In Defense of the Middleman: Quality Failures in the Generic Pharmaceutical Market

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Motivation: Increasing quality failures in the generics market

Generic prescription drugs are widely assumed to be interchangeable.

- E.g., generic Lipitor made by *Teva* is identical the version made by *Dr. Reddy's*
- High stakes: consumed by 2/3 of Americans each year and represent 90% of US drug volumes

Growing evidence suggests this is broadly incorrect.

- New data: manufacturing quality failures cause ≈1,000 recalls, 150 shortages each year.
- Impure or fails to perform approved purpose (e.g., contaminated, superpotent) Example

Motivation: What disciplines quality in the generics market?

Limited regulation or consumer demand supports generic quality.

- Despite non-binding FDA disclosures, consumers are uniquely uninformed about quality.

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- Despite non-binding FDA disclosures, consumers are uniquely uninformed about quality.

Instead, informed intermediaries make key quality purchasing decisions.

- E.g., grocery stores, gas stations, big-box retailers...
- In generics, pharmacies & wholesalers select nearly all products available to consumers.
- Can alleviate adverse selection—but may not fully internalize social benefits, leading to quality underprovision.

Q: How do pharmacies & wholesalers discipline quality in the generics market?

This paper

1. Documents the extent of generic quality failures
   - Assembles first, comprehensive data on drug-level manufacturing quality

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   - Assembles first, comprehensive data on drug-level manufacturing quality
2. Develops quasi-experimental evidence on pharmacy purchasing decisions
   - Estimates effects of disclosure policies and motivates the structural model
3. Estimates a model of pharmacy purchases and policy counterfactuals
   - Develops novel method for non-parametrically estimating scoring auctions with winning prices
   - Solves problem of recovering multi-dimensional buyer preferences, using commonly available data
   - Quantifies effects of pharmacies & recently proposed quality regulation

Preview of results

1. Quality failures are pervasive, even in the U.S. market.
   - Over 2000-2022, 57% of manufacturing facilities failed inspections, and 12% of drugs were recalled due to patient health risks.

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   - Quasi-experimental results: reduces pharmacy purchases of recalled drugs by 43% for up to 10yrs
   - But also increases supply disruptions, shortages (33%) and patient non-adherence (5%)

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    - Quasi-experimental results: reduces pharmacy purchases of recalled drugs by 43% for up to 10yrs
    - But also increases supply disruptions, shortages (33%) and patient non-adherence (5%)

3. In equilibrium, pharmacies increase the share of high-quality drugs by 27%.
    - Structural model results: pharmacies are willing to pay a premium for high-quality, reliable drugs: 2% for each 10% reduction in supply disruptions
    - Subsidies for high-quality drugs would improve quality but likely reduce competition.

This talk

- **Data & descriptive evidence**
- Quasi-experimental evidence
- Model
- Estimation
- Counterfactuals

Related literature

1. Industrial organization of pharmaceuticals
   - Pre-approval quality: Peltzman, 1973; Chandra et al., 2023; Kao, 2023; Atal et al., 2024
     Shortages: Galdin, 2023; Dubois et al., 2023; Auctions: Cuddy, 2020; Starc & Wollmann, 2022

   → New evidence on *post-approval* quality failures and their implications for patient welfare

2. Information intermediaries
   - Fiduciary intermediaries: Robles-Garcia, 2019; Gavazza and Lizzeri, 2021; Grennan et al., 2024
     Quality disclosure effects: Dranove & Jin, 2010; Vatter, 2022; Barahona et al., 2023

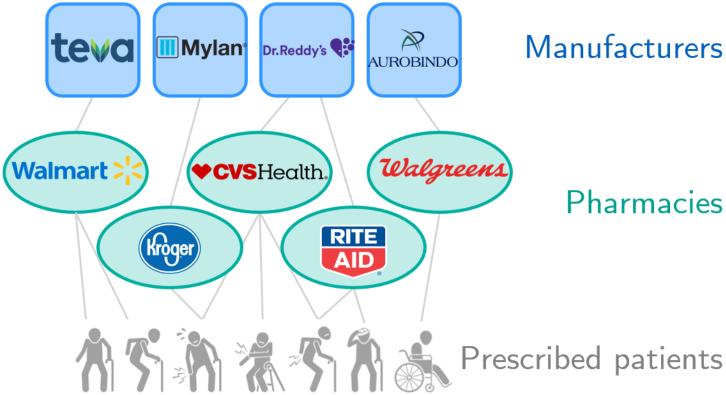
   → Role of *non-fiduciary* intermediaries and their interactions with disclosure

3. Empirical scoring auctions
   - Non-parametric estimation: Guerre et al. "GPV" 2000; Laffont et al. 2020
     Unobserved scoring rules: Krasnokutskaya et al., 2020; Allen et al., 2024

   → Novel estimation method using only winning prices

U.S. generic market structure

The atorvastatin-tablet market (illustrative)



Pharmacies purchase drugs (molecule-form-mfrs.) from competitive manufacturers to sell to patients.

Data

1. Quality: Internal FDA data

- Universe of FDA quality disclosures; trade secret location linkages (Conti et al., 2020; 2000-2022)
- Focus on inspection failure and recall announcements that signal a "reasonable probability" of causing serious injury or death[1]

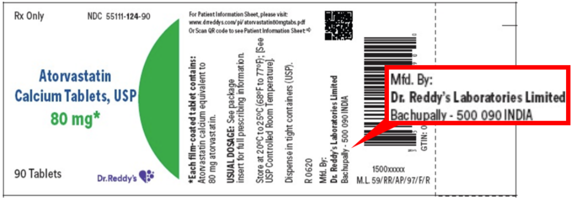
FOIA = Freedom of Information Act request.

1. Refers to Class I/II recalls, Official/Voluntary Action Indicated inspection grades. These types of disclosures do not withdraw drugs from the market.

Linking drugs to quality: An example

Where is atorvastatin-tablet-Dr. Reddy's made?

1. Drug label images
(National Library of Medicine)



2. Import/export data
(Import Genius)

Country of Origin	Shipper	Shipper address
india	dr reddys laboratories ltd	fto unit 3, sy no 41 bachupally mandal, india hyderabad 500090 india

Consignee	Consignee address	Product description
dr reddy laboratories inc	107 college road east princeton nj 08540	...atorvastatin calcium tablets 5mg/10mg...

3. OECD administrative records
(New Zealand, Europe)

Manufacturing step	*Manufacturer*
Manufacture of Final Dose Form	Dr Reddy's Laboratories Limited (Formulation Unit III) Generics Bachupally Telangana 500 090 INDIA

MEDSAFE New Zealand Medicines and Medical Devices Safety Authority

Data

1. Quality: Internal FDA data
   - Universe of FDA quality disclosures from FOIA; trade secret location linkages (2000-2022)
   - Focus on inspection failure and recall announcements that signal a "reasonable probability" of causing serious injury or death[1]
2. Pharmacy purchases: Optum claims data
   - 10K outpatient generic drugs; 64K pharmacies; 70k auctions; 63mm patients (2000-2022)
3. Prices: State and national Medicaid surveys
   - Pharmacy acquisition costs for multi-source, outpatient drugs from FOIA (2010-2022)

