Composition of Markets with Conflicting Incentives

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What if traders aren’t myopic?

- Logic of market scoring rules relies on assumption that traders don’t consider how their current report might influence outside payoffs.
- But what if traders try to game their opponents?
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- Logic of market scoring rules relies on assumption that traders don’t consider how their current report might influence outside payoffs.
- But what if traders try to game their opponents?
- We need a theory of manipulation incentives.
What goes wrong?

1. **Outcome manipulation:** Traders may be able to influence the variable they’re predicting through non-market channels.
   - Ottaviani & Sørensen (2007): Corporate prediction market where employees can sabotage the outcome—moral hazard.
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1. **Outcome manipulation**: Traders may be able to influence the variable they’re predicting through non-market channels.
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2. **Information manipulation**: Private information is your golden egg in an MSR. Participants have incentive to guard it jealously—this can produce inefficiency.
Outline

1. Motivation
   - Introduction
   - Example

2. Dimitrov & Sami
   - Model
   - Equilibrium
   - Further insights

3. Extensions and discussion
   - Chen et al.
   - Discussion
Example: Set-up (1)

A very simple scenario:

- **States** of the world: \( \{\omega_1, \omega_2, \omega_3, \omega_4\} \) with common prior \( p(\omega_i) = \frac{1}{4} \) for each \( i \).
- Two players: Alice and Bob with **type spaces** \( T_a = \{a, a'\} \) and \( T_b = \{b, b'\} \).
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- **Information structure**:

  ![Information structure diagram]

  - What is type \( b \) of Bob's posterior? What happens if we know both types?
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- Information structure:

```
    1   2
   ----
  1 | ● | ● |
   ----
  3 | ● | ● |
   ----
  4 | ● | ● |
```

- What is type \( b \) of Bob’s posterior? What happens if we know both types?
Set-up (2)

We’ll call this game $\Omega$ and it works as follows:

- Nature picks a state $\omega \in \Omega$ and players receive their types.
- Bob can move the market probability distribution from $p_0$ to $p_b$.
- Alice can move the distribution from $p_b$ to $p_a$. The report is public.
- The state of the world $\omega$ is revealed.
- Payments are computed.
Set-up (3)

- The payments are:
  - Bob is paid according to $\log(p_b(\omega_i)) - \log(p_0(\omega_i))$.
  - Alice is paid according to $\log(p_a(\omega_i)) - \log(p_b(\omega_i))$.

- Optimal strategy: report true $p_i$. 
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- If signals are distinguishable (and they are in this example), Bob’s strategy is an invertible mapping from types to actions.

- Therefore if Alice believes Bob is rational, $p_a = p(\omega_i \mid t_a, t_b)$.
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- Therefore if Alice believes Bob is rational, $p_a = p(\omega_i \mid t_a, t_b)$.

- Notice this is a weaker epistemic condition than equilibrium (only need rationality + 1 level of knowledge of rationality, not common knowledge).

- By a **backward backward induction** argument all information will always be revealed in this market.
Solution

The payments in equilibrium are:

- Bob will get $\log\left(\frac{1}{2}\right) - \log\left(\frac{1}{4}\right)$.
- Alice will get $\log(1) - \log\left(\frac{1}{2}\right)$. 
What if Alice’s type also includes information about something else? Now before we play game $\Omega$ we’ll play game $\Gamma$.

- Suppose we have more states we are interested in $\{\gamma_1, \gamma_2\}$ (so ‘true’ state space is $\Gamma \times \Omega$).
- Alice gets type $a$ if the state is $\gamma_1$ and $a'$ if the state is $\gamma_2$.
- Alice is asked to publicly report her assessment $p'_a$ on $\Gamma$ (true state will be revealed later when $\omega$ is revealed).
- Alice is paid $\lambda \log(p'_a(\gamma))$ at the end of game $\Omega$. 
Claim

In the compound game induced by playing $\Gamma$ then $\Omega$ we can set $\lambda$ such that there is no PBE where Alice reports $p'_a$ truthfully. However, there is always full revelation in $\Omega$. 
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- Heuristic: Suppose Alice reports $p'_a$ truthfully in equilibrium, she gets $\lambda \log(1)$ for sure. However, then $p_b(\omega_i) = 1$ for some $i$ and Alice loses $\log(1) - \log\left(\frac{1}{2}\right)$. For the game $\Omega$ the argument from before goes through.
2 \times \text{incentive compatible} \neq \text{incentive compatible}

Claim

In the compound game induced by playing \( \Gamma \) then \( \Omega \) we can set \( \lambda \) such that there is no PBE where Alice reports \( p'_a \) truthfully. However, there is always full revelation in \( \Omega \).

