Prediction Markets

Crowdsourcing and Human Computation Lecture ##

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Website: crowdsourcing-class.org

Outline of lecture

Definitions quickly, since you have seen this many times

Theory a basic pricing models, prices as probabilities

Practice examples of prediction markets working in the wild

Case Study interesting findings from Google's PM

Definitions

AKA information market or event futures

Traders buy/sell contracts which have a payout tied to the unknown outcome of some future event

Outcomes of events must be unambiguous and verifiable by some predetermined time

Definitions

Bid/Ask : buyers/sellers chose prices and trades occur only when they match

Market Makers : individuals agree to make trades, profit from spread

Definitions

Typical payout is like in horse racing - all money is pooled and then divided among winners

Incentive scheme can be real or virtual/play money

Definitions

Table 1: Contract Types—Estimating Uncertain Quantities or Probabilities

Contract	Example	Details	Reveals market expectation of…
Winner-takes-all	Event *y*: Al Gore wins the popular vote	Contract costs \$*p* Pays \$1 if and only if event *y* occurs Bid according to value of \$*p*	Probability that event *y* occurs, *p(y)*
Index	Contract pays \$1 for every percentage point of the popular vote won by Al Gore	Contract pays *\$y*.	Mean value of outcome *y*: *E[y]*
Spread	Contract pays even money if Gore wins more than y^*% of the popular vote.	Contract costs \$1 Pays \$2 if $y>y^*$ Pays \$0 otherwise. Bid according to the value of y^*.	Median value of *y*.

Theory

Some motivating observations and assumptions :

Prices should be (and often are) efficient : price should be equal to expected payout. (Although small markets may absorb information less quickly than larger markets.)

Marginal trades should be (and often are) rational : no systematic biases should arise. (Although people often trade according to desires rather than beliefs.)

Markets should (and often do) contain few arbitrage opportunities : the same contracts should trade at the same price on different exchanges

Theory

Quick example of arbitrage :

Market A sells "Obama wins" contract for $0.75
Market B sells "Obama wins" contract for $0.50

You are poor. You have not a penny to your name	$0	$0
You short sell 100 contracts on A. (I.e. you borrow contracts and sell them. You will have to return them later.)	+$75	$75
You buy 100 contracts in market B	-$50	$25

Theory

Market A sells "Obama wins" contract for $0.75
Market B sells "Obama wins" contract for $0.50

OBAMA WINS!!

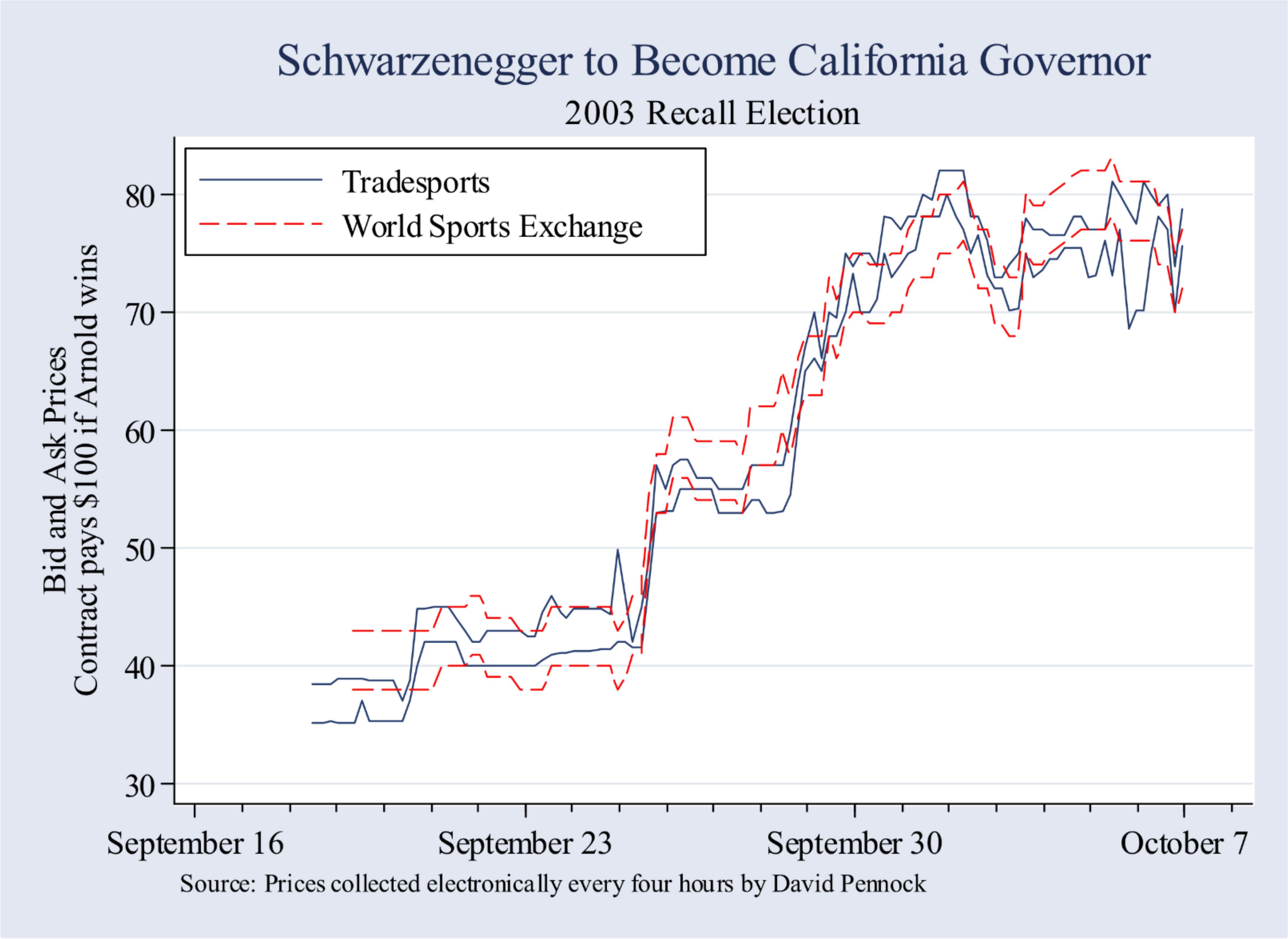
You are poor. You have not a penny to your name	$0	$0
You short sell 100 contracts on A. (I.e. you borrow contracts and sell them. You will have to return them later.)	+$75	$75
You buy 100 contracts in market B	-$50	$25
Your contracts on market B are worth $100.	+$100	$125
You return 100 shares that you borrowed on Market A (now worth $100).	-$100	$25
Profit		$25

Theory

Market A sells "Obama wins" contract for $0.75
Market B sells "Obama wins" contract for $0.50

OBAMA LOSES!!

