

# Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Collusion?

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The Eighteenth Annual  
Federal Trade Commission Microeconomics Conference  
Washington, DC  
February 24, 2026

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# Motivation

- Algorithmic pricing has gained popularity in many industries:
  - Revenue management tools were first adopted in the airline industry to dynamically set prices
  - They later spread to a wide variety of industries such as hotels, car rentals, groceries etc.
- Penetration in multifamily rentals has increased steadily:
  - Adoption started around 2005
  - Concentrated among a few players:
    - RealPage (YieldStar) and Rainmaker (LRO) prior to 2017
    - RealPage acquired LRO from Rainmaker in 2017 and now has with > 80% market share
  - By 2019, at least 25% of buildings (and 33% of units) have adopted some form of algorithmic pricing

# Motivation

- What do these pricing algorithms do?
1. Set prices that respond to changes in market conditions?
    - *“RealPage Revenue Management software prioritizes a property's internal **rent data and** internal **availability data** when determining whether **a rental price should be increased, decreased, or remain** at the current level.”*
    - *“[T]hen the software **uses aggregated, anonymized rent data** from a variety of sources to help determine **price elasticity of demand** ... and thus the appropriate magnitude of change in price.”*

## Revenue Management

- Balances supply and demand via price
- Considers internal dynamics and the competitive marketplace
- Can be leveraged to offer flexible leasing
- Provides enhanced operational controls
- Delivers critical decision support
- Facilitates collaboration among operations



#NAASStudentConf

## 2. Potential for coordinated pricing?

- Class action lawsuits
  - Oct 18, 2022: Bason v. RealPage (San Diego)
  - Nov 2, 2022: Navarro v. RealPage et. al. (Seattle)
  - Dec 14, 2022: Weaver v. RealPage Inc. et al. (Denver)
  - ... .. and many more
  - As of April 2023, all 20 cases are consolidated in the U.S. District Court
- State attorneys general lawsuits
  - Nov 1, 2023: Washington, DC
  - Feb 28, 2024: Arizona
  - March 4, 2024: North Carolina

☰ Q All Markets > Sectors >

THE REAL DEAL  
REAL ESTATE NEWS

TECH TEXAS

## RealPage could face real trouble with antitrust suits

Seven class action suits filed against Texas-based company since Oct. 18

### NATURE OF THE ACTION

1  
2  
3  
4  
5

1. Plaintiffs Sherry Bason, Lois Winn, Georges Emmanuel Njong Diboki, Julia Sims, and Sophia Woodland challenge a cartel among lessors of multifamily residential real estate leases (“Lessors”) to artificially inflate the prices of multifamily residential real estate in the United States above competitive levels.



FEDERAL TRADE COMMISSION  
PROTECTING AMERICA'S CONSUMERS

## Price fixing by algorithm is still price fixing

By: Hannah Garden-Monheit and Ken Merber

March 1, 2024



# Motivation

## 2. Potential for coordinated pricing?

- Department of Justice:
  - August 23, 2024: Filed a civil antitrust lawsuit against RealPage
  - Allegations include:
    - Decreasing competition among landlords in apartment pricing
    - Monopolizing the market for commercial revenue management software that landlords use to price apartments

32. RealPage frequently tells prospective and current clients that a “rising tide raises all ships.” A RealPage revenue management vice president explained that this phrase means that “there is greater good in everybody succeeding versus essentially trying to compete against one another in a way that actually keeps the industry down.”

IN THE UNITED STATES DISTRICT COURT  
FOR THE MIDDLE DISTRICT OF NORTH CAROLINA

UNITED STATES OF AMERICA  
U.S. Department of Justice  
950 Pennsylvania Avenue NW  
Washington, DC 20530

*Plaintiffs,*

v.

REALPAGE, INC.  
2201 Lakeside Blvd.  
Richardson, TX 75082,

*Defendant.*

**Case No. 1:24-cv-00710**

# Motivation

## 2. Potential for coordinated pricing?

- Department of Justice:
  - August 23, 2024: Filed a civil antitrust lawsuit against RealPage
  - January 7, 2025: Added six large landlords to the lawsuit
  - August 8, 2025: Proposed settlement with Greystar to end its participation
  - November 24, 2025: Proposed settlement with RealPage requires the defendant to:
    - Cease the use of competitors' non-public information in runtime operations
    - Remove features that limit price decreases
    - Refrain from discussions based on non-public data in user group meetings

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    - Refrain from discussions based on non-public data in user group meetings
- DOJ lawsuit is now settled, but the broader questions raised by algorithmic pricing remain:
  - Litigation by state AGs and against other algo pricing providers remains ongoing
  - **What is the economic impact of algorithmic pricing in the US multifamily rental markets?**

# Research Question:

- ***What is the impact of algorithmic pricing in the US multifamily rental markets?***
  1. ***Does algorithmic pricing lead to more responsive prices?***
  2. ***Does algorithmic pricing lead to price coordination?***

# Research Question: Preview of Results

- ***What is the impact of algorithmic pricing in the US multifamily rental markets?***
  1. ***Does algorithmic pricing lead to more responsive prices?***
    - Adopters charge higher prices than non-adopters during booms and *lower prices during busts*
    - Results during busts are consistent with more responsive (to changing market conditions) pricing
  2. ***Does algorithmic pricing lead to price coordination?***

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2. ***Does algorithmic pricing lead to price coordination?***

- As algorithm penetration increases, adopters charge higher prices and experience lower occupancies, suggestive of coordinated pricing
- A structural model of a demand system for rentals to formally test conduct
  - *Pair-wise testing favors coordination (i.e., joint-profit-maximization) over competition among users of the same algorithm, but not across users of different algorithms*
  - Significant markup implications due to “algorithmic collusion”: \$53 per month per unit across over 4.2 million adopted units
- Disclaimer: not forensic evidence of collusion or price fixing

# Related Literature

- Theoretical work on whether algorithmic pricing:
  - Miklos-Thal and Tucker (2019); Calvano, Giacomo, Denicol, and Pastorello (2020); Asker, Fershtman, and Pakes (2022); Johnson, Rhodes and Wildenbeest (2023), Banchio and Mantegazza (2023); Brown and MacKay (2025); Sugaya and Wolitzky (2025); Harrington (2022, 2024, 2025)
- Empirical work on algorithmic pricing:
  - Assad, Clark, Ershov, and Xu (2020)
  - Leisten (2022); Musolff (2022); Brown and MacKay (2023)
- Test of conduct:
  - Bresnahan (1982, 1989); Nevo (1998, 2001); Miller and Weinberg (2017); Berry and Haile (2014); Wollmann (2019, 2024); Backus, Conlon, and Sinkinson (2022); Duarte, Magnolfi, Sølvsten and Sullivan (2023), Duarte, Magnolfi, Quint, Solvsten, Sullivan (2025)
- **Our contribution:**
  1. Empirically evaluate the impact of algorithmic pricing and algorithmic collusion
    - First to evaluate the impact of algorithmic pricing through multiple channels
    - First to perform a conduct test in a full structural model of demand and supply
  2. Relevance for consumer and firm welfare in a major industry
    - Rent payments are the largest household expenditure item (30%) for renters
  3. Relevance for antitrust as algorithmic pricing expands across industries

# Data and Setting

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# Data on Algorithmic Pricing Adoption

- Adoption data hand-collected from a variety of sources:
  1. A series of surveys conducted at multifamily housing conferences
  2. Marketing materials by software companies:
    - Rainmaker LRO announced their major customer acquisition
- Quality of the data:
  - All 20 out of 20 top management companies flagged
  - If anything, we undercount adoption, which likely lead to attenuation in our regressions



## Firms Using RM

As of this writing (December 2010), about 12-15% of the apartment industry (measured in units) has adopted revenue management.

Below is a list of prominent apartment companies using revenue management software tools and the name of the system they are using. The purpose of this list is to show the breadth of companies adopting revenue management and also to provide easy references to firms that you may know.

This list is compiled from press reports and the records of the major revenue management providers. The list is updated periodically. Please contact us with any corrections and additions.

- AIMCO (PROFIT by Pricing Revenue Optimization Systems)
- Alliance Residential (LRO by The Rainmaker Group)
- Allison-Shelton Real Estate Services (LRO by The Rainmaker Group)
- Altman Management Companies (LRO by The Rainmaker Group)

Rainmaker LRO™ Adds More than 30 New Clients to Revenue Management Platform in Last 90 Days

Portfolios Range in Size and Asset Class; Represent 250,000 Units

ATLANTA, GA. (PRWEB) MAY 29, 2013

# Data on Multifamily Rentals

- REIS by Moody's Analytics
  - Time period: 2005 – 2019
- Coverage of our data sample:
  - Over 37,000 buildings and 7.2 million units
  - Top 50 metro markets (~600 submarkets)
  - Representing approximately 50% of all market-rate multifamily units in the US
- Information includes:
  - Building-level information (e.g., building class, address, management company, amenities)
  - Surveyed *both asking rents and occupancies*

# Penetration of Algorithmic Pricing in Multifamily Rentals

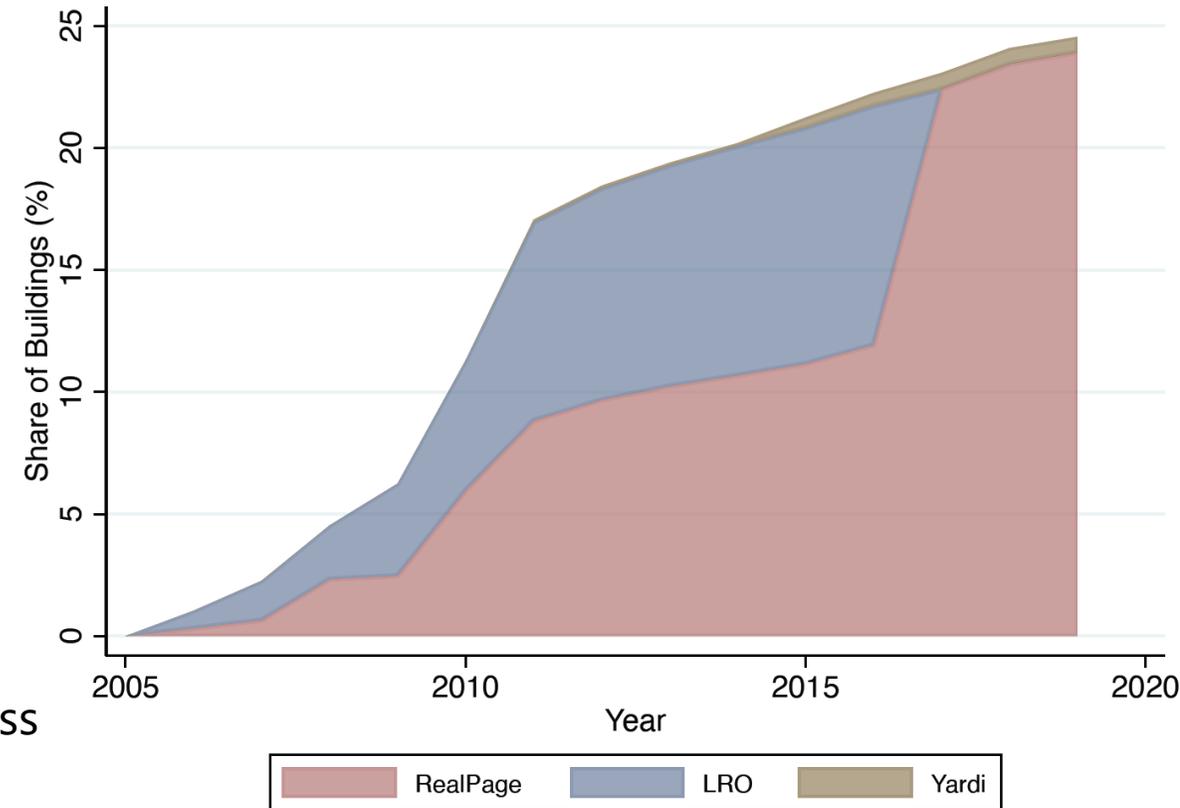
- Summary statistics:

- By 2019, penetration reaches
  - 25% at the building level
  - 33% for unit level

	By Building	By Unit
Adopter Count	9,124	2,416,779
Total Count	37,216	7,216,420
Fraction Adopted	25%	33%

- A lack of immediate integration post-merger:

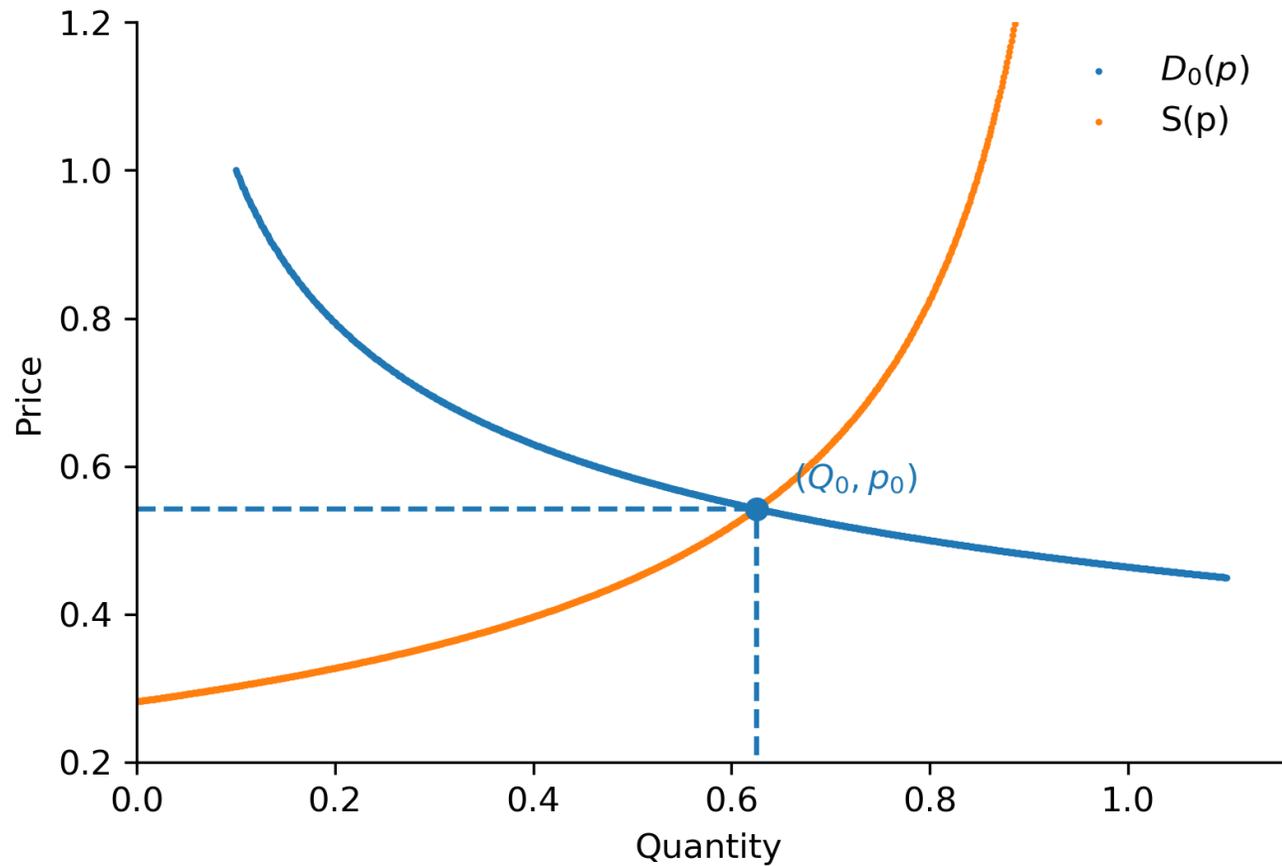
- “LRO does not have access to YieldStar/AIRM database, and the YieldStar and AIRM database does not have access to the LRO database” (RealPage disclosure, June 2024)
  - We do not use merger-induced market structure changes as a research design
  - Focus on the pre-merge period for our conduct test



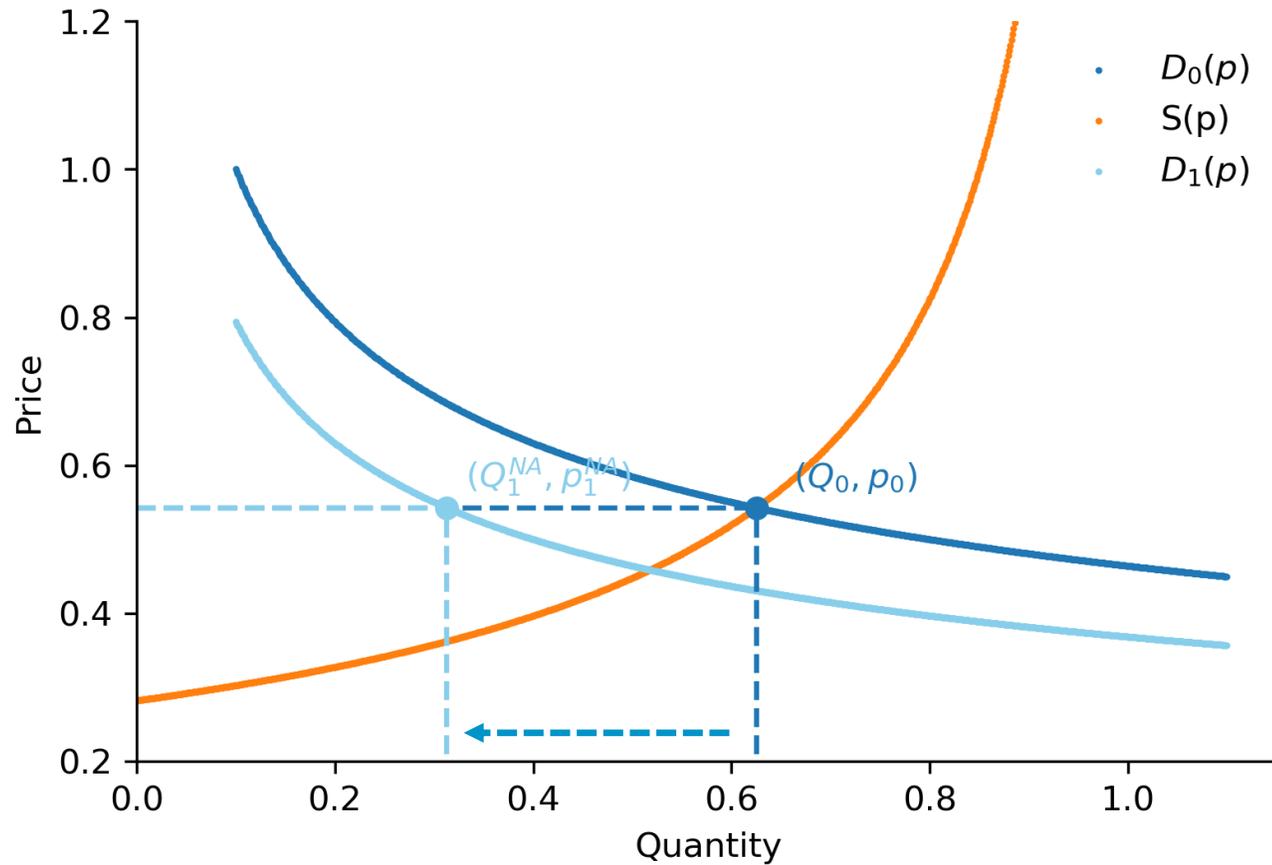
# Stylized Model

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# Stylized Model: Responsive Prices (Bust)

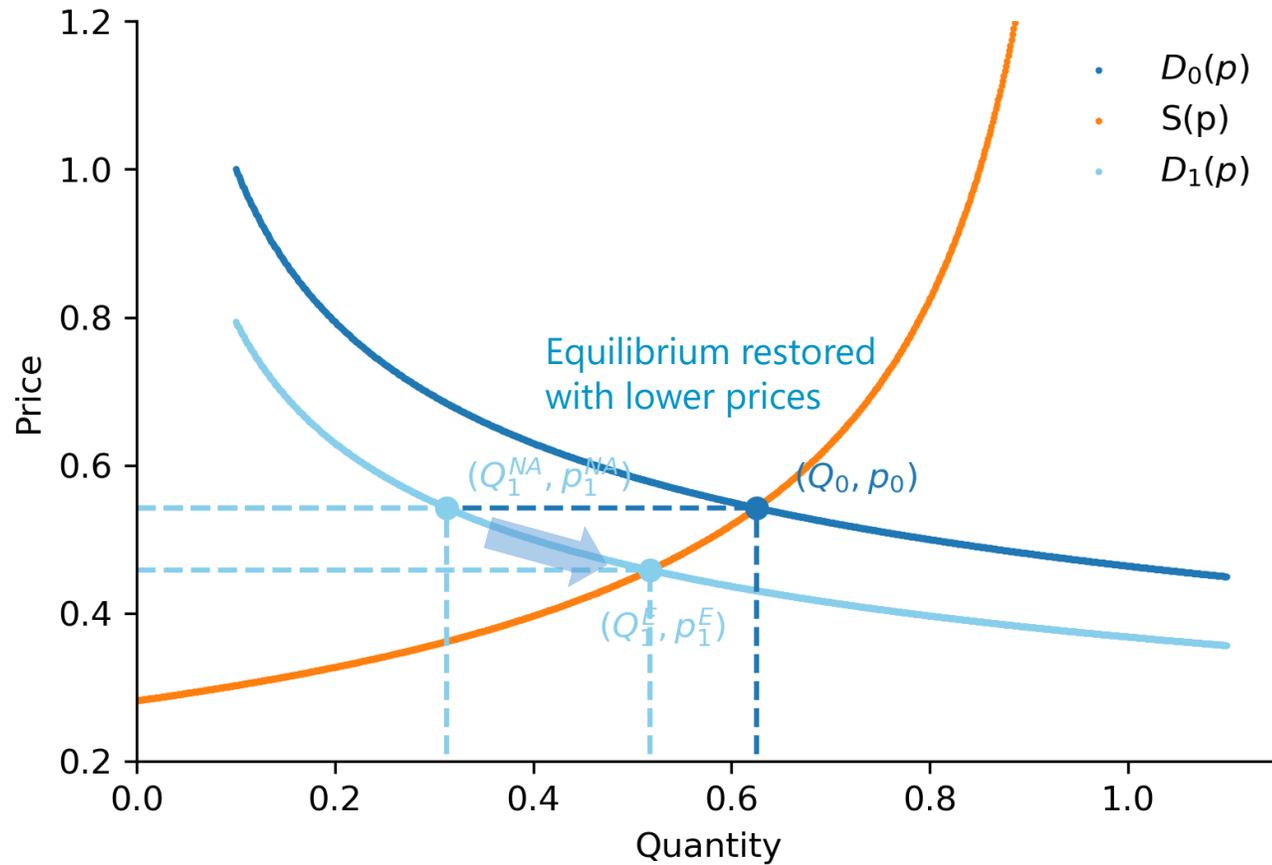


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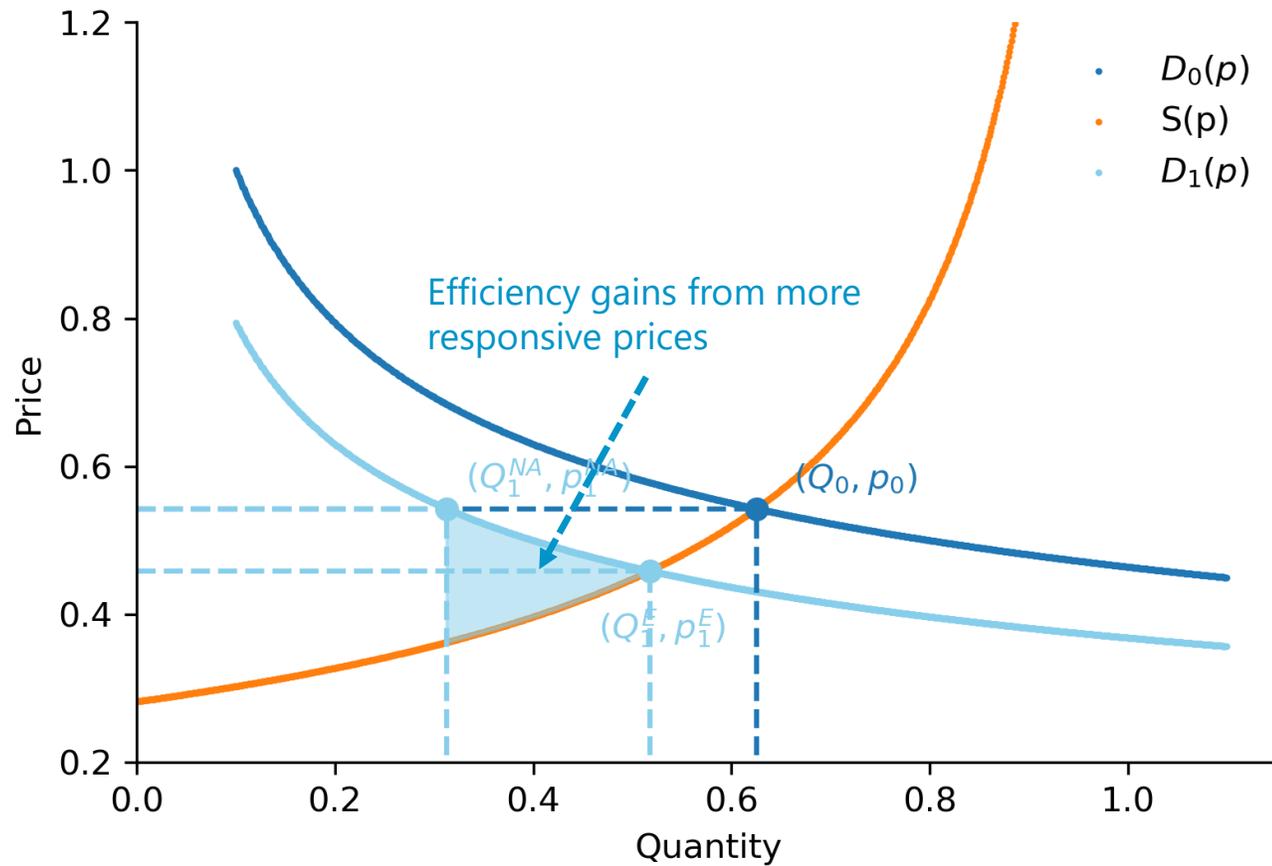


Vacancy increases first!

