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# Small Is Beautiful: An Empirical Study of Complementarities, Substitution and Spillovers in the OECD Countries' IT Industry

**YenChun Chou, Robert J. Kauffman, and Benjamin Shao**

**W. P. Carey School of Business**
**Arizona State University**

Workshop in IS and Economics, Phoenix, AZ, December 14-15, 2009

## Gist of the Study

- "Essentially, all models are wrong, but some are useful."
  – Box and Draper (1987)
- Explore the impacts of IT goods imports and IT offshoring on productivity and efficiency of IT industry in 14 OECD countries from 2000-2006
  - "Small is beautiful" approach to empirical research with hardly any data at all

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## Nuts and Bolts

- Integrated theories on knowledge spillover, substitution, and complementarities to study performance of IT industry
- Methods:
  - Productivity analysis: Cobb-Douglas function
  - Efficiency analysis: Two-stage stochastic frontiers
- Robustness check: small sample statistical
  re-sampling technique: *jackknifing*

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## Main Attractions

- Policy implication: "Is globalization good for domestic IT industries?" – Yes and no
- Welfare tradeoff involving IT outsourcing
- "Empiricism in the small:" what matters most is the *quality* of the problem being studied, not *availability* or *amount* of data that investigator uses to study it

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# Come and See Us!


"We're not adapting quickly to the new global economy. But yesterday I had Mexican food for lunch and today I'm having Chinese. It's a start!"

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## An Experimental Analyses on the Impact of Revelation Policies in Sequential Auctions with Cost Uncertainty

Tim Cason

Karthik Kannan

Ralph Siebert

# Motivation

- Theoretical models on information sharing: incentive for oneself to learn vs. inhibit learning by an opponent (e.g., Anand and Goyal, 2009; Kannan, 2009)

- Given the steep rationality requirements, are these effects observed in real-life?

- Kannan (2009): Sequential private-value auction with different revelation policies
  - Example: 2 bidders with an arbitrary probability of being one of two types
  - IIP: only winner's bid revealed between auctions
    - Incentive for oneself to learn about opponent
  - CIP: all bids are revealed between auctions
    - Desire to prevent an opponent from learning

# Experimental Design

- Two values of the prob. of low cost opponent: 0.5 and 0.9

- Within a session, we considered different ϴ treatments

- Across sessions, we varied policy (CIP or IIP)

- Each session had 50 rounds—25 for each treatment

- 12 subjects in each session
  - Each participant limited to one session
  - Randomly paired to avoid repeated game learning effects

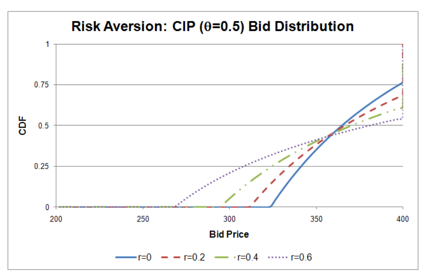
## Overview of Results

| Policy | | CIP | | IIP | |
|---|---|---|---|---|---|
| Prob. of low cost opponent | | 0.5 | 0.9 | 0.5 | 0.9 |
| All periods | Mean of the first stage bid | 355.37 | 298.14 | 368.33 | 287.06 |
| | % of faking bids in the first stage | 8.16% | 11.78% | 2.21% | 0.99% |
| Theoretical model | Expected first stage bid | 366.08 | 339.33 | 385.77 | 309.97 |
| | % of faking | 23.95% | 28.85% | 0% | 0% |

Remarkable consistency with theory involving risk neutral bidders

## Additional Insights

- We also develop a theoretical model including risk aversion
- Structural model to estimate risk aversion
- Given risk aversion, they are not able to correctly predict optimal actions
- Learning behavior from other bidders



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# Incentive and Equilibrium of User Content Generation

**Huaxia Rui and Andrew Whinston**

**University of Texas at Austin**

## The Age of User Generated Content

- One of the most important advantages of the Internet is that it has enabled people to access a huge amount of content at a very low cost.
- Part of this is because of powerful search engines like Google, Yahoo! and Bing, which are freely available to everyone.
- Equally important is the abundance of free content available on the Internet, an ever growing proportion of which is now generated by ordinary Internet users.

## Is It Sustainable?

- A fundamental question is what motivates people to contribute content.
- Producing content is often viewed as cooperative behavior while consuming without contributing content is regarded as a non-cooperative behavior.

## Time Is Money

- We view an online community as an economy where time is money.
- Consumers spend their time on the consumption of content generated by others.
- Producers invest their time producing content to be consumed by others, and in return, get attention from consumers.

## An Economy in Equilibrium

- Users in an online community self-selects into the group of consumers, producers, or prosumers. We give characterization of such segmentation.
- With certain conditions on the utility function, the group of prosumers vanish.
- We obtain empirical support by data collected from Twitter.

## The Social Efficiency of Fairness

An Information Economics Approach to Innovation

Gavin Clarkson,
Assistant Professor
University of Michigan
School of Information
School of Law
Native American Studies

Marshall Van Alstyne,
Associate Professor
Boston University & MIT

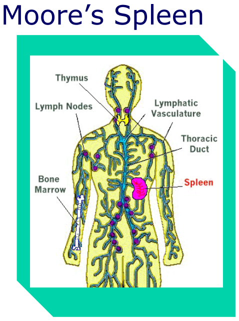
Paper on http://ssrn.com/author=253298.

We all lose when innovative activity that should take place does not take place because of avoidable market failures.

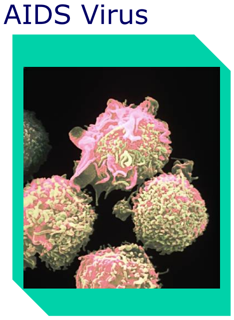
## Unfair Outcomes?

Storm Trooper

Moore's Spleen




AIDS Virus



British prop designer is sued by George Lucas for $10m after producing the outfits from his own original moulds and selling them for up to £1,800 each. Andrew Ainsworth has countersued Lucasfilm for a share of the £6bn merchandising revenue. [illegible] The unanticipated issue is who owns copyright?

[illegible] "I told Moore, 'I suppose I should tell you [illegible] could make money from this.' He said 'Well, are you gonna give me some?' And I said 'Well, that's not in my plan at this time, but if you want to we can talk about it.' He just laughed and let it lapse."

