Spillovers and Adjustments under Information and Search Frictions in a Developing Online Marketplace

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How should platforms address search and information frictions in emerging online markets?

- Online marketplaces are increasingly prevalent in emerging economies (e.g., e-commerce, ridesharing).
- Reduced frictions may improve welfare re; ICT interventions
  - (Aker 2010; Aker and Mbiti 2010; Allen 2014; Atkins and Donaldson 2015; Jensen 2007)

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  - (Aker 2010; Aker and Mbiti 2010; Allen 2014; Atkins and Donaldson 2015; Jensen 2007)
- Residual frictions may be functions of platform design and/or symptoms of other market failures:
  - Platform design balance search friction against competition in differentiated markets
    - (e.g., Dinerstein et al. 2018; Horton 2019; Fradkin 2015)
  - Market failures in developing economies (allocative inefficiency, entrepreneurial skills) exacerbate frictions
    - (Bai et al., 2020; Jin and Sun 2024)
- **Research question**: How does an information intervention in an emerging online market affect search and information frictions and induce spillovers/adjustments?

Context: Noisy price signals and search frictions in an online marketplace in Pakistan

- Listing services are increasing common platforms through which to collect information about, and buy/sell used vehicles in developing economies
  - otherwise rely on social networks
  - We partner with a leading platform in Pakistan, PakWheels.com

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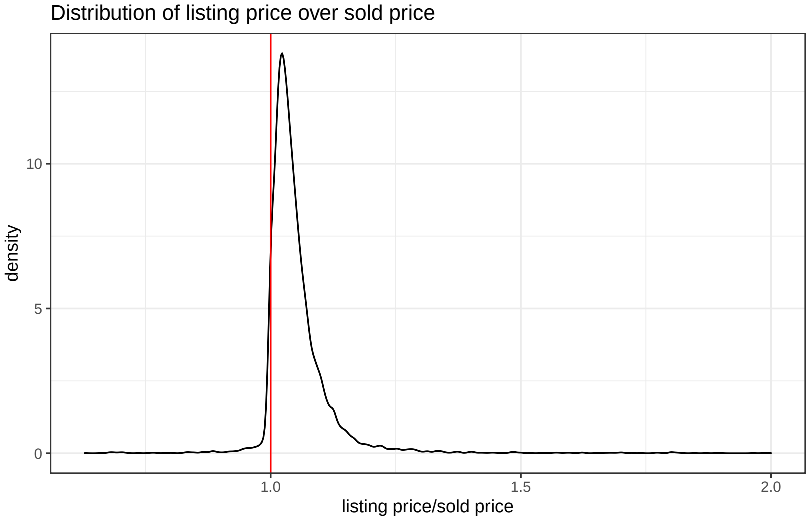
  - otherwise rely on social networks
  - We partner with a leading platform in Pakistan, PakWheels.com
- Limited info, noisy beliefs about demand, and high search frictions
  - No publicly accessible database of transaction prices, like kbb.com
  - Management: "sellers are not pricing 'right"'
  - Reported transaction: 33% of listings
- To promote their vehicles, sellers pay to increase visibility on PakWheels.com

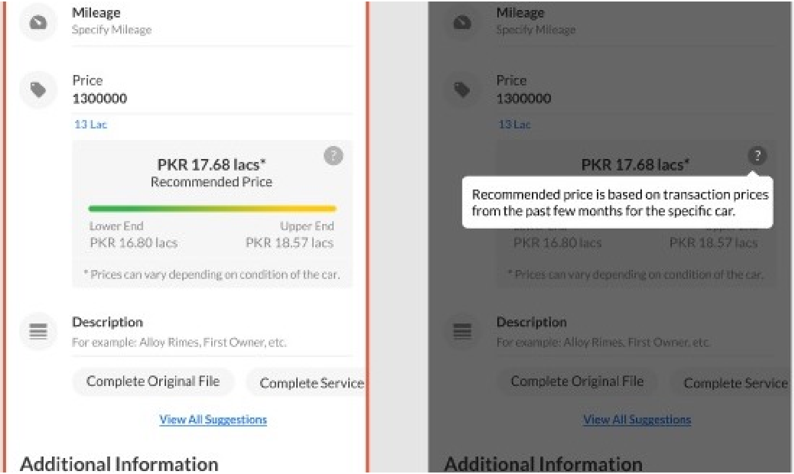
There is significant discrepancy between listing transaction prices



Intervention: private access to price information for sellers

- We ran a natural field experiment (List, 2007) in which we provide price information *privately* to randomly chosen sellers, across the majority of listings on PakWheels.
- Info: estimates from a new machine-learning (gradient boosting) based prediction model of transaction prices ("Price Calculator"). Old PC
- We provide the Price Calculator estimates to sellers of **new** posts.
- We randomized in two stages to measure direct effects and spillovers:
  - i Block-randomize 68 clusters (make-models) into Pure Control, Low Saturation, and High Saturation
  - ii Within clusters, randomly select 50% (low) or 90% (high) of new listings based on their user-ID.