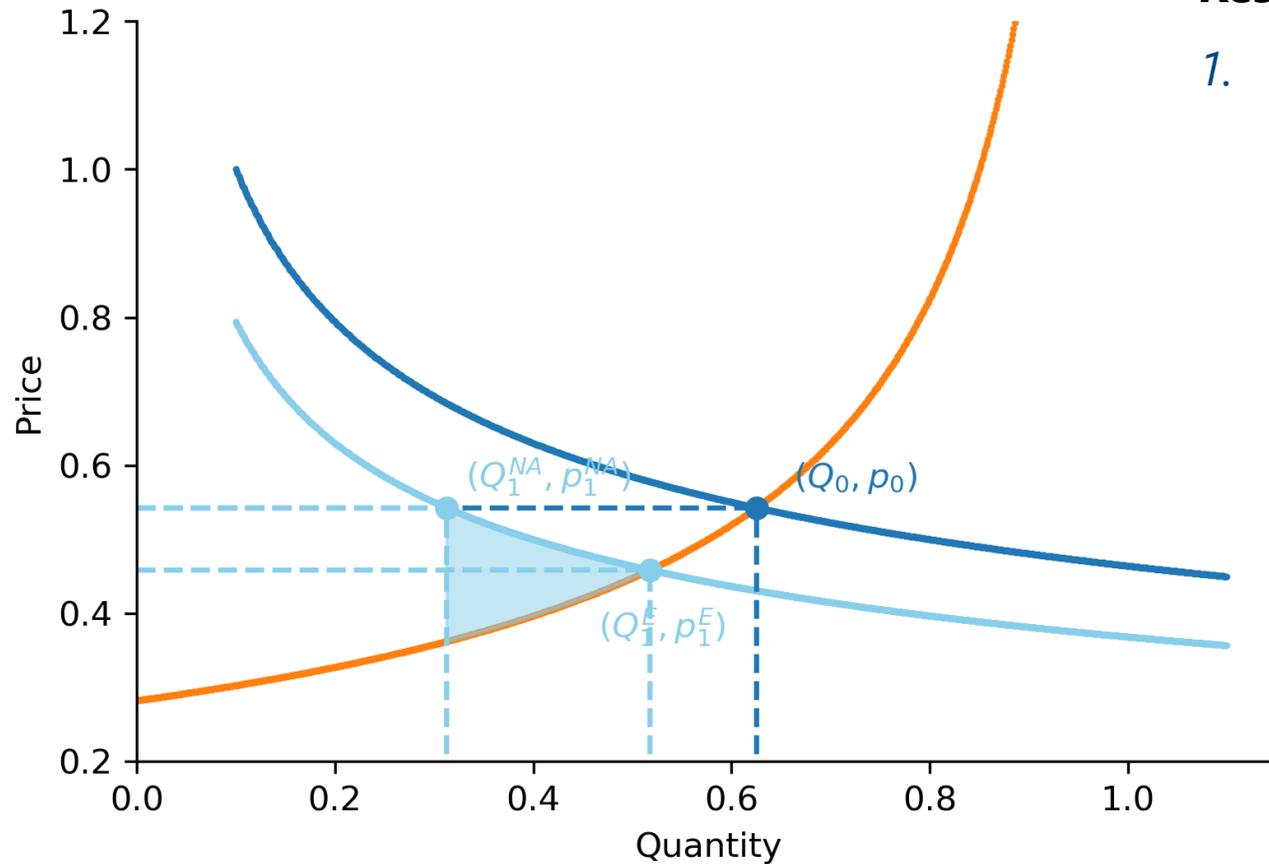
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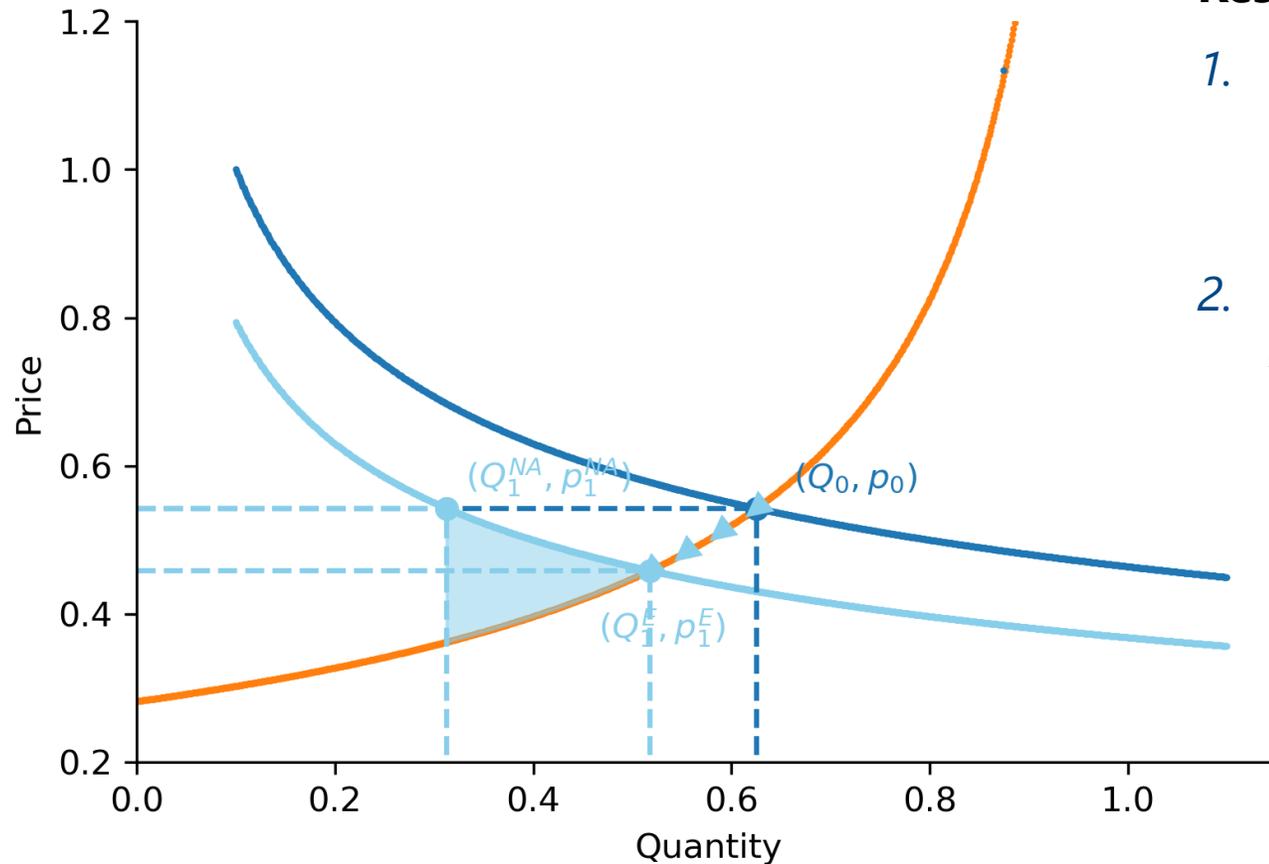


## Responsive pricing w/ a negative demand shock:

### 1. Compare **adopter vs. non-adopter within a market**

- Adopters charge **lower prices**
- Adopters experience **higher occupancy**

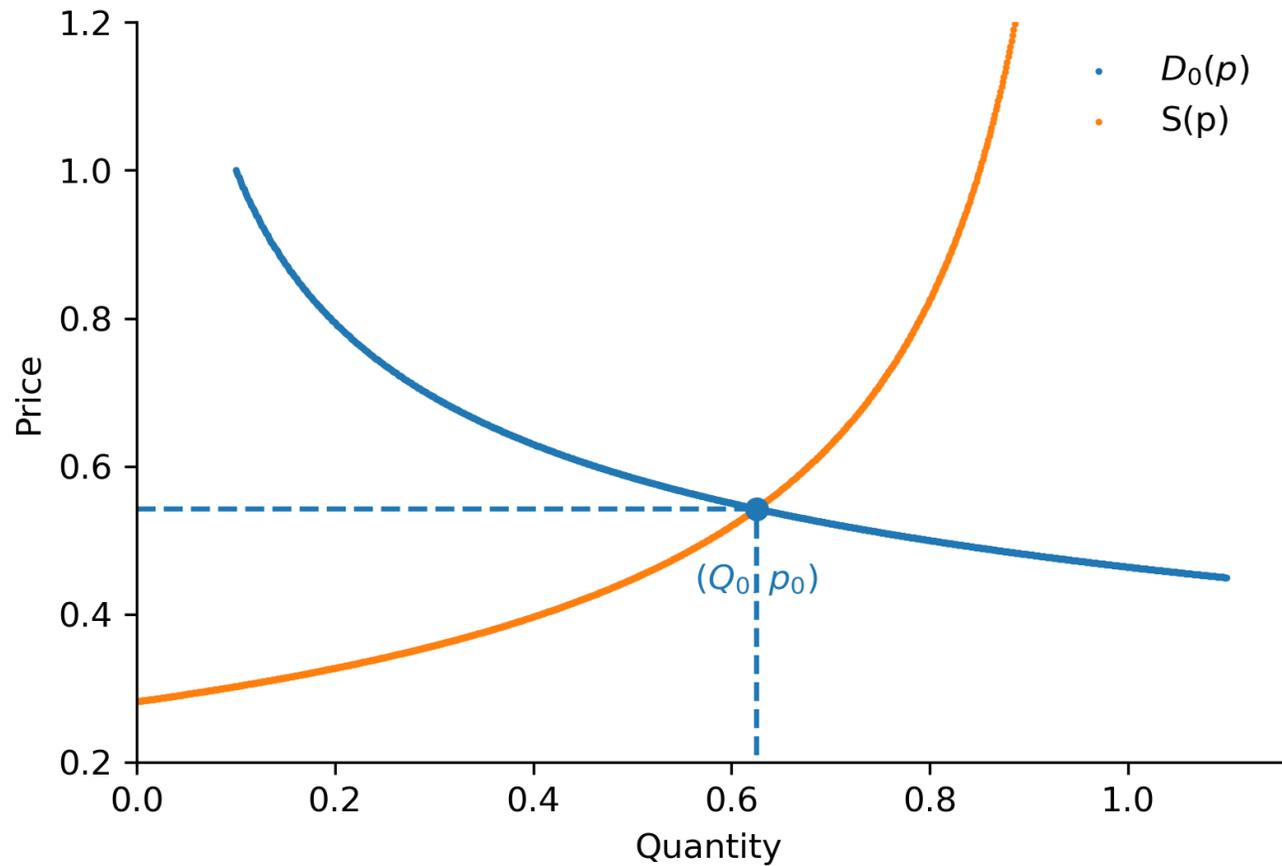
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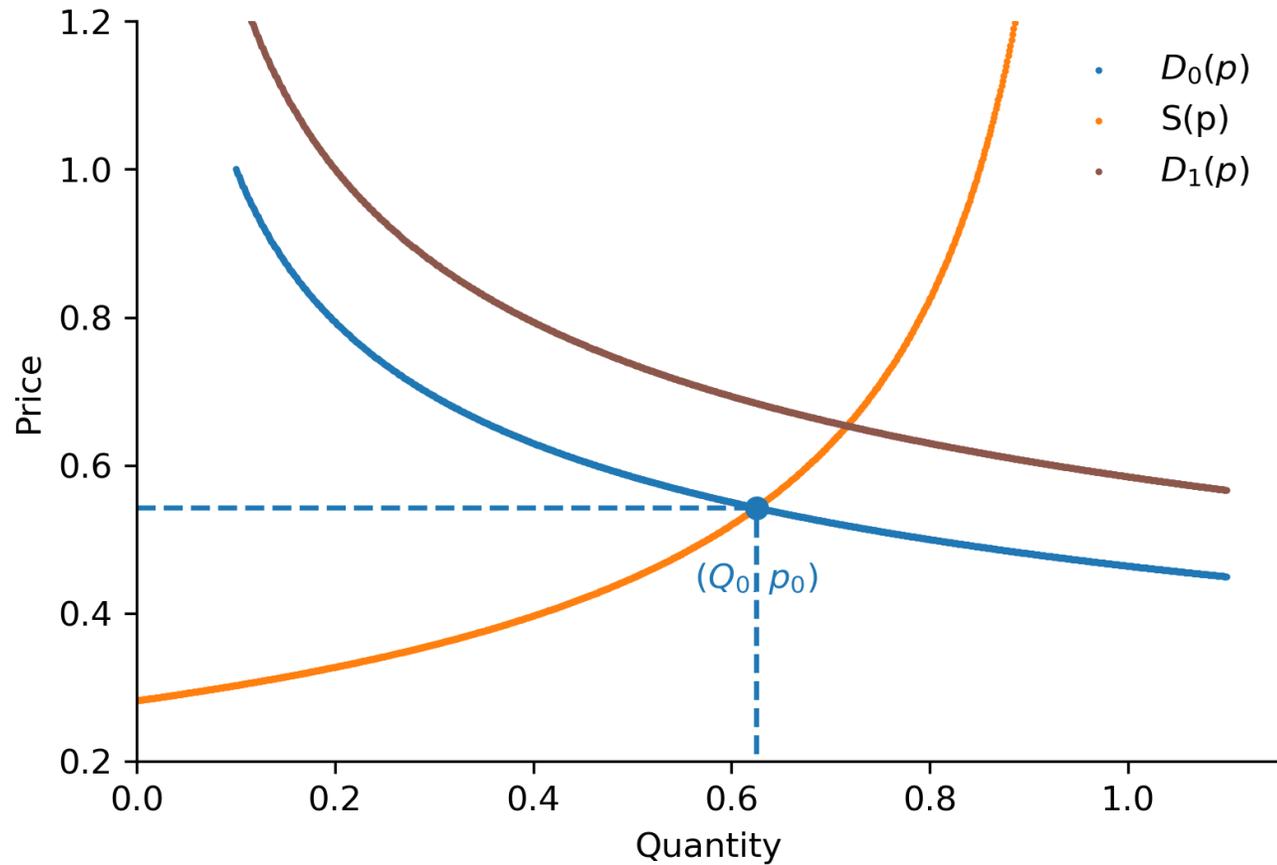
## Responsive pricing w/ a negative demand shock:

1. Compare **adopter vs. non-adopter within a market**
  - Adopters charge **lower prices**
  - Adopters experience **higher occupancy**
2. Compare **adopters as penetration increases across markets**
  - The fraction of under-producers shrinks
  - The residual demand per adopter weakens
    - Tracing down its supply curve
  - All else equal, with a negative demand shock, **adopter price and occupancy both decrease with  $h$**