National Cancer Institute (US) patents an AIDS test based on a [illegible] Institut Pasteur (France) [illegible] assay technique provided by the British. [illegible] "I'm afraid that the cooperation which has existed between our two institutions, and more generally between scientists, will be greatly damaged."

## Three Major Claims

1. Fairness increases the rate of innovation. Welfare improves both in the absolute sense of enabling new projects and in the relative sense of reordering the social sort order of which projects agents undertake.

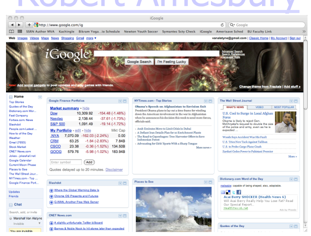
2. We prove self-interest alone is sufficient to justify fairness for a single event. No need for reciprocity, repeated play, or altruism.

3. We argue that liability rather than property rules can be more conducive to innovation based on

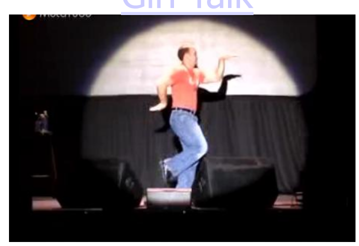
## Recombinant Information & Remix Culture

Robert Amesbury

Girl Talk




iGoogle & News



Evolution of Dance

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# DEMAND FOR RESOURCE ALLOCATION TECHNOLOGIES: ADOPTION OF HOSPITAL SURGICAL MANAGEMENT SOFTWARE

**Eli M. Snir* and Jeffrey S. McCullough****

*** Olin Business School, Washington University in St. Louis**
**** School of Public Health, University of Minnesota**

## Background

- **2 levels of scheduling**
  - **Time required for an individual procedure**
    - HSS problem I
      - Allocating insufficient time per procedure ($c_u$) more costly than allocating too much time ($c_o$) . Leads to HS room idle time
        - » Contrasts Olivares, Terwiesch, and Cassorla (2004)
  - **Allocating HSS capacity to specialties**
    - HSS problem II: Block Scheduling is fairly common (Gupta 2007)
      - As opposed to Open Scheduling or Hybrid

## Hypotheses

- H1: *HSS management system adoption increases in specialties served*
  - Although it is independent of the individual specialties served by HSS
- H2: *HSS management system adoption increases in HSS capacity*

## Analysis

- Hazard rate varies by hospital traits
  - Likelihood of IT adoption
- Key drivers
  - Total Capacity
  - Scope

| | exp(b) | |
|---|---|---|
| | Model 1 | Model 2 |
| OR # (number of units) | 1.09*** | 1.22*** |
| Surgical volume | 1.000 | 1.000 |
| OR # x Surgical volume | 1.000 | 1.000 |
| Number of Services (Scope) | | 1.17** |
| Scope x Surgical Volume | | 1.000 |
| OR # x Scope | | 0.97** |
| Obstetrics | 0.884 | |
| Orthopedic / Sports Medicine | 0.982 | |
| Cardiac Surgery | 1.016 | |
| Open Heart Surgery | 1.007 | |
| Neonatal Care | 1.228 | |
| Surgical Oncology | 1.35* | |
| Transplant Surgery | 1.043 | |
| Academic | 0.589 | 0.869 |
| For-profit | 1.51** | 1.60*** |
| Government owned | 1.162 | 1.229 |
| System member | 1.39** | 1.43*** |

Note that time dummies were included but not reported

## Summary

1. Formal OR model of the scheduling problems
2. Data: broad, longitudinal panel of US hospitals
3. Adoption patterns consistent with hypotheses

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# Co-Creation of Value in a Platform Ecosystem: The Case of Enterprise Software

**Marco Ceccagnoli, Chris Forman, Peng Huang and D.J. Wu**

**Georgia Institute of Technology**

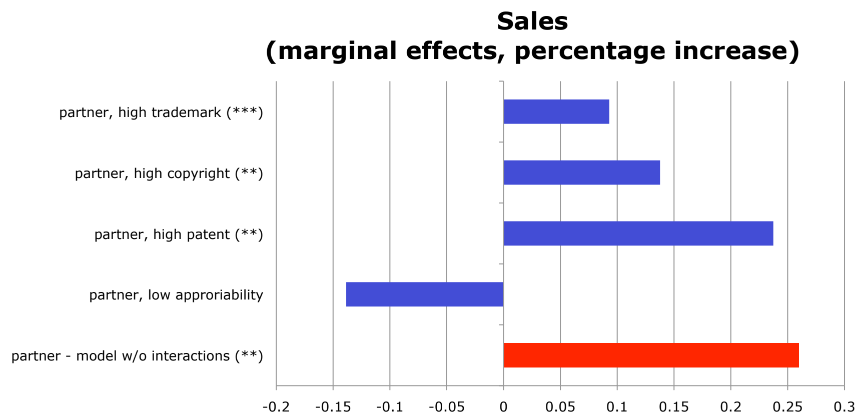
## Research Questions

- Platform technology owners nurture their platform ecosystems to seek complementary innovation
  - How does the decision to join a platform ecosystem affect small ISVs' business performance?
  - How do the performance impacts of partnering vary according to ISVs' appropriation strategies?
- Motivation
  - Limited understanding of the value of platform ecosystem
  - Ecosystem partnership is different from other inter-firm alliances
  - Few studies investigate value creation and value appropriation at the same time

## Methodology

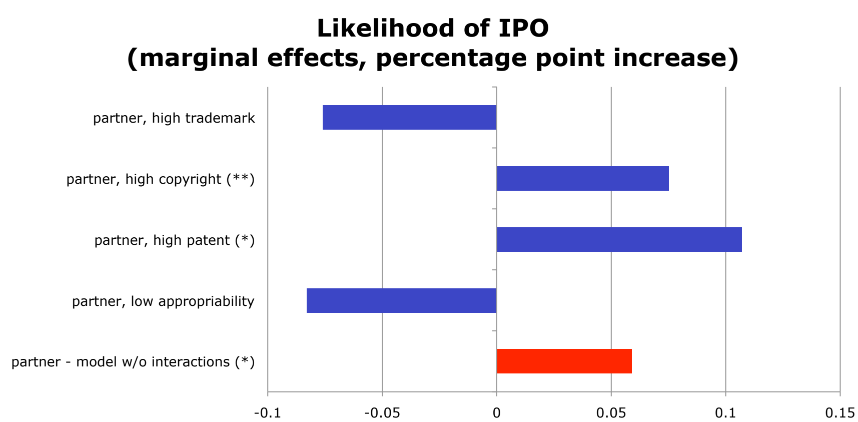
- Theoretical framework
  - Inter-firm alliances
  - Innovation commercialization
- Empirical exercises
  - We assemble a unique longitudinal data set of 1200+ ISV decisions to join SAP's platform over 1996-2004
  - Evaluate the effect of platform participation on the performance of small ISVs
  - Fixed effects models with ISV sales and likelihood of IPO as dependent variable
  - Potential econometric issues: reverse causality and omitted variable bias
    - Address through instrumental variables and a falsification exercise

