Online Appendix to "Informational Differences Among Rival Firms"

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December 2021

A Supply Estimation Details

In this model, δ_{jt} takes the following form:

$$\delta_{jt} = \begin{cases} 0, \ if \quad \lambda_t < \bar{\lambda}_j(x_t, \xi_{jt}) \\ 1, \ if \quad \lambda_t \geq \bar{\lambda}_j(x_t, \xi_{jt}) \end{cases}$$

where $\bar{\lambda}_j$ solves

$$q_j\Big(\bar{p}(x_t, \bar{\lambda}_j(x_t, \xi_{jt})), x_t, \xi_{jt}, \bar{\lambda}_j(x_t, \xi_{jt})\Big) = \bar{q}_j \tag{1}$$

and $\bar{q}_j$ is j's capacity, and $q_j(p, x_t, \xi, \lambda)$ is j's quantity sold for some x_t, ξ_t, and λ_t, and all hotels (including j) set a price of p. That is, $\bar{\lambda}_j(x_t, \xi_{jt})$ is the value of λ above which which j would expect to sell out of rooms if it set the same price as its rivals. I assume that rivals' prices can be linearly approximated as follows: $\bar{p}(x_t, \lambda_t) = \phi_0 + \phi_x x_t + \phi_\lambda \lambda_t$. I assume $z_{2j}(\delta_{jt}) = z_{0j} + z_{2j}\delta$, in line with the result from Example 2 in the main text that this model is only identified up to a location and scale parameter for z_{2j}. Finally, I assume that $s_{jt} = \lambda_t + \rho_j \sigma_\lambda \varepsilon_{jt}$, where ε_{jt} is an i.i.d. normal draw.

Estimation is by indirect inference. I regress p_{jt} on the demand shifters, λ_t, ξ_{jt} and x_t, as well as a constant, for each hotel. I record these coefficients and match them to the analogous coefficients that arise out of simulation of this model. These are the steps in detail, for a particular market-quality segment.

1. For each hotel j, regress p_{jt} on a constant, x_t, ξ_{jt} and λ_t to record coefficients $\hat{\phi}_{0j}$, $\hat{\phi}_{xj}$, $\hat{\phi}_{\xi j}$ and, $\hat{\phi}_{\lambda j}$. Average across j to obtain $\bar{\phi}_x$, $\bar{\phi}_\lambda$, and $\bar{\phi}_0$.

2. Do the same as (1) for the other quality segment b' in the same market to obtain $\hat{\phi}'$.

3. For each hotel, numerically invert Equation 1, imposing that $\bar{p} = \hat{\phi}_0 + \hat{\phi}_x x_t + \hat{\phi}_\lambda \lambda_t$. for each market segment. This yields an estimate of $\bar{\lambda}_j(x_t, \xi_{jt})$.

4. Search over $[z_{0j}, z_{1j}, z_{2j}, \rho_j]_{j \in \mathcal{J}}$ to minimize criterion $\mathcal{Q}$. To compute $\mathcal{Q}$ for a guess of parameters $z_{0j}, z_{1j}, z_{2j}, \rho_j$:

   (a) Compute signal responsiveness, $m_j(\rho_j) = \frac{1}{1+\rho_j}$ and j's signal precision, $\sigma_{\lambda j}(\rho_j) = \sigma_\lambda \sqrt{\frac{\rho_j}{1+\rho_j}}$. These can be computed because signals and λ_t are jointly normal.

   (b) Simulate n_s signal draws as i.i.d. normal with mean λ_t and standard deviation $(1+\rho_j)\sigma_\lambda$ for each hotel j and each night t. Calculate simulated posterior expectations and variance for each realized signal (a total of $(J \times T \times n_s)$ posterior expectations) using responsiveness and precision.

   (c) For each signal draw, compute $\mathbb{E}(\delta_{jt}|s_{jt}, x_t, \xi_{jt})$ as the conditional probability that $\lambda_t > \bar{\lambda}_j(x_t, \xi_{jt})$:

   $$\mathbb{E}(\delta_{jt}|s_{jt}, x_t, \xi_{jt}) = \Phi\left(\frac{\bar{\lambda}_j(x_t, \xi_{jt}) - \mathbb{E}(\lambda_t|s_{jt})}{\mathrm{var}(\lambda_t|s_{jt})}\right)$$

   where Φ is the standard normal cdf.