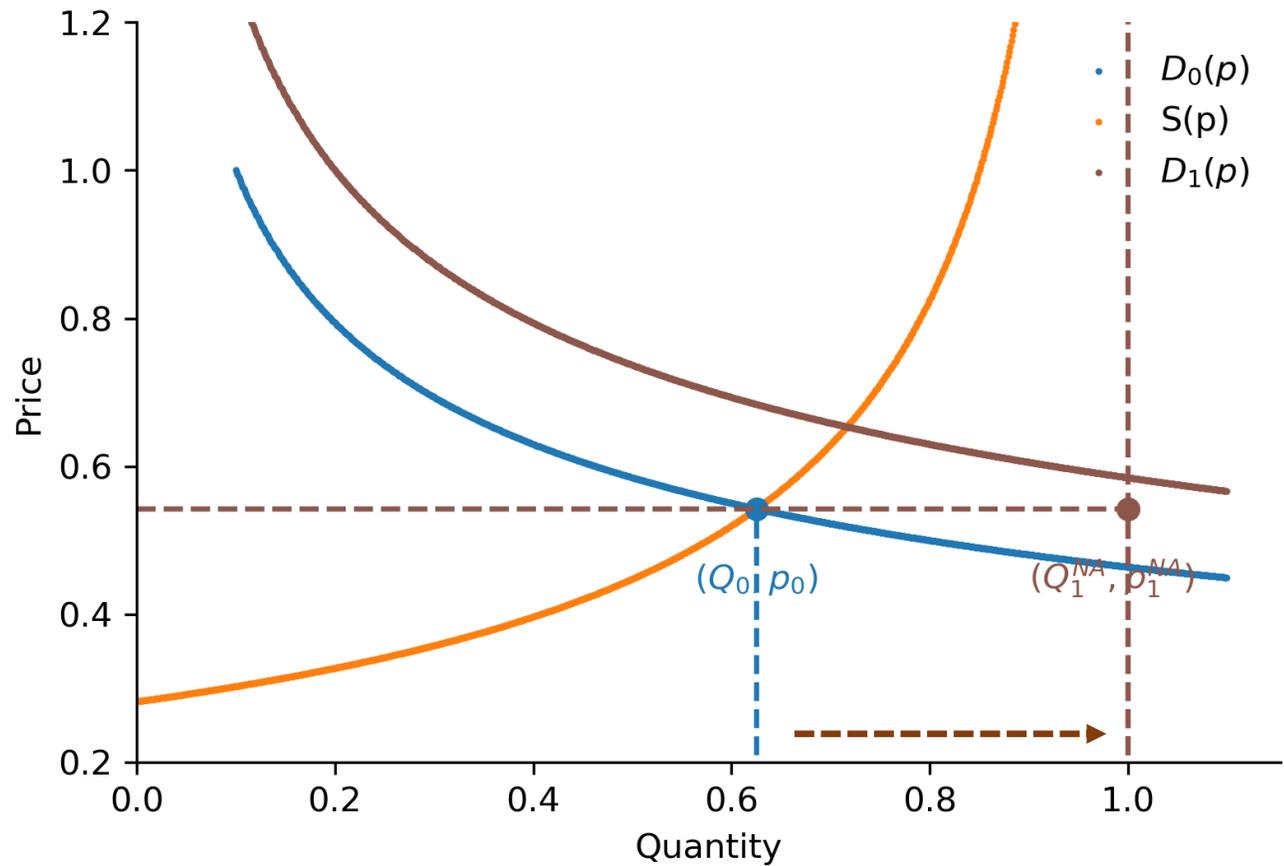
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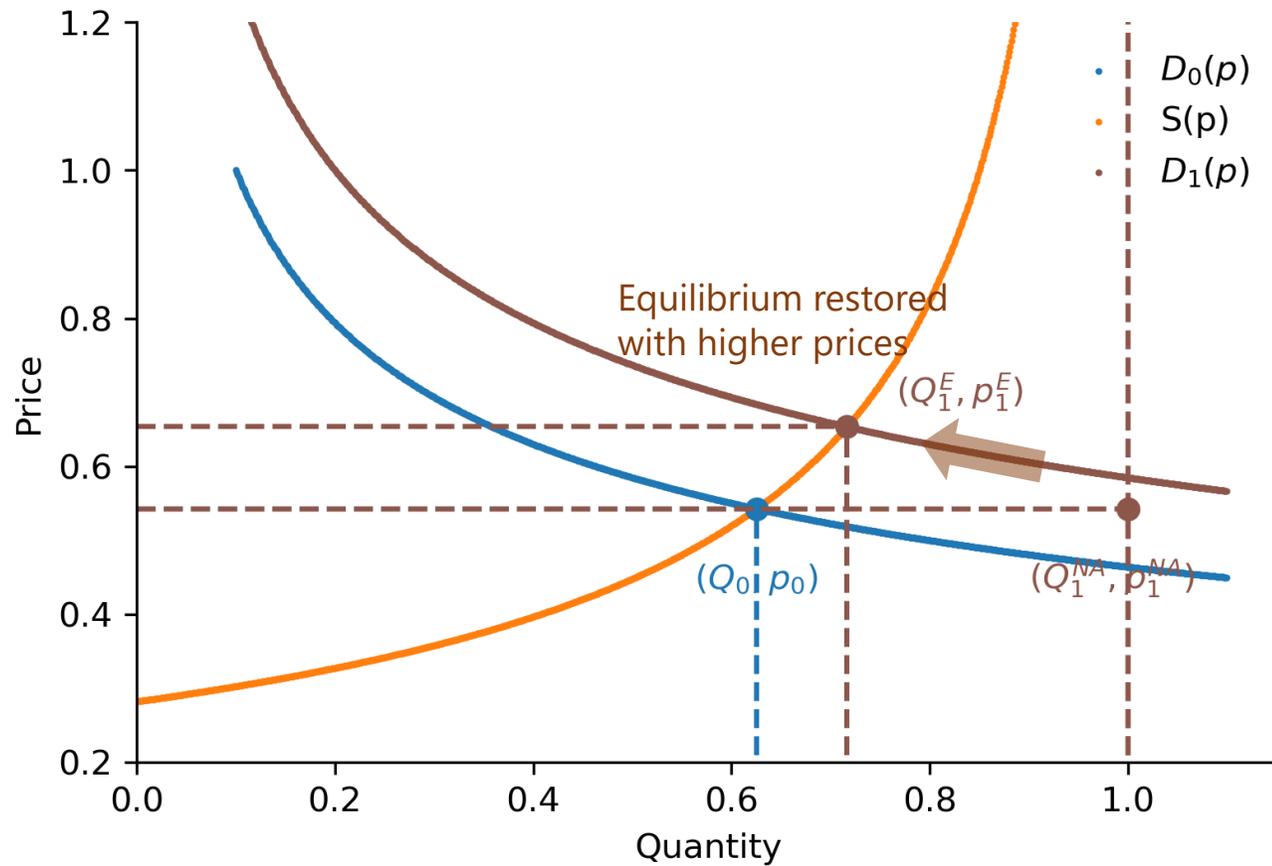


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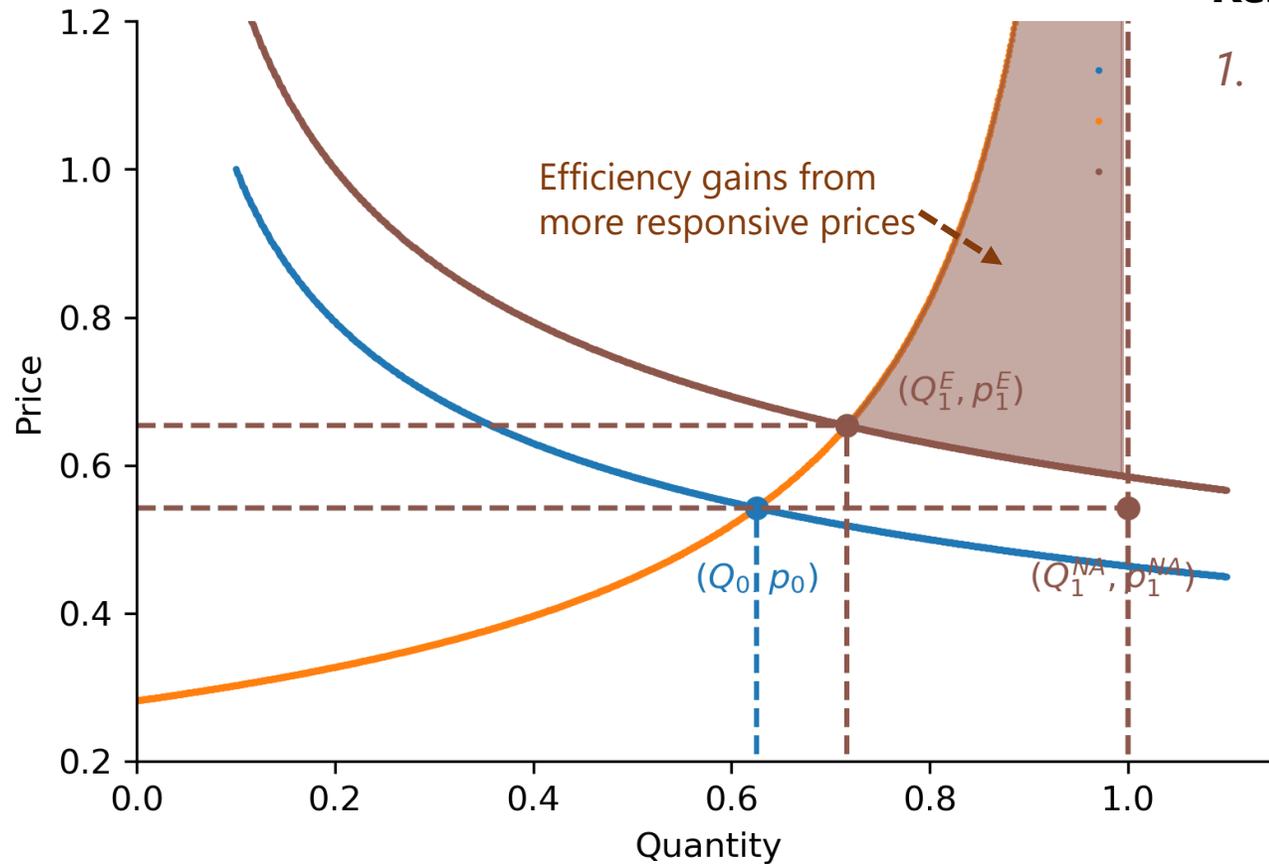


Vacancy drops before price increases

# Stylized Model: Responsive Prices (Boom)



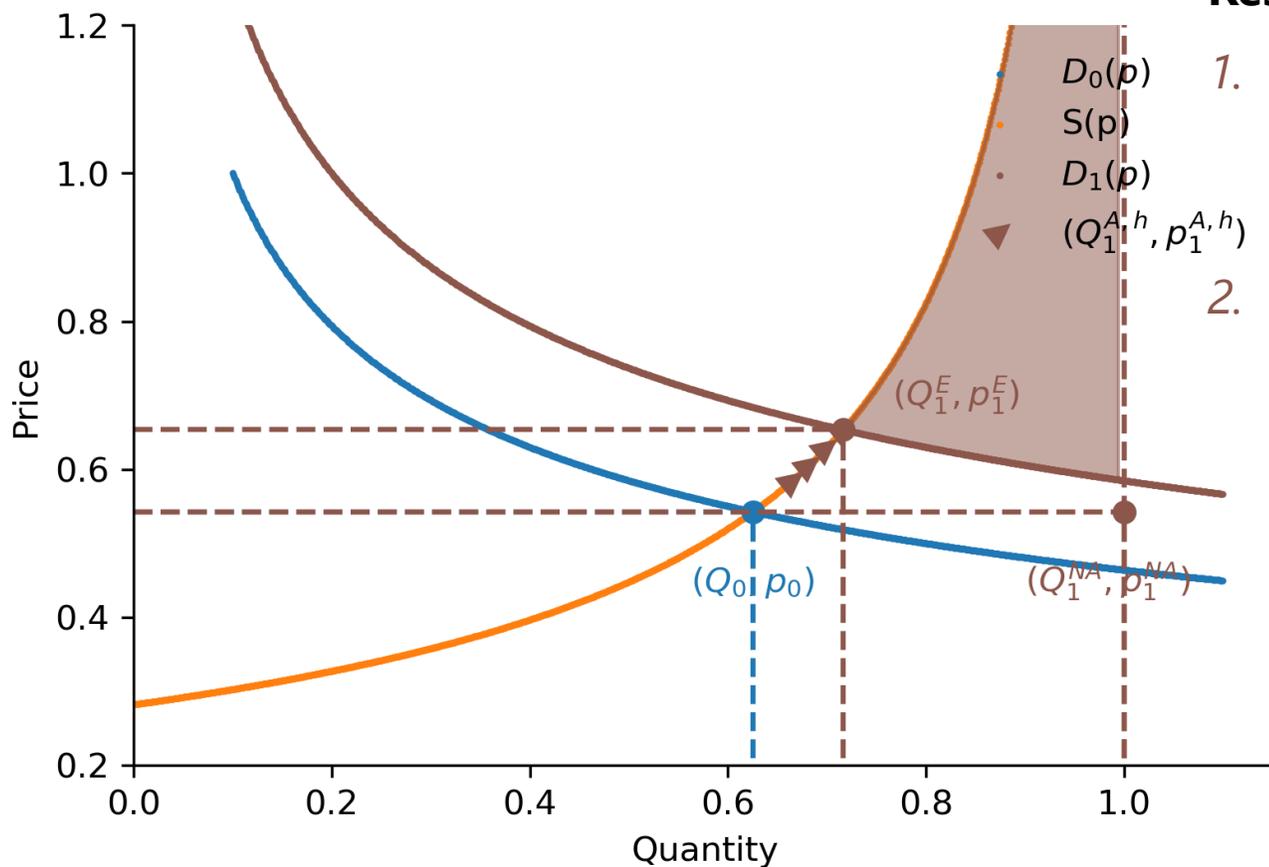
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## Responsive pricing w/ a positive demand shock:

1. Compare **adopter vs. non-adopter within a market**
  - Adopters charge **higher prices**
  - Adopters experience **lower occupancy**