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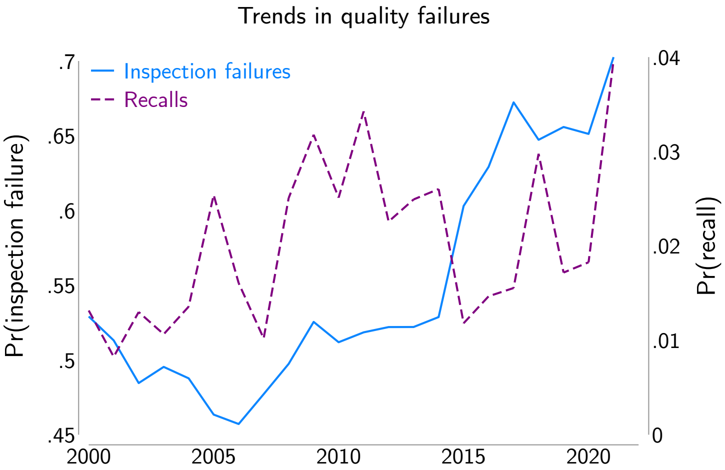
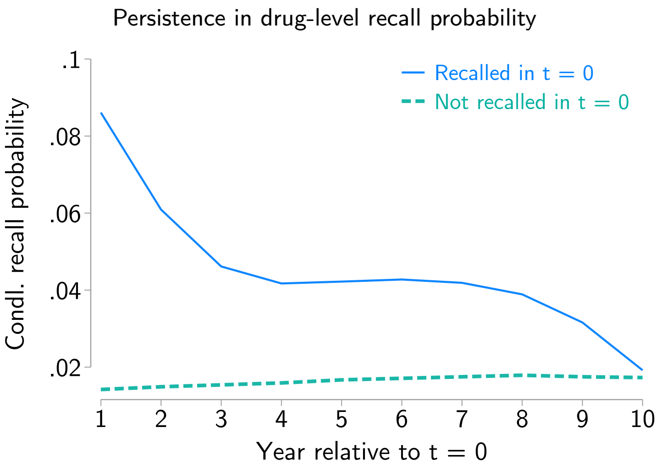
Descriptive evidence: Generic quality failures are pervasive and increasing



Over 2000-2022, 57% of facilities failed inspections and 12% of drugs (molecule-form-mfrs.) were recalled.

Descriptive evidence: Generic quality failures are persistent



Recalled drugs are 3.3x more likely to be recalled over the next decade. Distributions Market-level

This talk

- Data & descriptive evidence
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Quasi-experimental evidence: What are the effects of quality disclosure?

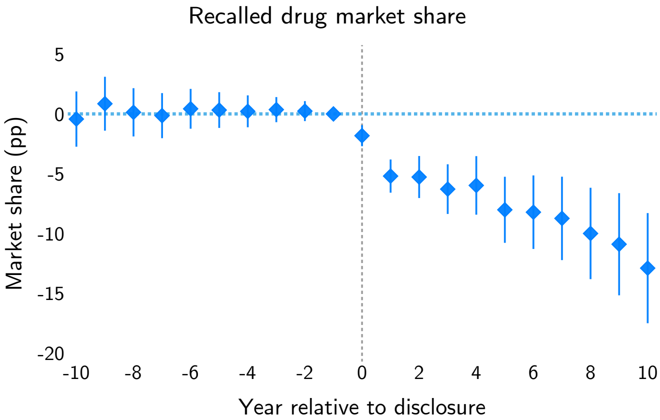
Compare trends for recalled and not-yet-recalled drugs, exploiting variation in disclosure timing.

I estimate the following staggered difference-in-differences event study:

$$Y_{dt} = \alpha_d + \alpha_t + \sum_{s \neq -1} \beta_s \, D_{d,t+s} + \varepsilon_{dt},$$

- where Y_{dt} is the outcome for drug (molecule-form-manufacturer) d in year t
- $D_{d,t+s}$ is an indicator of the s^{th} year after a drug's first disclosure
- Standard errors clustered at the drug-level Heterogeneity-robust estimator

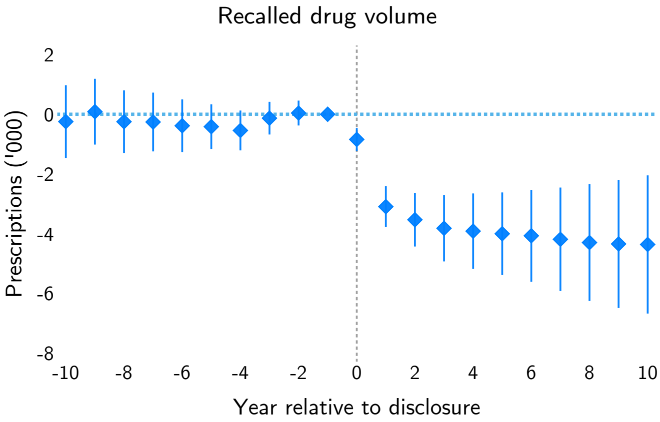
Effects of recall announcements on pharmacy purchases



Recall announcements reduce the share of low-quality, recalled drugs by 43% (4.4pp) on average.

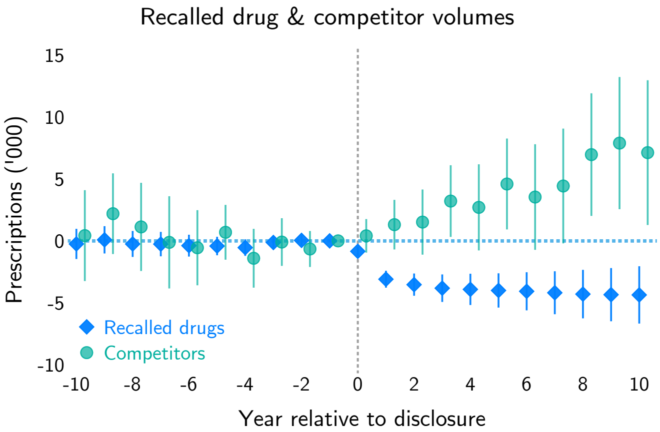
- *Market share*: fraction of pharmacies supplied by a manufacturer (baseline: 10%) Robustness

Effects of recall announcements on pharmacy purchases, cont'd



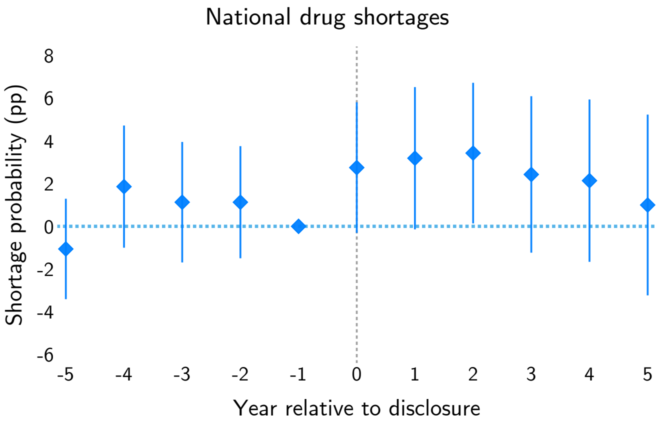
Recall announcements reduce the volume of low-quality drugs by 60%...

Effects of recall announcements on pharmacy purchases, cont'd



Recall announcements reduce the volume of low-quality drugs by 60%... which is eventually offset by substitution to competitor drugs.

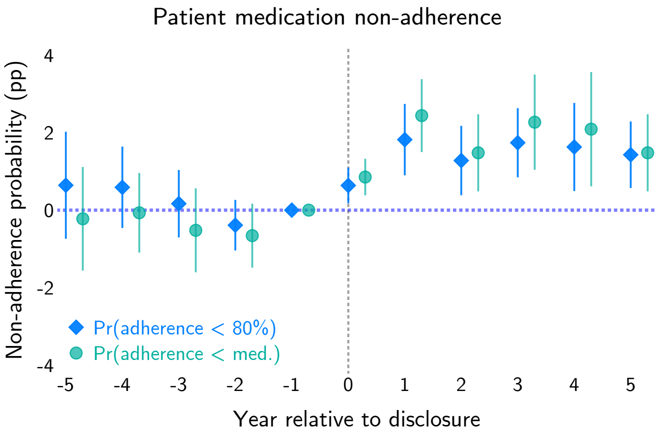
Effects of recalls on patients



Recalls increase the probability of a national drug shortage by 33% (from a baseline of 6%)...