Sellers are privately shown a Price Calculator estimate



We follow sellers' choices and outcomes

- Deviation of sellers' listing price from the Price Calculator estimate.
- Transaction outcomes (sale, price)
- Advertising: sellers buy and use advertising tools to increase visibility on search results
  - "bumps"
  - "features"
  - vehicle inspection and certification
- Buyer attention: click-throughs

Results:

- The price information intervention:
  - reduces price deviation from Price Calculator by 7-11% for treatment and spillovers
  - increases transaction probability by 1% spillovers, but **not** for treatment.
  - mediating (pre-specified) mechanism:
    - slightly reduces ad. use by treatment by 0.01 SD
    - increases page-views for spillover group by 0.03 SD

Results table: Main pre-specified outcomes (ITT)

Table 1: **Regressions on prespecified main outcomes**

	log(Price difference) (1) OLS	1 if sold (2) Logit	log(Transaction price) (3) OLS	Page-view index (4) OLS	Advertising index (5) OLS
Assignment	-0.0327**	-0.0499***	-0.0008	-0.0172***	-0.0095***
	(0.0135)	(0.0172)	(0.0037)	(0.0039)	(0.0025)
Spillover	-0.0779*	0.0488***	-0.0401	0.0332***	-0.0005
	(0.0443)	(0.0140)	(0.0335)	(0.0106)	(0.0042)
Spillover (high)	0.0736	-0.0138	-0.0031	-0.0092	0.0062
	(0.0537)	(0.0333)	(0.0457)	(0.0169)	(0.0059)
Observations	101,750	111,309	14,084	117,891	117,891
Squared Correlation	0.10797	0.01471	0.92874	0.12322	0.29329
Pseudo R^2	0.02959	0.01197	1.2997	0.08546	0.24067
BIC	383,275.7	141,831.7	-6,886.7	167,975.7	131,198.5
Q-values: Assignment	0.023	0.006	0.835	0.000	0.001
Q-values: Spillover	0.14	0.002	0.293	0.006	0.912
Q-values: Spillover (high)	0.741	0.848	0.945	0.848	0.741

ToT specified outcomes ITT specified outcomes by group Dist. price differences by group

To identify mechanisms behind our result:

- Pre-specified model of static search with information friction to identify change in beliefs as mechanisms.
- Conduct an endline survey to capture beliefs about demand and search frictions. Find effects only on directly treated sellers

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- Pre-specified model of static search with information friction to identify change in beliefs as mechanisms.
- Conduct an endline survey to capture beliefs about demand and search frictions. Find effects only on directly treated sellers
- Treated sellers adjust beliefs about demand Prices
  - Reduce deviations of price expectations from PC estimates by 22%
  - Slightly increase willingness to negotiate by PKR 5,600
- They have more optimistic beliefs about search frictions and market conditions Frictions
  - 0.05-0.07 Likert-scale reductions in their views on how difficult it is to get serious inquiries and good prices
- Directly treated sellers update beliefs about price and search, adjust listing price, and substitute away from advertising.
- Beliefs do not shift for spillover sellers. They respond to publicly visible choices of their competitors

Conclusion:

- Access to information can reduce frictions on emerging economies' online platforms.
    - Beyond mobile phones and SMSs (Aker 2010; Aker and Mbiti 2010; Jensen 2007)
- Small effect sizes may be due to:
    - spillovers
    - adjustment mechanisms (advertising) that counter direct treatment effects
    - magnitude of the effects being contingent on sellers' beliefs
- Platform-based intervention may be a cost-effective way to improve microentrepreneurs' decisions (Jin and Sun 2024; McKenzie and Woodruff 2014; Blattman and Ralston 2015)

Thank you!

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Our empirical questions

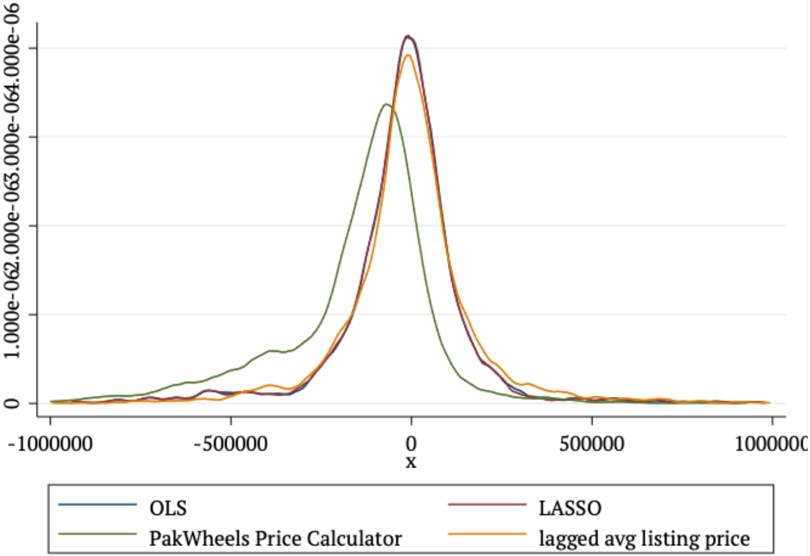
1. Does a price information intervention induce individual responses?
   1.1. **Do sellers adjust their listing prices toward the price signal they receive?**
      1.1.1. Does the intervention affect sellers' stated beliefs about the distribution of transaction prices?
   1.2. **Does the price information intervention improve sellers' returns from the platform?**
      1.2.1. **Does it increase page views?**
      1.2.2. **Does it increase the transaction probability?**
      1.2.3. **Does it affect the transaction price?**
   1.3. **Do sellers respond to the intervention by making strategic adjustments in advertising?**

