heterogeneity in the demand system. See Section V for more details.

C.2 Marginal cost

In Appendix Figure C.2, we report the distribution of marginal costs. Appendix Figure C.3 shows that the model fits well out of sample. The estimates imply markups that very closely align with figures reported by Teva Teva Pharmaceuticals Industries (2011-2016, 2012, 2013, 2014, 2015, 2016) in their financial statements. To obtain values implied by our model, we set the first order condition of the profit function with respect to price equal to zero, solve for $p_{dft} - mc_{dft}$, divide the resulting markups by prices, and average over drugs manufactured by Teva, weighting by revenue. To obtain analogous figures from Teva's annual reports, we extract segment-specific income statements and compute the ratio of operating profits to total revenue for their generic division.[1] Our model assumes competitive pricing and implies that profit margins average 19.7%, while Teva's financial statements imply 20.0% in the two years prior to NP joining Teva. In the two years after NP joins Teva, our model assumes NP has cartelized many drug markets and implies that profit margins average 39.6%, while Teva's financial statements imply 39.9%. In other words, forecasts from the model not only match profit rates in levels but also changes around cartel formation.[2]

[1]Operating margin is the right choice, given how Teva reports its income. Operating profit reduces total revenue by cost of goods sold and selling/marketing expenses, which are mostly variable, but not general/administrative expenses, (e.g., executive compensation, headquarters operations, etc.), which are mostly fixed/sunk.

[2]Although careful demand estimation contributed to this result, we believe that *such a close correspondence* between the model's predictions and the financial statement analysis is, at least in part, coincidental. The goal of this exercise was to see if the model was in the neighborhood of the annual reports—not whether it was a close match.

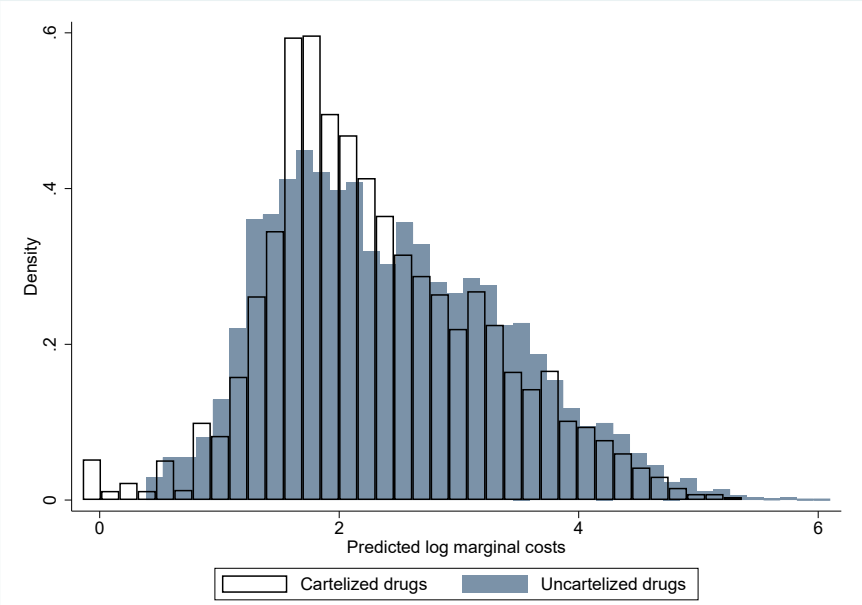

Figure C.2: *Distribution of average predicted log marginal cost*

This figure plots the density of predicted log marginal costs, $\hat{\gamma}_d + \hat{\gamma}_t$, separately for cartelized and uncartelized drugs. It comprises all drug-year observations. However, to avoid taking a stand on conduct prior to formalizing testing it, we estimate the parameters using unambiguously competitive drug-year observations (i.e., using (a) drugs whose prices were never fixed and (b) periods prior to cartelization for drugs whose prices were fixed).