   (d) Compute predicted prices (given $\nu_{jt} = 0$) as

   $$\log(p_{jt}) = z_{0j} + z_{1j}\left[\phi_{0b(j)} + \phi_{xb(j)} x_t + \phi_{\lambda b(j)} m_\lambda(\rho_j) s_{jt}\right] + z_{2j}\Phi\left(\frac{m_\lambda(\rho_j) s_{jt} - \bar{\lambda}(x_t, \xi_{jt})}{\hat{\sigma}_\lambda(\rho_j)}\right)$$

   (e) Regress the $T \times J \times n_s$ on predicted prices on hotel dummies and the interaction of hotel dummies and x_t, λ_t, and ξ_{jt} to generate reduced form coefficients $\hat{\phi}^{sim}_{0j}$, $\hat{\phi}^{sim}_{xj}$, $\hat{\phi}^{sim}_{\lambda j}$, and $\hat{\phi}^{sim}_{\xi j}$.

   (f) Letting

$$\hat{\phi} \equiv \left[\hat{\phi}_{01} \quad \hat{\phi}_{x1} \quad \hat{\phi}_{\lambda 1}\phi_{\xi 1} \ldots \hat{\phi}_{0J} \quad \hat{\phi}_{xJ} \quad \phi_{\lambda 1 J}\phi_{\xi J}\right]$$

and $\hat{\phi}^{sim}$ be defined analogously, compute criterion

$$\mathcal{Q} = \frac{1}{J}(\hat{\phi} - \hat{\phi}^{sim})' \, (\hat{\phi} - \hat{\phi}^{sim}).$$

5. Compute $\hat{\nu}_{jt}$ as the difference between observed prices and the prices predicted by the model.

B Counterfactual Simulation Details

Simulation of counterfactual prices, quantities, and revenues involves the following steps. Fix a geographic market. Let $\tau_s = 1, 2, \ldots, \tau_{n^s}$ index simulation draws of signals and $\tau_\nu = 1, 2, \ldots, \tau_{n^\nu}$ index simulation draws of pricing errors ν. Each τ_s contains a signal draw for each hotel-night and each τ_ν contains an error draw for each hotel-night.

1. Set counterfactual parameters (e.g., choose ρ_j for each hotel j).

2. Draw each element of τ_s and τ_ν from independent standard normal distributions.

3. Compute counterfactual prices:

   (a) Compute signal responsiveness, $m_j(\rho_j) = \frac{1}{1+\rho_j}$ and j's signal precision, $\sigma_{\lambda j}(\rho_j) = \sigma_\lambda \sqrt{\frac{\rho_j}{1+\rho_j}}$. These can be computed because signals and λ_t are jointly normal.

   (b) Compute signals as $\lambda_t + \sigma_\lambda \rho_j \tau_{s,jt}$ for each hotel-night. Compute posterior beliefs using responsiveness and signal precision.

   (c) Initialize $\hat{\phi}_b$ for each quality segment b by regressing p_{jt} on x_t, ξ_t, λ_t, and a constant for each hotel, then average the constant and the coefficients on x_t and λ_t across the hotels in segment b. Iterate the following steps until convergence:

      i. Impose that $\bar{p}_{bt} = \hat{\phi}_{b0} + \hat{\phi}_{bx}x_t + \hat{\phi}_{b\lambda}\lambda_t$ and invert Equation 1 for each hotel j to yield $\bar{\lambda}_j(x_t, \xi_{jt})$.

      ii. For each signal draw, compute $\mathbb{E}(\delta_{jt}|s_{jt}, x_t, \xi_{jt})$ as the conditional probability that $\lambda_t > \bar{\lambda}_j(x_t, \xi_{jt})$:

$$\mathbb{E}(\delta_{jt}|s_{jt}, x_t, \xi_{jt}) = \Phi\left(\frac{\bar{\lambda}_j(x_t, \xi_{jt}) - \mathbb{E}(\lambda_t|s_{jt})}{\text{var}(\lambda_t|s_{jt})}\right)$$

where Φ is the standard normal cdf.