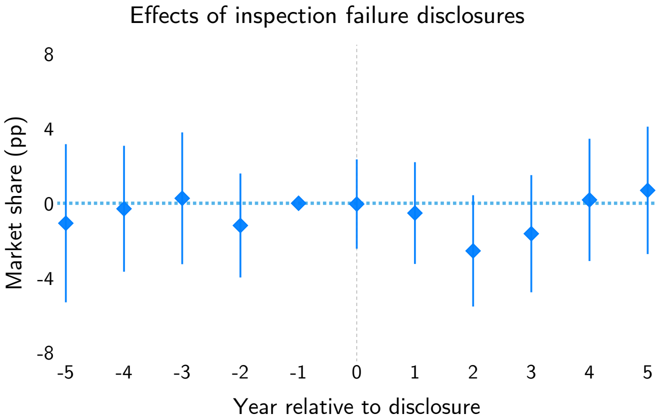
Small markets

Effects of recalls on patients, cont'd



Recalls increase the probability of a national drug shortage by 33% (from a baseline of 6%)... and of patient non-adherence by 5% (from 49%).

Effects of *quality vs. reliability* disclosures on pharmacy purchases



The disclosure of inspection failures—which reveal quality, but not reliability information—does not significantly affect pharmacy purchases. DDD specification Only OAI failures More evidence: heterogeneity

Quasi-experimental evidence: Takeaways

1. Quality disclosure decreases purchases of low-quality drugs by 43% for 10 years—far longer than the duration of a typical recall.
2. However, disclosure also reduces patient welfare through temporary supply disruptions.
3. Find stronger effects from signals of *reliability* than of *quality per se*.

- Potential channels: changes in pharmacy expectations, manufacturer costs and prices.[1]
- Develop a structural model to isolate the role of pharmacies and compare alternative policy instruments.

1. Limited effects from other channels such as inertia, anticipation, participation or within-manufacturer spillovers

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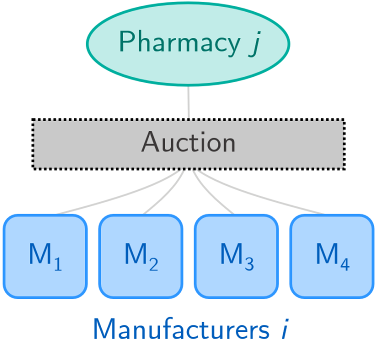
Overview: Pharmacies purchase generics through scoring auctions

Basic structure: CVS-CardinalHealth auctions off its metformin-tablet-500mg contract to four manufacturers, awarding one winner (FTC, 2011)

- Manufacturers submit private bids, and the winner is paid its price (first-score, sealed bid).



Overview: Pharmacies purchase generics through scoring auctions, cont'd

Key difference: pharmacies "score" both price and quality.

- Quality failures cause costly supply disruptions— "lapses in supply ruin relationships" (FTC, 2011).
- Model quantifies the extent to which pharmacies penalize low-quality drugs.

Supply Chain Excellence Award scoring

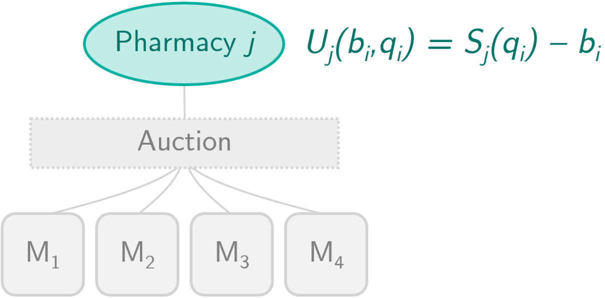
SCE	Maximum points	Score structure	
Manufacturer fill rate	30 pts	97-100% = 30 95-96% = 15 <95% = 0	
Supply chain excellence quality	20 pts	**Deductions based on:**	
		Class 3 recall/withdraw: -2	Incomplete recall notices: -2
		Class 2 recall: -4	Concealed shortage on control substances or list chemicals: -2
		Class 1 recall: -6	Complete, accurate and prompt recall notices: +1 (bonus)

Source: CardinalHealth supplier manual (2020)

Model: Pharmacy payoffs (Laffont et al., 2020)

Pharmacy j receives expected payoff $U_j(b_i, q_i)$ from price b_i and quality signal q_i.

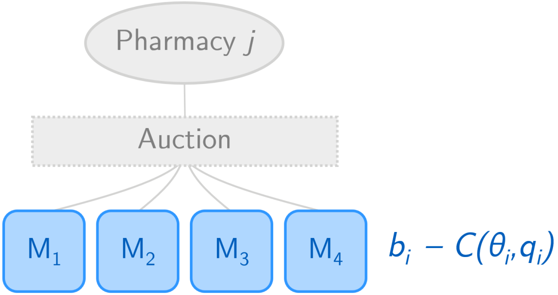
- Observes q_i from historical disclosures, assumed to be commonly-known and predetermined.
- $S(q_i)$ captures the pharmacy's expected value from quality, including supply disruption costs.



Model: Manufacturer payoffs

Manufacturer i receives payoff $b_i - C(\theta_i, q_i)$ if it wins the auction.

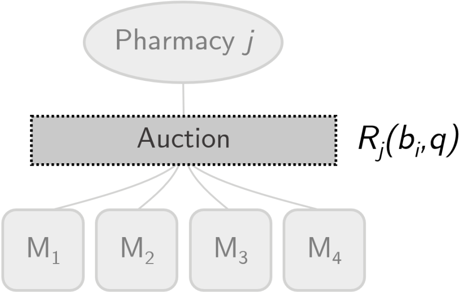
- Costs depend on its productivity shock θ_i and quality q_i.
- Assume shocks θ_i are independent and private, but $F(\theta_i|q_i)$ is commonly-known.



Model: Equilibrium allocation

The manufacturer with the highest score $R_j(b_i, q)$ wins the auction.

- In general, the scoring rule depends on the price b_i and quality q_i.
- Assume the scoring rule is commonly known—except to the econometrician—and propose an estimation method that accommodates arbitrary rules.



Model: Equilibrium prices

Manufacturers choose b_i to maximize expected profits $P(\theta_i, q)\ [b_i - C(\theta_i, q_i)]$,

- where the probability of winning, $P(\theta_i, q) = Pr(i \text{ has the highest score} \mid \theta_i, q)$. Equation

The type-symmetric, Bayesian Nash equilibrium bidding strategy is:

$$b_i = C(\theta_i, q_i) + \frac{\int_{\theta_i}^{\overline{\theta}} C_\theta(u, q_i) P(u, q) du}{P(\theta_i, q)}.$$

- Similar to price-only bid (Riley & Samuelson, 1981)—but incorporates pharmacy preferences $S_j(q_i)$ and manufacturer asymmetry (θ_i, q_i).

Model: Summary

The scoring auction model captures the key potential disclosure channels from the quasi-experimental results:

- Pharmacy preferences $S_j(q_i) \rightarrow$ increase static drug quality, differentiation and prices.
- Manufacturer costs $C(\theta_i, q_i)$ and prices $b_i(\theta_i, q) \rightarrow$ affect productive efficiency & quality.