You are poor. You have not a penny to your name	$0	$0
You short sell 100 contracts on A. (I.e. you borrow contracts and sell them. You will have to return them later.)	+$75	$75
You buy 100 contracts in market B	-$50	$25
Your contracts on market B are worth $0.	+$0	$25
You return 100 shares that you borrowed on Market A (now worth $0).	$0	$25
Profit		$25



Schwarzenegger to Become California Governor
2003 Recall Election
Tradesports
World Sports Exchange
Bid and Ask Prices
Contract pays $100 if Arnold wins
30
40
50
60
70
80
September 16
September 23
September 30
October 7
Source: Prices collected electronically every four hours by David Pennock

Theory

For simplicity, our definition of prediction markets :

- Does not include markets where holding the good is inherently enjoyable (e.g. sports betting)
- Does not include markets large enough to allow risk sharing
- Includes only risk neutral probabilities

(as always, these assumptions can be relaxed, if you feel like doing uglier math...)

Theory

Binary contracts paying $1 dollar if event occurs, $0 otherwise

Wealth is orthogonal to event outcome and to beliefs

Market is large, and participants are price takers

Log utility

Beliefs are heterogeneous and reflect private, noisy signals of whether the event will occur

$$\underset{\{x\}}{Max}\ EU_j = \text{P(winning) * (wealth if you win) + P(losing) * (wealth if you lose)}$$

$$yielding: \quad x_j^* = y\frac{q_j - \pi}{\pi(1-\pi)}$$

where y is wealth, xj is number of contracts person j should buy, pi is price of the contract, and qj is person j's believed P(event)

$$yielding: \quad x_j^* = y \frac{q_j - \pi}{\pi(1-\pi)}$$

Sooo...the point is that demand is :

- 0 when price is equal to beliefs
- Linear in beliefs: given y, demand increases with q
- Decreasing in risk : lower when pi close to ½
- Increasing in wealth : given q, demand increases with y
- Unique for prices between 0 and 1

Price equal to mean(q) when supply = demand

$$\int_{-\infty}^{\pi} y \frac{q-\pi}{\pi(1-\pi)} f(q)dq = \int_{\pi}^{\infty} y \frac{\pi-q}{\pi(1-\pi)} f(q)dq$$

$$\frac{y}{\pi(1-\pi)} \int_{-\infty}^{\pi} (q-\pi) f(q)dq = \frac{y}{\pi(1-\pi)} \int_{\pi}^{\infty} (\pi-q) f(q)dq$$

$$\pi = \int_{-\infty}^{\infty} qf(q)dq = \overline{q}$$

Price equal to mean(q) when supply = demand

$$\int_{-\infty}^{\pi} y \frac{q-\pi}{\pi(1-\pi)} f(q)dq =$$

At any price below equilibrium, consumers will be better off than producers (they are getting away with paying too little).

$$\frac{y}{\pi(1-\pi)} \int_{-\infty}^{\pi} (q-\pi) f(q)dq = \frac{y}{\pi(1-\pi)} \int_{\pi}^{\infty} (\pi-q) f(q)dq$$

$$\pi = \int_{-\infty}^{\infty} q f(q)dq = \overline{q}$$

Price equal to mean(q) when supply = demand

At any price above equilibrium, producers will be better off than consumers (they are getting away with charging too much).

$$= \int_{\pi}^{\infty} y \frac{\pi - q}{\pi(1-\pi)} f(q)dq$$

$$\frac{y}{\pi(1-\pi)} \int_{-\infty}^{\pi} (q-\pi) f(q)dq = \frac{y}{\pi(1-\pi)} \int_{\pi}^{\infty} (\pi - q) f(q)dq$$