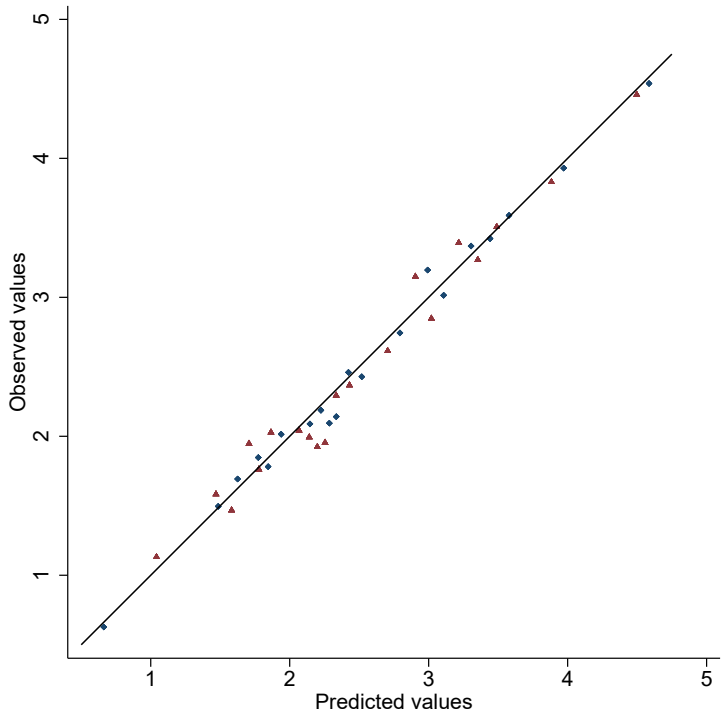

Figure C.3: *Out-of-sample evaluation of log marginal cost predictions*

This figure is constructed as follows. We restrict attention to 2008-2012 and "back out" marginal cost estimates assuming firms set Bertrand-Nash prices. Then, we estimate a regression using uncartelized drugs from 2008-2012 and cartelized drugs from 2008-2010. Next, we predict marginal costs for our "leave-out" sample, which comprises cartelized drugs from 2011-2012. Last, we plot ("binscatter") predicted marginal costs for the leave-out sample against our marginal cost estimates from those drugs and periods.

Appendix Figure C.4 plots the distribution of $\hat{\omega}$ separately for cartel members and nonmembers.