Estimation overview: New method non-parametrically identifies model primitives using only winning prices:

- Costs $C(\theta_i, q_i)$, productivities $F(\theta_i|q_i)$ and preferences $S_j(q_i)$

This talk

- Data & descriptive evidence
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- **Estimation**
- Counterfactuals

Estimation: Need approach to recover multi-dimensional preferences with commonly available data

Scoring auctions are widely used in real life when buyers care about quality, but most empirical models are price-only. How wrong?

Challenge: canonical estimation approaches (GPV extensions) require complete price data—not available in many empirical applications.

- Intuitively, need all prices to non-parametrically identify "discrete choice" preferences

This paper: how to estimate scoring auctions using only winning prices.

- Show generalized model is identified from correlations b/w prices and choice probabilities, and variation in the price and quality of alternatives across auctions Intuition
- Develop test of standard identifying assumption in this setting

Estimation: Sample and parameterization

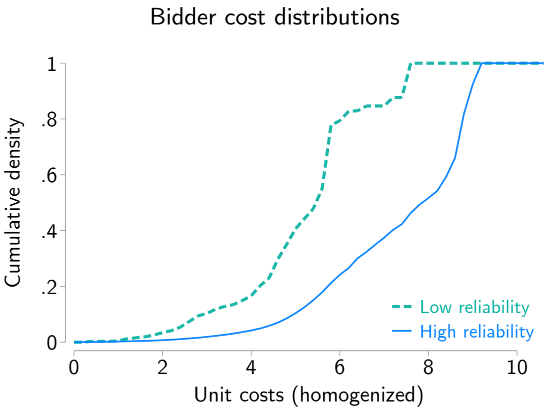
Sample of ≈70,000 oral generics auctions (2010-2021)

- Exclude collusive auctions (unsealed court records)
- Set aside 2022 as a test sample Out-of-sample fit

Parameterization:

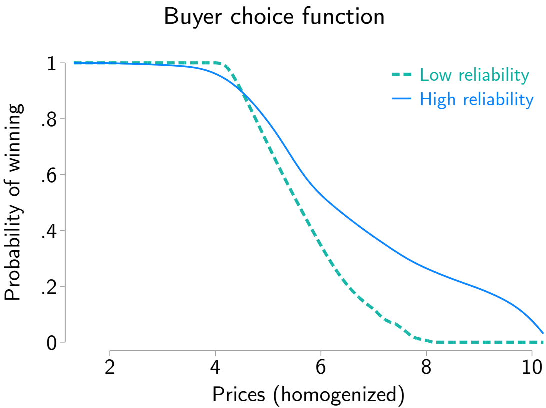
- Pharmacies use an optimal scoring rule → robustness to linear & pharmacy-specific rules Rules
- Quality q_i is as an indicator of whether a drug was *not* recalled in the past 5 years Robustness
- Control for auction-level heterogeneity using standard index method (Haile, 2003): *volume, pharmacy identity, therapeutic area, other drug characteristics* Homogenization

Results: High-quality drugs are more costly...



- High-quality, reliable drugs cost 31% more to manufacture, on average, with similar variance.
- Benchmark: model implies price-cost margins of 25% vs. manufacturers' reported 18-29%.

Results: High-quality drugs are more costly... and more preferred



- Pharmacies treat low-quality, unreliable drugs as if they were priced 13% higher.
- Are willing to pay a 2% premium for each 10% reduction in their 5-year recall risk.

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Counterfactuals: Overview

1. Decompose quasi-experimental disclosure policy effects
2. What are the equilibrium effects of pharmacies?
3. Study policy design by changing pharmacy preferences through subsidies

- Consider high-quality drug share, prices and profits—holding participation, quality investment and consumer demand fixed.

Counterfactuals: Overview

1. Decompose quasi-experimental disclosure policy effects
   - Pharmacy responses wholly explain policy's quality benefits
   - Disclosure benefits patients, but *not* manufacturers
2. What are the equilibrium effects of pharmacies?
3. Study policy design by changing pharmacy preferences through subsidies

- Consider high-quality drug share, prices and profits—holding participation, quality investment and consumer demand fixed.

Counterfactuals: The role of pharmacies

How would equilibrium outcomes change if pharmacies did not care for quality, or ran price-only auctions?

	Status quo
Preference $S(q_H)$	*13%*
High-quality share	64%
Price ($ per pill)	0.35
Manufacturer profits	675
Total producer surplus ($mm/year)	802

Counterfactuals: The role of pharmacies

How would equilibrium outcomes change if pharmacies did not care for quality, or ran price-only auctions?

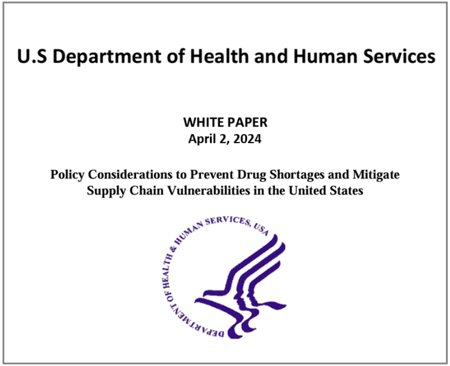
	Status quo	Price-only
Preference $S(q_H)$	*13%*	*0%*
High-quality share	64%	51%
Price ($ per pill)	0.35	0.34
Manufacturer profits	675	672
Total producer surplus ($mm/year)	802	797

- Pharmacies increase the share of high-quality drugs by 27%, almost certainly improving total static welfare.

Counterfactuals: Alternative quality subsidies

What if pharmacy incentives were better aligned with the social planner's?

- Vary $S(q_H)$ through subsidies for high-quality drugs, per recent proposals (HHS, FDA)


U.S Department of Health and Human Services

WHITE PAPER
April 2, 2024

Policy Considerations to Prevent Drug Shortages and Mitigate Supply Chain Vulnerabilities in the United States

DEPARTMENT OF HEALTH & HUMAN SERVICES, USA

Counterfactuals: Alternative quality subsidies

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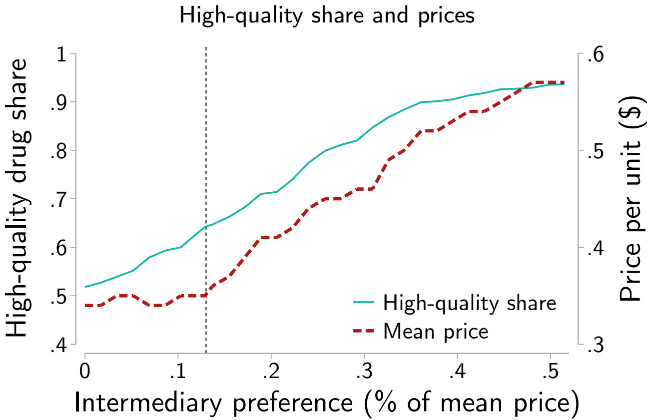
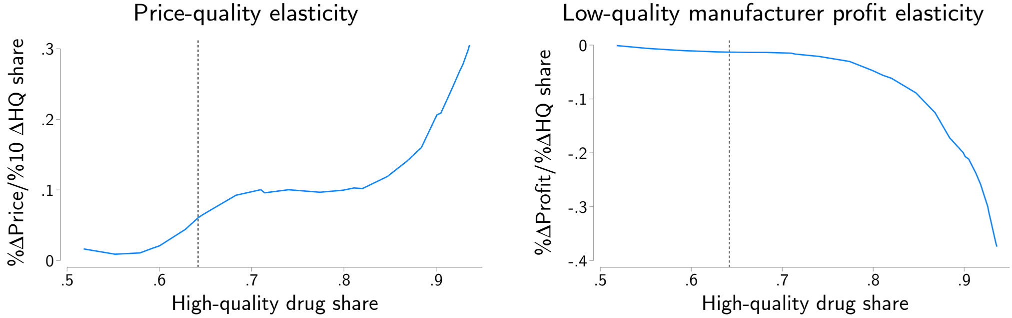


Counterfactuals: Alternative quality subsidies, cont'd

What if pharmacy incentives were better aligned with the social planner's?