$$\pi = \int_{-\infty}^{\infty} q f(q)dq = \overline{q}$$

Price equal to mean(q) when supply = demand

All the well-off-ness of consumers = **All the well-off-ness of producers**

Math

$\pi =$ **Average of all participants beliefs**

Prediction Markets in the wild

For business/pleasure : Intrade, Tradesports

For research : Iowa Election Markets

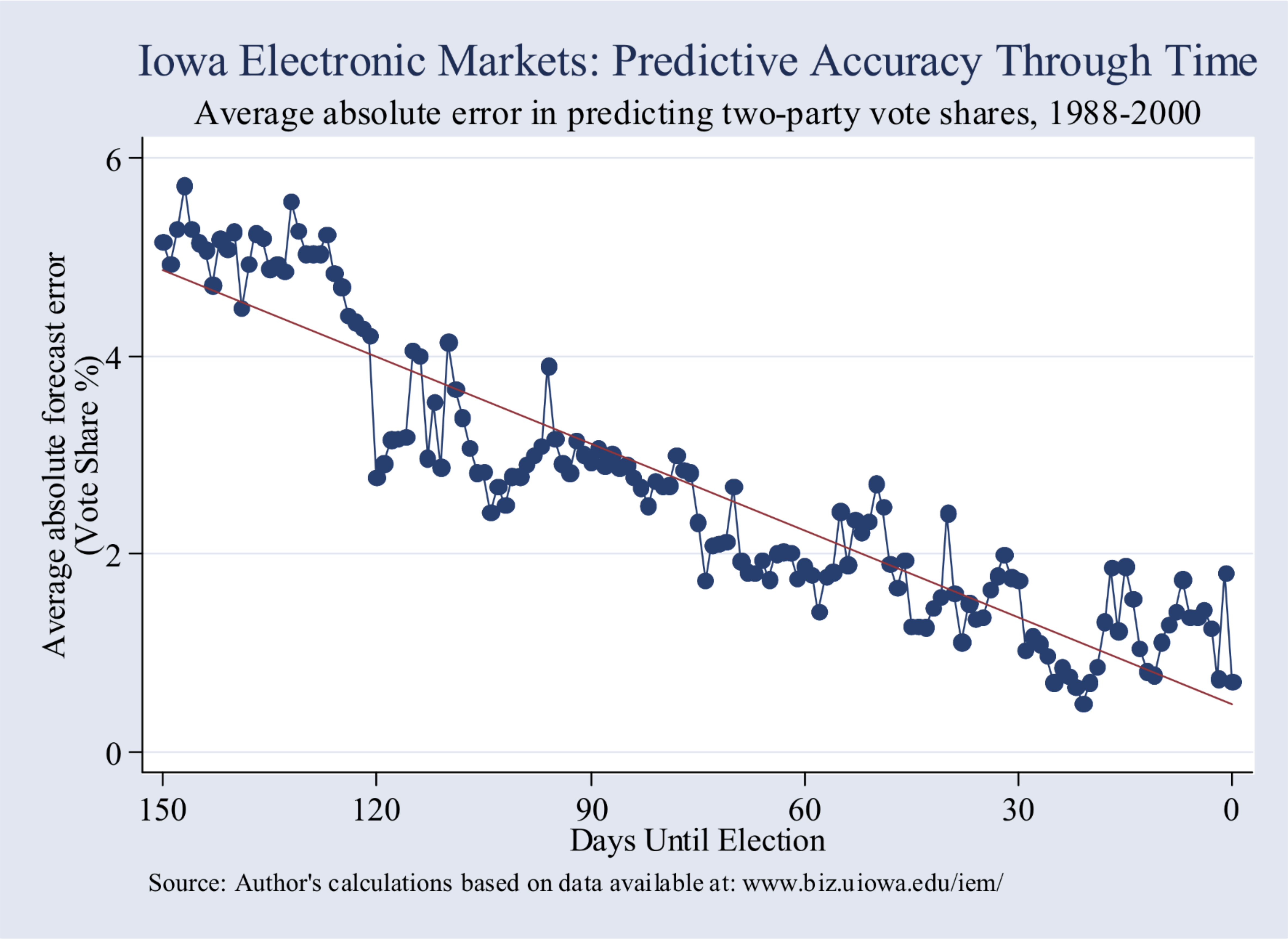
For government : PAM

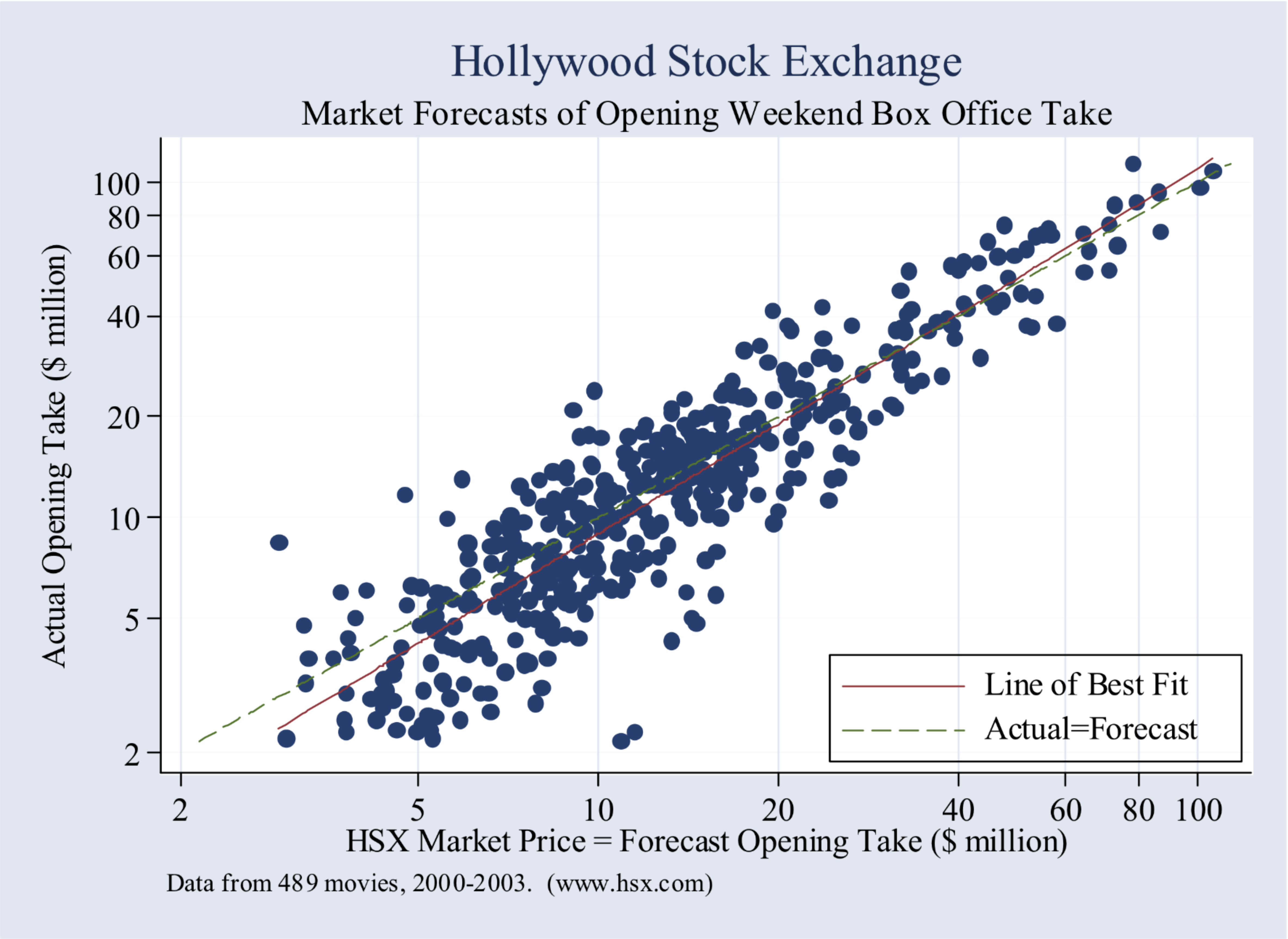
For companies internally: HP (printer sales), Siemens (ability to meet deadlines)