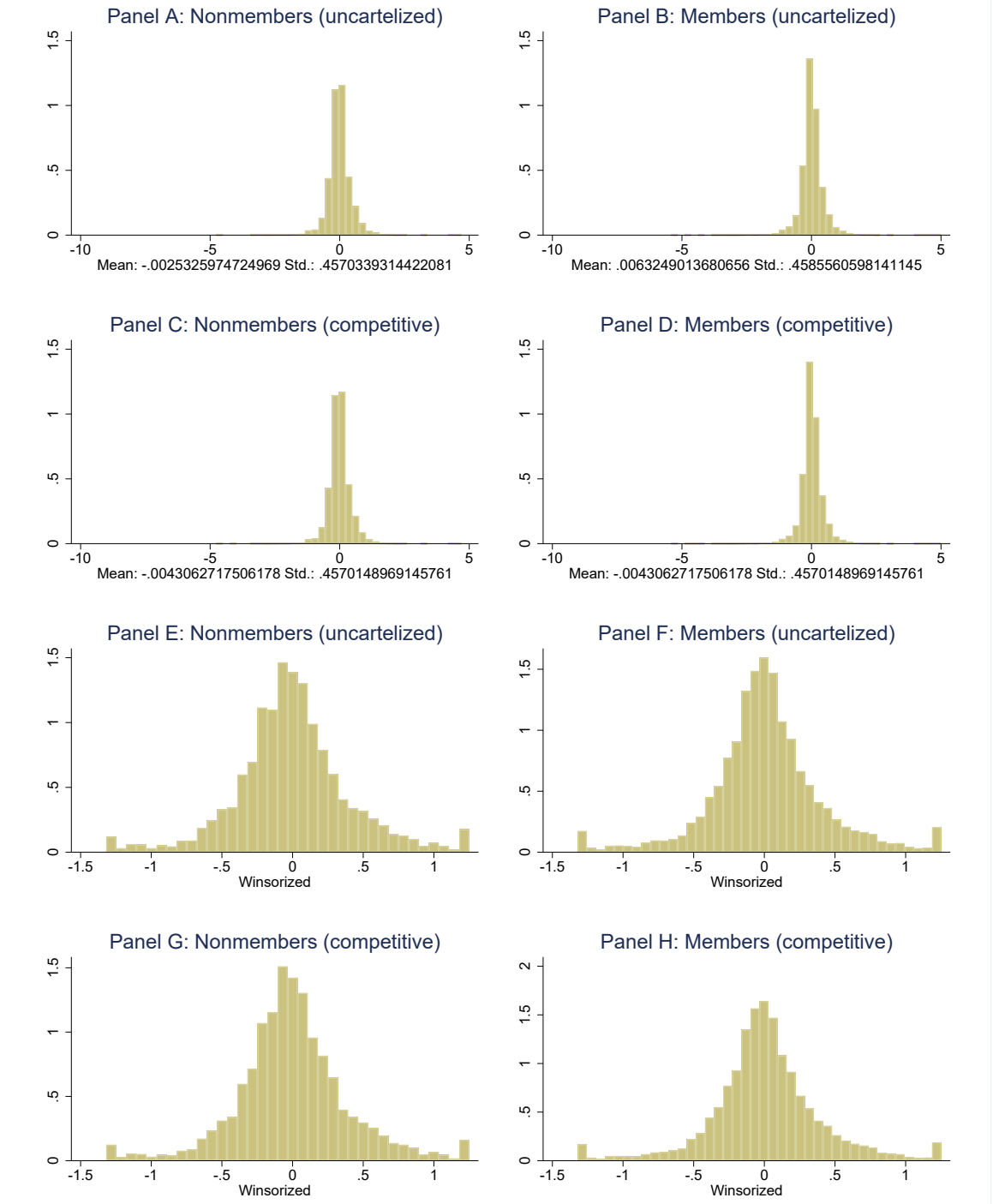

Figure C.4: *Distribution of predicted marginal cost shocks*

Left-hand side panels plot the distribution of marginal cost shocks for nonmembers, while right-hand side panels produce analogous graphs for members. The top four panels are based on the full distribution, while the bottom four are based on winsorized (at 1%) values. "Uncartelized" panels cover drugs whose prices were not cartelized. "Competitive" panels additionally cover, for drugs whose prices were cartelized, years prior to cartel formation.

C.3 Damage assessment

Using our model and demand estimates, we can compute damages to consumers. For each product in a cartelized drug market, we compute equilibrium prices under competition and collusion, and we multiply the difference by the number of observed prescriptions. The median price differences are \$6.1, \$6.4, and \$5.5 per prescription for 2013, 2014, and 2015, respectively. Mean price differences are slightly higher at \$10.0, \$7.3, and \$7.7, respectively. Damages total \$787 million, \$1.4 billion, and \$1.5 billion, respectively. That is, damages total \$3.8 billion over the three-year period, which averages out to \$18.2 million per drug per year.

Our figures are very similar to those reported in two other recent studies. Cuddy (2020) finds that collusion induced nationwide annual damages of \$49.5 million per substance-delivery-release combination.[3] Even though our data and models differ, we arrive at a similar figure, \$40.5 million. Clark et al. (2021) study six substance-delivery-release combinations that were affected by price fixing, estimating damages using a carefully constructed difference-in-difference research design. Again, we reach similar estimates.[4] Since the source of our quantity data is the same as theirs, we predict nearly identical damages for the substance-delivery-release combinations for which we overlap.

D Cartel rollout

As Section 2 in the body of the main text describes, the first price increase occurred on July 3, 2013. After the first round, opportunities for subsequent increases emerged. The Complaint suggests that these opportunities arose for two main reasons.

One source were leadership changes. If an employee with close ties to NP moved from Firm A to Firm B, then the likelihood of Firm B complying with the cartel agreement increased. For example, when Zydus, which was initially rated -3, hired NP's colleague, KG, the firm's score increased to 2. Subsequent phone and text records indicate that the two communicated extensively (Complaint, page 272-273).

Another source of opportunities involved supply disruptions. If a firm without close ties to NP lost access to the active pharmaceutical ingredient and left the market, then the likelihood of cartel formation increased. Suppose, for example, that a particular drug was manufactured by Teva, Mylan, and Orchid at the time that NP joined Teva. Mylan is rated 3 throughout the sample. However, Orchid is rated -3, so its presence discouraged cartel formation. Now, suppose Orchid suffers the unexpected shutdown of one of its production facilities and cannot produce this drug for the foreseeable future. This even leaves just Teva and Mylan, which drastically increases the likelihood that a cartel is formed.

For more details, please see Cuddy et al. (2024). The authors provide the exact timing of events, such as NP's maternity leave, which paused cartel formation for around six months. They also study the relationship between cartel formation, the number of firms in the market, and the score that NP assigned each of them.

[3] To arrive at \$49.5 million, we start with average annual damages for the insurer she studies (\$1.3755 billion, per her Table 8), scale up to nationwide damages (by a factor of 5.8, per her Section 6.4), and divide by the number of substance-delivery-release combinations in her sample (161, per her Appendix Table B.1.

[4] Whereas they estimate 44.2% and 13.5% price increases for nystatin and theophylline, respectively, our structural model predicts 41.4% and 20.8% changes. To arrive at these figures, we divide the estimated damages per defined daily dose by pre-collusion prices, both of which are reported by the authors in their Table 7. Specifically, we define \$0.21 by \$1.561 and \$0.155 by \$0.350.