# Key Findings - Sales




*: significant at .10 level
**: significant at .05 level
***: significant at .01 level

# Key Findings - IPO




*: significant at .10 level
**: significant at .05 level
***: significant at .01 level

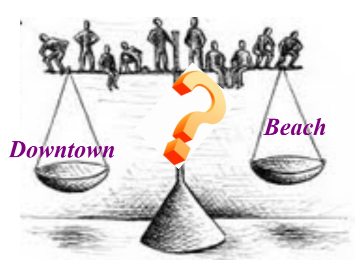
## The Economic Impact of User-Generated Content on the Internet: Combining Text Mining with Demand Estimation in the Hotel Industry

Anindya Ghose Panos Ipeirotis Beibei Li

Leonard N. Stern School of Business,
New York University

WISE 2009

*What* are the economic values of WOM? *How* can I locate a hotel with the "best value" under the existence of online UGC?




***Online Reviews?***

- Numerical rating:
  ( 1-D quality, Self-selection bias, Bimodal)
- Textual content: "Qualitative" nature

***Travel Search Engines?***

- Single ranking criterion, i.e., price, class.
- Multi-dimensional preference
- Consumer heterogeneity

**Main Goal:** Economic effect of UGC on product sales beyond the single-dimension numeric rating.

**Method:** Combine Text Mining, Image Classification, Social Geo-Tagging with Structural Modeling for Demand Estimation..

## Data

Transaction data: *Travelocity.com,* 2117 US hotels, 2008/11-2009/1

Service characteristics:

- JavaScript parsing engines: *TripAdvisor & Travelocity*
- Text Mining: Review-based content: "Rating", "Volume", "Subjectivity", "Readability", "Disclosure of Reviewer Identity"

Location characteristics:

- Social geo-tags: *Geonames.org,* "Public transportation"
- GeoMapping Search Tools: *Microsoft Virtual Earth SDK*
- Image Classification: "Beach", "Downtown"
- Human Annotations: *Amazon Mechanical Turk (AMT),* "Lake/River", "Highway"

## Random Coefficient-based Model

This model captures consumer heterogeneity from two levels: Purchase Context and Product Characteristics. It defines a consumer's choice decision follows 2 steps:

Step 1: Choose a "*Travel Context*" subset

*Business Trip, Friends Getaway, Family Trip, Romantic Getaway,…*

Step 2: Within the subset, choose a hotel based on evaluation of quality.

$$u_{ij_t^k} = X_{j_t^k}\beta_i - \alpha_i P_{j_t^k} + \xi_{j_t^k} + \varepsilon_{it}^k,$$

- $\beta_i$ and $\alpha_i$ ---- Consumer-specific *random coefficient*
- $\varepsilon_{it}^k$ ---- "Travel Context"-specific *shock*
- Estimation Strategy: *Contraction Mapping*, *GMM*

(Berry & Pakes 1995, 2007, Song 2008)

## Consumer Surplus-based Ranking

We propose a new ranking strategy based on the consumer surplus derived from our model:

$$CS_{j^k} = \sum_t \frac{1}{\alpha} \overline{\mu}_{ij^k t}$$

**Personalization and User Study:**

- We extend this ranking approach to a personalized level by interacting with consumer demographics (*income, age group*)
- Blind, pair-wise comparison with current baselines
- Other cities in different areas, i.e., LA, SFO, Orlando

## User Content Generation and Usage Behavior in Mobile Multimedia Settings: A Dynamic Structural Model of Learning

**Anindya Ghose and Sang-Pil Han**
**New York University**
**Stern School of Business**

## Content Generation and Usage in Mobile Multimedia Settings

- Mobile Content Services Industry **$ 200 billion market** in 2008 worldwide.
- **Two most frequently visited forums** for mobile users:
  - Multimedia Internet **social networking and community (SNC) sites**: Facebook, MySpace, Cyworld etc.
  - Multimedia **mobile portal sites**: portal sites created by the mobile phone companies.
  - Distinction between 2 website categories important for **mobile advertising.**
- Advertisers are grappling with what kinds of websites they can use to **monetize UGC**.

## Model

- What is the **underlying mechanism of user content generation and usage behaviors** in mobile multimedia settings?
  - "Content match value" model vs. "Content quality" model
- How accurate are the two kinds of **sources of learning**?
  - Direct experience vs. Indirect experience (Word-of-mouth)
- We develop a **dynamic structural model**.
  - Users do not know their match value with each content type, but **receive signals** which allow them to **update their beliefs** in a Bayesian fashion (DeGroot 1970).
  - We solve a **single agent, dynamic, discrete choice problem** by dynamic programming (DP) to derive a value function using **Bellman's equation**.
  - We estimate the model using simulated maximum likelihood (SML) method. This method is known as the **nested fixed point algorithm** (NFXP).

## Data/ Key Findings/ Discussion

- **70,923 individual-level user activity data of 500 3G users**
  - **Voice ca**lls/ text/ multimedia message data made by the same user
  - Content activity records of network neighbors of each of the 500 users
- We find that “**content match value” model better explains** than “content quality model” in both in-sample and out-of-sample data.
- The **accuracy of direct signals is higher** than that of indirect signals (WOM).
- Policy simulations suggest **insights for mobile advertising and targeting strategies**.
  - Embed advertisements in multi-media content on mobile portal sites.
  - Target high quality content to highly mobile users

## Summary

1. User-generated content in mobile multimedia settings
2. A dynamic structural model of learning
3. Unique data of individual-level user activity and activity of network neighbors of the user
4. Policy simulations & counterfactuals

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# Social Networks as Signaling Mechanisms: Evidence from Online Peer-to-Peer Lending

**Mingfeng Lin, Siva Viswanathan and N.R. Prabhala**

**University of Maryland, College Park**

## Goals

- Economic value of online social networks
- Context: online peer-to-peer lending
  - Decentralized online market for microloans
- Why?
  - Objectively measurable social networks
  - Information asymmetry in financial lending
  - Objective outcomes (funding probability; interest rate; risks of default)
- Research Questions
  - Does a borrower’s online social network add value over and above the hard credit information?
  - If so, what aspects of these networks matter? (structural vs. relational)

## Data & Empirical Models

- Data
  - Prosper.com loan requests (Jan 2007 – May 2008)
- Empirical models
  - Funding probability: Probit model
  - Interest rate: Heckman model
  - Risks of default: Cox proportional hazards model
- Variables
  - Hard credit information (credit grades, debt-to-income ratio etc.)
  - Network information (friendship network & groups)
  - Auction characteristics
  - Others (text, image, outside interest rate, etc.)

