Information and Market Power

Dirk Bergemann, Tibor Heumann and Stephen Morris

European Summer Symposium in Economic Theory, Gerzensee, July 2016
• A trader’s price impact measures how much increasing demand influences its market price
  • sometimes called market power

Introduction: Price Impact
A trader’s price impact measures how much increasing demand influences its market price

- sometimes called market power

**SUBSTANTIVE QUESTION 1:**
- How does price impact vary as we change the finite number of agents and asymmetric information structure?
A trader’s **price impact** measures how much increasing demand influences its market price

- sometimes called market power

**SUBSTANTIVE QUESTION 1:**
- How does price impact vary as we change the finite number of agents and asymmetric information structure?
- We will be looking at this question in the context of demand function competition: Klemperer and Meyer (1989) and Vives (2011)
A trader’s price impact measures how much increasing demand influences its market price
  • sometimes called market power

SUBSTANTIVE QUESTION 1:
  • How does price impact vary as we change the finite number of agents and asymmetric information structure?
  • We will be looking at this question in the context of demand function competition: Klemperer and Meyer (1989) and Vives (2011)

ANSWER:
  • For any fixed number of agents, every price impact (between 0 and $\infty$) arises in some information structure
A trader’s **price impact** measures how much increasing demand influences its market price

- sometimes called market power

**SUBSTANTIVE QUESTION 1:**

- How does price impact vary as we change the finite number of agents and asymmetric information structure?
- We will be looking at this question in the context of demand function competition: Klemperer and Meyer (1989) and Vives (2011)

**ANSWER:**

- For any fixed number of agents, every price impact (between 0 and \( \infty \)) arises in some information structure

**INTUITION:**

- Depending on confounding in agents’ signals, any inference from market price can arise
A trader’s price impact measures how much increasing demand influences its market price

- sometimes called market power

**SUBSTANTIVE QUESTION 1:**
- How does price impact vary as we change the finite number of agents and asymmetric information structure?
- We will be looking at this question in the context of demand function competition: Klemperer and Meyer (1989) and Vives (2011)

**ANSWER:**
- For any fixed number of agents, every price impact (between 0 and $\infty$) arises in some information structure

**INTUITION:**
- Depending on confounding in agents’ signals, any inference from market price can arise
- Such effects overwhelm large number of trader effects
• We will characterize what can happen for any information structure
Introduction: Methodology

- We will characterize what can happen for any information structure
- We have been thinking about this in a variety of settings
We will characterize what can happen for any information structure.

We have been thinking about this in a variety of settings.

Application of tools developed elsewhere to an environment with linear best responses, normal information and maintaining symmetry.
Introduction: Methodology

- We will characterize what can happen for any information structure.
- We have been thinking about this in a variety of settings.
- Application of tools developed elsewhere to an environment with linear best responses, normal information and maintaining symmetry.
- But can now compare all outcomes that can arise in the same environment for different mechanisms (e.g., Cournot, Kyle).
SUBSTANTIVE QUESTION 2:

- How do price impact, prices and quantity of trade vary with the market mechanism?
SUBSTANTIVE QUESTION 2:

- How do price impact, prices and quantity of trade vary with the market mechanism?

ANSWERS:

- Mean quantity of trade does not depend on the information structure under Cournot, moves with price impact under demand function competition.
SUBSTANTIVE QUESTION 2:

- How do price impact, prices and quantity of trade vary with the market mechanism?

ANSWERS:

- Mean quantity of trade does not depend on the information structure under Cournot, moves with price impact under demand function competition
- Any correlation of market variables can arise under Cournot, restricted under demand function competition
SUBSTANTIVE QUESTION 2:

- How do price impact, prices and quantity of trade vary with the market mechanism?

ANSWERS:

- Mean quantity of trade does not depend on the information structure under Cournot, moves with price impact under demand function competition
- Any correlation of market variables can arise under Cournot, restricted under demand function competition
- Arbitrary variance of output under under Cournot, bounded under demand function competition
SUBSTANTIVE QUESTION 2:

- How do price impact, prices and quantity of trade vary with the market mechanism?