- **Heuristic:** Suppose Alice reports \( p'_a \) truthfully in equilibrium, she gets \( \lambda \log(1) \) for sure. However, then \( p_b(\omega_i) = 1 \) for some \( i \) and Alice loses \( \log(1) - \log(\frac{1}{2}) \). For the game \( \Omega \) the argument from before goes through.

- **Intuition:** Since there is total revelation in \( \Gamma \), MSR induces split of total information payoff pie in proportion to information each trader adds. Alice gains in \( \Gamma \) at the expense of losing some pie in \( \Omega \).
Discussion

Questions about the example?
Dimitrov & Sami (2010): Basics

- Formalize incentive conflicts through (scoring rule) prices.
- Consider two privately informed traders: Alice and Bob.
- Before they each trade in a market $V$, Alice trades in a market $U$. Thus, Bob may extract information about Alice’s private signal.
Dimitrov & Sami (2010): Basics

- Formalize incentive conflicts through (scoring rule) prices.
- Consider two privately informed traders: Alice and Bob.
- Before they each trade in a market $V$, Alice trades in a market $U$. Thus, Bob may extract information about Alice’s private signal.
- Alice’s tradeoff: If Bob backs out her signal, she will not be able to make a profit in market $V$. 
Set-up (1)

- Two binary random variables that we want forecasted: $U, V \in \{0, 1\}$. Give rise to two markets.
- **Private signals:** Alice receives $X \in \mathcal{X}$ (realization $x$), Bob receives $Y \in \mathcal{Y}$ (realization $y$).
Set-up (2)

- Assume **common knowledge of joint distribution**. Priors:

  \[ f_0 = \Pr(U = 1), \quad g_0 = \Pr(V = 1). \]

- **Probability aggregates**:

  \[ f_x = \Pr(U = 1 \mid X = x), \]
  \[ f_y = \Pr(U = 1 \mid Y = y), \]
  \[ f_{xy} = \Pr(U = 1 \mid X = x, Y = y). \]

- Define \( g_x, g_y \) and \( g_{xy} \) similarly for \( V \).
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- **Assume \( V \)-distinguishability**: Conditional expectation of \( V \) given \( y \) is different for different values of \( y \).
Market scoring rule

- **Logarithmic market scoring rule:** If Alice changes the predicted probability in the $U$ market from $r$ to $q$, she earns

$$
\pi_U(u, r \rightarrow q) = \begin{cases} 
\lambda_U [\log q - \log r] & \text{if } u = 1 \\
\lambda_U [\log(1 - q) - \log(1 - r)] & \text{if } u = 0 
\end{cases},
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where $u$ is the realization of $U$.

- $\lambda_U > 0$ is a **weight** on the $U$-payoff.
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where $u$ is the realization of $U$.

- $\lambda_U > 0$ is a **weight** on the $U$-payoff.

- Define similarly the $V$ market payoff $\pi_V(v, r \rightarrow q)$ with weight $\lambda_V$. 

Sequence

- **Stage 1:** Alice trades in the $U$ market (*Bob observes Alice’s trade*).
- **Stage 2:** Bob trades in the $V$ market (*Alice observes Bob’s trade*).
- **Stage 3:** Alice trades in the $V$ market.
Strategies

Solution concept: Weak PBE.
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  - In Stage 1 Alice employs a mixed strategy $\sigma : \mathcal{X} \rightarrow \mathcal{D}([0,1])$.