E Technical appendix

E.1 Sunk cost estimation procedure

We require construct consistent upper and lower bounds on the parameters that determine sunk costs. The basis for the bounds are conditions that are necessary conditions for Nash equilibrium in first stage play. However, due to disturbances that are known by the firms but unobserved by us, we cannot naively take inequalities derived from these conditions to the data and compute simple averages. To see this, suppose we ignore selection induced by η, replace expected sunk costs with $\theta_0 + \theta_1 r_j + \theta_2 \ell_j$, and take inequalities 12-15 directly to the data. Since entry is especially common in markets where sunk cost shocks are small, this approach over-samples negative η when we compute lower bounds, resulting in upward bias. By the same logic, it over-samples positive η when we compute upper bounds, resulting in downward bias.

For lower bounds, the solution to the selection problem introduced by the structural errors lies in the fact that although the conditional expectation of η varies with observed entry, its unconditional expectation is nonetheless mean zero (Ishii, 2005; Ho, 2009; Pakes et al., 2015). To see this conceptually, suppose for the sake of illustration that at least one cartel member enters each substance-delivery-release combination. Further, suppose that we construct precisely one instance of inequality 12 for each substance-delivery-release combination, substitute measured objects for true values, ignore the error terms, pool the instances together, and calculate their mean. This process collects one η_j from each j, yielding an unselected set of disturbances whose expected value is zero.[5]

As stated in the main text, we compute

$$\frac{1}{J}\sum_j \frac{1}{\mu_j} \sum_{d \in \mathscr{D}_j} \frac{1}{2} \sum_{k \in \{M,N\}} \left[\widehat{VE}_d^k(\chi^M + \mathbb{1}\{k = M\}, \chi^N + \mathbb{1}\{k = N\}) - \theta_0 - \theta_1 r_j - \theta_2 \ell_j \right] h_j^\iota < 0. \tag{4}$$

Moments indexed by ι are formed by interacting the bracketed term with a weight function, denoted by h_j^ι. The weight function includes a constant, an indicator for standard delivery method drugs, an indicator for nonstandard delivery method drugs, and indicators for substance-delivery-release combinations available in one, two, and more than two strengths. J denotes the number of unique substance-delivery-release combinations, and μ_j denotes the number of drugs associated with each substance-delivery-release combination. $\widehat{VE}_d^M(\cdot)$ denotes $VE_d^M(\cdot)$ evaluated at our estimates of $\pi(\cdot)$, F_ξ, F_ω, and F_D rather than the true values. $\widehat{VE}_d^N(\cdot)$ is defined analogously.

For upper bounds, we take a slightly different approach, since not every substance-delivery-release combination experiences entry. To solve the selection problem, we exploit the symmetry of the distribution of η (Powell, 1986; Pakes et al., 2015). This approach requires additional notation. Let L be the set of j with at least one entrant, J_L be the size of that set, and w^i be a positive valued function of r_j and ℓ_j. Also, define

$$VE_j^+ = \frac{1}{2} \sum_{d \in \mathscr{D}_j} \sum_{k \in \{M,N\}} \left[\widehat{VE}_d^k(\chi^M + \mathbb{1}\{k = M\}, \chi^N + \mathbb{1}\{k = N\}) \right], \tag{5}$$

which represents the average of the cartel members' and nonmembers' entry values in j. Finally, for each

[5] This approach exploits the "ordered choice" nature of the problem. Ishii (2005) illustrates the approach most clearly. We differ from her approach by having two types of entrants—cartel members and nonmembers—and permitting expectational error to reconcile differences in the sunk costs implied by their decisions. See Section III.C of Wollmann (2018) for a general discussion of ways to relax this assumption. To name one, the econometrician could specify the shape of the structural error and take the "probability inequality" approach, proposed by Tamer (2003), though this approach is computationally infeasible in our setting.

moment i, order j by their values of $w_j^i VE_j^+$, and let Ψ_{wVE} denote the set of j that corresponds to the $J-J_L$ smallest values. As stated in the text, the second set of moments is then given by

$$\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]$$

$$-\frac{1}{J}\sum_{j\in\Psi_{wVE}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]<0. \quad (6)$$

In Online Appendix E, we prove that inequalities 4 and 6 produce consistent bounds.

Computing $\widehat{VE}_d^M$ and $\widehat{VE}_d^N$ under the de facto policy and eight alternative (counterfactual) policies is computationally burdensome. The most straightforward way to reduce the burden involves reducing the number of draws of (ξ,ω), but reducing the number can result in noisy estimates of the value of entry. To gain traction on the problem (and make it feasible for interested readers to exactly replicate our results), we cut the variance of the distributions from which we draw ξ and ω by a factor of five, and we calculated $\widehat{VE}_d^M$ and $\widehat{VE}_d^N$ based on 125 draws of those variables (for all periods, all hypothetical market structures arising, and all policies that we considered, including the de facto policy). To ensure that this did not affect our sunk cost estimates, we replicated the process (a) using 200 draws and a scaling factor of 2.5 rather than five and (b) using 50 draws and a scaling factor of 10. Either way, we arrived at very similar results.