Practice

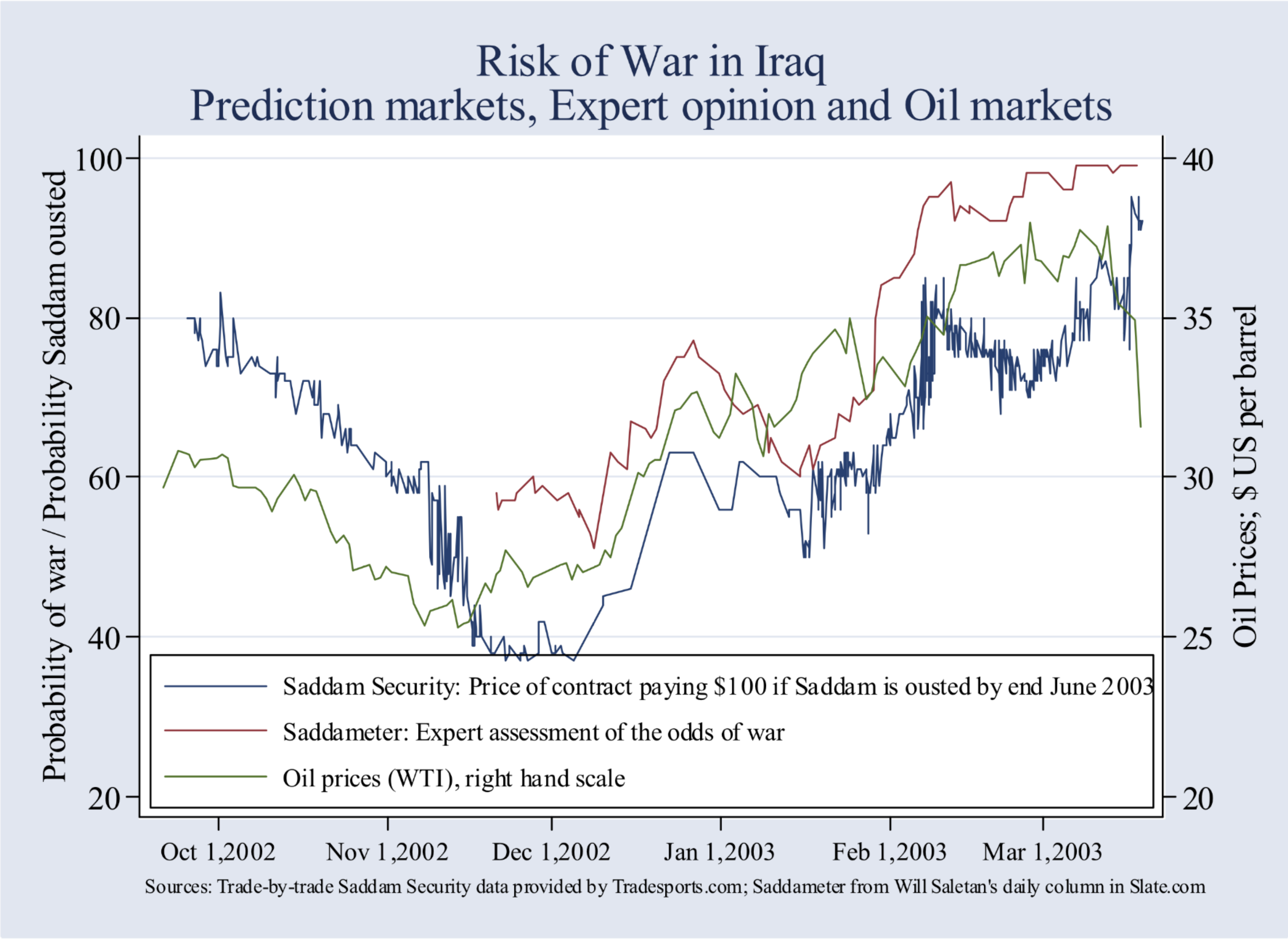
Table 2: Prediction Markets

Market	Focus	Typical turnover on an event ($US)
Iowa Electronic Markets <www.biz.iowa.edu/iem> *Run by University of Iowa*	Small-scale election markets. Similar markets are run by: UBC (Canada) <www.esm.buc.ca> and TUW (Austria) <http://ebweb.tuwien.ac.at/apsm/>	Tens of thousands of dollars (Traders limited to $500 positions)
TradeSports <www.tradesports.com> *For profit company*	Trade in a rich set of political futures, financial contracts, current events, sports and entertainment	Hundreds of thousands of dollars
Economic Derivatives <www.economicderivatives.com> *Run by Goldman Sachs and Deutsche Bank*	Large-scale financial market trading in the likely outcome of future economic data releases	Hundreds of millions of dollars
Newsfutures <www.newsfutures.com> *For profit company*	Political, finance, current events and sports markets. Also technology and pharmaceutical futures for specific clients.	Virtual currency redeemable for monthly prizes (such as a TV)
Foresight Exchange <www.ideosphere.com> *Non-profit research group*	Political, finance, current events, science and technology events suggested by clients.	Virtual currency
Hollywood Stock Exchange <www.hsx.com> *Owned by Cantor Fitzgerald*	Success of movies, movie stars, awards, including a related set of complex derivatives and futures. Data used for market research.	Virtual currency.


Iowa Electronic Markets: Predictive Accuracy Through Time
Average absolute error in predicting two-party vote shares, 1988-2000
Average absolute forecast error
(Vote Share %)
6
4
2
0
150
120
90
60
30
0
Days Until Election
Source: Author's calculations based on data available at: www.biz.uiowa.edu/iem/



Hollywood Stock Exchange
Market Forecasts of Opening Weekend Box Office Take
Actual Opening Take ($ million)
100
80
60
40
20
10
5
2
2
5
10
20
40
60
80
100
HSX Market Price = Forecast Opening Take ($ million)
Line of Best Fit
Actual=Forecast
Data from 489 movies, 2000-2003. (www.hsx.com)


Risk of War in Iraq
Prediction markets, Expert opinion and Oil markets
Probability of war / Probability Saddam ousted
Oil Prices; $ US per barrel
100
80
60
40
20
40
35
30
25
20
Saddam Security: Price of contract paying $100 if Saddam is ousted by end June 2003
Saddameter: Expert assessment of the odds of war
Oil prices (WTI), right hand scale
Oct 1,2002
Nov 1,2002
Dec 1,2002
Jan 1,2003
Feb 1,2003
Mar 1,2003
Sources: Trade-by-trade Saddam Security data provided by Tradesports.com; Saddameter from Will Saletan's daily column in Slate.com

Case Study : Google's Prediction Market

source : http://www.eecs.harvard.edu/cs286r/courses/fall10/papers/GooglePredictionMarketPaper.pdf

Case Study

"...internal prediction can provide insight into how organizations process information. Prediction markets provide employees with incentives for truthful revelation and can capture changes in opinion at a much higher frequency than surveys, allowing one to track how information moves around an organization and how it responds to external events."