- For patients, price-quality trade-off may not be worth it.
- For low-quality manufacturers, substantially reduced profits may encourage exit. Endog. quality



Concluding remarks

1. Using novel data, I show quality failures are pervasive in the U.S. generics market.
2. Quality is primarily disciplined by pharmacies, who prefer high-quality, reliable drugs.
   - Willing to pay a 2% premium for each 10% reduction in future recalls, which ultimately increases the share of high-quality drugs by 27%.
3. Auction methodology: multi-dimensional buyer preferences can be estimated from commonly available price data.
4. Policy lessons: non-fiduciary intermediaries can enhance the effects of disclosure.
   - Quality subsidies present advantages and disadvantages: can better align intermediary and social incentives, but are costly and anti-competitive.

Concluding remarks

Thank you!

Motivation: An example

Metformin, an anti-diabetic, is the 2^{nd} most commonly prescribed drug in the U.S.

Its generic manufacturers were approved over 20 years ago...

...but 15 have announced recalls since 2020.

Patient awareness of these recalls is low...

...and they can't differentiate between manufacturers.

This paper: Your local pharmacy stocks one manufacturer—how does it choose?

What do patients see? What are quality failures? Ex: generic Lipitor back

Motivation: Other examples

Atorvastatin (generic Lipitor), is the most popular drug in the U.S.

- Six of its manufacturers have been recalled since 2020, including the originator Pfizer. Back

Table 1: Recalls of top U.S. drugs (2020-2024)

	Generic name	Brand name	Patients (mm)	Recalled mfrs.
1	Atorvastatin	Lipitor	27.9	6
2	Metformin	Glucophage	19.5	15
3	Lisinopril	Prinivil	20.3	2
4	Albuterol	ProAir	19.3	11
5	Levothyroxine	Synthroid	18.1	6
6	Amlodipine	Katerzia	17.8	2
7	Metoprolol	Lopressor	15.5	6
8	Omeprazole	Prilosec	13.8	4
9	Losartan	Cozaar	13.2	7
10	Gabapentin	Neurontin	9.9	3

What do patients observe about generic drugs?

Uniquely uninformed: patients and physicians cannot differentiate between generic products, much less their quality. Back

- *Before purchase*, patients cannot observe the product (manufacturer) identity
- *After purchase*, packaging may or may not display the manufacturer
- Other barriers to information: inattention, inertia, symptom misattribution

Leading reasons for quality failures

	Recalls	Inspection failures
1	Failure to comply with GMPs	Failure to investigate out of spec results
2	Cross contamination (chemical or bacterial)	Inadequate sterilization processes
3	Lack of sterility	Lack of laboratory controls
4	Sub- or superpotent active ingredient	Inadequate process controls to assure purity
5	Lack of stability	Equipment is not regularly cleaned
6	Drug mixup	Records do not meet standards for trustworthiness
7	Drug tests out of specification	Quality control unit fails to investigate errors
8	Foreign substance in drug	Inappropriately designed equipment
9	Improper storage	Laboratory records lack necessary data
10	Defective packaging	Inadequate testing methods

How many patients are seriously injured by quality failures? Recall case studies:

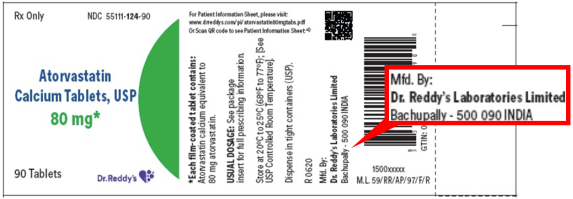
- Metformin (class II, 2020): 1/3500-1/8000
- Heparin (class I, 2008): 1/5000 back

GMP = Good Manufacturing Practices

Linking drugs to quality: An example

Where is atorvastatin-tablet-Dr. Reddy's made? back

1. Drug label images
(National Library of Medicine)



2. Import/export data
(Import Genius)

Country of Origin	Shipper	Shipper address
india	dr reddys laboratories ltd	fto unit 3, sy no 41 bachupally mandal, india hyderabad 500090 india

Consignee	Consignee address	Product description
dr reddy laboratories inc	107 college road east princeton nj 08540	...atorvastatin calcium tablets 5mg/10mg...

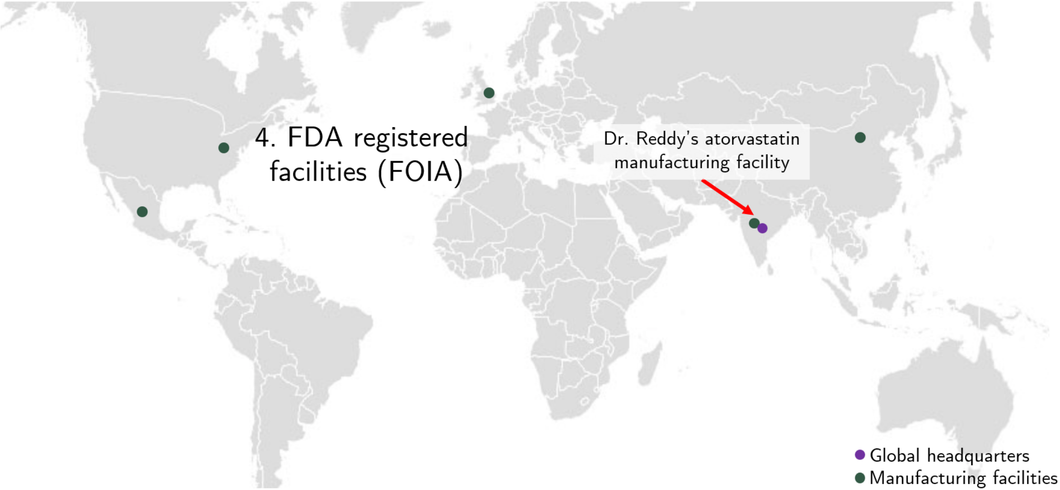
3. OECD administrative records
(New Zealand, Europe)

Manufacturing step	*Manufacturer*
Manufacture of Final Dose Form	Dr Reddy's Laboratories Limited (Formulation Unit III) Generics Bachupally Telangana 500 090 INDIA

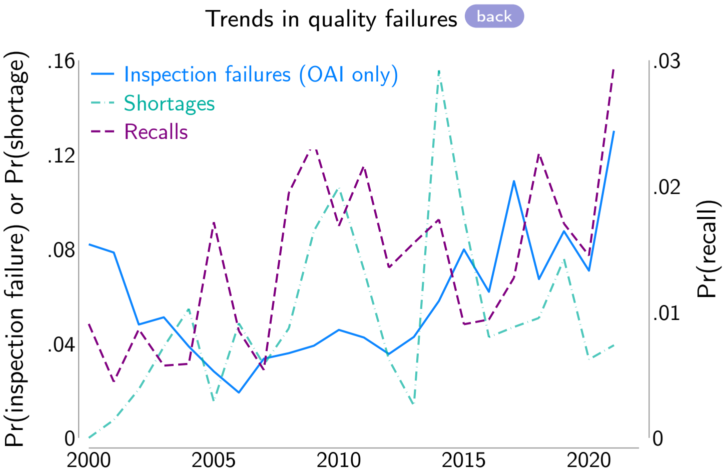
MEDSAFE
New Zealand Medicines and Medical Devices Safety Authority