E.2 Counterfactual simulations

Since we have two types of entrants (i.e., members and nonmembers), multiple equilibria may exist in Stage 1 play. For example, in a particular market, equilibrium entry may involve one member entrant and two nonmember entrants and also involve two member entrants and one nonmember entrant. As a result, when we simulate the effect of counterfactual policies, we may need to select a particular equilibrium in Stage 1. Since equilibrium selection boils down to choosing the composition of entrants, we choose ones whose ratio of member to nonmember entrants is as close as possible to the average ratio we observe in the data following cartel formation.

To assess whether our equilibrium selection rule matters to the results we report in Section 8, we simulated outcomes based on two separate rules. One rule selected equilibria with comparatively high proportions of member entrants, while the other selected ones with comparatively low proportions of member entrants. Empirically, consumer welfare does not vary much across the choices. Why? In the first stage, nonmembers drive down profit much more than members do. In other words, informally speaking, nonmember entry "clears" the market in that point in the game. As a result, we typically do not find more than two equilibria, which almost which differ only by whether they have one more or less nonmember entrant. Thus, there is not much scope for the selection rule to affect consumer welfare.[6]

One other consequence of multiplicity is that θ_0, θ_1, and θ_2 are set- rather than point-identified. In

[6]There is another, more practical reason why equilibrium selection is unlikely to impact consumer welfare in the markets we study. In our data, cartel formation attracts a large number of entrants. For this group in particular, there is no reason to think that the mix of member and nonmember entrants varies based on the policy we evaluate. In other words, if the equilibria we select differ from the ones that would actually be played, then the differences are probably confined to changes in the composition of *additional* entrants—ones that enter only because entry costs and delays are reduced under the counterfactual policies we evaluate. However, the simulations indicate that marginal entrants have small effects on consumer welfare. (Notice that this is the same conclusion we reach when we compare Figure V and Table V. Figure V shows that entry plays a major role in disciplining prices in cartelized markets. Yet, columns 1-4 of Table V show that additional entry, which occurs only as a result of reduced entry costs, plays a comparatively minor role.)

other words, we only obtain bounds on the parameters that determine sunk cost. When we simulate counterfactual equilibrium outcomes, we chose values equal to the midpoints of the bounds of the 95% confidence intervals. As we revised our analysis (e.g., by changing the number of draws used to compute the value of entry), the bounds differed slightly. Given the comparatively small changes in the midpoint values, the trivial effect this has on our counterfactual policy analysis, and our desire to maintain as much continuity across the drafts as possible, we fixed our choices at $\theta_0 = 1.61$, $\theta_1 = 1.22$, and $\theta_0 = 3.10$—values we reported in our first submission to the journal. Simulating counterfactual outcomes using large numbers of draws is approximately as burdensome as computing $\widehat{VE}_d^M$ and $\widehat{VE}_d^N$. Hence, to speed the process up, we reduced the variance of ξ and ω by a factor of 5 and averaged outcomes over 100 draws of each disturbance. Again, to ensure that this did not affect our results, we cut the number of draws and the variance of the disturbances further, and we checked that we arrive at very similar results.

E.3 Moment Inequalities

THEOREM I. *Moments indexed by i and given by*

$$\frac{1}{J}\sum_j \frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\frac{1}{2}\sum_{k\in\{M,N\}} h_j^i\Big[\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]<0 \tag{7}$$

produce consistent upper bounds.

PROOF.
For each moment indexed by i, we have

$$\begin{aligned}
&\frac{1}{J}\sum_j \frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\frac{1}{2}\sum_{k\in\{M,N\}} h_j^i\Big[\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad=\frac{1}{J}\sum_j \frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\frac{1}{2}\sum_{k\in\{M,N\}} h_j^i\Big[VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad=\frac{1}{J}\sum_j \frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\frac{1}{2}\sum_{k\in\{M,N\}} h_j^i\Big[VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\theta_{jk}+\eta_j\Big]\\
&=\frac{1}{J}\sum_j \frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\frac{1}{2}\sum_{k\in\{M,N\}} h_j^i\Big[VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\mathscr{E}(\theta_{jk}|\mathscr{I}_{jk})-\nu_{jN}+\eta_j\Big]\\
&\quad<\frac{1}{J}\sum_j\Big[h_j^i\eta_j\Big]-\frac{1}{J}\sum_j\Big[h_j^i\nu_{jN}\Big]\xrightarrow{p}\mathbb{E}[h^i\eta]-\mathbb{E}[h^i\nu_{jN}]=\mathbb{E}[h^i]\mathbb{E}[\eta]-\mathbb{E}[h^i]\mathbb{E}[\nu_{jN}]=0.
\end{aligned} \tag{8}$$

