



# Microsoft Research Faculty Summit 2013



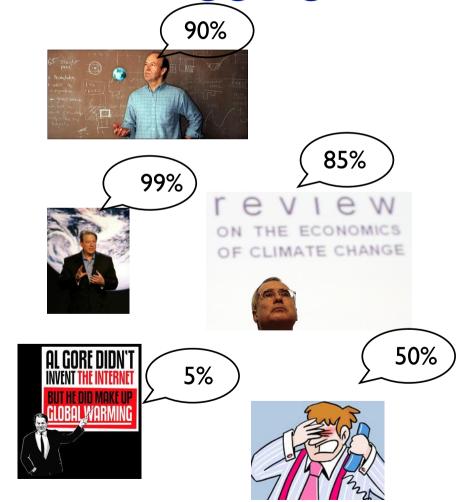
Two Challenges For Prediction Markets: Microstructure and Manipulation

Sanmay Das RPI -> Virginia Tech -> Wash. U in St Louis



## What are prediction markets good for?

Information Aggregation



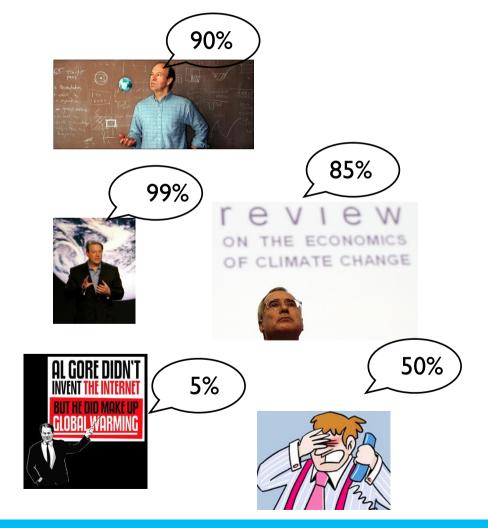


Pr (Global avg temp in 10 years will be >.2C higher than today)?

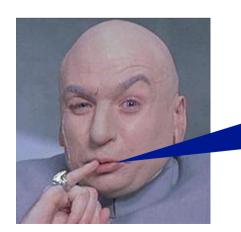


## What are prediction markets good for?

#### Information Dissemination







I'm going to focus LASERS on the earth!



### Have they worked?

### Information aggregation

Elections: Iowa Electronic Markets / Intrade / Betfair (real money) (Rothschild, 2009; Wolfers & Zitzewitz, 2004; Berg et al, 2001, ...)

Combinatorial market for the 2012 elections (play money / field experiment) (Dudik et al, 2013)

HP, Google, ...: sales forecasts, etc.

Lab experiments (e.g. Hanson et al, 2007)

. . .

#### Information dissemination

Microsoft product release case (play money / field experiment) (Cherry, 2007)

Gates-Hillman prediction market at CMU (Othman & Sandholm, 2013)

Instructor Rating Markets (Chakraborty et al, 2013)



### Two big research questions

### What's the right microstructure / market design?

Binary or continuous outcome markets: analogies to financial markets abound.

Options include CDAs, market-makers (e.g. LMSR (Hanson 2003, 2007) or a Bayesian MM (Das & Magdon-Ismail, 2008; Brahma *et al*, 2012))

Combinatorial or interval markets (Hanson 2003, 2007; Chen *et al*, 2013; Othman & Sandholm, 2013 Interesting questions at the interface of pricing and user experience (e.g. Dudik *et al*, 2013)

#### Is manipulation a problem?

Lab experiments suggest...not always (Hanson et al, 2007)

Let's say "betting on terrorism" is never going to happen. But presidential election markets are widely accepted!

Where does the line lie? What would work and what wouldn't?

Useful research direction: medium-sized field experiments (e.g. the Gates-Hillman markets, and the Instructor Rating Markets I will talk about)

## Market making

Standard design: continuous double auctions

Markets can be thin

#### Market makers provide liquidity

Always willing to execute transactions

#### De facto standard: LMSR (Hanson, 2003, 2007)

Many nice properties: bounded loss, extensibility to combinatorial markets, etc. Issues: loss-making, plus price properties are heavily dependent on single parameter Various extensions, e.g. liquidity-sensitive MM of Othman *et al* (2010)

# A Bayesian market maker (Das 2005, 2008; Das & Magdon-Ismail, 2008; Brahma et al, 2012)

Learns from information content of trades

Not necessarily loss-making, but can have unbounded loss

Intuitive market properties: higher spreads during times of uncertainty, lower spreads in stable times.

### How to compare?

#### Lab experiments

Highly controlled

Limited by subject availability, very time consuming, difficult to scale

#### Field experiments / deployment experience

Can operate at greater timescales and scale to much larger populations

Less controlled, especially for comparisons; incentives may (sometimes) be hard to align with the realworld.

#### Trading-agent experiments / tournaments

Cheap to run on a massive scale (great for debugging!)