iii. Compute predicted prices (given $\nu_{jt} = 0$) as

$$\log(p_{jt}) = z_{0j} + z_{1j}\left[\phi_{0b(j)} + \phi_{xb(j)}x_t + \phi_{\lambda b(j)}m_\lambda(\rho_j)s_{jt}\right] + z_{2j}\Phi\left(\frac{m_\lambda(\rho_j)s_{jt} - \bar{\lambda}(x_t, \xi_{jt})}{\hat{\sigma}_\lambda(\rho_j)}\right).$$

iv. For each hotel, regress the $T \times \tau_{n^s}$ prices on a constant, x_t, λ_t, and ξ_{jt}, and then average coefficients across all hotels in a segment to obtain $\hat{\phi}'_b$ for each segment.

v. Stack $\hat{\phi}_b$ $\hat{\phi}'_b$ for each quality segment to obtain $\hat{\phi}$ and $\hat{\phi}'$. Compute $D_\phi \equiv (\hat{\phi}' - \hat{\phi})'\ (\hat{\phi}' - \hat{\phi})$. If $D_\phi > 0$, set $\hat{\phi} = \hat{\phi}'$ and return to step i.

(d) Compute the final set of simulated prices given the convergent value of $\hat{\phi}$. Compute simulated values of $\nu_{jt} = \sigma_j \tau_\nu$ and add to simulated prices.

4. Given counterfactual prices for each hotel, night, and simulation draw, compute counterfactual quantities for each night and simulation draw as follows:

(a) Use nested logit formula and estimated demand parameters to obtain estimated shares s_{jt} for each hotel and night, for a given draw of the simulated prices.

(b) Use definition of market size M_t to find quantities: $q_{jt}^{(\tau)} = s_{jt}^{(\tau)} M_t$.

(c) Record hotels in nest b that are over capacity: $\mathcal{J}_b^{cap} \equiv \{j \in \mathcal{J}_b : Cap_j < q_{jt}^{(\tau)}\}$. Reallocate excess capacity in nest b, $Excess_t^{(\tau)} \equiv \sum_{j \in \mathcal{J}_b^{cap}} \left[q_{jt}^{(\tau)} - Cap_j\right]$ among remaining hotels. In my main specification, I reallocate excess capacity within-nest according to IIA; if hotel j in nest b is below capacity, it receives additional customers $Excess_t^{(\tau)}\left(\frac{s_{jt}^{(\tau)}}{s_{bt}^{(\tau)}}\right)$. That is, j receives additional customers according to its within-nest share.

(d) Record hotels that are still over capacity (e.g., through reallocation from other above-capacity hotels) and repeat step (c) until convergence; that is, until there are no more hotels above capacity.

(e) If convergence does not occur (i.e., nest share is larger than nest capacity, so all hotels sell out), move excess capacity to outside good.

5. Generate revenues $R_{jt} = q_{jt}p_{jt}$
6. Average over all simulation draws and sum over days t to obtain expected annual revenues for each hotel j.

C Supply-Side Endogeneity

The supply model in Section 2 of the main text assumes that the error term, ν_{jt} is independent across all jt and independent of the demand shifters, λ_t, x_t, and ξ_{jt}. In this Appendix, I informally discuss strategies for dealing with one relaxation of these assumptions, namely that ν_{jt} is independent of λ_t and x_t.

I do so using a single-firm, highly stylized variant of my model. Suppose pricing for lone firm is linear in the expectation of market-wide demand, as follows:

$$p_t = z\mathbb{E}[x_t + \lambda_t | s_t, x_t, \nu_t] + \nu_t.$$

Note that ν_t is observed by the firm and thus may affect its expectation about demand. Assume that the variables that enter For comparison, assume that x_t, λ_t, and ν_t are independent normal draws, and that s_t is normal and independent of all variables but λ_t. Assume all variances are equal to one for simplicity. More precisely:

$$\begin{bmatrix} x_t \\ \lambda_t \\ s_t \\ \nu_t \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & \rho & 0 \\ 0 & \rho & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}\right)$$

with information quality $\rho \in (0, 1]$. These independence assumptions mean the pricing equation can be rewritten as

$$p_t = zx_t + z\mathbb{E}[\lambda_t | s_t] + \nu_t.$$

Joint normality implies linearity of expectations. Taking expectations over the variables unobserved to the econometrician yields

$$\mathbb{E}[p_t|x_t, \lambda_t] = zx_t + z\rho\lambda_t.$$

It is immediately apparent that both z and ρ can be recovered through linear regression of prices on x_t and λ_t. Now consider a case in which ν_t is correlated with x_t but not λ_t:

$$\begin{bmatrix} x_t \\ \lambda_t \\ s_t \\ \nu_t \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} 1 & 0 & 0 & \gamma \\ 0 & 1 & \rho & 0 \\ 0 & \rho & 1 & 0 \\ \gamma & 0 & 0 & 1 \end{bmatrix}\right)$$

with $\gamma \in (0, 1]$. Then the pricing equation can be written as

$$p_t = zx_t + z\mathbb{E}(\lambda_t|s_t) + \nu_t$$

and

$$\mathbb{E}[p_t|x_t, \lambda_t] = zx_t + z\rho\lambda_t + \mathbb{E}[\nu_t|x_t].$$

A regression of prices on x_t and λ_t will no longer yield unbiased estimates of z and ρ. However, it is readily apparent that we can still recover these parameters using a standard instrumental variables approach. Re require an instrumental variable w_t that is correlated with x_t conditional on λ_t and that is independent of s_t and ν_t.

Less straightforward is the case in which ν_t is correlated with x_t, λ_t, and s_t. That is:

$$\begin{bmatrix} x_t \\ \lambda_t \\ s_t \\ \nu_t \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} 1 & 0 & 0 & \gamma_1 \\ 0 & 1 & \rho & \gamma_2 \\ 0 & \rho & 1 & \gamma_3 \\ \gamma_1 & \gamma_2 & \gamma_3 & 1 \end{bmatrix}\right)$$

In this case, the firm can theoretically learn about λ_t by knowing ν_t:

$$p_t = zx_t + z\mathbb{E}[\lambda_t|s_t, \nu_t] + \nu_t.$$

In this case, there are two threats to identification. The first is classic endogeneity: x_t and λ_t will be correlated with the unobserved ν_t. The second is more unique to this setting: because ν_t is correlated with λ_t (and thus must necessarily be correlated with signal s_t), the responsiveness of the firm's prices to changes in λ will depend not only on signal quality ρ, but on the entire correlation structure between demand shifters, signals, and ν_t. Therefore, even if the endogeneity problem is solved using instruments so reduced-form coefficients from a regression of prices on demand shifters are unbiased, it is necessary to know the γ terms in the covariance matrix in order to recover primitive ρ from these coefficients. The conditions and data requirements to recover these γ terms are beyond the scope of this appendix, but future work may yield insighst.

However, if we assume *the firm does not observe or respond to* ν_t, the problem becomes easier. In this case, ν_t enters the data-generating process, but not through the firm's decision; it is effectively measurement error in prices. In this case,

$$p_t = zx_t + z\mathbb{E}[\lambda_t|s_t]$$

and the econometrician observes $p_t + \nu_t$. Taking expectations:

$$\mathbb{E}[p_t + \nu_t|x_t, \lambda_t] = zx_t + z\rho\lambda_t + \mathbb{E}[\nu_t|\lambda_t, x_t].$$

Again, the correct reduced-form coefficients $(z, z\rho)$ are identified if the econometrician obtains instruments w_t that are correlated with x_t and λ_t and independent of ν_t and s_t conditional on x_t and λ_t.

A note on appropriate instruments. The practical question remains of what sort of variables could be used as instruments in these cases. They must (1) affect prices through demand shifters x_t and λ_t and (2) only affect prices through these shifters. An appropriate instrument thus depends on the interpretation of the error term ν_j.

In the first case I presented (in which the error is only correlated with x_t, the error may be "structural" in that it is observed by the firm and shifts prices accordingly. An example of this might be a marginal cost shock that is correlated with x_t. In such a case, an appropriate instrument would affect common-knowledge demand but would not affect prices otherwise. Such instruments may be difficult to find, as common-knowledge demand x_t is already considered a primitive of the market.

In either case presented, it is also possible that the error is not structural (e.g., measurement error) that does not affect the firm's choice, but does affect the prices the econometrician observes in a manner correlated with demand shifters. In this case, "repeated measure" demand shifts (that is, the same demand shift, measured differently) may be useful as an instrument.