Linking drugs to quality: An example, cont'd

Where is atorvastatin-tablet-Dr. Reddy's made? back

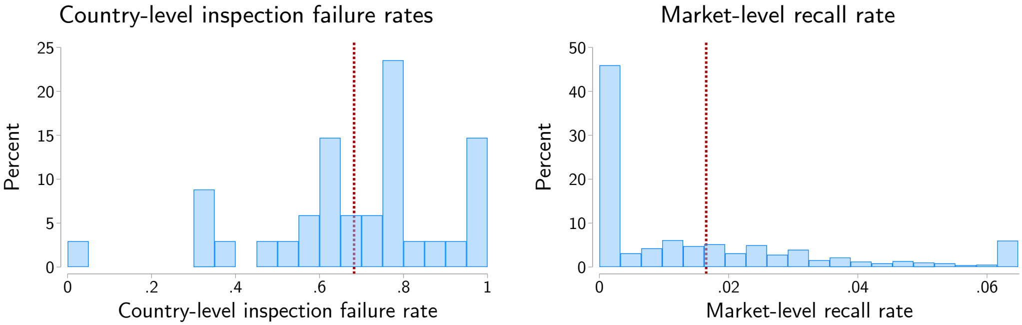


Descriptive evidence: Generic quality failures are increasing



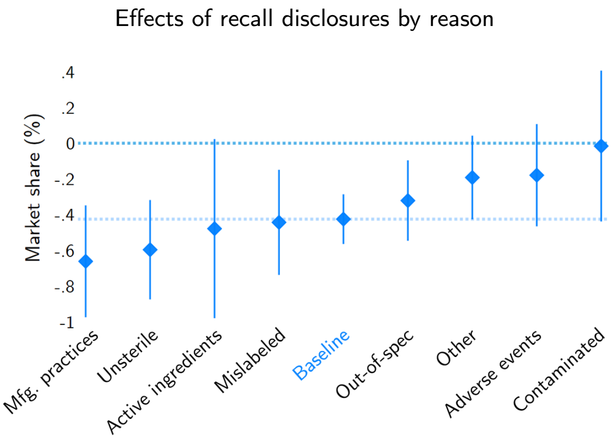
Over 2000-2022, 28% of facilities received "official action indicated" inspection grades.

Descriptive evidence: Generic quality failures are pervasive



Quality failures are not isolated to a few bad actors, countries or markets. back

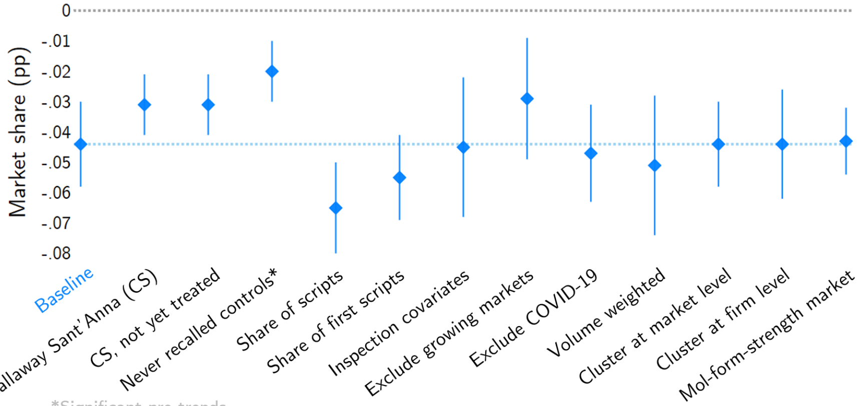
Effects of *quality vs. reliability* disclosures on pharmacy purchases



Recall disclosures related to supply reliability reduce pharmacy purchases significantly more than those related to patient adverse events. back

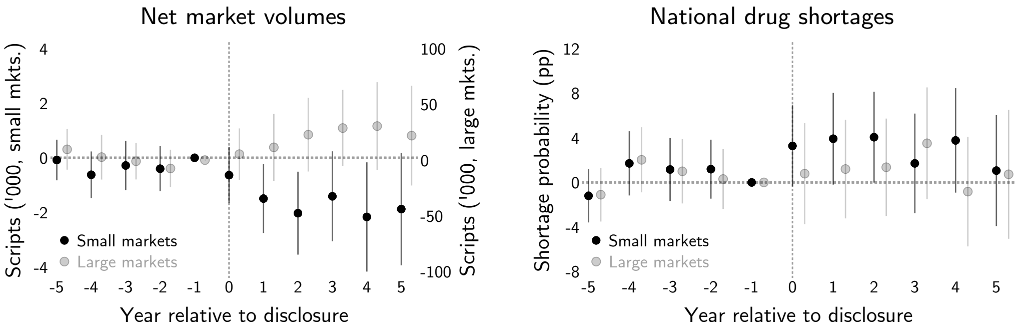
Quasi-experimental evidence: Robustness

- Heterogeneous treatment effects with staggered treatment (Callaway & Sant'Anna, 2021)
- Alternative control groups, outcome measures, covariates, samples, weighting, clustering, market definitions back



*Significant pre-trends

Effects of recalls on drug shortages by market size



Recalls increase the probability of a drug shortage by 41% in small markets (with few competitors) and have insignificant effects in large ones. back

Quasi-experimental evidence: Effects of quality vs. reliability disclosure

Compare trends for drugs that pass and fail inspections, exploiting variation in inspection grades and timing. back

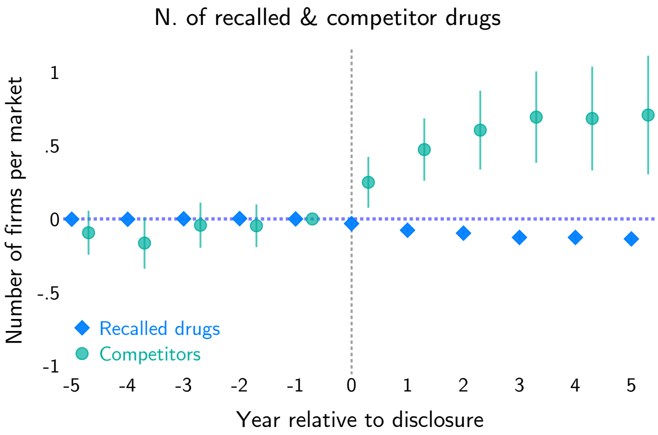
- Inspection failures disclose similar quality information to recalls without affecting reliability.

I estimate the following staggered DDD event study:

$$Y_{dt} = \alpha_d + \alpha_t + \sum_{s \neq -1} \left(\beta_s \, D_{d,t+s} + \gamma_s \, D_{d,t+s} \times 1\{\mathit{failed}_d\} \right) + \varepsilon_{dt},$$

  - where $1\{\mathit{failed}_d\}$ is an indicator of failing an inspection
  - Estimates effects of negative quality disclosure, controlling for potential selection bias

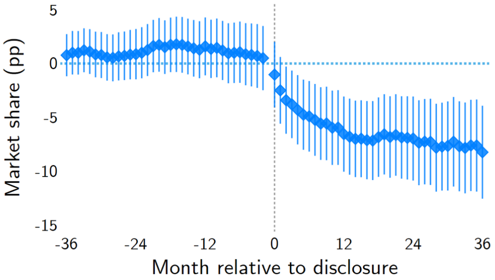
Effects of recalls on manufacturer participation



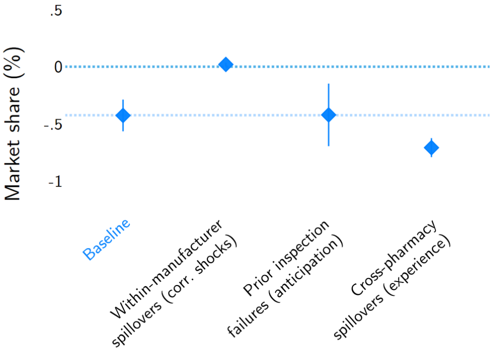
Recalls increase the number of firms per market by 0.6. However, the effects of recalls on pharmacy purchases are indistinguishable in growing and static markets. back

How do pharmacies update expectations about reliability?