Cowgill, Wolfers, and Zitzewitz 2009

Research Questions

Optimism in entrepreneurial firms : "Entrepreneur's curse" suggests that entrepreneurial firms tend to be optimistically biased about their potential for success.

Employee communication in organization : Firms pay high costs to cluster in places like Silicon Valley; prediction markets can be used as high-frequency, market-incentivized surveys to track information flows in real-time.

Social networks and information flows among investors : Prediction markets as a way to test the importance of physical proximity and social networks in facilitating information sharing.

Research Questions

Market Overview

Launched April 2005, each quarter from 2005Q2 to 2007Q3 had 25-30 markets

Question that has 2-5 mutually exclusive and exhaustive answers, e.g.
Q: “How many users will Gmail have?”
A : “Fewer than X users”, “Between X and Y”, “More than Y”.

Answer corresponds to a security that is worth one “Gooble” if the answer turns out to be correct

At the end of the quarter, Goobles were converted into raffle tickets and prizes were raffled off

Prize budget was $10,000 per quarter ($25-100 per trader)

Out of 6,425 employees who had accounts, 1,463 placed at least one trade.

Table 1. Prediction markets at Google

Type	Example	Share of markets
Demand forecasting	# of Gmail users at end of quarter	20%
Performance	Google Talk quality rating	15%
Company news	Russia office to open	10%
Industry news	Will Apple release an Intel-based Mac?	19%
Decision markets	Will users of feature A users use feature B more?	2%
Fun	How many "rotten tomatoes" will Episode III get?	33%
Unique participants		1,463
Orders		253,192
Trades		70,706
Markets run (questions)		270
Securities (answers)		1,116

Market Overview

Short selling is not allowed; traders can buy a set of securities and then sell the ones they choose.

There is no automated market maker, but several employees did create robotic traders that sometimes played this role.

Volume in “fun” and “serious” markets are positively correlated

Market Overview

Participants were not representative of Google as a whole

More likely to be in programming roles

More likely to be in Mountain View or New York campuses

More quantitative backgrounds (e.g. undergraduate major)

More interest in investing or poker (e.g. mailing lists)

Employed longer, less likely to leave after study

Slightly more senior (levels from CEO)

Market Overview

Overpricing of favorites

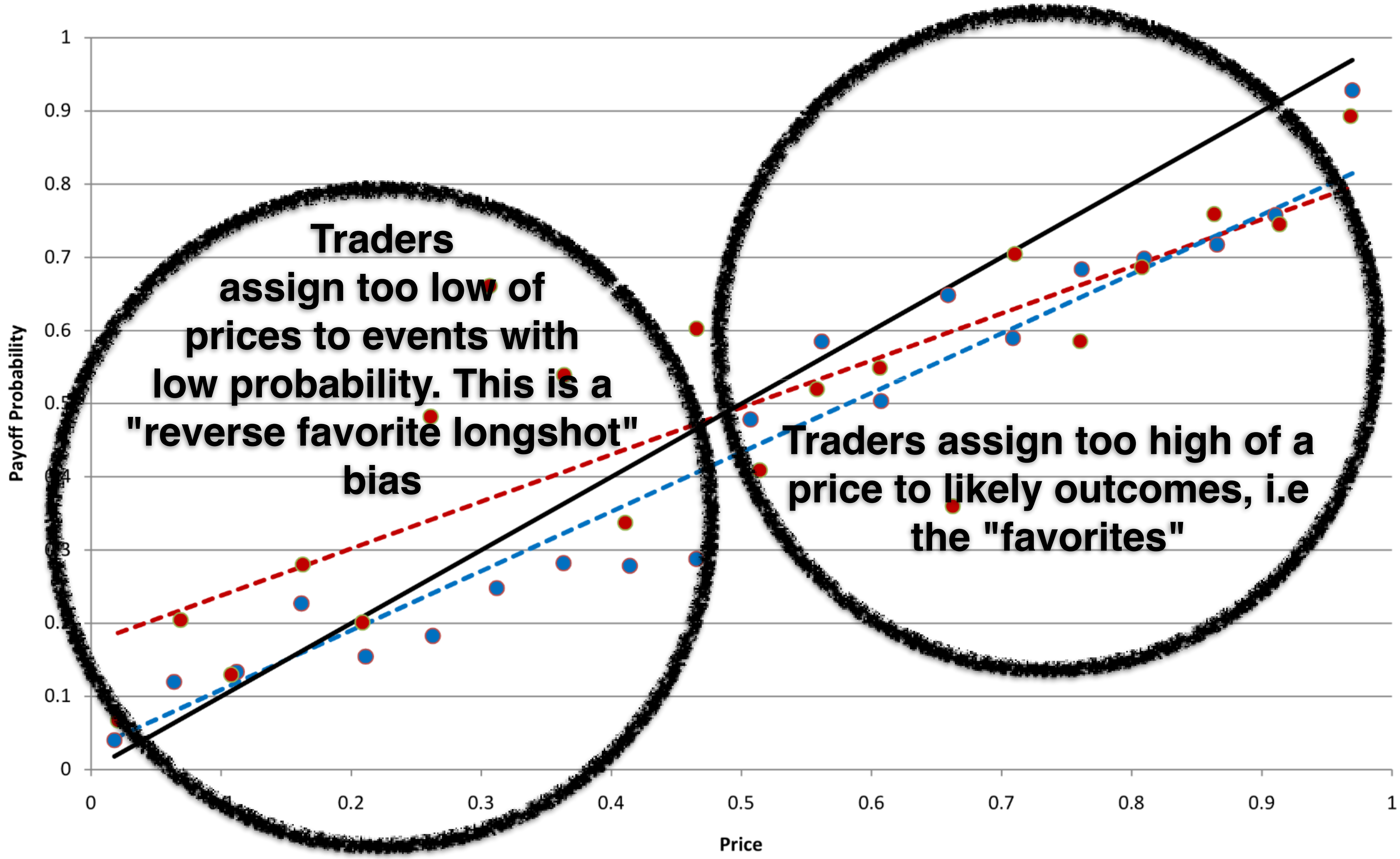
Underpricing of extreme outcomes

Short aversion

Optimism

Biases

Figure 2. Prices and Probabilities in Two and Five-outcome Markets



Trades in two (red) and five-outcome (blue) markets (22,452and 42,416, respectively) are sorted into 20 bins according to price (i.e., 0-5, 5-10, etc.), and then average price and payoff probability for the bin is plotted. Dashed lines plot regression equations using OLS.