The first equality results from replacing $\widehat{VE}_d^k(\cdot)$ with $VE_d^k(\cdot)$. $\widehat{VE}_d^k(\cdot)$ is a function of $\hat{\pi}_{d,t}^k(\cdot)$, $\hat{F}_\xi$, $\hat{F}_\omega$, and $\hat{F}_D$, and $VE_d^k(\cdot)$ is a function of $\pi_{d,t}^k(\cdot)$, F_ξ, F_ω, and F_D. Since $\pi_{d,t}^k(M,N,\xi_{dt},\omega_{dt})$, F_ξ, F_ω, and F_D are measured without error, and since the value entry depends on only those objects, entry values are measured without error. The second equality results from replacing $\theta_0+\theta_1 r_j+\theta_2\ell_j$ with $\theta_{jk}-\eta_j$, which follows directly from equation 16. The third equality results from replacing θ_{jk} with $\mathscr{E}[\theta_{jk}|\mathscr{I}_{jk}]+\nu_{jN}$, which follows directly from the definition of an expectational error. The inequality follows from the necessary conditions of a simultaneous move Nash equilibrium, which require $VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})-\mathscr{E}(\theta_{jk}|\mathscr{I}_{jk})<0$. (If this condition were false, then another firm would have expected to profitably enter.) The next step follows from the law of large numbers. Since h^i depends on r and ℓ, η is independent of r and ℓ, ν is

independent of r and ℓ, the fourth inequality holds. To arrive at the final inequality, notice that η and ν are both unconditionally mean zero (i.e., $\mathbb{E}[\eta] = 0$ and $\mathbb{E}[\nu] = 0$). ■

THEOREM II. *Moments indexed by i and given by*

$$\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]$$
$$-\frac{1}{J}\sum_{j\in\Psi_{wVE}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\geq 0 \quad (9)$$

produce consistent lower bounds.

PROOF.
For each moment i, order j by their value of $w_j^i\eta_j$, let $L_{w\eta}$ denote the set of j that correspond to the smallest J values, and let $\Psi_{w\eta}$ correspond to the smallest $J-J_L$ values. For each moment indexed by i, we have

$$\begin{aligned}
&\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\geq\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\widehat{VE}_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&=\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\theta_0-\theta_1 r_j-\theta_2\ell_j\Big]\\
&\quad=\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_{jk}+\eta_j\Big]\\
&\quad\quad-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\mathbb{E}(\theta_{jk}|\mathscr{I}_{jk})+\eta_j\Big]\\
&\quad=\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{\mathbb{1}\{\chi^k\geq 1\}VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{\mathbb{1}\{\chi^M\geq 1\}+\mathbb{1}\{\chi^N\geq 1\}+\mathbb{1}\{\chi^M=0,\chi^N=0\}}-\theta_{jk}+\eta_j-\nu_{jN}\Big]\\
&\quad\quad-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\frac{VE_d^k(\chi^M+\mathbb{1}\{k=M\},\chi^N+\mathbb{1}\{k=N\})}{2}-\mathbb{E}(\theta_{jk}|\mathscr{I}_{jk})+\eta_j-\nu_{jN}\Big]\\
&\quad\quad\geq\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\eta_j-\nu_{jN}\Big]-\frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\eta_j-\nu_{jN}\Big]. \quad (10)
\end{aligned}$$

The first inequality follows from the construction of set Ψ_{wVE}. The first equality results from replacing $\widehat{VE}_d^k(\cdot)$ with $VE_d^k(\cdot)$. $\widehat{VE}_d^k(\cdot)$ is a function of $\hat{\pi}_{d,t}^k(\cdot)$, $\hat{F}_\xi$, $\hat{F}_\omega$, and $\hat{F}_D$, and $VE_d^k(\cdot)$ is a function of $\pi_{d,t}^k(\cdot)$, F_ξ, F_ω, and F_D. Since $\pi_{d,t}^k(M, N, \xi_{dt}, \omega_{dt})$, F_ξ, F_ω, and F_D are measured without error, and since the value entry depends on only those objects, entry values are measured without error. The second equality results from replacing $\theta_0 + \theta_1 r_j + \theta_2 \ell_j$ with $\theta_{jk} - \eta_j$, which follows directly from equation 16. The third equality results from replacing θ_{jk} with $\mathscr{E}[\theta_{jk}|\mathscr{I}_{jk}] + \nu_{jN}$, which follows directly from the definition of an expectational error. The second inequality follows from the necessary conditions of a simultaneous move Nash equilibrium. That is, for $k \in \{M, N\}$, these conditions require $VE_d^k(\chi^M, \chi^N) - \mathscr{E}(\theta_{jk}|\mathscr{I}_{jk}) \geq 0$ as well as $VE_d^k(\chi^M + \mathbb{1}\{k = M\}, \chi^N + \mathbb{1}\{k = N\}) - \mathscr{E}(\theta_{jk}|\mathscr{I}_{jk}) < 0$.