## Key Findings

- Can online social networks serve as a signaling mechanism?
  - It depends. Identity, role and action of friends matter more than mere presence.
  - True for both friendship and group network
  - Negative social capital does exist (inaction of friends)
- Usury law
- Hard credit information

## Summary

- Pipes vs. Prisms
  - Poldony (2001)
  - Evidence:
    - Networks as a "Prism"
    - Mitigates information asymmetry
- Design of microfinance / microlending markets
- Role of technology in hardening soft information

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# The Longer Tail:
## The Changing Shape of Amazon's Sales Distribution Curve

**Erik Brynjolfsson*, Yu (Jeffrey) Hu**, Michael D. Smith*****

*** MIT**
**** Purdue University**
***** Carnegie Mellon University**

# The Long Tail Literature

- Book Market
  - Brynjolfsson, Hu, and Smith (2003)
- Anderson (2004)
- Video and Music Markets:
  - Elberse and Oberholzer-Gee (2008)
  - Chellappa et al. (2007)
- Drivers of the Long Tail
  - Brynjolfsson, Hu, and Smith (2008)
- The same forces that created the Long Tail may make it longer
  - Lower search costs, cheaper "shelf space", better recommendation tools

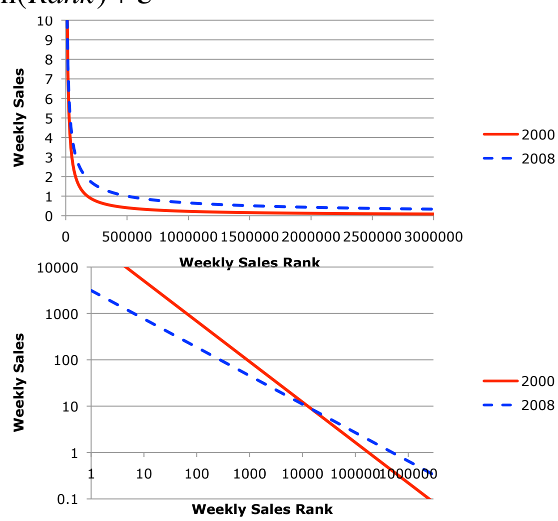
# Amazon's Long Tail in 2000 vs. 2008

$$\ln(Sales) = \beta_0 + \beta_1 \ln(Rank) + \varepsilon$$

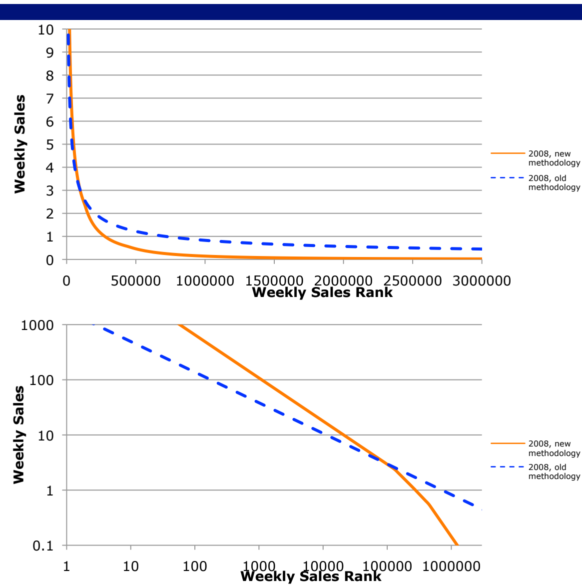
$\beta_1$ estimate:

-0.871 in 2000

-0.613 in 2008



## Power Law approximation is Imperfect
## Negative Binomial and Spline Fitting




## Key Findings

- Niche books account for a **larger** share of Amazon's sales in 2008 than in 2000 (matched sample)
  - From the Long Tail to the Longer Tail
- The Power Law relationship tails off for Niche books
  - Negative Binomial and spline fitting improves fit
  - Different forces at work at the far end of the tail?
- Books ranked above 100,000 account for 36.7% of Amazon's total sales in 2008
  - An increase of 125% compared to 2000 sample when consistent methods are used
- Selling niche books ranked above 100,000 leads to a consumer surplus of $4-5 billion in 2008

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# Information Asymmetry and the Productivity of Information Workers

**David Fitoussi*, Frank MacCrory* and Alain Pinsonneault****

*** University of California, Irvine**
**** McGill University**

## Background

- Important to understand and measure productivity at the worker level
  - Information work is a large and growing part of the economy
  - Decades of field research into productivity, but most miss important characteristics of information work
- Gaps in previous research
  - Typically, find information workers for whom individual input or output is *easily measured*
  - Unrealistic in most knowledge work settings and not appropriate in socially complex environments
- Most knowledge work is in teams
  - How does team structure affect the incentives facing information workers?
  - How does team structure affect the efficiency of monitoring?