Monthly recalled drug share (anticipation)

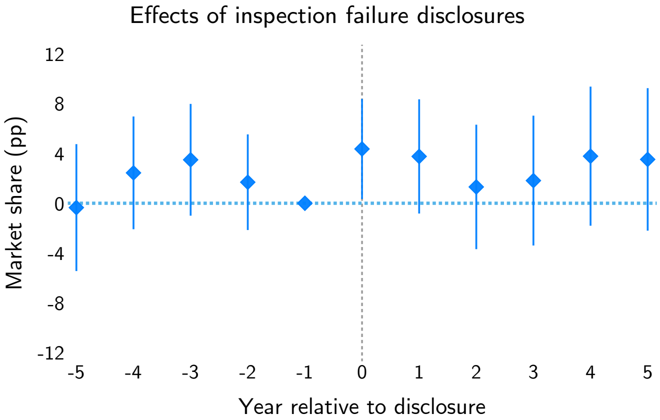


Effects of recall disclosures by information channel



Find minimal anticipatory effects or within-manufacturer spillovers. However, strong cross-pharmacy spillovers suggest pharmacies may rely on FDA disclosures to learn about quality. back

Effects of *quality vs. reliability* disclosures on pharmacy purchases, cont'd



The disclosure of *OAI* inspection failures—which reveal severe quality failures, but not reliability information—does not significantly affect pharmacy purchases. back

Intuition for identification

1. Symmetric auctions—with uniform bidder types—can be treated like price-only ones.
   - Use canonical methods to identify costs & productivities: order statistics (Athey & Haile, 2003) + FOC inversion (GPV)

2. Asymmetric auction primitives can be recovered up to a guess of the preferences.
   - Use *new methods*: new order statistics (this paper) + multidim. FOC inversion (Laffont, 2020)
     Estimation details back

3. Identifying assumption: productivity is identically distributed across auctions
   - Conditional on auction-level characteristics & bidder type; standard & partly testable
   - Pin down preferences by matching recovered productivities in symmetric & asymmetric auctions.

Estimation roadmap

1. Recover underlying price distribution: $\hat{G}(b_i|q, \text{i wins}) \rightarrow \hat{G}(b_i|q)$ back
   - Convert using new order statistics—up to a guess of the preferences.
2. Then, manufacturer costs: $\tilde{b}_i \rightarrow \hat{C}(\theta_i, q_i)$
   - Invert the bidding function (GPV, Laffont).
3. Next, productivities: $\hat{C}(\theta_i, q_i) \rightarrow \hat{F}(\theta_i|q_i)$
   - Project costs on quality.
4. Finally, pharmacy preferences: $\hat{F}(\theta_i|q_i) \rightarrow \hat{S}(q_i)$
   - Match estimated productivities across different auctions.

Green objects are estimated directly from the data or recovered.

1: Convert observed price distributions into underlying ones

In symmetric auctions—with uniform manufacturer types—the winning (minimum) price is sufficient to identify the underlying distribution:

$$\hat{G}(b_i|i\ wins) = N\big[1 - G(b_i)\big]^{N-1} g(b_i).$$

In asymmetric (non-i.i.d.) auctions, we can extend this logic using Bayes' Rule:

- For the linear score $R(b_i, q_i) = S(q_i) - b_i$ and two types $\{H, L\}$:

$$\hat{G}(b_{H,i}|i\ wins) = N\big[1 - G_H(b_{H,i})\big]^{N_H-1}\big[1 - G_L(b_{H,i} - S(q_H))\big]^{N_L} g_H(b_{H,i})$$
$$\hat{G}(b_{L,i}|i\ wins) = N\big[1 - G_L(b_{L,i})\big]^{N_L-1}\big[1 - G_H(b_{L,i} + S(q_H)\big]^{N_H} g_L(b_{L,i}).$$

- Define a system of functional equations in $g_H(b), g_L(b)$, up to a guess of $S(q_i)$.

2-3. Invert bidding function to recover costs and productivities

FOC inversion (GPV, Laffont): to recover costs, rewrite the bidding function as

$$\tilde{b}(\theta_i, q) = C(\theta_i, q_i) - \frac{H(b_i, q)}{H_b(b_i, q)},$$

where, again using Bayes', the choice probability is

$$H(b_i, q) = \frac{\hat{G}(b_i | \text{i wins}, q)\hat{G}(\text{i wins} | q)}{\hat{G}(b_i | q)}.$$

Next, project costs on quality to recover θ_i (Laffont):

$$\log \hat{C}(\theta_i, q_i) = \log C_0(q_i) + \log \theta_i.$$

4. Match $\hat{F}(\theta_i|q_i)$ from symmetric and asymmetric auctions to recover preferences

Intuition: Symmetric auctions can be treated like price-only ones—only asymmetric auction estimates depend on quality preferences.

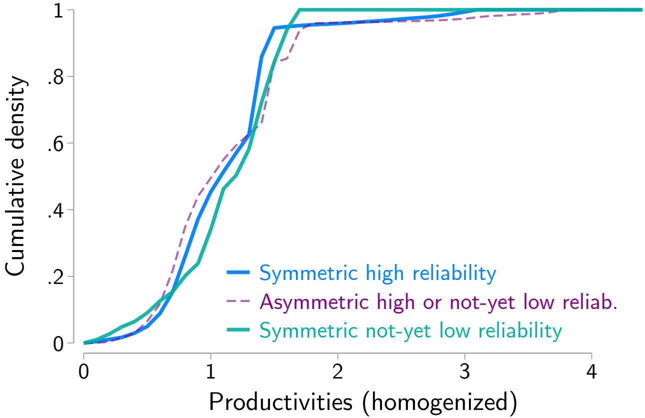
- Compare $\hat{F}_{asym}(\theta_i|q_i, S(q_i))$ to $\hat{F}_{sym}(\theta_i|q_i)$ to pin down $S(q_i)$.

Identifying assumption: productivity is identically distributed across auctions,

- Conditional on auction-level characteristics & manufacturer type.
- Microfoundation: random manufacturer entry (Athey & Haile, 2002)
- Standard in empirical literature; supported by balance tests back

Evidence: Identifying assumption holds pre-recall

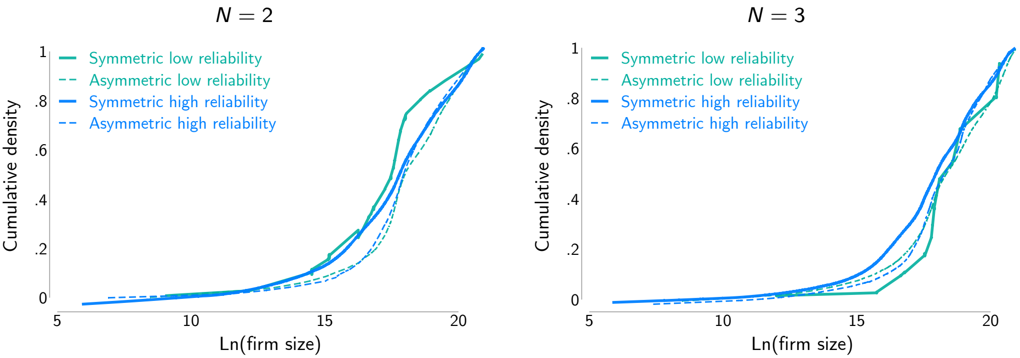
Productivity distributions in future symmetric & asymmetric auctions back



Estimated productivities do not differ across *future* auction types prior to the first recall.