Research questions

… and on indirect effects and their mechanisms

2. **Does the intervention induce spillovers in terms of listing prices, transaction outcomes, and the use of advertising?**
   2.1. changes in stated belief about the distribution of transaction prices
   2.2. changes in use of advertising
   2.3. zero-sum shift in buyer attention
   2.4. changes in congestion?

Price forecasts could be improved



To identify mechanisms behind our result:

- Pre-specified model of static search with information friction, with: Theory: motivation
  - sellers with noisy beliefs about buyers' WTP
  - leading to suboptimal pricing and probability of sale
  - sellers engaging in costly actions to counter search friction, to increase match rate

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- Takeaways: Theory predictions
  1. Price information should bring listing price closer to what it would be under no information friction.
  2. Advertising usage depends on seller's beliefs about expected returns from the platform.
  3. Spillovers occur in response to changes in competitors' choices of listing prices and advertising

Theoretical Framework

- We use a framework of static search.
- Models used in related papers:
  - focus on geographical arbitrage via access to price information (Allen 2014; Atkins and Donaldson 2015)
  - assume full knowledge of other parameters/demand (Baye, Morgan, and Scholten, 2007).

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  - assume full knowledge of other parameters/demand (Baye, Morgan, and Scholten, 2007).
- We deviate in following ways:
  - Sellers have noisy beliefs about the distribution of buyer willingness-to-pay (WTP).
  - This may lead to suboptimal pricing and probability of sale *ex post*.
  - Sellers may engage in costly actions to increase match rate, i.e. advertising.

Mechanisms intro

We generate the following predictions on direct treatment effects

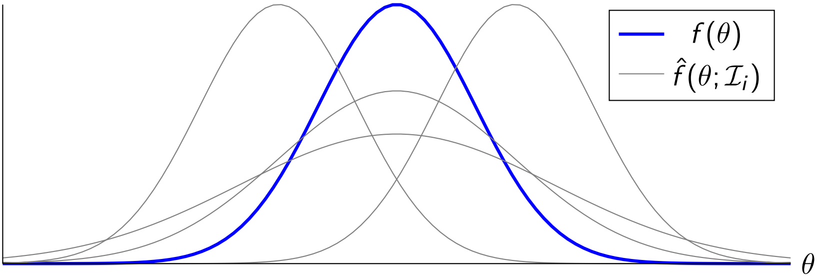
1. Information intervention brings listing price closer to what it would be under no noise in beliefs about demand. (Research question 1.1.)
2. The information intervention increases *ex-post* returns from the platform. (Research question 1.2.)
3. The information intervention increases advertising expenditure **if** sellers' beliefs about expected returns from the platform are adjusted upward.(Research question 1.3.)

We generate the following predictions on spillovers

4. Information spillovers would bring listing price closer to what it would be under no noise in beliefs about demand, increase *ex-post* returns. If so, then would increase advertising expenditure. (Research question 2.)
5. If the intervention pulls buyer attention away from untreated sellers, then it would result in lower *ex-post* returns for them. (Research question 1.2.1.)
6. A higher match rate as a result of reduced congestion increases advertising expenditure. (Research question 2.4.)

Mechanisms intro

Noisy beliefs $\hat{f}(\theta; \mathcal{I}_i)$ relative to true WPT $f(\theta)$



Theoretical Framework: Steps

- Seller i forms their prior belief about the distribution of buyers' willingness to pay (WTP) for their asset based on the information set $\mathcal{I}_i$.

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- Some sellers are provided with the Price Calculator estimate denoted as x_i. Sellers then form their posterior belief about demand distribution.
- Seller i chooses a listing price p^l and amount of advertisements a, based on their (posterior) belief about WTP and their preferences s_i.

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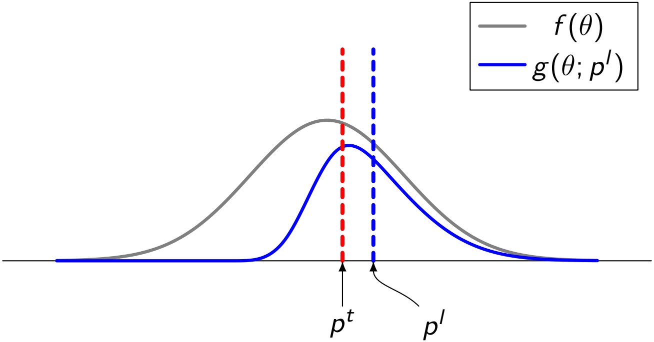
- Seller i chooses a listing price p^l and amount of advertisements a, based on their (posterior) belief about WTP and their preferences s_i.
- p^l affects $g()$, the distribution of potential buyers with whom seller i is matched via a Poisson process. a affects the Poisson match rate.
- Once matched, seller i makes TIOLI offer p^t.
- Transaction occurs if matched buyer's WTP is higher than p^t.