## Setting and methods

- Extend Holmstrom’s model of team production
  - CES technology with high substitutability within a role but low substitutability across roles

$$f(\mathbf{E}) = \left( \sum_{g=1}^{G} \left[ \left( \sum_{i=1}^{N} e_{g,i}^{\rho} \right)^{\frac{1}{\rho}} \right]^{\mathrm{P}} \right)^{\frac{1}{\mathrm{P}}}$$

- Measuring unobservable individual effort
  - If real sickness is random, any changes in sick days correlated with changes in observability are shirking
  - Examine using panel Tobit & negative binomial methods
- Measuring unobservable team effort
  - Complementarity/externalities between workers increases the information available to the manager
  - Manager’s span of control reflects team efficiency
  - Fixed effects and other controls for manager ability

## Key Findings

- Free-riding increases in larger subteams
  - Developers only “care” about other developers on the team, business analysts only “care” about other business analysts on the team, etc.
- Free-riding decreases if the employee is in a high-visibility position on the team
  - Assigning ownership of tasks can artificially increase visibility, mitigating some 1/*N* effects
- More homogenous teams are easier to manage
  - 1/*N* problem increases, but so does information leakage
  - Information leverage effect dominates

## Summary

1. Addresses key feature of information work: team output with unobservable effort
2. Theoretical model that accommodates something between all identical and all unique workers
3. Unique data set allows testing of the model's predictions
4. Results as predicted, and robust to several specifications

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# Interdependence of Alternative Service Channels on Bank Performance

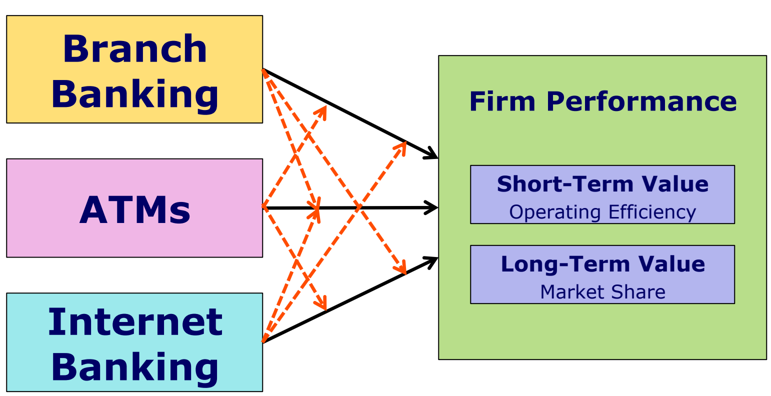
**Rajiv Banker***
**Pei-Yu Chen***
**Fang-Chun Liu***
**Chin-Shyh Ou****

*** Temple University**
**** National Chung Cheng University**

## Research Background

- The use of alternative service channels has changed the traditional way of understanding and undertaking banking activities
  - Strategically utilizing IT-based channels enables banks to optimize their operating performance
  - Traditional branch channel is transformed to provide more personalized services to serve and attract high-end customers
- Banks' Challenge
  - How to choose the right mix of service channels to deliver products and services profitably to their various market segments, which requires understanding of how each channel individually and jointly impact firm performance

## Research Model



# Key Findings

- Operating Efficiency
  - Two-stage Data Envelopment Analysis (DEA)
- Market Share
  - Multiplicative Competitive Interaction (MCI)

| | **Efficiency** | **Market Share** |
|---|---|---|
| **Direct Effect** | | |
| *Branch Banking* | Positive | Positive |
| *ATM* | Positive | Positive |
| *Internet Banking* | Negative | Positive |
| **Complementarity** | | |
| *Branch Banking * Internet Banking* | Positive | Positive |
| *Branch Banking * ATM* | Positive | Positive |
| *ATM * Internet Banking* | Positive | Positive |

- Prais-Winsten estimators adjust for serial correlation

# Summary

- In spite of the presence of IT-based service channels, the traditional branch-based channel has a positive impact on bank performance
- The impact of IT-based service channels on firm performance is contingent on the IT
  - ATMs: revenue-driven
  - Internet Banking: cost-driven
- Efficient channel mix strategy not only enables bank to compete sufficiently in short term but also enhance banks' long-term market competition ability

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# Will People Pay When it's Free: The Effect of Piracy on the Own Price Elasticity of Digital Music

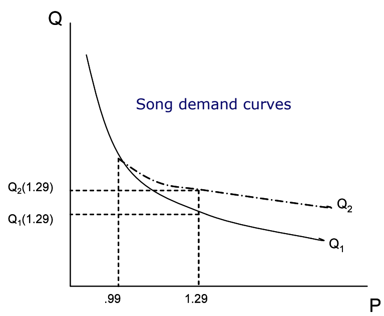
**Brett Danaher**

**Wharton School, University of Pennsylvania**

## Questions

- Will individuals who would otherwise pirate choose to purchase legally if offered the option to purchase digitally?
- Is there a measureable "cost" to music piracy – when the price of legal digital downloads increases, will some people turn to piracy?
- Does piracy affect the own price elasticity of digital music?
  - Piracy seen as a good substitute → very elastic legal demand curve
  - Piracy seen as poor substitute → less elastic legal demand curve
- How does all of this effect music industry producer surplus?

## Theory




- Observe "exogenous" price change on digital songs from 99 cents to $1.29
- Q1 represents demand response of songs for which piracy is a good substitute
- Q2 represents demand response of songs for which piracy is a poor substitute
- Q2(1.29) – Q1(1.29) = how many additional lost sales due to "piracy is a good substitute"
- Value to firms of making piracy less desirable

**Factors affecting quality of piracy as a substitute?**

- Song-driven factors – search cost, quality
- Audience driven factors – learning cost, moral cost
    - I don't observe these individually, but rather a proxy for their total
- Observe popularity of each song on P2P file sharing networks, holding constant popularity of song on iTunes or on charts

## Overview of Results

**Demand Curve Estimates for Songs Within Each Quartile of Popularity on P2P Networks**

**Regression of Log(Digital Sales) on 30% Price Increase**

| | 1st Quartile | 2nd Quartile | 3rd Quartile | 4th Quartile |
|---|---|---|---|---|
| 30% Price Increase | -0.063 | -0.130+ | -0.182** | -0.279** |
| | (0.046) | (0.078) | (0.071) | (0.110) |
| Constant | 7.042* | 5.028* | 6.653* | 8.489* |
| | (0.489) | (0.950) | (0.658) | (0.375) |
| Observations | 4004 | 3984 | 4127 | 3770 |
| Number of Songs | 120 | 119 | 126 | 116 |
| R-squared | 0.35 | 0.228 | 0.343 | 0.377 |

- Least popular songs on P2P networks experience 6% decline in legal digital sales in response to 30% price increase
- Most popular songs on P2P networks experience 28% decline in legal digital sales in response to 30% price increase
- Later I ensure that this is not simply a head/tail story by controlling for overall popularity of song on iTunes

## Implications

**Policy implications**

1. Piracy displaces sales of digital content
2. Optimal firm pricing (industry profits) affected by piracy
3. Study suggests a way to calculate the value of policies that make piracy less desirable

**Firm Strategy**

1. Value to firm of catering to less piracy-prone consumers
2. Results suggest price discrimination strategy based on piracy data
3. One major label planning to experiment with this strategy

## WISE 2009
## December 14-15, 2009, Phoenix, AZ

# Pricing Data Services: by Hours, by Gigabytes, or by Mega Bytes per Second?

**Ke-Wei Huang**
**Dept. of Information Systems,**
**National University of Singapore**

**&**

**Ying-Ju Chen**
**Dept. of IEOR,**
**UC Berkeley**

## Background

- Internet Service Providers used different versioning strategies based on different pricing units.
  - Dial-up: by the minutes of Internet connection
  - Broadband (ADSL or Cable): by connection speed
  - Mobile broadband (3G): by the total GB downloaded
- In 2008, Time Warner experimented in Texas a per-GB broadband pricing, in order to boost the revenue by "avoiding the consequences of unfairness pricing‟.