Assume that $J_L/J \xrightarrow{p} q$ by the law of large numbers. We then have

$$\begin{aligned}
&\frac{1}{J}\sum_{j\in L}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\eta_j - \nu_{jN}\Big] - \frac{1}{J}\sum_{j\in\Psi_{w\eta}}\frac{1}{\mu_j}\sum_{d\in\mathscr{D}_j}\sum_{k\in\{M,N\}} w_j^i\Big[\eta_j - \nu_{jN}\Big] \\
&\qquad = \frac{1}{J}\sum_{j\in L}\Big[w_j^i\eta_j\Big] - \frac{1}{J}\sum_{j\in\Psi_{w\eta}}\Big[w_j^i\eta_j\Big] - \left(\frac{1}{J}\sum_{j\in L}\Big[w_j^i\nu_{jN}\Big] - \frac{1}{J}\sum_{j\in\Psi_{w\eta}}\Big[w_j^i\nu_{jN}\Big]\right) \\
&\qquad \geq \frac{1}{J}\sum_{j\in L_{w\eta}}\Big[w_j^i\eta_j\Big] - \frac{1}{J}\sum_{j\in\Psi_{w\eta}}\Big[w_j^i\eta_j\Big] - \left(\frac{1}{J}\sum_{j\in L}\Big[w_j^i\nu_{jN}\Big] - \frac{1}{J}\sum_{j\in\Psi_{w\eta}}\Big[w_j^i\nu_{jN}\Big]\right) \\
&\xrightarrow{p} \mathbb{E}[\eta|\eta<F^{-1}(q), w^i{=}1] - \mathbb{E}[\eta|\eta<F^{-1}(1-q), w^i{=}1] - (\mathbb{E}[\nu|\eta<F^{-1}(q), w^i{=}1] - \mathbb{E}[\nu|\eta<F^{-1}(1-q), w^i{=}1]) \\
&\qquad = \mathbb{E}[\eta|\eta<F^{-1}(q)] - \mathbb{E}[\eta|\eta<F^{-1}(1-q)] - (\mathbb{E}[\nu] - \mathbb{E}[\nu]) = 0. \quad (11)
\end{aligned}$$

The first equality follows from the fact that w^i and η_j, and ν_{jN} do not depend on d or k. The first inequality follows from the construction of $L_{w\eta}$. The third step follows from the law of large numbers. The second equality follows from the fact that η and ν are independent of r and ℓ, on which w^i depends. Thus, for example, $\mathbb{E}[\eta|\eta<F^{-1}(q), w^i{=}1] = \mathbb{E}[\eta|\eta<F^{-1}(q)]$. To arrive at the final step, notice that $\mathbb{E}[\eta|\eta<F^{-1}(q)]$ and $\mathbb{E}[\eta|\eta<F^{-1}(1-q)]$ are values that are equidistant from zero, so their difference is zero. Also, notice that ν is independent of η and is unconditionally mean zero. ■

E.4 Procurement scoring auctions vs. nested logit demand

E.4.1 Purchase probabilities and market shares

Consider the procurement scoring auction described in the body of the main text, and omit drug and time subscripts to simplify notation. Let $\mathscr{F}$ denote the set of firms with products in this market, $\mathscr{P}(\cdot)$ denote the probability that the event in the parentheses occurs, and $\mathscr{P}_{if}$ denote the probability that i buys the drug from f. $\mathscr{P}_{if}$ can be written as

$$\begin{aligned}
&\mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p_{if} \geq \lambda + \xi_{f'} + \zeta_i + (1-\sigma)\epsilon_{if'} + \alpha p_{if'}\ \forall f' \in \mathscr{F}) \\
&\qquad\qquad \times \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p_{if} \geq \epsilon_{i0}). \quad (12)
\end{aligned}$$

Since ϵ and ζ are not known by the firms when they submit proposals and are i.i.d. with respect to i (and other indices), f sets the same price to all i. Thus, $\mathscr{P}_{if}$ can be rewritten as

$$\mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p_f \geq \lambda + \xi_{f\prime} + \zeta_i + (1-\sigma)\epsilon_{if\prime} + \alpha p_{f\prime} \ \forall f' \in \mathscr{F}) \\ \times \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p_f \geq \epsilon_{i0}). \quad (13)$$