Short aversion :

1,747 instances where the bid prices of the securities in a particular market added to more than $1

Arbitrage opportunity from buying a bundle of securities for $1 and then selling the components

Only 495 instances where the ask prices added to less than 1 (arbitrage opportunity of buying the components of a bundle for less than $1).

This is called "short aversion," bias toward holding long positions rather than short ones

Markets overpriced securities tied to optimistic outcomes by 10 percentage points.

The optimistic bias was significantly greater on and following days when Google stock appreciated.

Partly driven by the trading of newly hired employees; employees with longer tenure were better calibrated.

Biases

The optimistic bias was largest in :

Two outcome markets

Early in the sample period

Earlier in each quarter.

Categories where outcomes are under the control of Google employees i.e. company news (office openings), performance (project completion and product quality).

Biases

Table 5. Optimistic bias in the Google markets

	Obs.	Avg price	Avg payoff	Return (SE)	
All markets	70,706	0.357	0.342	-0.015***	(0.003)
Markets with implication for Google	37,910	0.310	0.293	-0.017***	(0.004)
Two-outcome markets with implication for Google	9,023	0.509	0.492	-0.017***	(0.006)
Best outcome for Google	4,556	0.456	0.199	-0.256***	(0.063)
Worst	4,467	0.563	0.790	0.227***	(0.064)
Five-outcome markets with implication for Google	26,511	0.239	0.222	-0.017***	(0.005)
Best outcome for Google	5,592	0.244	0.270	0.027	(0.040)
2nd	5,638	0.271	0.246	-0.025	(0.066)
3rd	5,539	0.296	0.179	-0.118**	(0.053)
4th	5,199	0.206	0.178	-0.028	(0.041)
Worst	4,543	0.162	0.236	0.074	(0.056)

Notes: Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets.

Biases

Table 6. Optimism bias by subsample
Dependent variable: returns to expiry
Independent variable: optimism of security (scaled -1 to 1)

Sample	Obs.	Unique markets	Coeff.	S.E.	Constant	S.E.
All markets with implication for Google	37,910	157	-0.105***	(0.036)	-0.013***	(0.004)
Company News	7,430	22	-0.182***	(0.064)	-0.015**	(0.006)
Demand forecasting	12,387	51	-0.042	(0.042)	-0.022***	(0.008)
External News	6,898	42	0.100**	(0.041)	-0.011	(0.009)
Performance (e.g., schedule, product quality)	10,057	38	-0.211***	(0.077)	0.000	(0.010)
2 outcome markets	9,023	50	-0.242	(0.227)	-0.015***	(0.005)
5 outcome markets	26,511	96	-0.013	(0.032)	-0.017***	(0.005)
2005 (Q2 to Q4)	12,224	50	-0.210***	(0.065)	-0.013***	(0.005)
2006 (Q1 to Q4)	20,847	67	-0.026	(0.039)	-0.019***	(0.006)
2007 (Q1 to Q3)	4,839	44	-0.086	(0.066)	-0.007	(0.006)
First month of calendar quarter	15,397	106	-0.121**	(0.054)	-0.010*	(0.006)
Second month	14,234	120	-0.105**	(0.045)	-0.012**	(0.006)
Third month	8,279	105	-0.073**	(0.034)	-0.023**	(0.009)

Notes: Each row is a regression. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets. Optimism is scaled so that the worst outcome for Google is coded -1 and the best is coded 1. I.e., (-1, 1), (-1, 0, 1), (-1, -0.33, 0.33,1), and (-1, -0.5, 0, 0.5, 1) for 2, 3, 4, and 5 outcome markets, respectively.

Biases

Table 9. Regressions predicting trade characteristics from traders' attributes
Dependent variable: Security characteristic*(1 if buy, -1 if sell)

Dependent variable	Optimism (scaled -1 to 1)		Favorite Price - 1/N		Extreme Abs(Optimism)		Buy		Return	
Relationship with returns	Neg.		Neg.		Pos.		Neg.			
Coder? (Participated in code review)	0.033		-0.102	***	-0.284	***	-0.404	***	0.072	***
	(0.049)		(0.022)		(0.081)		(0.139)		(0.023)	
Level (Distance from CEO)	0.006		0.004		0.066	**	0.102	**	0.023	**
	(0.019)		(0.007)		(0.029)		(0.040)		(0.009)	
Hire date (in years)	0.051	**	-0.032	***	-0.093	***	-0.224	***	0.005	
	(0.021)		(0.008)		(0.034)		(0.041)		(0.009)	
NYC-based	-0.169		-0.050	*	0.028		0.014		0.017	
	(0.105)		(0.029)		(0.086)		(0.121)		(0.024)	
Mountain View (MTV)-based	-0.119		-0.101	***	0.161	*	-0.005		0.045	
	(0.105)		(0.031)		(0.096)		(0.122)		(0.029)	
Distance to Noname Café in miles (0 if non-MTV)	0.032		0.085	*	-0.161		-0.597	**	0.069	
	(0.125)		(0.047)		(0.179)		(0.294)		(0.043)	
Experience [Ln(1 + previous trades)]	-0.014		-0.044	***	-0.049	***	-0.094	***	0.026	***
	(0.011)		(0.004)		(0.019)		(0.031)		(0.003)	
Trades	37,910		70,706		37,910		70,706		70,706	
Unique traders	1,126		1,463		1,126		1,463		1,463	

Note: Each observation is a side of a trade. Regressions use trader chatacteristics to predict security characteristics, multipled by -1 if the side in question is a sell. Regressions include trade fixed effects and a dummy variable for one particular extremely prolific trader. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Biases

New hires more likely to take optimistic positions and more likely to hold short positions, but less likely to over invest in favorites...