ANSWERS:

- Mean quantity of trade does not depend on the information structure under Cournot, moves with price impact under demand function competition
- Any correlation of market variables can arise under Cournot, restricted under demand function competition
- Arbitrary variance of output under under Cournot, bounded under demand function competition
- Kyle model relaxes both constraints
Talk

1. Environment
2. Noise Free Information and Demand Function Competition
3. General Information Structures
4. General Mechanisms
• $i = 1, \ldots, N$ agents (buyers)
• agent $i$’s net utility from $a_i$ units of an asset (good) purchased at price $p$ is

$$u_i(\theta_i, a_i) = \theta_i a_i - \frac{1}{2} a_i^2 - p a_i$$

• agent $i$’s "valuation" (marginal value of first unit) is $\theta_i$
• valuations are normally and symmetrically distributed:

$$
\begin{pmatrix}
\theta_i \\
\theta_j
\end{pmatrix}
\sim \mathcal{N}
\left(
\begin{pmatrix}
\mu_\theta \\
\mu_\theta
\end{pmatrix},
\begin{pmatrix}
\sigma^2_\theta & \rho_{\theta\theta}\sigma^2_\theta \\
\rho_{\theta\theta}\sigma^2_\theta & \sigma^2_\theta
\end{pmatrix}
\right)
$$

with mean $\mu_\theta > 0$, standard deviation $\sigma_\theta > 0$ and correlation coefficient $\rho_{\theta\theta} \in (0, 1)$
Demand

- \( i = 1, ..., N \) agents (buyers)
- agent \( i \)'s net utility from \( a_i \) units of an asset (good) purchased at price \( p \) is
  \[
  u_i (\theta_i, a_i) = \theta_i a_i - \frac{1}{2} a_i^2 - pa_i
  \]
- agent \( i \)'s "valuation" (marginal value of first unit) is \( \theta_i \)
- valuations are normally and symmetrically distributed:
  \[
  \begin{pmatrix}
  \theta_i \\
  \theta_j
  \end{pmatrix} \sim \mathcal{N}
  \left(
  \begin{pmatrix}
  \mu_\theta \\
  \mu_\theta
  \end{pmatrix},
  \begin{pmatrix}
  \sigma_\theta^2 & \rho_{\theta\theta}\sigma_\theta^2 \\
  \rho_{\theta\theta}\sigma_\theta^2 & \sigma_\theta^2
  \end{pmatrix}
  \right)
  \]
  with mean \( \mu_\theta > 0 \), standard deviation \( \sigma_\theta > 0 \) and correlation coefficient \( \rho_{\theta\theta} \in (0, 1) \)
- interdependent valuations: idiosyncratic and common payoff shocks
  - as \( \rho_{\theta\theta} \to 0 \): pure private values
  - as \( \rho_{\theta\theta} \to 1 \): pure common values
(inverse) aggregate supply function:

\[ p = c_0 + cA, \quad c_0, c \in \mathbb{R}_+ \]

could be derived from quadratic cost function
• individual values are normally distributed:

\[
\begin{pmatrix}
\theta_i \\
\theta_j
\end{pmatrix}
\sim \mathcal{N}
\left(
\begin{pmatrix}
\mu_{\theta} \\
\mu_{\theta}
\end{pmatrix},
\begin{pmatrix}
\sigma^2_{\theta} & \rho_{\theta \theta} \sigma^2_{\theta} \\
\rho_{\theta \theta} \sigma^2_{\theta} & \sigma^2_{\theta}
\end{pmatrix}
\right)
\]
Payoff Shocks

- Individual values are normally distributed:

\[
\begin{pmatrix}
\theta_i \\
\theta_j
\end{pmatrix}
\sim \mathcal{N}
\begin{pmatrix}
\begin{pmatrix}
\mu_\theta \\
\mu_\theta
\end{pmatrix},
\begin{pmatrix}
\sigma_\theta^2 & \rho_{\theta\theta}\sigma_\theta^2 \\
\rho_{\theta\theta}\sigma_\theta^2 & \sigma_\theta^2
\end{pmatrix}
\end{pmatrix}
\]