# Stylized Model: Responsive Prices (Boom)



## Responsive pricing w/ a positive demand shock:

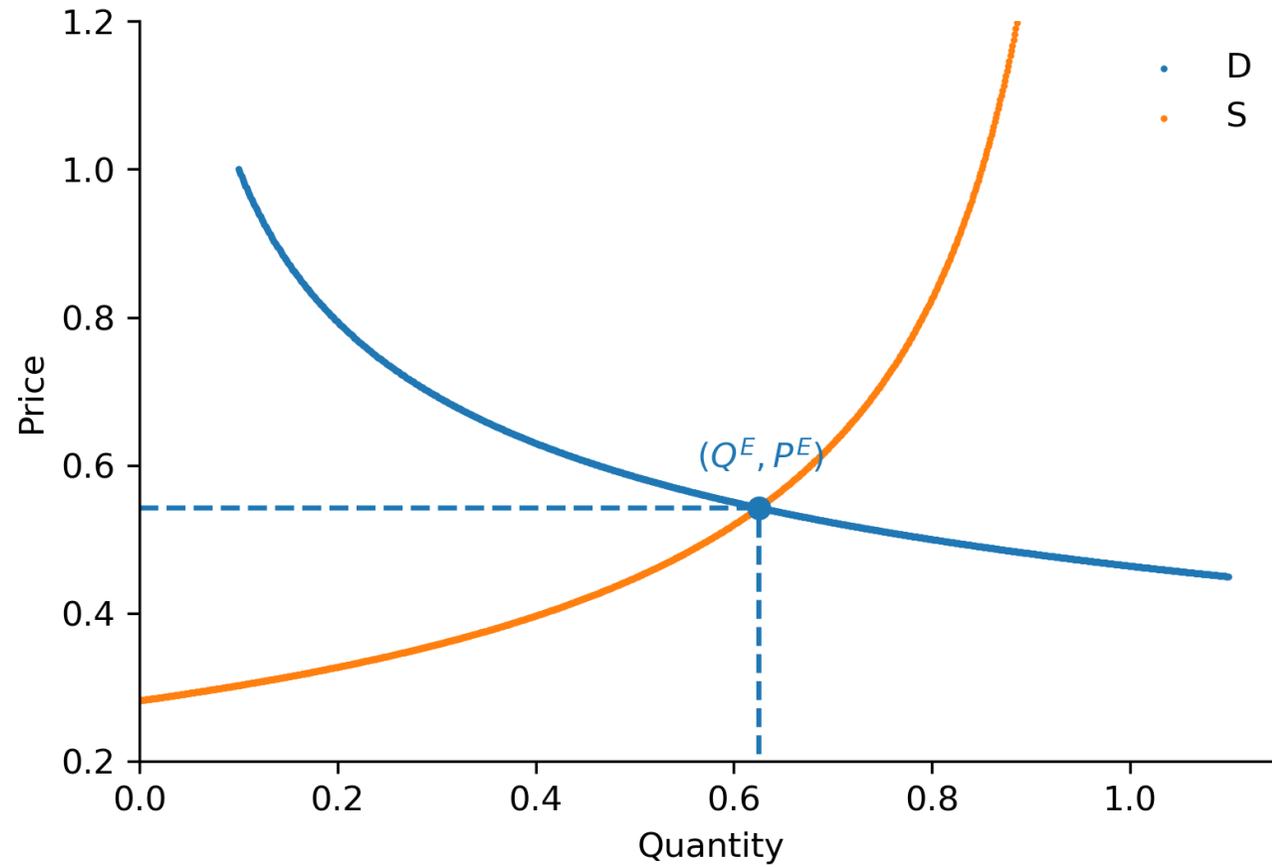
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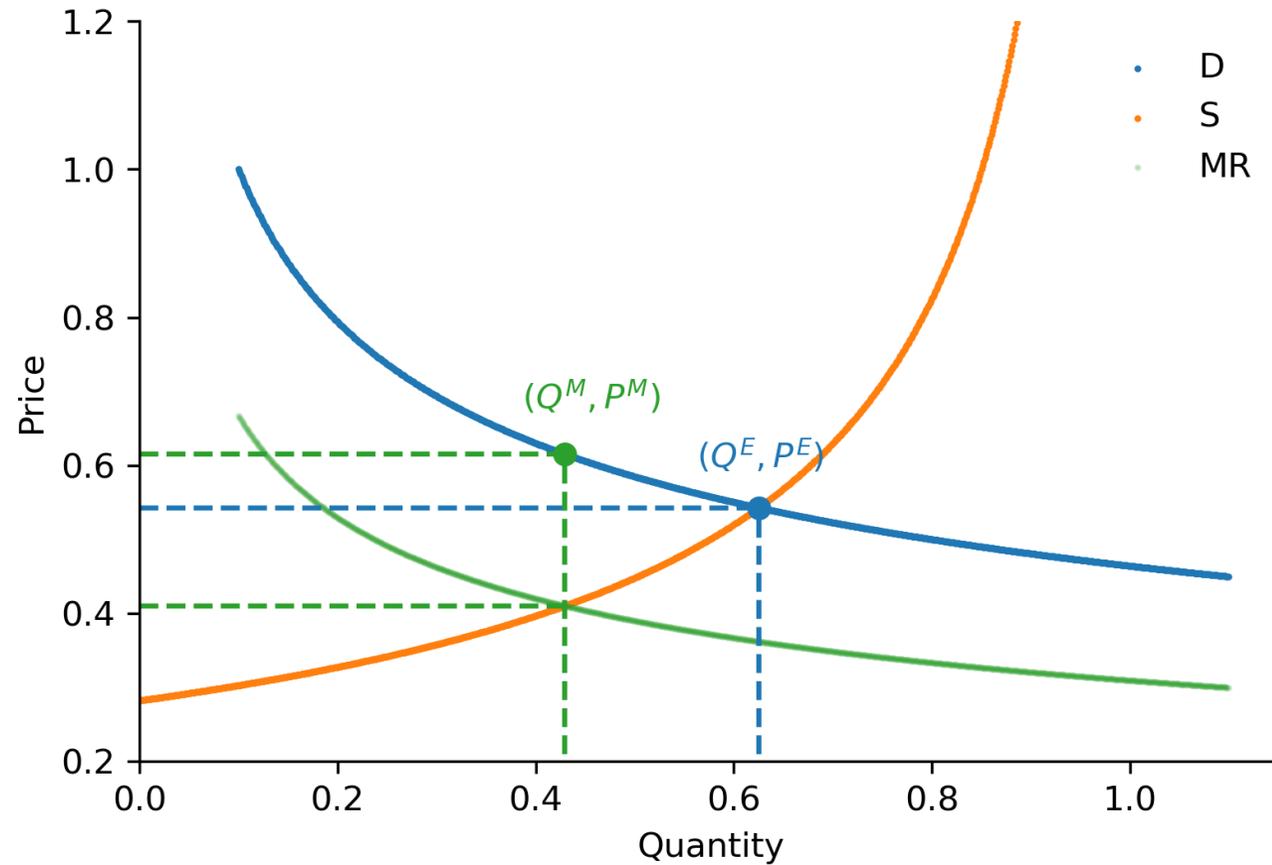
### 2. Compare **adopters as penetration increase across markets**

- The fraction of over-producers shrinks
- The residual demand per adopter strengthens
  - Tracing out its supply curve
- All else equal, with a positive demand shock, **adopter price and occupancy both increase with  $h$**

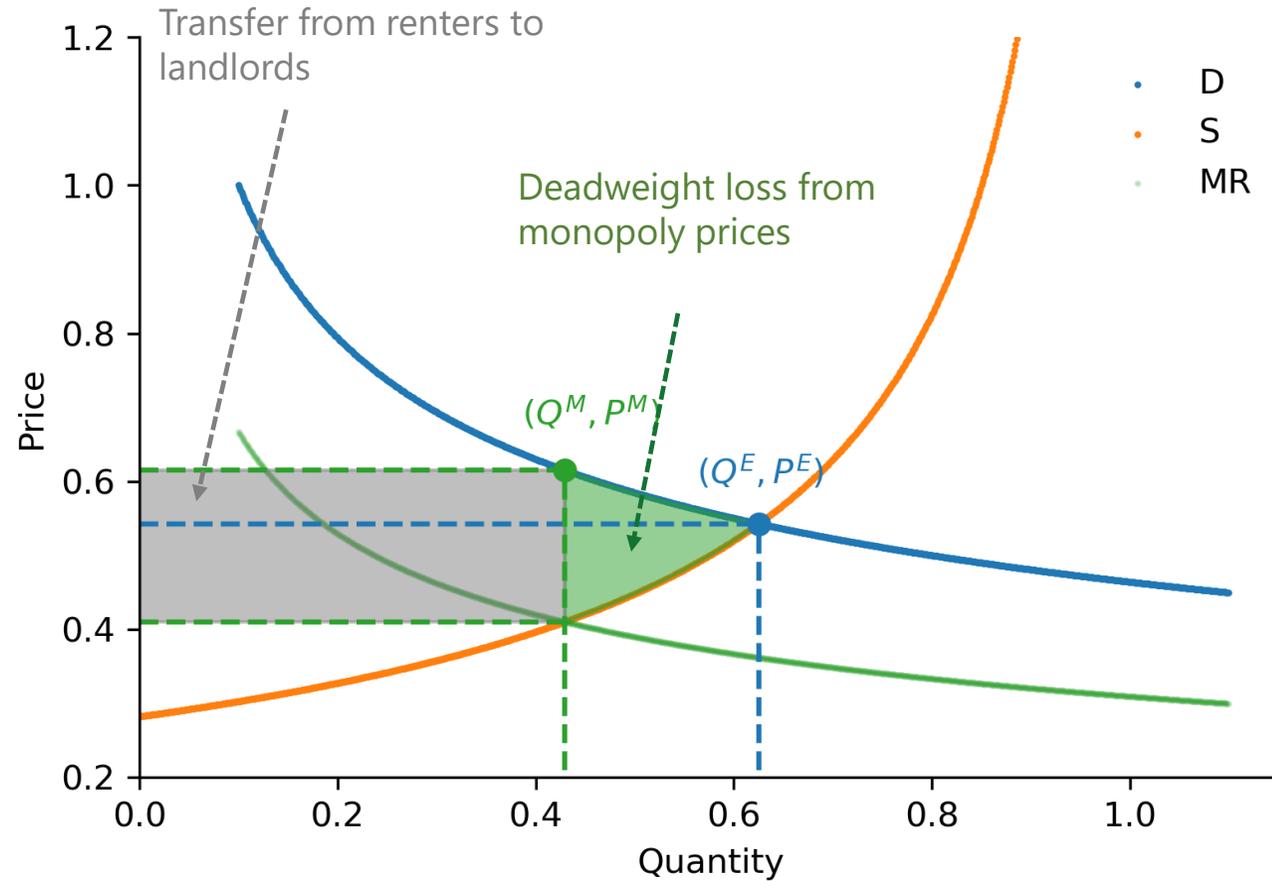
# Stylized Model: Coordinated Prices



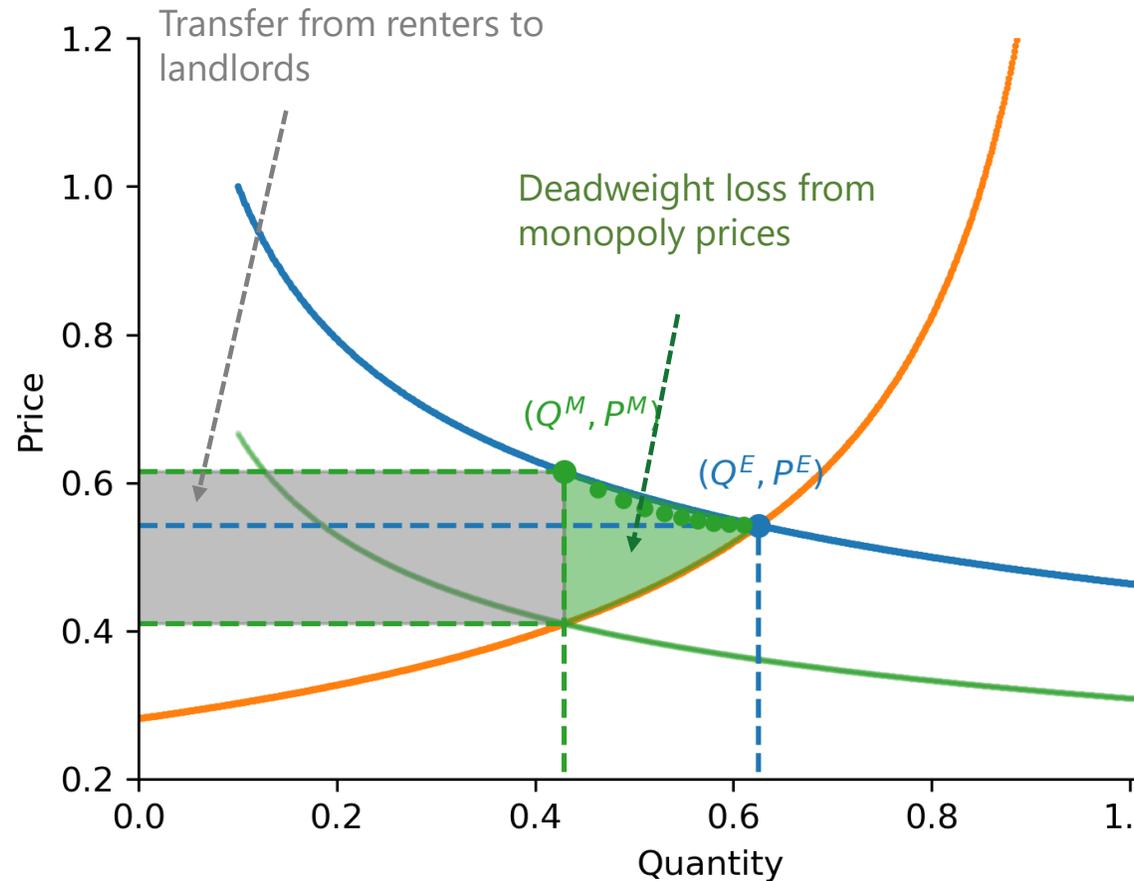
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# Stylized Model: Coordinated Prices



- A model of joint-profit-maximization

- Monopoly  $\frac{p^M - mc}{p^M} = \frac{1}{\epsilon_D(p^M)}$

- When a fraction of the owners are adopters (A), *joint maximization* over the residual demand:

$$\frac{p^A - mc}{p^A} = \frac{1}{\epsilon_{DA}(p^A)}$$

Predictions under joint-profit maximization:

1. Compare adopter vs. non-adopter within a market
  - Adopters *charge the same price*
  - Adopters *experience lower occupancy*
2. Compare adopters as penetration increases across markets
  - All else equal, **adopter price increases but occupancy decreases** with penetration  $h$