Since ϵ and $[\zeta + (1-\sigma)\epsilon]$ are distributed Type 1 extreme value, $\mathscr{P}_{if}$ can further be rewritten as

$$\frac{e^{\lambda + \alpha p_f + \xi_f}}{\Lambda^\sigma (1+\Lambda)^{1-\sigma}}, \quad (14)$$

where $\Lambda = \sum_{f' \in \mathscr{F}} e^{\lambda + \alpha p_{f\prime} + \xi_{f'}}$.

Let w_i denote the size of buyer i and s_f denote the market share of f. s_f equals the weighted average probability of winning the procurement scoring auctions, which is given by $\frac{\sum_i w_i \mathscr{P}_{if}}{\sum_i w_i}$. If the buyers are approximately symmetric, then $\frac{\sum_i w_i \mathscr{P}_{if}}{\sum_i w_i} \approx \frac{\sum_i w \mathscr{P}_{if}}{\sum_i w} = \frac{1}{n_i}\sum_i \mathscr{P}_{if}$, where n_i denotes the number of buyers. If the number of buyers is very large, then $\frac{1}{n_i}\sum_i \mathscr{P}_{if} \approx \mathbb{E}[\mathscr{P}_{if}]$, which is the same as the individual probability that i purchases the drug from f, since $\mathscr{P}_{if}$ does not depend on i. Hence, $s_f = \frac{e^{\lambda + \alpha p_f + \xi_f}}{\Lambda^\sigma (1+\Lambda)^{1-\sigma}}$.

Thus, under the collection of procurement scoring auctions described in the body of the main text, each firm's market share is approximately equal to the market share obtained under a nested logit demand system.

E.4.2 Bids and prices

Consider the procurement scoring auction described in the body of the main text, and omit drug and time subscripts to simplify notation. Let $\mathscr{P}(\cdot)$ denote the probability that the event in the parentheses occurs. Each firm f wishes to maximizes its profit, so it solves

$$\max_p \Big\{ \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p \geq \lambda + \xi_{f\prime} + \zeta_i + (1-\sigma)\epsilon_{if\prime} + \alpha p_{if\prime}) \ \forall f' \in \mathscr{F}) \\ \times \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p_{if} \geq \epsilon_{i0})(p - mc_f) \Big\}. \quad (15)$$

As in the explanation above, since ϵ_{if} and ζ_i are not known by the firms when they submit proposals and are i.i.d. with respect to i (and other indices), each f' sets the same price to all buyer (i.e., $p_{if\prime} \equiv p_{f\prime}$). Thus, the preceding optimization problem can be rewritten as

$$\max_p \Big\{ \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p \geq \lambda + \xi_{f\prime} + \zeta_i + (1-\sigma)\epsilon_{if\prime} + \alpha p_{f\prime} \ \forall f' \in \mathscr{F}) \\ \times \mathscr{P}(\lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p \geq \epsilon_{i0})(p - mc_f) \Big\}. \quad (16)$$

Since ϵ_{if} and $[\zeta_i + (1-\sigma)\epsilon]_{if}$ are distributed Type 1 extreme value, the preceding optimization problem can further be rewritten as

$$\max_p \left\{ \frac{e^{\lambda + \alpha p + \xi_f}}{\Lambda^\sigma (1+\Lambda)^{1-\sigma}} (p - mc_f) \right\}, \quad (17)$$

where $\Lambda = \sum_{f' \in \mathcal{F}} e^{\lambda + \alpha p_{f'} + \xi_{f'}}$.

Separately, consider a nested logit demand model. Let the buyer's "utility" takes the same form as its "payoff" in the procurement auction, so that $u_{if} = \lambda + \xi_f + \zeta_i + (1-\sigma)\epsilon_{if} + \alpha p$, and let ξ_f, ζ_i, and ϵ_{if} have the same distributional assumptions as in the procurement auction case. Firm f multiplies the product of market share and per-unit profit margin, i.e., it solves

$$\max_p \left\{ \frac{e^{\lambda + \alpha p + \xi_f}}{\Lambda^\sigma (1+\Lambda)^{1-\sigma}} (p - mc_f) \right\}. \tag{18}$$

where $\Lambda = \sum_{f' \in \mathcal{F}} e^{\lambda + \alpha p_{f'} + \xi_{f'}}$.

Thus, bid setting under the procurement scoring auction described in the body of the main text is isomorphic to price setting in a nested logit demand system.

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