- Useful alternative representation by orthogonal elements:

  common payoff shock

\[
\bar{\theta} \triangleq \frac{1}{N} \sum_i \theta_i
\]

  and idiosyncratic payoff shock

\[
\Delta \theta_i \triangleq \theta_i - \bar{\theta}
\]
Payoff Shocks

- Individual values are normally distributed:

\[
\begin{pmatrix}
\theta_i \\
\theta_j
\end{pmatrix}
\sim \mathcal{N}
\left( \begin{pmatrix}
\mu_{\theta} \\
\mu_{\theta}
\end{pmatrix},
\begin{pmatrix}
\sigma^2_{\theta} & \rho_{\theta\theta}\sigma^2_{\theta} \\
\rho_{\theta\theta}\sigma^2_{\theta} & \sigma^2_{\theta}
\end{pmatrix}\right)
\]

- Useful alternative representation by orthogonal elements:

  - Common payoff shock

\[
\bar{\theta} \triangleq \frac{1}{N} \sum_i \theta_i
\]

  - Idiosyncratic payoff shock

\[
\Delta \theta_i \triangleq \theta_i - \bar{\theta}
\]

- Resulting distribution of payoff uncertainty:

\[
\begin{pmatrix}
\Delta \theta_i \\
\bar{\theta}
\end{pmatrix}
\sim \mathcal{N}
\left( \begin{pmatrix}
0 \\
\mu_{\theta}
\end{pmatrix},
\begin{pmatrix}
(1 - \rho_{\theta\theta})\sigma^2_{\theta} & 0 \\
0 & \rho_{\theta\theta}\sigma^2_{\theta}
\end{pmatrix}\right)
\]
• agent \( i \) has private but imperfect information about the payoff shocks

• signals \( s_i \in \mathbb{R}^K \) are normally and symmetrically distributed:

\[
\begin{pmatrix}
\theta_i \\
\theta_j \\
\theta_s
\end{pmatrix}
\sim \mathcal{N}
\begin{pmatrix}
\mu_\theta \\
\mu_\theta \\
\mu_s
\end{pmatrix},
\begin{pmatrix}
\Sigma_{\theta\theta} & \Sigma_{\theta s} \\
\Sigma_{\theta s} & \Sigma_{ss}
\end{pmatrix}
\]

• signal \( s_i \in \mathbb{R}^K \) of each agent can be multi-dimensional

• large class of possible information structures
Each agent submits a demand function (schedule):

\[ x_i : \mathbb{R}^K \times \mathbb{R} \rightarrow \mathbb{R} \]

expressing a price contingent demand:

\[ x_i(s_i, p) \in \mathbb{R} \]

aggregate demand:

\[ \sum_i x_i(s_i, p) \]

market clearing:

\[ p^* = c_0 + c \sum_i x_i(s_i, p^*) \]
Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \epsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]
Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]

Klemperer and Meyer (1989) considered the case where \( \lambda = 1 \) and no shocks
• Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]

• Klemperer and Meyer (1989) considered the case where \( \lambda = 1 \) and no shocks

• Vives (2011) consider the case where \( \lambda = 1 \) and \( \varepsilon_i \) are i.i.d. and does comparative statics with variance
Each agent observes

$$s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i,$$

for some weight

$$\lambda \in \mathbb{R}$$

Klemperer and Meyer (1989) considered the case where $\lambda = 1$ and no shocks

Vives (2011) consider the case where $\lambda = 1$ and $\varepsilon_i$ are i.i.d. and does comparative statics with variance

We will...

- first consider "noise free information structures where $\lambda \neq 1$ and no shocks
Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]

Klemperer and Meyer (1989) considered the case where \( \lambda = 1 \) and no shocks

Vives (2011) consider the case where \( \lambda = 1 \) and \( \varepsilon_i \) are i.i.d. and does comparative statics with variance

We will...

- first consider "noise free information structures where \( \lambda \neq 1 \) and no shocks
- and then consider the case where \( \lambda \neq 1 \) and shocks are characterized by correlation as well as variance;
Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]

Klemperer and Meyer (1989) considered the case where \( \lambda = 1 \) and no shocks.