Dependent on agent design, but remember: we're not modeling, we're testing!

Must be especially careful in interpreting results



### Trading agent experiments

Trading bots with access to successive coin flip outcomes from the true distribution

Slowly improving information (simulates our lab experiments)

Compare performance of MMs based on composition of trading population. 3 types of traders

Fundamentals traders

Learning ("rational expectations") traders

Technical traders

	Average profit		Spread		RMSD		RMSDeq	
	bmm	lmsr	bmm	lmsr	bmm	lmsr	bmm	lmsr
10%	-823.74	-1915.51	2.38	2.35	16.09	19.27	5.97	6.63
40%	16630.89	-1496.90	1.24	1.94	12.19	12.95	3.58	6.30
60%	23630.75	-1097.00	1.06	1.88	10.81	14.05	3.10	6.15
100%	-295.61	-3055.04	0.94	1.95	9.28	8.42	3.04	4.87
$\overline{ m RE}40\%$	34494.88	-2008.72	1.62	2.02	13.32	14.61	4.87	4.59
RE60%	25223.28	-2312.65	1.28	1.99	11.60	12.05	3.62	4.81
RE100%	-738.83	-3077.43	1.03	1.98	9.67	9.10	3.15	4.56



### Instructor Rating Markets: Motivation

Provide *dynamic* feedback to instructors on the progress of their classes

Study incentives and manipulation in the equivalent of small election-type markets

(Conveniently, field experiments for comparing microstructures!)



### Instructor Rating Markets: Design

10 courses: each has a security liquidating from 0 to 100. All orders go through a market-making algorithm (BMM or LMSR)

Students can trade in any market, but only rate instructors for their own classes

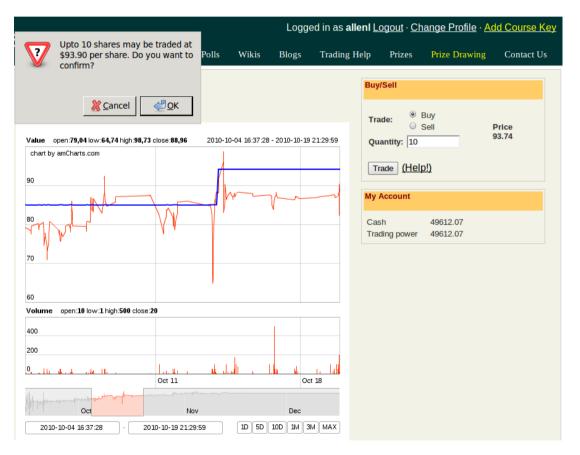
#### Two-week rating periods

Accounts start with initial fake money/shares Students in each course rate their instructor Markets liquidate based on this rating

#### Prizes

4 rank-based

1 participation





### Prices incorporate new information Linear model predicting future liquidations

Previous liquidations Market price average

#### Price average is more predictive

R-squared (0.58 vs 0.48)

Previous liquidations insignificant in linear model

$$\operatorname{Liq}_{s,\rho} = \beta_1 \operatorname{Liq}_{s,\rho-1} + \beta_2 \operatorname{Price}_{s,\rho} + \alpha$$

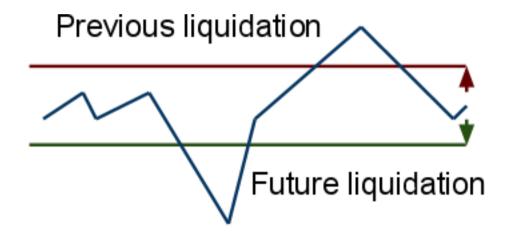
$\alpha$ est.	$\beta_1$ est.	$\beta_2$ est.	Sample Size
$\overline{7.02}$	0.17	0.72 **	40
		**p < 0.01	



### Raters provide new information

We know which traders are raters for a class ("in class")

How do we tell the informational difference between "in class" and "out of class" traders? Examine trades that originate at prices in between previous and future liquidations



In class traders: toward future liquidations 54% of the time

Out of class traders: toward future liquidations only 48% of the time



## System manipulation

#### Closed system: are the IRMs a fake world?

No. Correlation of IRM ratings for 7 CS classes with official institute ratings: 0.86 (prices 0.75) Prices predict ratings, ratings predict evaluations, despite:

Small sets of raters

Manipulation potential

#### Generalizability?

Altruism in the university setting Insufficient incentives for manipulation?



### Takeaways

#### Exciting applications of prediction markets

Instructor ratings
Important policy questions
Product launch dates
Combinatorial outcomes

. . .

### Design must be right to get them to work

E.g. without a market maker, they may be too illiquid to get people trading
Interesting new questions at the interface of market design and user interface design
Possibility of manipulation *could* compromise some markets but doesn't necessarily!

Don't just throw it away because of the *possibility* that bad things will happen
Weigh the risks and benefits