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Biases

Coders act the same way...

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Biases

More experienced traders are more likely to trade against the market's biases...

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Mountain View (MTV)-based	-0.119		-0.101	***	0.161	*	-0.005		0.045	
	(0.105)		(0.031)		(0.096)		(0.122)		(0.029)	
Distance to Noname Café in miles (0 if non-MTV)	0.032		0.085	*	-0.161		-0.597	**	0.069	
	(0.125)		(0.047)		(0.179)		(0.294)		(0.043)	
Experience [Ln(1 + previous trades)]	-0.014		-0.044	***	-0.049	***	-0.094	***	0.026	***
	(0.011)		(0.004)		(0.019)		(0.031)		(0.003)	
Trades	37,910		70,706		37,910		70,706		70,706	
Unique traders	1,126		1,463		1,126		1,463		1,463	

Note: Each observation is a side of a trade. Regressions use trader chatacteristics to predict security characteristics, multipled by -1 if the side in question is a sell. Regressions include trade fixed effects and a dummy variable for one particular extremely prolific trader. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Biases

Study information flows using measures of "proximity" :

Geographical
Organizational
Social
Demographic

Correlations

Take the participants in each trade to be exogenous. (This is reasonable, since it would be largely determined by when they have time available e.g., while code is being compiled and tested.)

Predict the size and direction of the trades from the prior positions of proximate colleagues

Correlations

If trader i buys a security from trader j at some price, we can infer that i's subjective belief about its payoff probability is higher than j's.

If a third trader k holds a large long position in the security prior to the trade, we can infer that her subjective belief about the value of the security is higher than if she were holding a short position.

Test whether the buyer in a particular transaction is more proximate to other traders with prior long positions.

Correlations

Table 10. Geography and trading correlations

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)
Geographical proximity						
Same city	0.006	0.000	0.003	-0.001	-0.002	-0.002
	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor				0.025 ***	-0.019 *	-0.020 *
				(0.009)	(0.010)	(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

Table 10. Geography and trading correlations

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

Worst colum[illegible]dings ever!

	(1)	(2)	(3)	(4)	(5)	(6)
Geographical proximity						
Same city	0.006	[illegible]	0.003	-0.001	-0.002	[illegible]
	(0.004)	[illegible]	(0.007)	(0.006)	(0.006)	[illegible]
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor				0.025 ***	-0.019 *	-0.020 *
				(0.009)	(0.010)	(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

Table 10. Geography and trading correlations
Dependent variable: net shares purchased (normalized)
Independent variables: Proximity-weighted normalized sums of colleagu

Mystery dimension of increasingly narrowing definition of proximate

Geographical proximity						
Same city	0.006	0.000	0.003	-0.001	-0.002	-0.002
	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor				0.025 ***	-0.019 *	-0.020 *
				(0.009)	(0.010)	(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

kind of in same general area

one person sitting on the other's lap

Table 10. Geography and trading correlations

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagu

Geographical proximity						
Same city	0.006	0.000	0.003	-0.001	-0.002	-0.002
	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor				0.025 ***	-0.019 *	-0.020 *
				(0.009)	(0.010)	(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

kind of in same general area

one person sitting on the other's lap

Table 10. Geography and trading correlations
Dependent variable: net shares purchased (normalized)
Independent variables: Proximity-weighted normalized sums of colleagu

Most correlation between employees sharing an office

Geographical proximity						
Same city	0.006	0.000	0.003	-0.001	-0.002	-0.002
	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor				***	-0.019 *	-0.020 *
					(0.010)	(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

kind of in same general area

one person sitting on the other's lap

Table 10. Geography and trading correlations

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagu

Geographical proximity						
Same city	0.006	0.000	0.003	-0.001	-0.002	-0.002
	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Proximity within city		0.010 *	-0.004	-0.014 *	-0.014 *	-0.013
(100ft/distance between buildings, min = 0, max = 1)		(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Same building			0.022 ***	0.008	-0.001	0.002
			(0.005)	(0.007)	(0.007)	(0.007)
Same floor						-0.020 *
						(0.010)
Proximity on floor					0.090 ***	0.053 ***
(10ft/distance between offices, min = 0, max = 1)					(0.015)	(0.017)
Same office						0.055 ***
						(0.016)
Building information missing for either party		-0.004	-0.005	0.000	0.000	-0.001
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Room information missing for either party				-0.021 ***	-0.025 ***	-0.025 ***
				(0.008)	(0.008)	(0.008)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.0352	0.0354	0.0359	0.0378	0.0395	0.0399

Correlation decreases with distance, even on the same floor

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Correlations

Table 11. Social and work relationships and correlated trading

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)
Social connections						
Self-reported professional relationship?	0.016 *	0.009	0.010	0.012	0.017	0.020 *
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Self-reported friendship?	-0.001	-0.044 **	-0.050 **	-0.050 **	-0.040 *	-0.054 **
	(0.019)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)
# of overlapping email lists	0.000	-0.001	-0.003	-0.004	-0.005	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Work history						
Reviewed each other's code		0.028 ***	0.027 ***	0.019 **	0.023 **	0.017 *
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Overlapped on project?		0.034 ***	0.010	-0.031 **	-0.050 ***	-0.026
		(0.012)	(0.014)	(0.015)	(0.016)	(0.016)
Organizational proximity						
Same SVP (one level below CEO)			0.016 ***	0.014 **	0.015 ***	0.015 **
			(0.006)	(0.006)	(0.006)	(0.006)
Same "2-Levels-below-CEO" manager			-0.011 *	-0.008	-0.007	-0.007
			(0.006)	(0.008)	(0.008)	(0.008)
Same "3-Levels-below-CEO" manager			0.033 **	-0.018	-0.026	-0.026
			(0.014)	(0.017)	(0.017)	(0.017)
1-2 steps away on org chart				0.102 ***	0.061 ***	0.068 ***
				(0.018)	(0.017)	(0.017)
3 steps away on org chart				-0.016	-0.020 *	-0.019 *
				(0.011)	(0.011)	(0.011)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Geographic proximity variables (from Table 10, cols 6)					X	X
Demographic similarity						X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.035	0.0357	0.0372	0.0392	0.0423	0.0433

Notes: The last column includes 8 variables capturing the pre-trade positions of colleagues who are similar along a demographic dimension (attended the same undergraduate school, had the same undergrad major, are both or neither in programming roles at Google, are both native English speakers, share a common non-English native language, or are similar according to three commonly studied demographic variables).