Vives (2011) consider the case where \( \lambda = 1 \) and \( \varepsilon_i \) are i.i.d.

and does comparative statics with variance.

We will...

- first consider "noise free information structures where \( \lambda \neq 1 \) and no shocks
- and then consider the case where \( \lambda \neq 1 \) and shocks are characterized by correlation as well as variance;

this three dimensional class of information structures is then

- without loss for one dimensional symmetric normal information structures...
• Each agent observes

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i, \]

for some weight

\[ \lambda \in \mathbb{R} \]

• Klemperer and Meyer (1989) considered the case where \( \lambda = 1 \) and no shocks
• Vives (2011) consider the case where \( \lambda = 1 \) and \( \varepsilon_i \) are i.i.d.
  and does comparative statics with variance
• We will...
  • first consider "noise free information structures where \( \lambda \neq 1 \)
    and no shocks
  • and then consider the case where \( \lambda \neq 1 \) and shocks are
    characterized by correlation as well as variance;
• this three dimensional class of information structures is then
  • without loss for one dimensional symmetric normal information structures...
Solving for Equilibrium

- Noise free information

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} \]
• Noise free information

\[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} \]

• In symmetric linear equilibrium, agents will submit linear demand functions:

\[ x_i(s_i, p) = \beta_0 + \beta_s s_i + \beta_p p \]  \hspace{1cm} (1)
Solving for Equilibrium

- Noise free information
  \[ s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} \]

- In symmetric linear equilibrium, agents will submit linear demand functions:
  \[ x_i (s_i, p) = \beta_0 + \beta_s s_i + \beta_p p \]  

- Price Impact
  \[ m = \frac{\partial p}{\partial x} \]
  will also be an equilibrium parameter because agent \( i \) will want to set
  \[ x_i = \frac{\mathbb{E} [\theta_i | s_i, p] - p}{1 + m} \]
Solving for Equilibrium

- Solve for \((\beta_0, \beta_s, \beta_p, m)\)
- We will focus on price impact \((m)\) and price sensitivity \((\beta_p)\)
• if agent \(i\) demanded \(x\) units of the good at price \(p\), then market clearing would imply that

\[
p = c_0 + c \left( x + \sum_{j \neq i} \left( \beta_0 + \beta_s s_j + \beta_p p \right) \right)
\]

and so

\[
m = \frac{\partial p}{\partial x} = \frac{c}{1 - (N - 1) c \beta_p}
\]

(2)

• by symmetry and linearity, these two equilibrium variables \((m, \beta_p)\) are numbers and, in particular, so not depend on the agent, signals (of him and others) and the price
Two reasons to condition on price changes:

- prices represent opportunity cost
Price Sensitivity depends on Price Impact

Two reasons to condition on price changes:

- prices represent opportunity cost
- price conveys information
• If $\lambda = 1$, there is no information effect
If $\lambda = 1$, there is no information effect

In this case, will set

$$\beta_p = -\frac{1}{1 + m}$$
If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?
• If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?
• If the price is more than expected, it must be that $\bar{\theta}$ is more than expected
• If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?
• If the price is more than expected, it must be that $\bar{\theta}$ is more than expected.
• What does this imply about agent’s valuation $\theta_i = \Delta \theta_i + \bar{\theta}$?
• If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?

• If the price is more than expected, it must be that \( \bar{\theta} \) is more than expected

• What does this imply about agent’s valuation \( \theta_i = \Delta \theta_i + \bar{\theta} \)?
  • if \( \lambda \gg 1 \)...
    • the agent’s signal is mostly about the common component
If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?

If the price is more than expected, it must be that $\bar{\theta}$ is more than expected.

What does this imply about agent’s valuation $\theta_i = \Delta \theta_i + \bar{\theta}$?

- if $\lambda >> 1$...
  - the agent’s signal is mostly about the common component
  - his expectation of the idiosyncratic component will drop...
• If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?
• If the price is more than expected, it must be that \( \bar{\theta} \) is more than expected
• What does this imply about agent’s valuation \( \theta_i = \Delta \theta_i + \bar{\theta} \)?
  • if \( \lambda \gg 1 \)...
    • the agent’s signal is mostly about the common component
    • his expectation of the idiosyncratic component will drop...
    • his expected value of the good will decline
If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?