Choice of p_i^l affects draw of potential buyers



The objective function under no information friction

$$V(p^l, a; s_i) = -c - k(a) + \gamma(a) \int \max_{p^t} [\pi(p^t; p^l, s_i)] g(\theta; p^l)\, d\theta \tag{1}$$

- We assume a 1:1 mapping of p^l to p^t conditional on individual preference.

$$V(p^l, a; s_i) = -c - k(a) + \gamma(a) \pi(p^t(p^l; s_i)) \Omega(p^t(p^l), s_i), \tag{2}$$

where $1 \geq \Omega(p^t(p^l), s_i) = \int_{p^t(p^l)}^{\infty} g(\theta; s_i, p^l) d\theta$ (3)

p^l: FOC under no information friction

$$\Omega(p^t(p^l), s_i)\pi'(p^t)\frac{dp^t}{dp^l} = \frac{d\Omega(p^t(p^l), s_i)}{dp^l}\frac{dp^t}{dp^t}\pi(p^t(p^l; s_i)) \qquad (4)$$

- LHS: "marginal benefit" of price adjustment
  - marginal change in the seller's payoff ($\pi'(p^t)\frac{dp^t}{dp^l}$)
  - probability that a matched buyer accepts the TIOLI price ($\Omega(p^t(p^l), s_i)$)
- RHS "marginal cost" of price adjustment
  - marginal effect of the changes in listing price on the probability of TIOLI price's acceptance ($\frac{d\Omega(p^t(p^l),s_i)}{dp^t}\frac{dp^t}{dp^l}$)
  - the payoff ($\pi(p^t(p^l; s_i))$).

a: FOC under no information friction

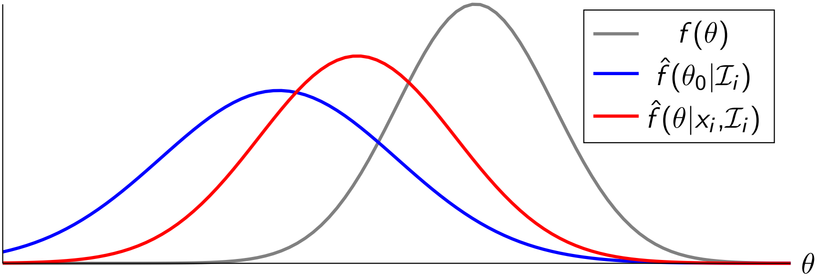
$$\frac{d\gamma}{da}\pi(p^t(p^l;s_i))\Omega(p^t(p^l),s_i) = k'(a) \tag{5}$$

- LHS: Marginal gain from advertising,
  - changes in the Poisson match rate ($\frac{d\gamma}{da}$)
  - expected payoff ($\pi(p^t(p^l;s_i))\Omega(p^t(p^l),s_i)$)
- RHS: Marginal cost of advertising ($k'(a)$)

What happens under information friction

- Sellers do not know the exact $f(\theta)$ but holds a belief $\hat{f}(\theta)$
- This would affect their expectations about $g(\theta)$.
- Prior: $\hat{f}(\theta_0|\mathcal{I}_i) \sim\ N(\mu_{i,0}, \sigma_0^2)$
- Price Calculator estimates: contains information signal x_i, drawn from $f(x) \sim\ N(\mu, \sigma^2)$
- Rational Bayesian updating process leads to posterior belief
- $\hat{f}(\theta|x_i, \mathcal{I}_i) \sim\ N(\frac{a\mu_0 + bx}{a+b}, \frac{1}{a+b})$
- $a = \frac{1}{\sigma_0^2}$, and $b = \frac{1}{\hat{\sigma_i}^2}$.
- $\hat{\sigma_i}^2$: individual's perception about the credibility of the information signal (variance of f and/or the standard error of the Price Calculator)

Information signal x_i helps sellers rationally update toward $f()$



Information intervention brings p_i^l to p^{l*}

- Bayesian updating: Price Calculator estimate helps update $\hat{f}()$,on average, toward $f()$
- We assume that the value function w.r.t p^l is quasiconcave
- Then choice of p_i^l made on posterior belief is closer to p^{l*}.

Information intervention increases *ex post* payoffs

- Posterior beliefs about $f()$ is more accurate and would result in p^l closer to p^{l*} on average.
- p^{l*} optimizes the value function, so p^l closer to it would result in higher returns *ex post*.

$$\begin{aligned}&\pi(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))\\ \geq&\pi(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\end{aligned} \tag{6}$$

Information intervention may increase a

- Under no information friction, MB(advertising) $=$ MC.
- Under information friction, $\hat{M}B$(advertising) $= \hat{M}C$.

$$\frac{d\gamma(a;s_i,\mathcal{I}_i)}{da}\overline{\pi(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))} = k'(a;s_i,\mathcal{I}_i) \tag{7}$$

- If expectations about $\hat{M}B$ advertising is greater with Price Calculator signal, then:

$$\frac{d\gamma(a;s_i,\mathcal{I}_i)}{da}\overline{\pi(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))} \geq k'(a;s_i,\mathcal{I}_i) \tag{8}$$

- Then the agent should increase a.