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  - Denote Bob’s Stage 2 beliefs by \( \mu_r(x) \). Due to honesty in equilibrium, the authors identify his strategy with these beliefs.
- **Strategy pair:** \( (\sigma, \mu) \).
Payoffs

- **Efficiency in markets:**

\[
\text{Eff}_U(\sigma) = \sum_{x \in X} \Pr(X = x) \sum_{r \in R} \sigma_x(r) \pi_U(f_x, f_0 \rightarrow r),
\]

\[
\text{Eff}_V = \sum_{X=x, Y=y} \Pr(X = x, Y = y) \pi_V(g_{xy}, g_0 \rightarrow g_{xy}),
\]

where e.g.

\[
\pi_U(f_x, f_0 \rightarrow r) = f_x \pi_U(1, f_0 \rightarrow r) + (1 - f_x) \pi_U(0, f_0 \rightarrow r).
\]
Payoffs

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  \[ \text{Eff}_V = \sum_{x \in X} \sum_{y \in Y} \Pr(X = x, Y = y) \pi_V(g_{xy}, g_0 \rightarrow g_{xy}), \]

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  \[ \pi_U(f_x, f_0 \rightarrow r) = f_x \pi_U(1, f_0 \rightarrow r) + (1 - f_x) \pi_U(0, f_0 \rightarrow r). \]

- If Alice learns Bob’s \( \mu \) in Stage 3, her payoff can be written

  \[ \pi_A(\sigma, \mu) = \text{Eff}_U(\sigma) + \text{Eff}_V - \pi_B(\sigma, \mu). \]

- Looks almost like constant-sum game!
Minimax (1)

- Game isn’t exactly constant-sum: Total payoff depends on how far Alice moves market \( U \).
- Constant-sum games may be analyzed using minimax strategies (goes back to birth of game theory).
- Turns out we can use this concept for our purposes.
Minimax (2)

**Definition**

A *maximin pair* $(\sigma, \mu)$ solves

$$\sigma \in \arg \max_{\sigma'} \min_{\mu'} \pi_A(\sigma', \mu'),$$

$$\mu \in \arg \min_{\mu'} \pi_A(\sigma, \mu').$$

**Interpretation:** Alice maximizes over worst possible payoffs; Bob minimizes given this.
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\sigma \in \arg\max_{\sigma'} \pi_A(\sigma', \mu).
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**Interpretation:** Bob minimizes over Alice’s best payoffs; Alice maximizes given this.
Main results (1)

Lemma (1)

The minimax and maximin values of $\pi_A$ coincide, and there exists a pair $(\sigma, \mu)$ for which this holds.
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Proof outline: Show that $\pi_A$ is concave in $\sigma$ and convex in $\mu$—follows readily from properties of the logarithmic function. Use result from the literature.
Main results (2)

Lemma (3)

Any two minimax strategy pairs \((\sigma, \mu)\) and \((\sigma', \mu')\) lead to the same payoff for every report by Alice and Bob.
Main results (2)

**Lemma (3)**

*Any two minimax strategy pairs \((\sigma, \mu)\) and \((\sigma', \mu')\) lead to the same payoff for every report by Alice and Bob.*

*Proof outline:* Check that \((\sigma, \mu')\) is also minimax. Consider two different convex combinations \((0.6\sigma + 0.4\sigma', \mu')\) and \((0.4\sigma + 0.6\sigma', \mu')\) and suppose they lead to different \(\text{Eff}_U\).
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Main results (3)

Theorem (5)

There exists a minimax pair such that Bob's beliefs are consistent (Lemma 4). Such a pair represents a Weak PBE.
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*Proof outline:* Follows readily from optimality conditions of a minimax pair.

**Theorem (6)**

*Let \((\sigma^*, \mu^*)\) be a minimax pair. In any Weak PBE the payoffs to Alice and Bob are \(\pi_A(\sigma^*, \mu^*)\) and \(\pi_B(\sigma^*, \mu^*)\), respectively.*
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Let \((\sigma^*, \mu^*)\) be a minimax pair. In any Weak PBE the payoffs to Alice and Bob are \(\pi_A(\sigma^*, \mu^*)\) and \(\pi_B(\sigma^*, \mu^*)\), respectively.

*Proof outline:* Easy to see that any Weak PBE strategy pair must be minimax, so we can use Lemma 3.
Main results (4)

- **Take-home message:** The payoffs in any Weak PBE can be computed by finding the minimax value of Alice’s payoff function $\pi_A$. 
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- **Take-home message:** The payoffs in any Weak PBE can be computed by finding the minimax value of Alice’s payoff function $\pi_A$.