# Stylized Model Summary

## Adopter vs. Non-Adopter Within a Market

Difference	Responsive Prices (Bust)	Responsive Prices (Boom)	Coordinated Prices
$p^A - p^{NA}$	—	+	NA
$Q^A - Q^{NA}$	+	—	—



Can isolate responsive pricing



Cannot isolate coordination

# Stylized Model Summary

## Adopter vs. Non-Adopter Within a Market

Difference	Responsive Prices (Bust)	Responsive Prices (Boom)	Coordinated Prices
$p^A - p^{NA}$	—	+	NA
$Q^A - Q^{NA}$	+	—	—



Can isolate responsive pricing



Cannot isolate coordination

## Adopter Outcomes by Penetration Across Markets

As Adoption Increases	Responsive Prices (Bust)	Responsive Prices (Boom)	Coordinated Prices
$p^A$	↘	↗	↗
$Q^A$	↘	↗	↘



Price and quantity move in the **same** directions



Price and quantity move in **opposite** direction  
 Could be indicative of coordination

Could be confounded by unobserved cost shocks -> conduct test

# Results

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## 1. Reduced-Form Analysis

- Within-Market Comparison of Adopter vs. Non-adopters
- Cross-Market Comparison of Adopters by Algo Penetration

## 2. Conduct Test

# Results

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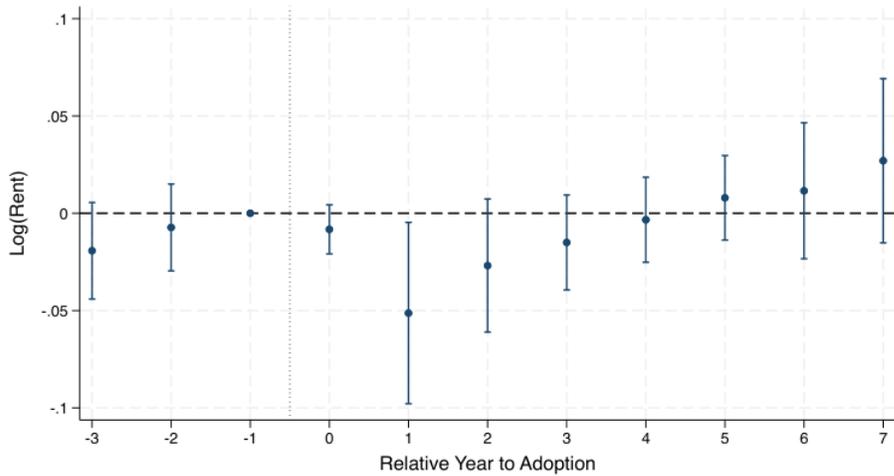
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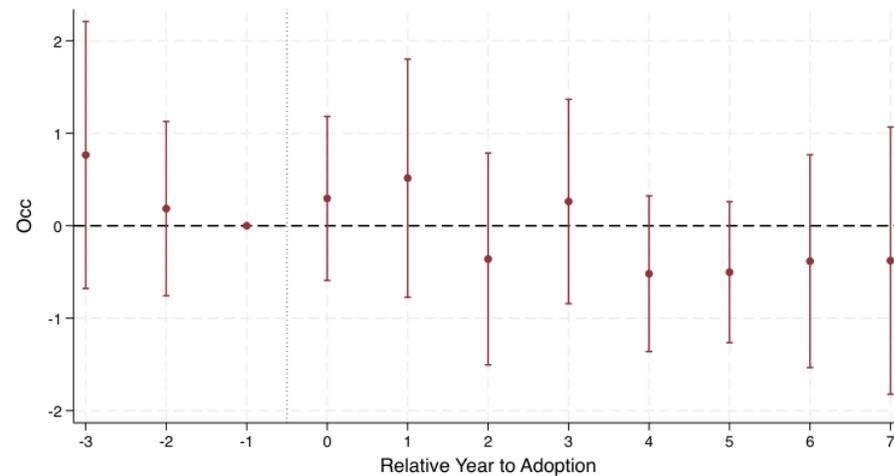
## 2. Conduct Test

# Within-Market Comparison of Adopter vs. Non-adopters: By Adoption Cohorts

(a) 2008 Cohort of Adopters vs. Never Adopters

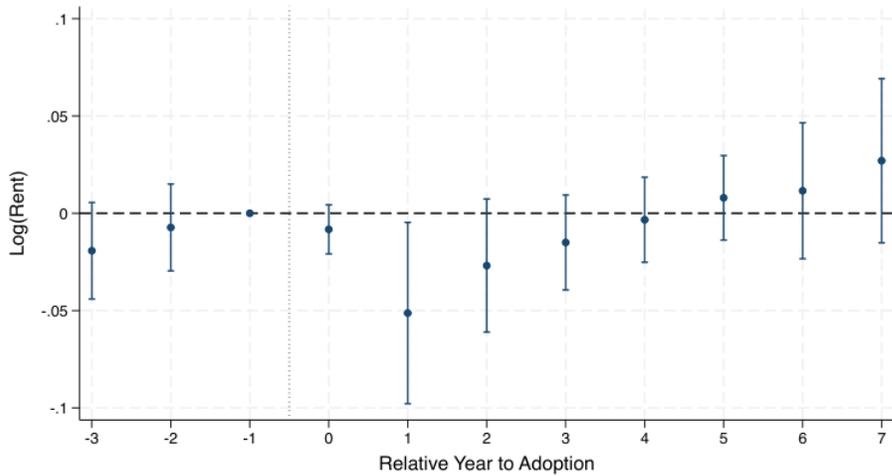


- For 2008 cohort, adoption leads to lower prices and higher occupancy during GFC

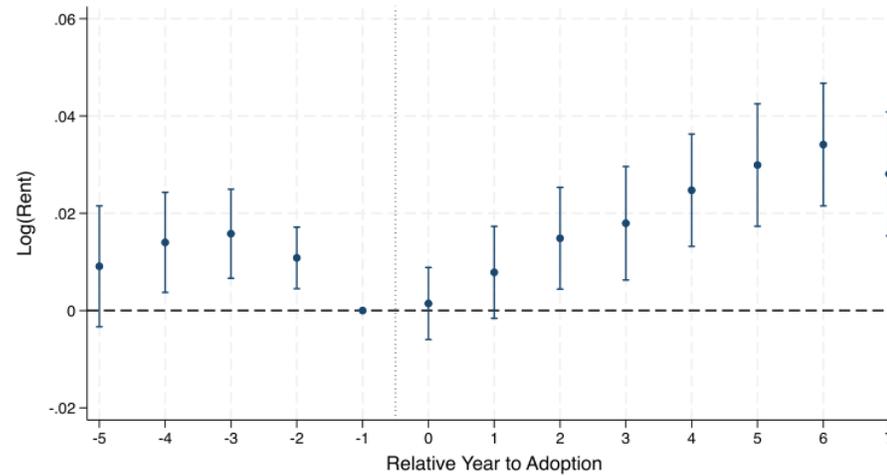


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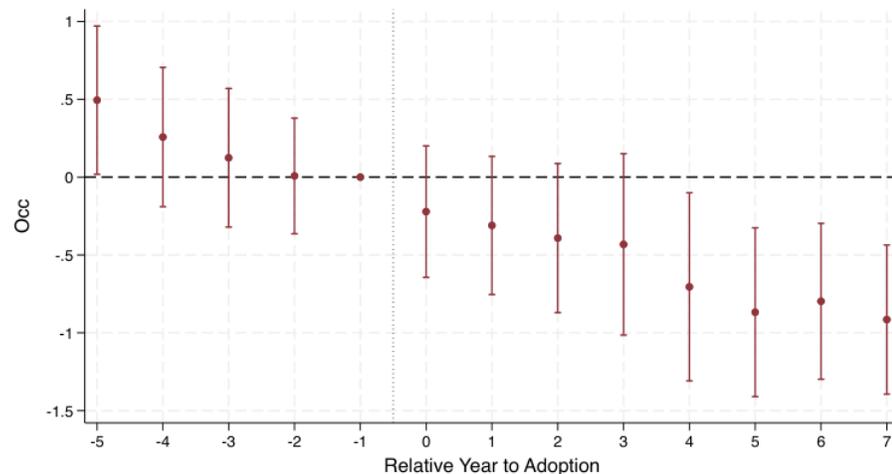
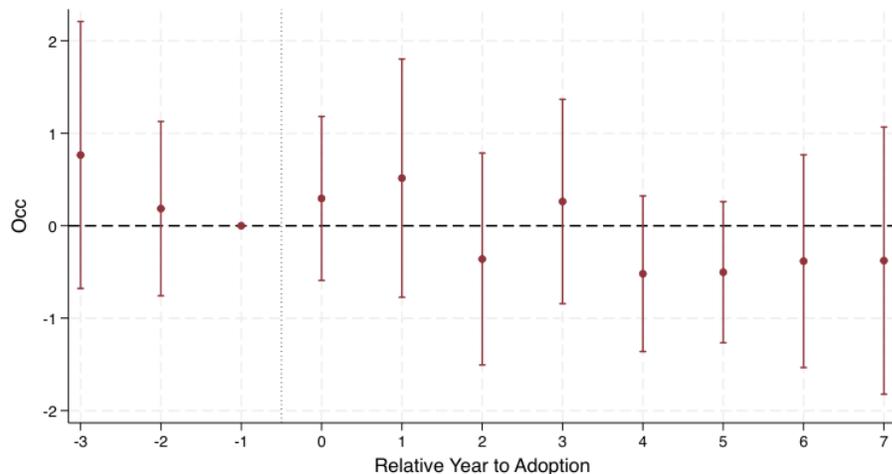
(a) 2008 Cohort of Adopters vs. Never Adopters



(b) 2010 Cohort of Adopters vs. Never Adopters



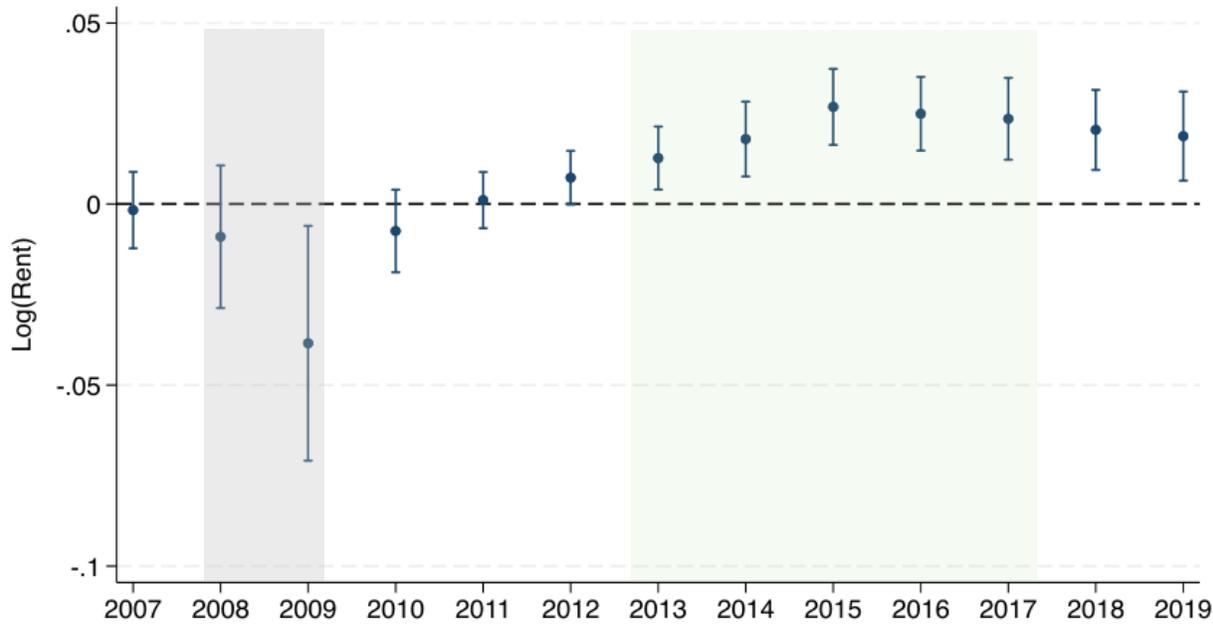
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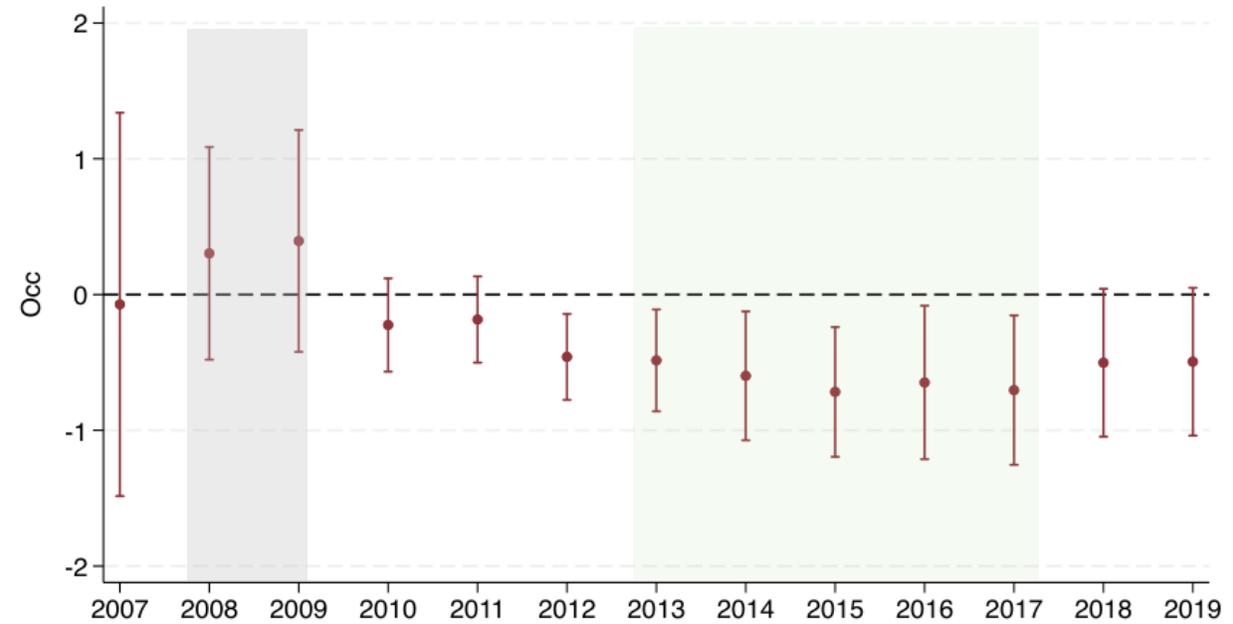
- For the 2010 cohort, adoption leads to higher prices and lower occupancy in later years