Research Question?

- **Which one of these three options is profit-maximizing when designing a versioning pricing plan (nonlinear pricing plan)?**

## Method

- An game-theoretic analytical study.
- This paper assumes a standard framework for investigating second-degree price discrimination (versioning).
- In the baseline model, consumers have a quadratic utility function in terms of total data usage, Q=M*B.
- The monopoly seller can choose one of three pricing options: per-Q, per-M, or per-B pricing.
- Given a pricing plan, users can self-select one item on the pricing menu and also Q, M, or B (similar to a moral hazard model).

## Key Findings

1. Per-GB pricing is equivalent to per-minute pricing.
   - Intuition: users all self-select the highest connection speed, which makes two pricing options equivalent.
2. Per-Mbps pricing is always suboptimal.
   - In the baseline model, the monopoly even offers only one price without price discrimination.
   - Intuition:
     When facing per-GB or per-minute pricing, users all self-select the highest connection speed; In contrast, when facing per-Mbps pricing, users will self-select different data usages. **This self-selection may eliminate the price discrimination power of the ISP.**

## Summary

1. These findings does not depend on the functional forms of utility function and can be generalized.
2. Two important criteria about selecting pricing units: (1) removing buyers' self-selection (moral hazard) activities. (2) a pricing unit that can best differentiate buyers (reducing the information rent the most).
3. Surprisingly, the previous results also hold when we impose a total bandwidth constraint on the monopoly seller.
4. Two extensions that might make per-mbps pricing attractive in theory: (1) usage uncertainty (2) Peak and load balance issues

**WISE 2009**
**December 14-15, 2009, Phoenix, AZ**

# An Asset Approach to Information Value

**Adam Saunders* and Erik Brynjolfsson****

*** The Wharton School, University of Pennsylvania**
**** MIT Sloan School of Management**

## Motivation

- Intangible assets are a large and growing component of corporate value.
- Yet, they are not included in company balance sheets or official government statistics.
- This research aims to identify and value intangibles in U.S. companies.

## Three Types of Intangibles

- "Digital" Assets
  - External IT services such as business process consulting and integration services.
  - Internal IT services such as customizing software and designing new software.
  - IT-related training.
- Research and Development (R&D)
  - R&D flow data converted to an asset stock.
- Brand
  - Advertising spending converted to an asset stock.

## Key Findings

New Contribution:

- A dollar of "digital assets" and a dollar of R&D are valued by the market at approximately $1 each.
  - But there is huge dispersion among companies.

Confirmation of Existing Literature:

- Physical capital and other assets such as receivables and inventory are valued by the market at an average of $1.  There is little dispersion among companies.

## Takeaways

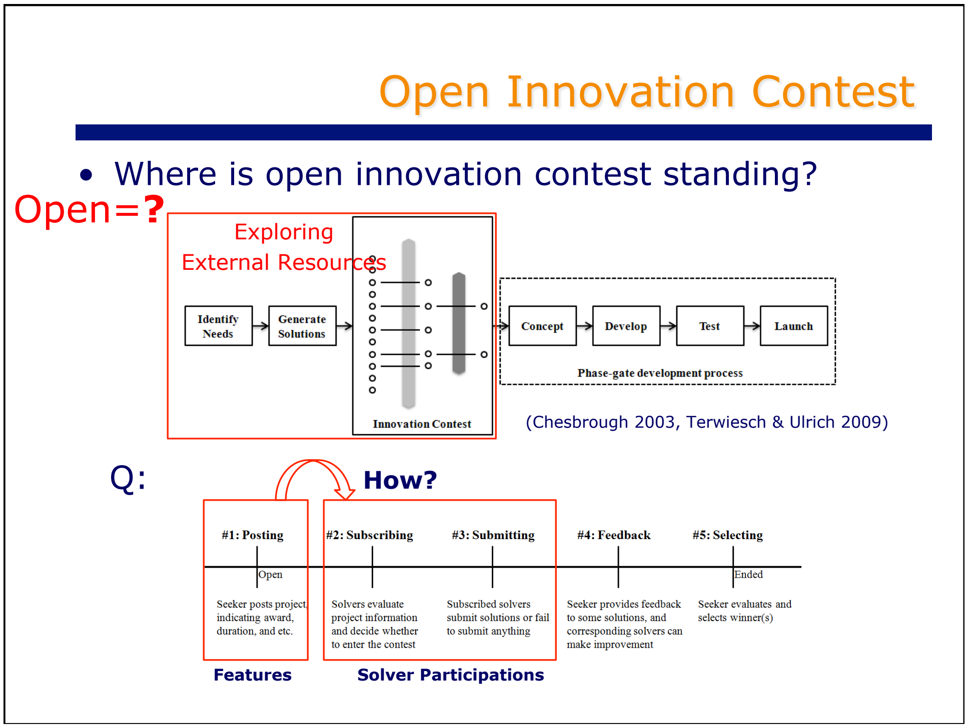
- You cannot manage what you don't measure, which is why it's important to measure the value of intangible assets.
- While similar amounts of physical assets among companies will yield similar returns, the companies exhibit a large variation in the returns to their intangible assets.
- What will separate companies in the 21st century is how they manage their intangibles.