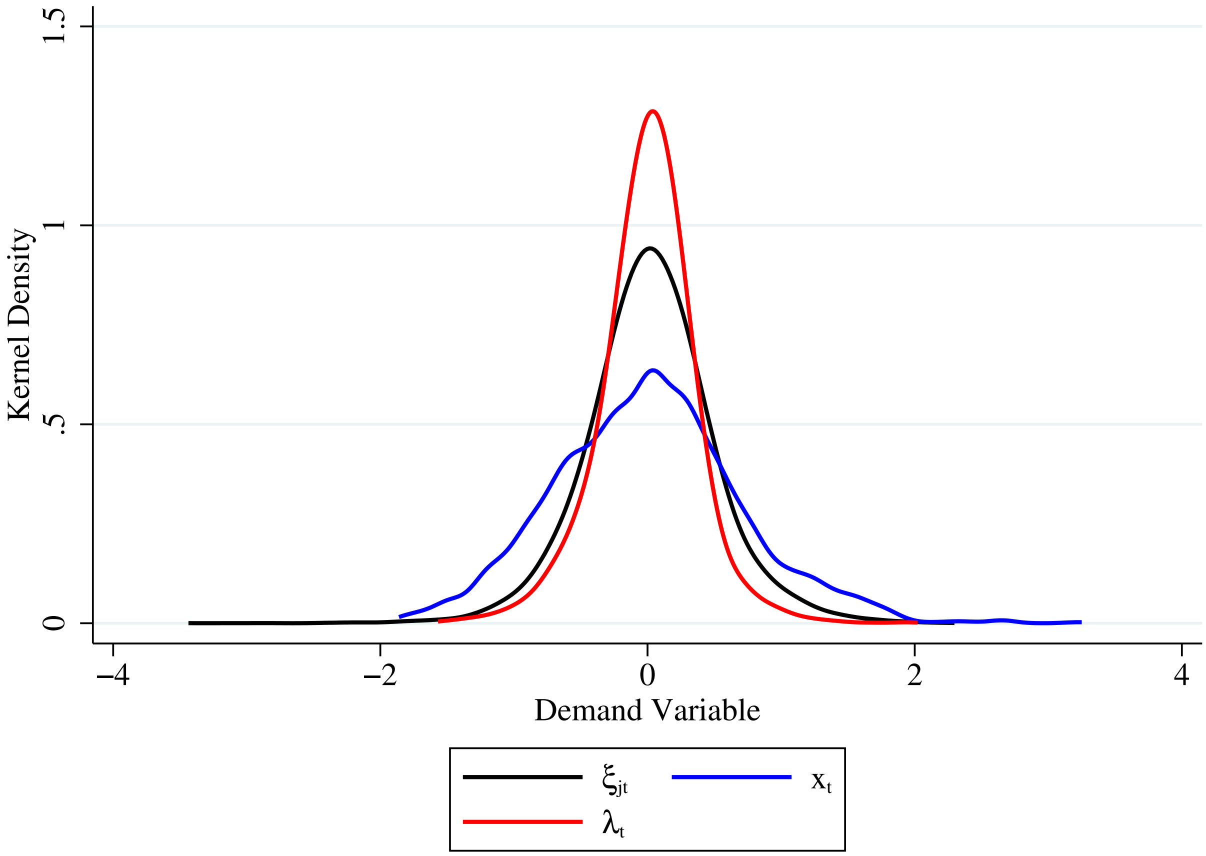
D Additional Figures

Table 1: Estimated demand elasticities

		Cross-Price Elasticities	
	Own-	Within-Nest	Without-Nest
Downscale, Weekday	−2.908	0.075	0.014
Downscale, Weekend	−2.009	0.054	0.011
Midscale, Weekday	−2.911	0.075	0.014
Midscale, Weekend	−2.011	0.054	0.012
Upscale, Weekday	−2.588	0.403	0.013
Upscale, Weekend	−1.788	0.281	0.011

Data source: STR LLC.

Figure 1: Kernel density plot of market demand shifters



Data source: STR LLC.

Table 2: Additional supply analysis: weekday vs. weekend

	(1) Shannons	(2) Shannons
Large Chain	−0.167	−0.054
	(0.072)	(0.072)
Weekday	1.482	1.483
	(0.122)	(0.106)
Downscale		0.438
		(0.111)
Observations	1,444	1,444
Adjusted R^2	0.282	0.301

Data source: STR LLC. Standard errors are for regression only and do not reflect the fact that information quality is estimated in prior stages. Stanard errors are clustered at the market-quality segment-1[Weekday] level.

References