- **Section 5.2 illustrates how one may compute the minimax strategies in practice. The problem is nonlinear.**
Noisy channel (1)

\[ \text{Eff}_U(\sigma) = \sum_{x \in \mathcal{X}} \Pr(X = x) \sum_{r' \in \mathcal{R}} \sigma_x(r') \pi_{U}(f_x, f_0 \rightarrow r') \]

\[ = \lambda_U \sum_{x \in \mathcal{X}} \sum_{r' \in \mathcal{R}} \sum_{u \in \{0,1\}} \left\{ \Pr(X = x) \Pr(r = r' \mid X = x) \right. \]

\[ \times \Pr(U = u \mid X = x) \log \frac{\Pr(U = u \mid r = r')}{\Pr(U = u)} \left\} \right. \]

\[ = \lambda_U \sum_{r'} \sum_{u} \Pr(r = r', U = u) \log \frac{\Pr(U = u \mid r = r')}{\Pr(U = u)} \]

\[ \text{Note: } \Pr(r' \mid x) \Pr(u \mid x) = \Pr(r', u \mid x). \]
Due to LMSR, $\text{Eff}_U$ can directly be thought of as the **mutual information** between $U$ and the garbled report $r$.

Also: Consider a modified game where Alice’s signal structure is such that she receives signal $\sigma(x)$ instead. Since $(\sigma, \mu)$ was optimal in the original game, it must now be optimal for Alice to report truthfully in $U$ market.
The greater the ratio $\lambda_V / \lambda_U$, the more does Alice want to conceal her true signal in market $U$. 
Limiting ratio (1)

- The greater the ratio $\lambda_V / \lambda_U$, the more does Alice want to conceal her true signal in market $U$.
- Fixing all other primitives than the payoff weights, define the limiting ratio to be the maximum ratio $\lambda_V / \lambda_U$ such that Alice has no profitable deviation from a truthtelling equilibrium.
- Note: The limiting ratio can be $+\infty$. 
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Note: The limiting ratio can be $+\infty$.

Fixing $\lambda_U$, if truthtelling is optimal for $\lambda_V^*$ it is also optimal for all $\lambda_V \leq \lambda_V^*$, since such a reduction leaves the honest payoff constant while reducing dishonest gains.
Limiting ratio (2)

- The limiting ratio can be interpreted as a measure of **alignedness** of incentives for honesty.
- Theorem 7 characterizes the limiting ratio of combinations of general forecast values with discrete support in \([0, 1]\).
Discussion

- Is this about two markets?
- Real-life examples of such information tradeoffs?
Chen et al. (2009)

- The problem here is that market participants want to hold on to their information.
- We can think about the game as one market with the following rules:
  - Alice moves market probability from $p_0$ to $p_a$.
  - Bob sees Alice’s move and moves the market probability from $p_a$ to $p_b$. 
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**Timing:** Would I rather be Bob or Alice in this game?
This depends on the signal structure. Suppose we have states of the world $\Omega$ and type space $T_a \times T_b$, symmetric distinguishable signal distributions and we use a LMSR to elicit information.
Chen et al. (2)

This depends on the signal structure. Suppose we have states of the world $\Omega$ and type space $T_a \times T_b$, symmetric distinguishable signal distributions and we use a LMSR to elicit information.

**Definition**

Say that the signal structure is *conditionally independent* if

$$p(t_a, t_b \mid \omega) = p(t_a \mid \omega)p(t_b \mid \omega).$$

**Examples:** Most information structures we’ve studied so far.
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**Definition**

*Say the signal structure is unconditionally independent if*

$$p(t_a, t_b) = p(t_a)p(t_b).$$

**Examples:** Elections, my type is $D$ or $R$ and outcome is determined based on majority vote.
Theorem

If signals are conditionally (unconditionally) independent then

\[ \pi^*_\text{Alice} \geq (\leq) \pi^*_\text{Bob}. \]
Theorem

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\[ \pi^*_A \geq (\leq) \pi^*_B. \]

Intuition: All possible information is revealed in the end, so the question is how much of the information pie each person gets.

- If signals are conditionally independent, I want to go first: My signal is information substitute for part of your signal.
- If signals are unconditionally independent, I want to go second: You learn nothing about my signal from your signal, but I learn something about the state of the world from your report.
Motivation
Dimitrov & Sami
Extensions and discussion

Chen et al. (3)

Theorem

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This means in infinitely repeated LMSR games we might not get information revelation in finite time.
What’s next?

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  - Common prior
  - Exogenous timing
  - Exogenous entry
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- Future research?
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- Future research?
  - Test qualitative predictions/assumptions
  - How to get closer to real world?