# Within-Market Comparison of Adopter vs. Non-adopters: By Calendar Time

(a) Calendar Year TE on Log(Rent)



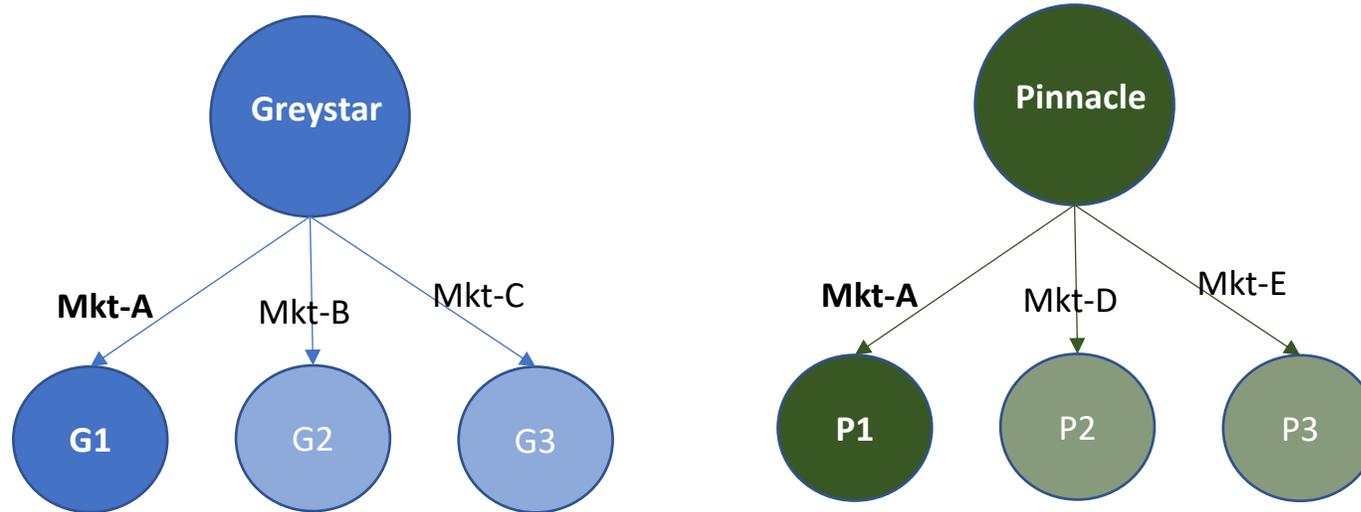
(b) Calendar Year TE on Occupancy (%)



- Compared adopted and non-adopted buildings in the same market-segment (metro by quality quartile)
  - Estimation using CSDID (Callaway and Santa'Anna 2021) to account for staggered adoption
  - Adopters charged lower prices and experienced higher occupancy than non-adopters during the recession
  - Adopters charged higher prices and experienced lower occupancy than non-adopters during the recovery

# Within-Market Comparison of Adopter vs. Non-adopters: IV

- Instrument for adoption:
  - Adoption decision is made at the management company level, so we use the penetration of other buildings in different metros of the same management company to instrument for the adoption likelihood of the focal building
    - First-stage F-stat is significant at 55.1
    - Results consistent and robust to using the instrumented adoption



If market B has more adoption than market D, then G1 is more likely to adopt than P1

# Within-Market Comparison of Adopter vs. Non-adopters: By Calendar Time

Year	TWFE		2SLS		CSDID	
	Log(Rent)	Occ(%)	Log(Rent)	Occ(%)	Log(Rent)	Occ(%)
2006	0.030*** (0.004)	-0.493** (0.203)	-0.082 (0.163)	3.901 (8.968)	0.003 (0.022)	-0.482 (0.728)
2007	0.011*** (0.004)	-0.181 (0.245)	0.021 (0.037)	-6.813 (4.793)	-0.002 (0.005)	-0.072 (0.720)
2008	0.006 (0.005)	-0.042 (0.148)	-0.020 (0.015)	-1.716* (0.956)	-0.009 (0.010)	0.303 (0.400)
2009	-0.036*** (0.009)	0.262** (0.129)	-0.173*** (0.038)	-0.507 (0.822)	-0.038** (0.017)	0.395 (0.417)
2010	-0.015*** (0.004)	-0.191* (0.113)	-0.073*** (0.016)	-0.697* (0.387)	-0.007 (0.006)	-0.224 (0.175)
2011	-0.006** (0.003)	-0.173 (0.107)	-0.040*** (0.008)	-0.922*** (0.302)	0.001 (0.004)	-0.184 (0.162)
2012	0.002 (0.002)	-0.388*** (0.104)	-0.023*** (0.007)	-1.120*** (0.289)	0.007* (0.004)	-0.459*** (0.162)
2013	0.007** (0.003)	-0.175 (0.108)	-0.015** (0.006)	-0.715*** (0.276)	0.013*** (0.004)	-0.485** (0.191)
2014	0.013*** (0.003)	-0.305** (0.124)	0.006 (0.006)	-0.829*** (0.283)	0.018*** (0.005)	-0.599** (0.242)
2015	0.026*** (0.003)	-0.355*** (0.115)	0.036*** (0.007)	-0.953*** (0.260)	0.027*** (0.005)	-0.717*** (0.244)
2016	0.027*** (0.003)	-0.407*** (0.116)	0.039*** (0.007)	-0.854*** (0.256)	0.025*** (0.005)	-0.648** (0.288)
2017	0.025*** (0.003)	-0.352*** (0.122)	0.040*** (0.007)	-0.620** (0.258)	0.024*** (0.006)	-0.704** (0.281)
2018	0.023*** (0.004)	-0.280** (0.124)	0.043*** (0.008)	-0.414 (0.269)	0.020*** (0.006)	-0.502* (0.278)
Control Group	Pooled	Pooled	Pooled	Pooled	Never	Never
Building FE	Y	Y	Y	Y	Y	Y
Metro-Renttile-Year FE	Y	Y	Y	Y	Y	Y
F-Stat			55.1	55.1		
$N_{obs}$	413,850	413,850	413,850	413,850	392,991	392,991

- Main results are robust to:
  - Instrumented adoption
  - Traditional TWFE specification
  - Alternative definitions of market segments
  - Comparison to never adopters and/or not-yet-adopters

# Results

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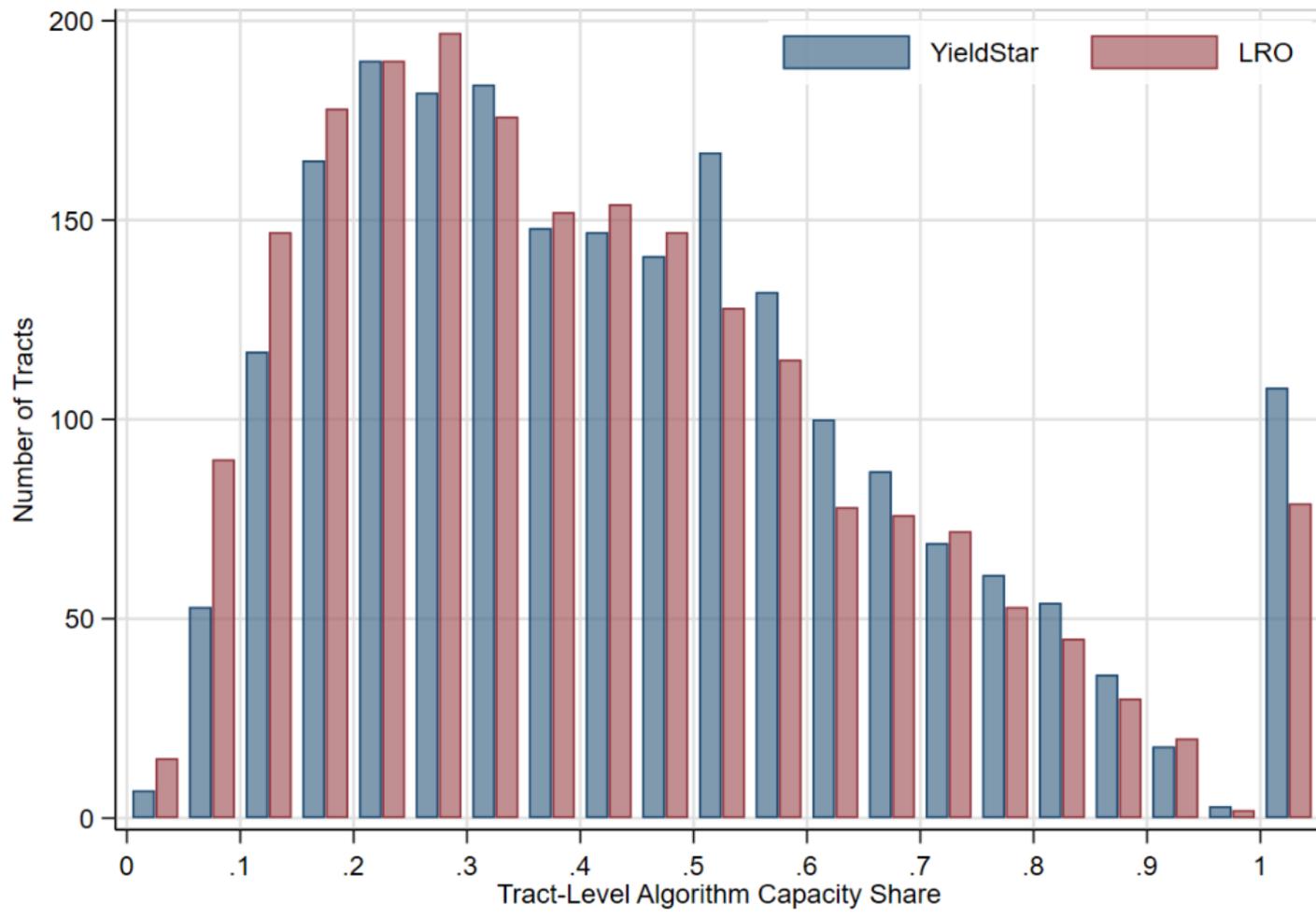
## 1. Reduced-Form Analysis

- Within-Market Comparison of Adopter vs. Non-adopters
- Cross-Market Comparison of Adopters by Algo Penetration

## 2. Conduct Test

# Cross-Neighborhood Comparison of Adopters by Algo Penetration

Distribution of Algorithm Penetration Across Census Tracts (2019)



- Compare neighborhoods (tracts) within the same metro area
  - Holding fixed unobserved market shocks at the metro level

# Cross-Neighborhood Comparison of Adopters by Algo Penetration

	Tract-Level Penetration			
	(1) ln(p)	(2) occ	(3) ln(p)	(4) occ
is YS =1 × YS share (tract)	0.0405*** (0.0154)	-4.0090*** (0.7144)	0.0406*** (0.0154)	-3.7444*** (0.8082)
is LRO=1 × LRO share (tract)	0.0711*** (0.0198)	-5.5832*** (1.5464)	0.0742*** (0.0180)	-5.1862*** (1.4221)
is YS =1 × LRO share (tract)			-0.0025 (0.0140)	1.5127 (1.7581)
is LRO=1 × YS share (tract)			0.0108 (0.0154)	1.3036 (0.9276)
Building FE	Y	Y	Y	Y
Segment-Year FE	Y	Y	Y	Y
N	53,408	53,408	53,408	53,408

- Compare adopters across varying levels of penetration
  - Adopter rent **increases** with penetration
  - Adopter occupancy **decreases** with penetration
  - P and Q move in **opposite** direction as penetration rises
    - *Cannot be explained by responsive pricing alone*
    - *Could be indicative of coordinated pricing*

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    - *Cannot be explained by responsive pricing alone*
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      - Especially among users of the same software
- But:
  - Penetration could be correlated with unobserved cost shocks
    - **Hypotheses about conduct cannot be separated from hypotheses about marginal costs**
  - A structural model of demand and supply allows us to leverage instruments to formally test conduct with exclusion restrictions on marginal costs