If the price is more than expected, it must be that $\bar{\theta}$ is more than expected.

What does this imply about agent’s valuation $\theta_i = \Delta \theta_i + \bar{\theta}$?

- If $\lambda >> 1$...
  - the agent’s signal is mostly about the common component
  - his expectation of the idiosyncratic component will drop...
  - his expected value of the good will decline

- If $\lambda \approx 0$...
  - the agent’s signal is mostly about the idiosyncratic component
• If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?

• If the price is more than expected, it must be that $\bar{\theta}$ is more than expected

• What does this imply about agent’s valuation $\theta_i = \Delta \theta_i + \bar{\theta}$?
  
  • if $\lambda >> 1$...
    
    • the agent’s signal is mostly about the common component
    • his expectation of the idiosyncratic component will drop...
    • his expected value of the good will decline

  • if $\lambda \approx 0$...
    
    • the agent’s signal is mostly about the idiosyncratic component
    • his expectation of the common component will go up
Information Effect

- If the price is more than expected, how does an agent’s valuation change relative to his prior expectation?
- If the price is more than expected, it must be that $\bar{\theta}$ is more than expected.
- What does this imply about agent’s valuation $\theta_i = \Delta \theta_i + \bar{\theta}$?
  - if $\lambda >> 1$...
    - the agent’s signal is mostly about the common component
    - his expectation of the idiosyncratic component will drop...
    - his expected value of the good will decline
  - if $\lambda \approx 0$...
    - the agent’s signal is mostly about the idiosyncratic component
    - his expectation of the common component will go up
    - his valuation of the good will increase
• Overall (including both effects):

\[ \beta_p = -\frac{1}{1 + m} + (1 - \lambda) \left( \frac{1}{Nc} + \frac{1}{1 + m} \right) \]
• Overall (including both effects):

\[ \beta_p = -\frac{1}{1 + m} + (1 - \lambda) \left( \frac{1}{Nc} + \frac{1}{1 + m} \right) \]

• Price sensitivity switches from negative to positive for some \( \lambda \) between 0 and 1
Two Equations in Two Unknowns

\[ m = \frac{c}{1 - (N - 1)c\beta_p} \]

\[ \beta_p = -\frac{1}{1 + m} + (1 - \lambda) \left( \frac{1}{Nc} + \frac{1}{1 + m} \right) \]
Price Impact and Price Sensitivity

\[ m, \beta_p \]

Slope of Equilibrium Demand Function ($\beta_p$)
A trick

- Solving for each information structure at once is hard work
- Without loss of generality, we can restrict attention to information structures where all an agent knows is his action in equilibrium (i.e., demand function):
  - "Bayes correlated equilibrium"
• write \( \Delta a_i = a_i - \bar{a} \)

• symmetry implies statistically equivalent description over 4 variables

\[
\begin{pmatrix}
\Delta a_i \\
\bar{a} \\
\Delta \theta_i \\
\bar{\theta}
\end{pmatrix}
\]

with mean

\[
\begin{pmatrix}
0 \\
\mu_a \\
0 \\
\mu_\theta
\end{pmatrix}
\]

and variance-covariance matrix....
\[
\begin{pmatrix}
\frac{N-1}{N} (1 - \rho_{aa}) \sigma_a^2 & 0 & \rho \Delta \Delta \sigma \Delta a \sigma \Delta \theta \\
0 & \frac{(1+(N-1)\rho_{aa}) \sigma_a^2}{N} & 0 \\
\rho \Delta \Delta \sigma \Delta a \sigma \Delta \theta & 0 & \frac{N-1}{N} (1 - \rho_{\theta \theta}) \sigma_\theta^2 \\
0 & 0 & \rho_{\tilde{a} \tilde{\theta}} \sigma_{\tilde{\theta}} \sigma_{\tilde{a}} \\
\rho_{\tilde{a} \tilde{\theta}} \sigma_{\tilde{\theta}} \sigma_{\tilde{a}} & 0 & \frac{(1+(N-1)\rho_{\theta \theta}) \sigma_\theta^2}{N}
\end{pmatrix}
\]
• normality implies mean vector $\mu$ and variance-covariance matrix $\Sigma$ is necessary and sufficient for characterization
• outcome variables only, no reference to signals/information
• exogenous variables $\mu_\theta, \sigma^2_\theta, \rho_{\theta\theta}$
• endogenous variables $\mu_a, \sigma^2_a, \rho_{aa}, \rho_{\bar{a}\bar{\theta}}, \rho_{\Delta\Delta}$
what happens if you impose best response condition