Information spillover

- Idea: sellers' choices of p^l may generate changes to the quality of information signals available in treated market segments
- Better information set: $\mathcal{J}_i \equiv \mathcal{I}_i \cup I(\bigcup_{i \in T} p_i^l)$

$$\begin{aligned} &\pi(p^t(p^l; \hat{f}(\theta|\mathcal{J}_i), s_i))\Omega(p^t(p^l; \hat{f}(\theta|\mathcal{J}_i), s_i)) \\ \geq\ &\pi(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))\Omega(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i)) \end{aligned} \tag{9}$$

Distributions of buyer attention

- Idea: treated seller's choices of p^l and a would shift attention away from untreated ones, or affect their ability to draw potential buyers.
- i.e. the Price Calculator treatment may affect the shape of $g()$ or its cumulative mass Ω that is ≤ 1.

Distributions of buyer attention

- Idea: treated seller's choices of p^l and a would shift attention away from untreated ones, or affect their ability to draw potential buyers.
- i.e. the Price Calculator treatment may affect the shape of $g()$ or its cumulative mass Ω that is ≤ 1.
- One possibility: Intervention makes g more sensitive to the listing price p^l , further reducing $\frac{\delta\Omega}{\delta p^l}$ which is < 0.
- Unbeknownst to sellers in the short run, this would:
  - reduce the optimal p^l compared to the world without spillovers
  - make deviations from the optimal p^l come at greater cost

$$
\begin{aligned}
&\pi(p^t(p^l;\hat{f}(\theta|\mathcal{I}_i),s_i))\tilde{\Omega}(p^t(p^l;\hat{f}(\theta|\mathcal{I}_i),s_i)) \\
\leq\, &\pi(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))
\end{aligned}
\tag{10}
$$

Congestion and match rate

- Idea: treatment may affect numbers of sellers and buyers and alter the value of $\gamma()$
- If intervention increases match rate, i.e. $\tilde{\gamma}(a) \geq \gamma(a)$, $\forall a$, then

$$a^*|_{\tilde{\gamma}} \geq a^*|_{\gamma} \tag{11}$$

Checks on balance

- Contextual wrinkles:
  - No baseline outcome measures from experimental sample
  - Two-step randomization over 68 heterogeneous first-stage groups (vehicle make-model)
- Balance test:
  - listings from pre-experimental time period (of identical duration as actual experiment)
  - *not* the same individuals as in experimental period
  - Run placebo regressions using identical specification and tests as in experiment

specified outcomes

Balance table: placebo regressions

Table 2: **Balance table: placebo regressions on prespecified main outcomes**

	log(Price difference)	1 if sold	log(Transaction price)	Page-view index	Advertising index
	(1)	(2)	(3)	(4)	(5)
	OLS	Logit	OLS	OLS	OLS
Assignment	-0.0209	-0.0317*	-0.0015	-0.0067	0.0061*
	(0.0195)	(0.0190)	(0.0025)	(0.0065)	(0.0035)
Spillover	0.0074	0.0318	-0.0063	0.0512**	-0.0094
	(0.0543)	(0.0420)	(0.0556)	(0.0197)	(0.0075)
Spillover (high)	-0.0120	0.0304	-0.0751	-0.0136	0.0056
	(0.0540)	(0.0431)	(0.0662)	(0.0212)	(0.0063)
Observations	104,485	116,314	19,222	117,715	117,715
Squared Correlation	0.05454	0.01119	0.89064	0.09523	0.25887
Pseudo R^2	0.01385	0.00882	1.0964	0.05739	0.21179
BIC	419,391.9	151,714.6	-1,993.4	195,543.5	133,310.6
Q-values: Assignment	0.383	0.237	0.565	0.383	0.237
Q-values: Spillover	0.91	0.749	0.91	0.053	0.535
Q-values: Spillover (high)	0.826	0.655	0.655	0.655	0.655

Notes:

balance table

Balance table: mean by treatment group

Table 3: **Balance table: mean by treatment group**

	Pure control (N=63242)		Assigned (N=50619)		Spillover (high) (N=2185)		Spillover (low) (N=30514)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
log(Price difference)	11.422	1.814	11.197	1.910	11.168	1.806	11.262	1.849
1 if sold	0.339	0.474	0.351	0.477	0.358	0.480	0.356	0.479
log(Trnsaction price)	14.342	0.650	14.091	0.713	13.947	0.712	14.179	0.712
Page view index	-0.003	0.580	-0.004	0.574	0.053	0.608	-0.015	0.572
Advertising index	-0.052	0.523	-0.108	0.442	-0.107	0.444	-0.111	0.437

Notes:

Back

Results table: Main pre-specified outcomes by treatment group

Table 4: **Regressions on prespecified main outcomes**

	log(Price difference)	1 if sold	log(Transaction price)	Page-view index	Advertising index
	(1)	(2)	(3)	(4)	(5)
	OLS	Logit	OLS	OLS	OLS
GroupSatAssigned(high)	-0.0316	-0.0238	-0.0441	0.0060	-0.0018
	(0.0372)	(0.0207)	(0.0370)	(0.0113)	(0.0053)
GroupSatAssigned(low)	-0.1135***	0.0046	-0.0407	0.0166	-0.0090**
	(0.0408)	(0.0212)	(0.0353)	(0.0122)	(0.0043)
GroupSatSpillover(high)	-0.0511	0.1117**	-0.0421	0.0312**	0.0162**
	(0.0552)	(0.0552)	(0.0427)	(0.0119)	(0.0066)
GroupSatSpillover(low)	-0.0749*	0.0431***	-0.0401	0.0327***	-0.0007
	(0.0435)	(0.0145)	(0.0335)	(0.0106)	(0.0042)
Observations	101,750	111,309	14,084	117,891	134,781
Squared Correlation	0.10799	0.01474	0.92874	0.12322	0.29973
Pseudo R^2	0.02960	0.01199	1.2997	0.08546	0.25504
BIC	383,285.7	141,840.4	-6,877.1	167,986.9	142,368.9
Q-values: Assignment group (high)	0.663	0.626	0.626	0.729	0.729
Q-values: Assignment group (low)	0.036	0.83	0.315	0.293	0.094
Q-values: Low spillover group	0.15	0.007	0.292	0.007	0.872
Q-values: High spillover group	0.359	0.072	0.359	0.038	0.038

Notes: by mutually exclusive treatment groups

ITT specified outcomes

Results table: Main pre-specified outcomes (ToT)

Table 5: **Regressions on prespecified main outcomes**

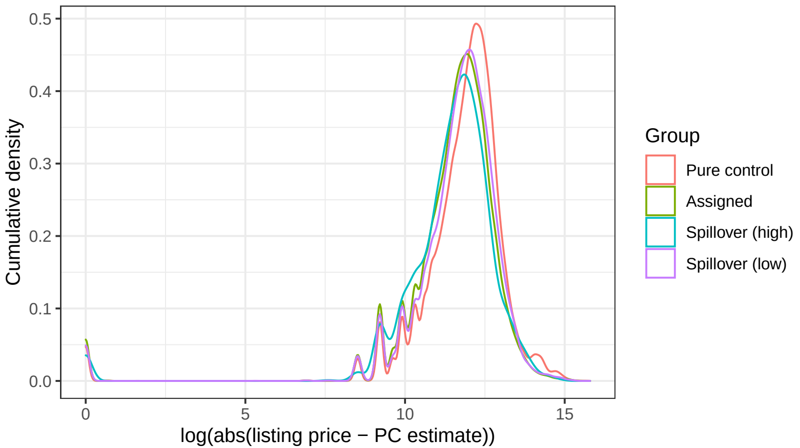
	log(Price difference) (1)	1 if sold (2)	log(Transaction price) (3)	Page-view index (4)	Advertising index (5)
Treatment	-0.0440**	-0.0160***	-0.0011	-0.0252***	-0.0140***
	(0.0180)	(0.0060)	(0.0055)	(0.0067)	(0.0041)
Spillover	-0.0775*	0.0103***	-0.0401	0.0329***	-0.0007
	(0.0442)	(0.0030)	(0.0335)	(0.0106)	(0.0042)
Spillover (high)	0.0743	-0.0043	-0.0032	-0.0110	0.0053
	(0.0541)	(0.0075)	(0.0456)	(0.0174)	(0.0061)
Observations	101,750	111,312	14,084	117,891	117,891
R^2	0.10787	0.01464	0.92873	0.12284	0.29303
Within R^2	0.02809	0.00451	0.75561	0.01610	0.00609
Q-values: Assignment	0.022	0.015	0.835	0.001	0.003
Q-values: Spillover	0.14	0.004	0.293	0.006	0.869
Q-values: Spillover (high)	0.705	0.705	0.945	0.705	0.705

Notes:

ITT specified outcomes

Distribution of price differences by treatment group

Figure 1: log(absdiff(PC estimate - listing price)+1)



ITT specified outcomes

Results table: price outcomes

Table 6: **Regressions on price-related outcomes**

	log(Listing price)	Price updated	N. price updates	log(Abs. price change)
	(1)	(2)	(3)	(4)
	OLS	Logit	OLS	OLS
Assignment	-0.0005	-0.0144	0.0092	-0.0585
	(0.0014)	(0.0194)	(0.0096)	(0.0511)
Spillover	-0.0211	-0.0230	-0.0401**	-0.0451
	(0.0256)	(0.0222)	(0.0166)	(0.0505)
Spillover (high)	-0.0034	0.0587***	0.0361*	0.1356***
	(0.0418)	(0.0226)	(0.0194)	(0.0488)
Observations	117,891	117,891	117,891	117,891
Squared Correlation	0.93107	0.02790	0.03762	0.03023
Pseudo R^2	1.2508	0.02253	0.01069	0.00500
BIC	-61,139.6	144,326.4	420,509.3	721,911.2