Evidence: Manufacturers are observably balanced across auction types

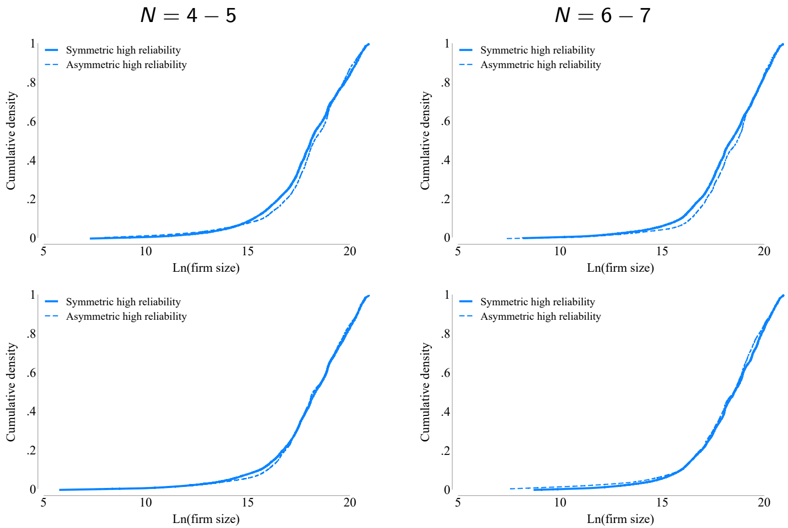
Firm size distributions in symmetric & asymmetric auctions back



Manufacturers are balanced across auction types, consistent with the identifying assumption.

Evidence: Manufacturers are observably balanced across auction types

Firm size distributions in symmetric & asymmetric auctions back



Scoring rules: Optimal rule

For the optimal scoring rule (s.t. first score, IC, IR constraints)

$$R_{optimal}(\theta_i, q) = S(q_i) - \frac{F(\theta_i|q_i)}{f(\theta_i|q_i)} C_\theta(\theta_i, q_i), \tag{1}$$

each manufacturer's probability of winning is:

$$P(\theta_i, q) = \prod_{j \neq i} \left[1 - F\left(\Gamma^{-1}(S(q_j) - S(q_i) + \Gamma(\theta_i, q_i), q_j) | q_j \right) \right], \text{ where}$$

$$\Gamma(\theta_i, q_i) = \frac{F(\theta_i|q_i)}{f(\theta_i|q_i)} C_\theta(\theta_i, q_i).$$

back Parameterization

Scoring rules: Linear rule

For the linear scoring rule

$$R_{linear}(\theta_i, q) = S(q_i) - b(\theta_i, q), \tag{2}$$

each manufacturer's probability of winning is:

$$P(b_i(\theta_i, q), q) = \prod_{j \neq i} \left[1 - G\Big(S(q_j) - S(q_i) + b_i(\theta_i, q) | q\Big)\right], \text{ where } b_i | q \sim G(\cdot).$$

back Parameterization

First stage price homogenization

Dependent variable	Price
Therapeutic area (ATC-1)	
Blood and blood forming organs	2.471***
Sensory organs	1.128***
Antiparasitics	0.798***
Genitourinary system	0.245***
Nervous system	0.242***
Antineoplastic/immunomodulating	0.139*
Systemic hormonal preparations	0.087
Antiinfectives for systemic use	-0.031
Cardiovascular system	-0.444
Musculo-skeletal system	-0.509***
Alimentary tract and metabolism	-0.599***
Dermatologicals	-0.886***
Respiratory system	-1.683***
Various therapeutic areas	-0.389**

Dependent variable (cont'd)	Price
Volume	-0.166***
Volume^2	0.000***
Extended release	0.783***
Oral formulation	-5.445***
Topical formulation	-3.383***
Intermediary 2	-0.147***
Intermediary 3	-0.154***
Intermediary 4	-0.173***
Intermediary 5	-0.168***
N. participants FE	x
Year FE	x
Observations	90,759
Dependent var. mean ($ / pill)	1.70

Parameterization

Structural model robustness

	Preferences (ΔS / $\bar{b}$)	Costs (High vs. low quality)
1. Optimal score (baseline)	0.13	0.31
2. Long-run reliability	0.07	0.39
3. Auctions with N=2 bidders	0.15	0.03
4. Recalled & not-yet-recalled drugs	0.37	0.47
5. Balanced panel	0.05	0.24
6. Linear score	0.18	0.77

Parameterization

Note: "Preferences" are expressed as fractions of the mean price. "Costs" are the difference between high and low quality unit costs, expressed as a fraction of the low quality mean.

Counterfactuals: Decompose effects of disclosure

What are the effects of disclosure in the absence of pharmacy or supply-side cost and price responses?

$$\Delta y = \underbrace{y\Big[R(\theta_i', q'), C(\theta_i', q_i'), b(\theta_i', q')\Big]}_{\text{Post}} - \underbrace{y\Big[R(\theta_i, q), C(\theta_i, q_i), b(\theta_i, q)\Big]}_{\text{Pre}}$$

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Channel	Description
1. Preferences	Pharmacies update expectations based on quality signals

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Channel	Description
1. Preferences	Pharmacies update expectations based on quality signals
2. Costs	Manufacturers re-optimize production effort
3. Prices	Manufacturers strategically set prices

Counterfactuals: Decompose disclosure effects, cont'd

			Decomposition		
	Pre-recall	Δy	Prefs.	Costs	Prices
High-quality share	57%	6%			
Price ($ per pill)	0.37	-12%			
Manufacturer profits	184	-28%			
Total producer surplus ($mm/year)	208	-14%			

- Disclosure benefits patients—consistent with reduced form results—but not manufacturers.

Counterfactuals: Decompose disclosure effects, cont'd

			Decomposition		
	Pre-recall	Δy	Prefs.	Costs	Prices
High-quality share	57%	6%	18%		
Price ($ per pill)	0.37	-12%	22%		
Manufacturer profits	184	-28%	7%		
Total producer surplus ($mm/year)	208	-14%	7%		

- Disclosure benefits patients—consistent with reduced form results—but not manufacturers.
- Pharmacy responses explain more than 100% of the quality benefits.

Counterfactuals: Decompose disclosure effects, cont'd

			Decomposition		
	Pre-recall	Δy	Prefs.	Costs	Prices
High-quality share	57%	6%	18%	–	
Price ($ per pill)	0.37	-12%	22%	–	
Manufacturer profits	184	-28%	7%	6%	
Total producer surplus ($mm/year)	208	-14%	7%	5%	

- Disclosure benefits patients—consistent with reduced form results—but not manufacturers.
- Pharmacy responses explain more than 100% of the quality benefits.
- Supply-side cost reductions partially offset these benefits and intensify price competition.

Counterfactuals: Decompose disclosure effects, cont'd

			Decomposition		
	Pre-recall	Δy	Prefs.	Costs	Prices
High-quality share	57%	6%	18%	–	-11%
Price ($ per pill)	0.37	-12%	22%	–	-32%
Manufacturer profits	184	-28%	7%	6%	-41%
Total producer surplus ($mm/year)	208	-14%	7%	5%	-26%

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Counterfactual 1: Decompose disclosure policy effects

			Decomposition		
	Pre-recall	Recall eff.	Prefs.	Costs	Prices
High-quality share					
Price ($ per pill)					
Manufacturer profits					
Total producer surplus ($mm/year)					

Counterfactual 1: Decompose disclosure policy effects

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