\[ a_i = \frac{1}{1 + m} \mathbb{E}[\theta_i - c_0 - cN\bar{a}a_i, \bar{a})], \quad \forall i, a_i, \bar{a} \]

on statistical model?

where \( m \) is a measure of price impact (market power)
Characterization of Demand Function Competition

Theorem

Demand function competition implies:

1. mean of traded quantity is:

\[ \mu_a = \frac{\mu_\theta - c_0}{1 + Nc + m}; \]

2. second moments of trades are:

\[ \sigma_{\Delta a} = \frac{\rho_{\Delta \Delta} \sigma_{\Delta \theta}}{1 + m}, \sigma_{\bar{a}} = \frac{\rho_{\tilde{\theta} \bar{a}} \sigma_{\bar{\theta}}}{1 + c + m}; \]

3. idiosyncratic and average correlation coefficients are:

\[ \rho_{\Delta \Delta}, \rho_{\tilde{\theta} \bar{a}} \in (0, 1]. \]

4. market power \( m \in (-1/2, \infty) \)
Bayes correlated equilibrium pins down joint distribution of $a_i$, $\Delta \theta_i$ and $\bar{\theta}$.

- with three parameters $m$, $\rho_{\Delta\Delta}$ and $\rho_{\bar{\theta}\bar{\theta}}$

General one dimensional symmetric information structures given by

$$s_i = \Delta \theta_i + \lambda \cdot \bar{\theta} + \varepsilon_i,$$

- with three parameters $\lambda$, $\rho_{\varepsilon\varepsilon}$ and $\sigma_{\varepsilon}$

One to one map in parameter space
what happens if you impose best response condition

\[ a_i = \frac{1}{1 + c} \mathbb{E}[\theta_i - c_0 - cN\bar{a}|a_i] \]

on statistical model?
Characterization of Cournot Competition

Theorem
(Bergemann, Heumann and Morris (2015)) Demand function competition implies:

1. **mean of traded quantity is:**

   \[ \mu_a = \frac{\mu_0 - c_0}{1 + Nc + c}; \]

2. **standard deviation of individual actions is:**

   \[ \sigma_a = \frac{\rho_{a\theta} \sigma_\theta}{1 + Nc \rho_{aa} + c}; \]

3. **correlation coefficients satisfy:**

   \[ \rho_{a\theta} = \rho_{\Delta\Delta} \sqrt{(1 - \rho_{aa})(1 - \rho_{\theta\theta})} + \rho_{\bar{a}\bar{\theta}} \sqrt{\rho_{aa} \rho_{\theta\theta}} \]
• Can map back into the same three parameter one dimensional signal structure.
First moment:
- Under Cournot competition, price impact is independent of information structure.
- Under demand function competition:
  - price impact varies
  - there is an additional degree of freedom in the first moment

Second moments:
- Agents are less informed under Cournot competition:
  - Arbitrary variance of total output is possible
- Under demand function competition:
  - it is as if agents know the equilibrium price (and thus total quantity)
  - there is an additional restriction in the second moment
• Condition on noisy prices: move smoothly from demand function competition to Cournot, continuity in characterizations

• Variation on static Kyle model
  • richer because we have common and idiosyncratic shocks
  • add noise traders
  • market maker plays role of best response function

• outcomes are superset of demand function competition and Cournot
  • do not condition on prices
  • there is variable price impact
• Useful, feasible and insightful to abstract from fine details of the information structure
• Can get new insight into price impact in this framework
• Can compare alternative mechanisms in common outcome space