Notes:

Results table: transaction outcomes

Table 7: **Regressions on transaction-related outcomes**

	1 if sold (1)	log(Transaction price) (2)	log(Seller revenue) (3)
Assignment	-0.0110***	-0.0008	-0.0457
	(0.0038)	(0.0037)	(0.0363)
Spillover	0.0105***	-0.0401	0.0185
	(0.0030)	(0.0335)	(0.0407)
Spillover (high)	-0.0033	-0.0031	0.0307
	(0.0071)	(0.0457)	(0.0367)
Observations	111,312	14,084	117,891
R^2	0.01478	0.92874	0.01112
Within R^2	0.00465	0.75562	0.00343

Notes:

Results table: page-view outcomes

Table 8: **Regressions on variables included in the page-view index outcome**

	Page views (1)	Phone number views (2)	Page-view index (not winsorized) (3)	Page-view index (4)
Assignment	-59.91***	-0.4050**	-0.0335***	-0.0172***
	(12.37)	(0.2041)	(0.0070)	(0.0039)
Spillover	57.39***	1.151***	0.0499***	0.0332***
	(18.23)	(0.3713)	(0.0145)	(0.0106)
Spillover (high)	8.431	-0.3183	-0.0054	-0.0092
	(25.02)	(0.7047)	(0.0245)	(0.0169)
Observations	117,891	117,891	117,891	117,891
R^2	0.10683	0.06462	0.09405	0.12322
Within R^2	0.01673	0.00938	0.01082	0.01652

Notes:

Results table: advertising outcomes

Table 9: **Regressions on variables included in the advertising index outcome**

	N. bumps	1 if featured	1 if certified	Advertising index (not winsorized)	Advertising index
	(1)	(2)	(3)	(4)	(5)
	OLS	Logit	Logit	OLS	OLS
Assignment	-0.0456***	-0.0948**	-1.182***	-0.0578***	-0.0095***
	(0.0153)	(0.0398)	(0.1601)	(0.0108)	(0.0025)
Spillover	0.0146	-0.0525	0.0984	0.0165	-0.0005
	(0.0159)	(0.0488)	(0.0933)	(0.0108)	(0.0042)
Spillover (high)	0.0472***	0.0638	0.7654***	0.0415***	0.0062
	(0.0174)	(0.0618)	(0.1381)	(0.0136)	(0.0059)
Observations	117,891	116,346	91,159	117,891	117,891
Squared Correlation	0.07426	0.29549	0.11528	0.21337	0.29329
Pseudo R^2	0.02057	0.29896	0.26361	0.08105	0.24067
BIC	435,153.9	50,519.6	7,744.6	322,880.4	131,198.5

Notes:

Robustness: DiD/Event study framework

Figure 2: Assigned

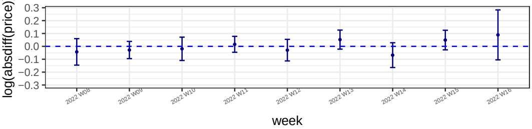


Figure 3: Spillover

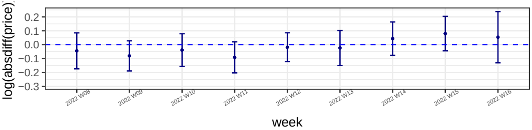
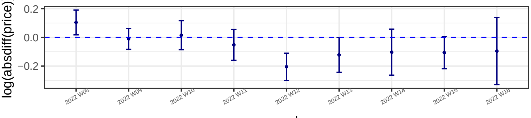


Figure 4: Spillover (high)



Robustness: DiD/Event study framework

Table 10: **DiD on main outcomes**

	log(Price difference)	1 if sold	log(Transaction price)	Page-view index	Advertising index
	(1)	(2)	(3)	(4)	(5)
	OLS	Logit	OLS	OLS	OLS
Assignment	-0.0296***	-0.0120	-0.0007	-0.0033	0.0034
	(0.0107)	(0.0107)	(0.0019)	(0.0030)	(0.0026)
Experimental period	0.2430***	-0.0836***	0.0348***	-0.0884***	0.0029*
	(0.0215)	(0.0254)	(0.0046)	(0.0141)	(0.0016)
Spillover	-0.0183	0.0364*	-0.0321	0.0384***	-0.0031
	(0.0327)	(0.0194)	(0.0361)	(0.0127)	(0.0046)
Spillover (high)	0.0853**	0.0017	-0.0071	-0.0185**	0.0049
	(0.0400)	(0.0239)	(0.0460)	(0.0089)	(0.0051)
Assignment × Experimental period	-0.0031	-0.0395**	0.0007	-0.0142***	-0.0133***
	(0.0183)	(0.0180)	(0.0041)	(0.0041)	(0.0023)
Experimental period × Spillover	-0.0432	0.0019	0.0014	-0.0060	0.0051
	(0.0288)	(0.0411)	(0.0103)	(0.0249)	(0.0033)
Experimental period × Spillover (high)	-0.0159	-0.0185	0.0047	0.0009	0.0025
	(0.0344)	(0.0394)	(0.0100)	(0.0224)	(0.0046)
Observations	290,174	324,914	47,140	334,655	334,655
Squared Correlation	0.07978	0.01227	0.92680	0.11965	0.27774
Pseudo R^2	0.02102	0.00973	1.2912	0.07634	0.22871
BIC	1,125,525.7	417,008.3	-25,922.6	518,209.3	369,401.5