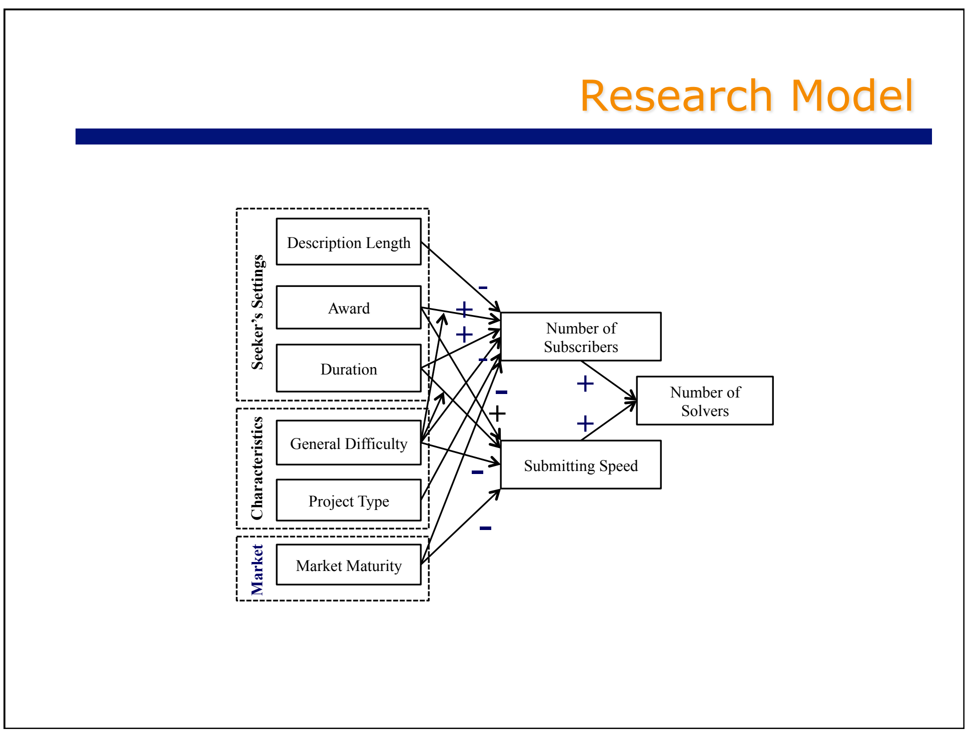
WISE 2009 December 2009, Phoenix, AZ

# Open Innovation: Impact of Online Contest Features to Solver Participations

**Yang Yang, Pei-yu Chen and Paul A. Pavlou**

**Temple University**


Open Innovation Contest
• Where is open innovation contest standing?
Open=?
Exploring
External Resources
Identify Needs
Generate Solutions
Innovation Contest
Concept
Develop
Test
Launch
Phase-gate development process
(Chesbrough 2003, Terwiesch & Ulrich 2009)
Q:
How?
#1: Posting
#2: Subscribing
#3: Submitting
#4: Feedback
#5: Selecting
Open
Ended
Seeker posts project, indicating award, duration, and etc.
Solvers evaluate project information and decide whether to enter the contest
Subscribed solvers submit solutions or fail to submit anything
Seeker provides feedback to some solutions, and corresponding solvers can make improvement
Seeker evaluates and selects winner(s)
Features
Solver Participations


Research Model
Seeker's Settings
Description Length
Award
Duration
Characteristics
General Difficulty
Project Type
Market
Market Maturity
Number of Subscribers
Submitting Speed
Number of Solvers

## Key Findings

- Impact of Online Contest Features to Solver Participation Decisions:
  - A contest with higher award, shorter description, longer duration, lower difficulty will attract more subscribers, make them submit faster, and result in more solvers (intuitive).
  - However, the marginal effect of award and duration on number of solvers differ across project with different difficulty levels, suggesting that increase award is more effective for some projects while increase duration is more effective for some others.

## Summary

1. Our study enlarge the scope of contest research by considering more contest features, other than just award structure.
2. Our data was collected from a large online contest marketplace
3. Our model provides a set of mix options of how to generate solutions with online contest.

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**December 14-15, 2009, Phoenix, AZ**

# Determinants Of Output Quality In Offshore Outsourcing Of Services: Evidence From Field Research

Ravi Aron, Eric Clemons, Siddarth Jayanty, Ying Liu, Deepa Mani, **Praveen Pathak**

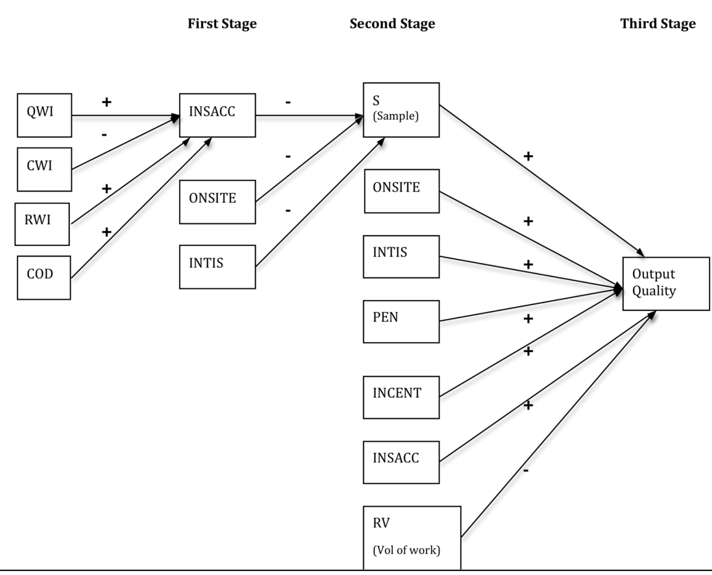
## Research Issues

- In offshore production of services, how do process attributes (the nature of information work), contract attributes (penalties, incentives, presence of onsite managers), and use of inter-organizational IS impact on the following?
  - The actual quality of output
  - The effort made by the buyer in inspecting the supplier's (offshore provider's) work?

## Key Features Of Research Design

- Time series data from 6 quarters on the actual quality of output in services.
- Data from offshore providers in 4 countries.
- A Balanced panel of buyers and suppliers of services (throughout the 6 measurement periods).
- We investigate how inspection accuracy (of the buyer) is impacted by process features.
- We investigate the nature and extent of buyers' inspection efforts as a function of the inspection accuracy, process features, use of inter-organizational IS and the presence of onsite managers (of the buyer).
- Finally, we comment on how these factors together impact on the quality of output.