Table 11. Social and work relationships and correlated trading

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)
Social connections						
Self-reported professional relationship?	0.016 *	0.009	0.010	0.012	0.017	0.020 *
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Self-reported friendship?	-0.001	-0.044 **	-0.050 **	-0.050 **	-0.040 *	-0.054 **
	(0.019)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)
# of overlapping email lists	0.000	-0.001	-0.003	-0.004	-0.005	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Work history						
Reviewed each other's code		0.028 ***	0.027 ***	0.019 **	0.023 **	0.017 *
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Overlapped on project?		0.034 ***	0.010	-0.031 **	-0.050 ***	-0.026
		(0.012)	(0.014)	(0.015)	(0.016)	(0.016)
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]
			(0.014)	(0.017)	(0.017)	(0.017)
1-2 steps away on org chart				0.102 ***	0.061 ***	0.068 ***
				(0.018)	(0.017)	(0.017)
3 steps away on org chart				-0.016	-0.020 *	-0.019 *
				(0.011)	(0.011)	(0.011)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Geographic proximity variables (from Table 10, cols 6)					X	X
Demographic similarity						X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.035	0.0357	0.0372	0.0392	0.0423	0.0433

Notes: The last column includes 8 variables capturing the pre-trade positions of colleagues who are similar along a demographic dimension (attended the same undergraduate school, had the same undergrad major, are both or neither in programming roles at Google, are both native English speakers, share a common non-English native language, or are similar according to three commonly studied demographic variables).

"We find that measures of social connections, either self-reported on the April 2006 survey or inferred from subscriptions to email lists, do not explain trading correlations well. A history of reviewing each other's code or overlapping on a project does, however."

Table 11. Social and work relationships and correlated trading

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)
Social connections						
Self-reported professional relationship?	0.016 *	0.009	0.010	0.012	0.017	0.020 *
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Self-reported friendship?	-0.001	-0.044 **	-0.050 **	-0.050 **	-0.040 *	-0.054 **
	(0.019)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)
# of overlapping email lists	0.000	-0.001	-0.003	-0.004	-0.005	-0.007
						(0.005)
Work history						
Reviewed each						0.017 *
						(0.009)
Overlapped on						-0.026
						(0.016)
Organizational proximity						
Same SVP (one level below CEO)			0.016 ***	0.014 **	0.015 ***	0.015 **
			(0.006)	(0.006)	(0.006)	(0.006)
Same "2-Levels-below-CEO" manager			-0.011 *	-0.008	-0.007	-0.007
			(0.006)	(0.008)	(0.008)	(0.008)
Same "3-Levels-below-CEO" manager			0.033 **	-0.018	-0.026	-0.026
			(0.014)	(0.017)	(0.017)	(0.017)
1-2 steps away on org chart				0.102 ***	0.061 ***	0.068 ***
				(0.018)	(0.017)	(0.017)
3 steps away on org chart				-0.016	-0.020 *	-0.019 *
				(0.011)	(0.011)	(0.011)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Geographic proximity variables (from Table 10, cols 6)					X	X
Demographic similarity						X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.035	0.0357	0.0372	0.0392	0.0423	0.0433

"The single best explanator is being within one or two steps on the organization chart (i.e., sharing a manager, being someone's manager, or being someone's manager's manager)."

Notes: The last column includes 8 variables capturing the pre-trade positions of colleagues who are similar along a demographic dimension (attended the same undergraduate school, had the same undergrad major, are both or neither in programming roles at Google, are both native English speakers, share a common non-English native language, or are similar according to three commonly studied demographic variables).

Correlations

Table 11. Social and work relationships and correlated trading

Dependent variable: net shares purchased (normalized)

Independent variables: Proximity-weighted normalized sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)
Social connections						
Self-reported professional relationship?	0.016 *	0.009	0.010	0.012	0.017	0.020 *
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Self-reported friendship?	-0.001	-0.044 **	-0.050 **	-0.050 **	-0.040 *	-0.054 **
	(0.019)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)
# of overlapping email lists	0.000	-0.001	-0.003	-0.004	-0.005	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Work history						
1-2 steps away on org chart				0.102 ***	0.061 ***	0.068 ***
				(0.018)	(0.017)	(0.017)
3 steps away on org chart				-0.016	-0.020 *	-0.019 *
				(0.011)	(0.011)	(0.011)
Other controls						
Trade fixed effects	X	X	X	X	X	X
Initial position	X	X	X	X	X	X
Geographic proximity variables (from Table 10, cols 6)					X	X
Demographic similarity						X
Observations	140,768	140,768	140,768	140,768	140,768	140,768
R-squared	0.035	0.0357	0.0372	0.0392	0.0423	0.0433

Notes: The last column includes 8 variables capturing the pre-trade positions of colleagues who are similar along a demographic dimension (attended the same undergraduate school, had the same undergrad major, are both or neither in programming roles at Google, are both native English speakers, share a common non-English native language, or are similar according to three commonly studied demographic variables).

"...employees most likely to have correlated trading are those who are proximate organizationally or geographically and are not friends. One admittedly speculative interpretation of this result is that friends have better things to discuss than the subjects of prediction markets, while the prediction markets provide a topic of conversation for those who are not friends."

Prediction markets are simple securities markets that allow traders to profit from correct private information about the outcomes of future events

Individuals' desires to make money allows the market to aggregate all of the traders' beliefs, reflected in the price

These markets have been shown to behave efficiently, and provide correct predictions with high accuracy

Markets can be used by companies and researchers to make business decisions, study organizational structures, and measure social networks

Using prediction markets for this kind of research is more "real-time" and possibly more accurate than using retrospective surveys

Summary

Prediction Markets
by Justin Wolfers and Eric Zitzewitz
http://www.nber.org/papers/w10504.pdf

Using Prediction Markets to Track Information Flows: Evidence from Google
by Bo Cowgill, Justin Wolfers, and Eric Zitzewitz
http://www.eecs.harvard.edu/cs286r/courses/fall10/papers/GooglePredictionMarketPaper.pdf

Sources