Notes:

List price adjustments and their expectations: Treated sellers' expectations are adjusted toward PC, and are willing to offer more bargains

Table 11: **Regressions on survey measures**

	log(absdff(Expectation))			Amt. bargain	Searched listings
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	Logit
Assignment	-0.2128***	-0.0531	-0.1945	5,561.1***	0.1338
	(0.0765)	(0.0743)	(0.1692)	(1,670.5)	(0.1845)
Spillover	0.0233	-0.1126	0.0777	-642.9	-0.1345
	(0.1025)	(0.1005)	(0.1069)	(2,697.6)	(0.1537)
Spillover (high)	0.1712	0.1324	0.1398	3.690	-0.0276
	(0.1239)	(0.1246)	(0.1510)	(3,644.3)	(0.1391)
Observations	2,046	2,045	2,045	2,321	2,185
Squared Correlation	0.09972	0.16112	0.10842	0.08766	0.05688
Pseudo R^2	0.02475	0.04524	0.02552	0.00370	0.05098
BIC	9,618.9	8,733.0	10,113.1	58,576.7	3,010.0

Beliefs about returns from platform and search frictions: Treatment induces more optimistic views about search frictions

Table 12: **Regressions on survey measures**

	Difficult to get inquiry (1)	Difficult to get good price (2)	Buyers have good info (3)	Sellers have good info (4)
Assignment	-0.0658**	-0.0532**	0.0275	0.0239
	(0.0324)	(0.0232)	(0.0477)	(0.0392)
Spillover	-8.42×10^{-5}	-0.0163	0.0457	0.0221
	(0.0286)	(0.0221)	(0.0316)	(0.0368)
Spillover (high)	0.0197	0.0469	-0.0868**	-0.0176
	(0.0282)	(0.0306)	(0.0394)	(0.0292)
Observations	2,311	2,311	2,310	2,310
R^2	0.11718	0.13054	0.10224	0.10057
Within R^2	0.00257	0.00212	0.00299	0.00100

Endline results

…but not believed efficacy of price info tools or advertising per se

Table 13: **Regressions on survey measures**

	1 if WTP at Rs100	WTP	Ad useful-high price	Ad useful-sell faster
	(1)	(2)	(3)	(4)
	Logit	OLS	OLS	OLS
Assignment	-0.2485	-5.674	0.0239	0.0251
	(0.1624)	(3.584)	(0.0392)	(0.0400)
Spillover	0.0314	3.710	0.0221	0.0252
	(0.1094)	(3.503)	(0.0368)	(0.0323)
Spillover (high)	0.1901	3.429	-0.0176	-0.0152
	(0.1313)	(2.107)	(0.0292)	(0.0286)
Observations	2,247	2,261	2,310	2,301
Squared Correlation	0.05775	0.08011	0.10057	0.10072
Pseudo R^2	0.04635	0.00781	0.06402	0.06679
BIC	3,578.5	25,149.6	4,764.8	4,597.6

Endline results

Survey results confirm PC info is observed only by the directly treated

Table 14: **Regressions on survey measures**

	Seen PC (1) Logit	Others seen PC (2) Logit	1 if sold (3) Logit	log(Transaction price) (4) OLS
Assignment	0.7749***	0.4057**	0.0207	-0.0130
	(0.1287)	(0.1622)	(0.1224)	(0.0179)
Spillover	0.0013	0.1678	0.1606	0.0219
	(0.1596)	(0.1060)	(0.1430)	(0.0372)
Spillover (high)	-0.0925	-0.0550	0.0078	-0.0694
	(0.1238)	(0.1712)	(0.1727)	(0.0463)
Observations	2,202	2,195	2,280	1,397
Squared Correlation	0.09259	0.06356	0.09186	0.76180
Pseudo R^2	0.08516	0.06132	0.06989	0.65933
BIC	3,150.7	2,823.5	3,820.6	2,034.9

Notes:

Implications: tying back to research questions

- What are the internal mechanisms through which agents in developing markets make pricing and other complementary decisions, given certain search and information frictions?
  - Strategic choices (advertising) are made simultaneously with pricing.
  - Evidence suggests they are substitutes, and/or
  - Price info might signal to agents market conditions more broadly, but
  - Given noise/uncertainty about efficacy of advertising and pricing tools w.r.t. transaction, their choices may backfire.

Implications: tying back to research questions

- Do information interventions induce spillover effects in the presence of (said) information and search frictions? Do agents respond strategically to shifts in choices of their competitors in such an environment?
  - Agents respond to listing price choices made by their competitors.
  - But perhaps not about search frictions/market conditions overall–noisier information gathering process.

Making sense of the results

References I