# Results

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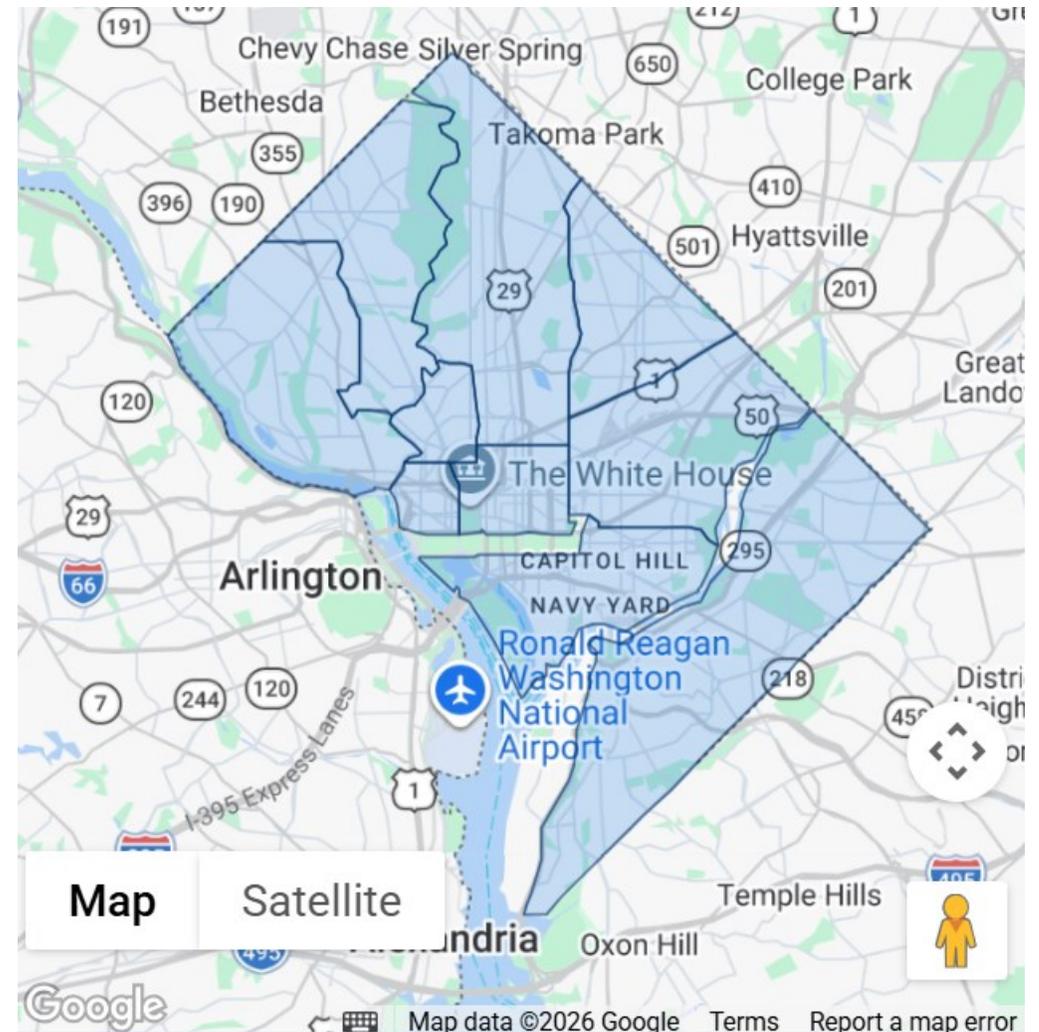
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## 2. Conduct Test

# Conduct Test: Demand Estimation

- Estimation sample based on ten cities:
  - Atlanta, Charlotte, Dallas, DC, Houston, Los Angeles, Minneapolis, Portland, San Diego, and Seattle
  - Further divided into over 200 submarkets
  - Selected by size and data availability
- REIS buildings:
  - Average rent: \$1,431/mo
  - Average occupancy: 94.8%
- Adoption:
  - Average fraction of buildings adopted (2019): 25%
  - Average fraction of units adopted (2019): 32%
  - Units adopted: 588k (out of 2.4 million)



# Conduct Test: Demand Estimation

- Demand is modeled as a multinomial discrete choice problem across differentiated rental housing units
  - Each product is a building-bedroom type (e.g., 2-bed in 2116 Chestnut St)
  - Utility is based on rent, building characteristics, and unobservable quality

$$u_{ijt} = \alpha_i p_{jt} + X'_{jt} \beta_i + \phi_j + \theta_{mt} + \xi_{jt} + \epsilon_{ijt}$$

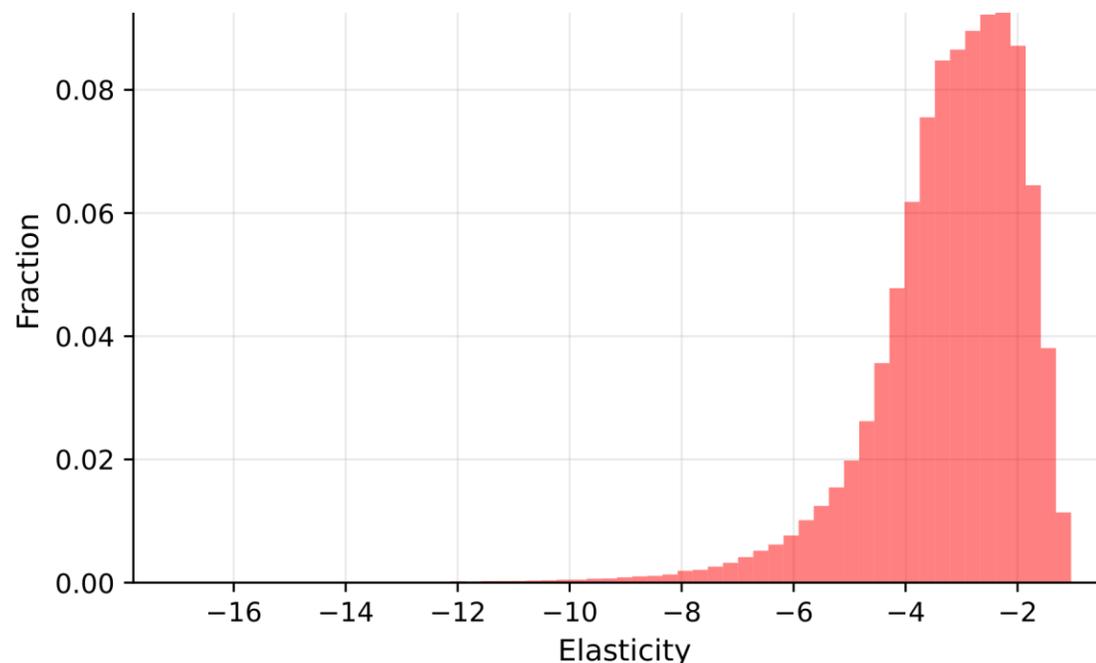
- Our panel data allows us to include building fixed effects and submarket-year fixed effects
- Estimation using BLP with micro-moments (Petrin 2002; Conlon and Gortmaker 2023):
  1. Match the REIS-building quantity based on occupancy data
  2. Match the covariance between household demographics and housing attributes
    - ACS micro-data:
      - Bedroom x (household size, child)
      - Building age x (income, age)
      - Inside good x (income, household size, child, age)
    - Augment it with Data Axle address history data:
      - Class A x (income)

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- Demand instruments:
  - Differentiation instruments (Gandhi and Houde 2019)
  - Approximated optimal instruments (Chamberlain 1987, Conlon and Gortmaker 2023)
- Estimated elasticities:
  - Median own elasticity: -3.26
  - Median aggregate elasticity: -1.30
  - Median outside good diversion: 0.79



# Conduct Test: Test Procedure

- A model of pricing for differentiated products that allows for
  1. Coordination ( $\tau^A$ ): Internalization of competitor's profits among adopters

$$\mathcal{H}_t(\tau^A, 1) = \begin{pmatrix} 1 & \tau^A & 0 \\ \tau^A & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

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$$p_t - mc_t = - \left( \mathcal{H}_t(\tau^A, \tau_t^{NA}) \odot \boldsymbol{\Omega}_t(\mathbf{p}) \right)^{-1} \mathbf{D}_t(\mathbf{p})$$

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- Key insight:
  - The inverse of a cross-diagonal matrix is also cross diagonal
  - We *can* isolate the FOC and test conduct among just adopters, irrespective of non-adopters' pricing behavior

$$\begin{bmatrix} \mathbf{p}_t^A - \mathbf{mc}_t^A \\ \mathbf{p}_t^{NA} - \mathbf{mc}_t^{NA} \end{bmatrix} = \begin{bmatrix} - \left( \mathcal{H}_t(\tau^A) \odot \boldsymbol{\Omega}_t^A(\mathbf{p}) \right)^{-1} \mathbf{D}_t^A(\mathbf{p}) \\ - \left( \mathcal{H}_t(\tau_t^{NA}) \odot \boldsymbol{\Omega}_t^{NA}(\mathbf{p}) \right)^{-1} \mathbf{D}_t^{NA}(\mathbf{p}) \end{bmatrix}$$

# Conduct Test: Test Procedure

- A model of pricing for differentiated products:
  - For any given model of conduct  $m$ , we can infer the marginal cost
    - Because the mark-up  $\eta^m$  is a known function of demand, internalization matrix, and conduct  $m$

$$mc_t^A = p_t^A - \eta_t^A(\mathcal{H}_t(\tau^A))$$

$$mc_{jt}^A(x_{jt}, occ_{jt}) = h(x_{jt}, occ_{jt}) + \omega_{jt} = \frac{\kappa_a}{(occ_{jt} - 1 - \delta_\epsilon)^2} + \delta_j + \omega_{jt}$$

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- Model marginal cost as a convex function in occupancy, building fixed effects, and cost shocks
- Test of conduct
  - “Instruments”  $z_t$  that affect demand, but are excluded from marginal cost shocks

$$\mathbb{E}[\omega_{jt} | z_t^S] = 0$$

- Differentiation IV as the markup shifter (Gandhi and Houde 2019)
    - Optimal instruments (Conlon and Gortmaker 2020)

# Conduct Test: Testing Procedures

- **Implementation:**

- Estimation of the internalization parameter  $\tau$  (Nevo 2000, Miller and Weinberg 2017)

- **Pair-wise testing:**

- Backus, Conlon, and Sinkinson (2021), Rivers and Vuong (2002); Duarte, Magnolfi, Solvsten, and Sullivan (2023)
- Even if models are mis-specified, the test can still test which of the two models of conduct is “preferred”
  - Null hypothesis: two models of conduct fit the data equally well
  - Alternative hypothesis (two-sided): one model is *avored* over the other model
  - Test statistics:
    - **Negative**: test favors Model 1 (Competition - Own Profit Maximization)
    - **Positive**: test favors Model 2 (Coordination - Joint Profit Maximization)

- Specification:

- $\tau_L^A$  for LRO users pre-acquisition (2009-2017)
- $\tau_R^A$  for RealPage users pre-acquisition (2009-2017)
- $\tau_M^A$  for the merged RealPage users post-acquisition (2018-2019)
- $\tau_{RL}^A$  for cross-software coordination (2009-2017)

# Pair-wise Testing: Competition vs. Coordination

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
$\tau_{L,1}^A = 0$ vs $\tau_{L,2}^A$	2.97	2.85	2.82	2.74	2.71	2.61	2.46	2.50	2.24	2.21
$\tau_{R,1}^A = 0$ vs $\tau_{R,2}^A$	3.39	3.53	3.31	3.19	3.13	3.15	3.08	3.00	2.92	2.82
$\tau_{M,1}^A = 0$ vs $\tau_{M,2}^A$	3.85	3.63	3.45	3.21	2.96	2.70	2.45	2.15	1.82	1.48
$\tau_{RL,1}^A = 0$ vs $\tau_{RL,2}^A$	1.92	1.68	1.76	1.65	1.50	1.37	1.07	1.19	0.86	0.46

- **Specifications:**

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- **Results:**

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- **Results:**

- Tests favor coordination among the users of the same software, especially RealPage
- Tests cannot differentiate competition and coordination between users of different software

# Back-of-Envelope Analysis: “Cost of Algorithmic Collusion”

- Significant markup implications:
  - Average markup impact due to “algorithmic collusion”: \$53 per month per unit
  - With over 4.2 million adopted units reported by 2024, it amounts to *substantial* markup
- Caveat:
  - Not a full counterfactual analysis because  $\tau_t^{NA}$  governing non-adopter behaviors is not “deep”
  - Prices are strategic complements:
    - This is likely a lower bound

Year	Algo Adoption Fraction (%)	Prices (\$/mo)	Coordination Markup			
			(\$/mo)	p(25)	p(50)	p(75)
2009	6.5	1724.4	13.6	2.5	7.6	17.6
2010	11.8	1517.5	11.3	1.5	5.5	15.7
2011	20.8	1314.3	12.3	3.0	9.1	15.9
2012	19.3	1527.3	11.9	2.0	7.4	15.7
2013	20.5	1531.1	22.6	6.4	16.1	32.3
2014	21.5	1595.0	22.7	7.3	17.3	34.1
2015	21.5	1722.7	23.2	8.2	19.7	32.7
2016	22.8	1740.6	24.3	8.5	19.9	35.7
2017	23.5	1759.2	25.4	8.6	20.9	36.9
2018	23.9	1773.4	24.0	8.8	21.1	35.5
2019	24.5	1798.2	24.9	8.9	21.7	36.8
2018*	23.9	1773.4	51.3	19.3	45.5	75.0
2019*	24.5	1798.2	53.1	20.4	46.3	78.0

# Conclusion

- We use comprehensive building-level data and hand-collected adoption decisions to estimate the impact of algorithmic pricing on US multifamily rental markets
  1. We find adopters charge higher prices than non-adopters during booms and lower prices during busts
    - Consistent with algorithms facilitating more responsive price setting
  2. We find adopters charge higher prices and experience lower occupancy as levels of algorithmic penetration increase across neighborhoods
    - Could be indicative of coordinated pricing, but not conclusive w/o additional assumptions on costs
  3. A structural model of demand to test conduct
    - Pair-wise testing favors coordination over competition among users of the same algorithm, but not across users of different algorithms
    - Significant markup implications due to “algorithmic collusion”

# Conclusion

- Bigger Picture:
  - Algorithmic pricing could affect prices and welfare through various channels:
    1. Responsive prices -> Welfare enhancing
    2. Optimal markup -> Welfare reducing, but having market power per se is not illegal
    3. Coordinated prices -> Welfare reducing, most likely cause for antitrust concerns
  - All lead to higher prices, but varying welfare and regulatory implications

Questions or Comments?

- What do these pricing algorithms do, according to RealPage?
  - RealPage FAQ:
    - *“RealPage Revenue Management software is fundamentally built on the disruptive idea that a property’s internal supply/demand dynamics are much more important than a competitor’s rents.”*
    - *“RealPage Revenue Management software prioritizes a property’s internal **rent data and internal availability data** when determining whether **a rental price should be increased, decreased, or remain** at the current level.”*
    - *“If such information indicates that a price should be adjusted either upward or downward, then the software **uses aggregated, anonymized rent data** from a variety of sources to help determine **price elasticity of demand**- that is, how sensitive demand is to upward or downward adjustment in price – and thus the appropriate magnitude of change in price.”*