## A Three Stage Model Of Effects



## Some Key Hypotheses that are supported

- *H1A: Processes that are characterized by higher levels of quantitative work index will result in higher inspection accuracy.*
- *H1B: Processes characterized by higher Codifiability will result in higher inspection accuracy.*
- *H2A: Higher the inspection accuracy of a process, lower the inspection effort by the buyer (firm).*
- *H2B: Use of Inter-Organizational Information Systems to monitor work in progress leads to lower levels of inspection effort (of finished output).*
- *H3A: The presence of onsite managers of the buyer managing the execution of work at the supplier's site will improve quality of output.*
- *H3B: Use of Inter-Organizational Information Systems will result in higher levels of output quality.*
- *H4A: The size of the Incentives will have no impact on the quality of output.*
- *H4B: The size of Penalty will have no impact on the quality of output*
- *H5A: Inspection Accuracy and Penalty size have an interaction effect and together will increase the quality of output.*
- *H5B: Inspection Effort and Penalty size have an interaction effect and together will increase the quality of output.*

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**December 14-15, 2009, Phoenix, AZ**

# Reputation Mechanisms in Online Social Media

**Qian Tang, Bin Gu and Andrew Whinston**

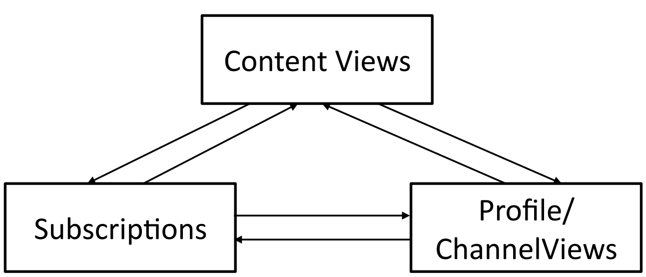
**University of Texas at Austin**

## Reputation Mechanisms in Online Social Media

- Online social media vs. offline social network
  - Reduced search costs
  - User Profiles / User Channels
    - User information
    - Links to all user-generated contents
    - Comments
    - Friends
  - Subscription
    - Automatic and constant updates


## Research Questions

- How do the reputation mechanisms influence the diffusion of information in online social media?
- How do the reputation mechanisms facilitate reputation formation in online social media?



## Methodology and Key Findings

- Research context
  - Youtube.com (April to August 2007)
- Information diffusion
  - Each video has its own Bass diffusion parameters
  - Assess the incremental influence of reputation mechanisms on video viewership
- Reputation formation
  - Assess the influence of video viewership on channel viewership
  - Assess the influence of video viewership and channel viewership on subscriptions

| Equation | Variable | Coefficient (se.) |
|---|---|---|
| Video views | $LgSubscribers_{t-1}$ | .03420*** |
| | $LgChannelViews_{t-1}$ | .02965*** |
| Channel views | $LgTotalVideos_{t-1}$ | .11005*** |
| | $LgAvgVideoViews_{t-1}$ | .00000 |
| | $LgVarVideoViews_{t-1}$ | .00000 |
| Subscription | $LgChannelViews_{t-1}$ | .00429*** |
| | $LgTotalVideos_{t-1}$ | .00958*** |
| | $LgAvgVideoViews_{t-1}$ | .00000*** |
| | $LgVarVideoViews_{t-1}$ | .00000** |

## Summary

1. Reputation mechanisms have a significant influence on information diffusion in online social media.
2. Total provision of contents generates interests in content providers.
3. Total provision of contents and content quality generate subscriptions.
4. “Stroke of genius” effect for subscription.

WISE 2009
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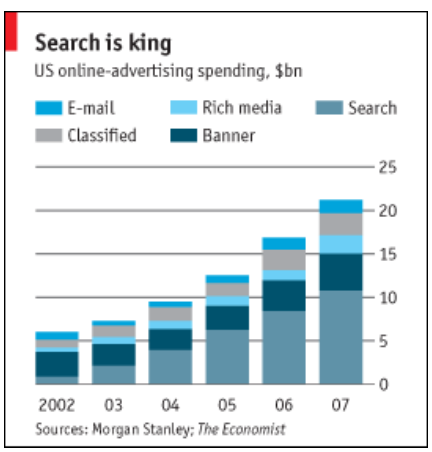
# Search Engine Advertising: Empirical Analysis of Advertisers' Bids & Performance

Ashish Agarwal* and Tridas Mukhopadhyay**

* University of Texas, Austin
** Carnegie Mellon University

## Sponsored Search



## Search & Advertiser Characteristics

- Consumers are in different stages of information acquisition
  - Generic queries vs. Specific queries

  For example: 'shirt', 'dress shirt',' J Crew blue dress shirt'
- Product popularity varies
  - Volume distribution of web queries follows a power law
- Advertisers differ in ad spending
  - Advertisers differ in their portfolio of keywords and bid amounts
  - Click performance influenced by quality perception

## Key Findings

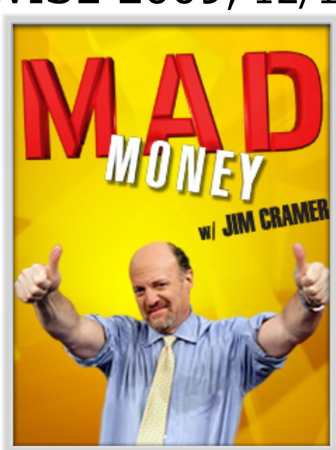
- How do search characteristics impact overall click performance?
  - Higher click performance for more specific key phrases and less popular key phrases
- How does ad spending impact performance?
  - Higher ad spending is associated with higher quality and higher click performance irrespective of the ad rank
  - Higher rank leads to higher performance for advertisers with higher keyphrase specific spending
- How do advertisers bid in relation to performance?
  - Higher bids for higher performing keywords
  - Advertisers with higher budgets tend to bid higher amounts

## Summary

1. Evaluates the interplay of search and advertiser characteristics on ad performance
2. Comprehensive model to account for consumer, advertiser and search engine decisions
3. Unique data set (several hundred advertisers , 5 product categories)
4. Interesting results

# Cramer's Rule:
## How Information Moves Markets

WISE 2009, 12/14-15 2009, Phoenix, AZ



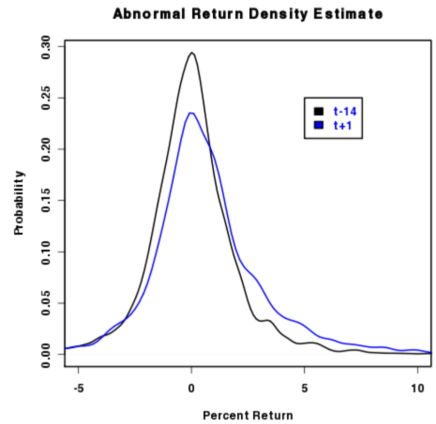

- Sinan Aral*
- Panos Ipeirotis**
- Sean J Taylor**

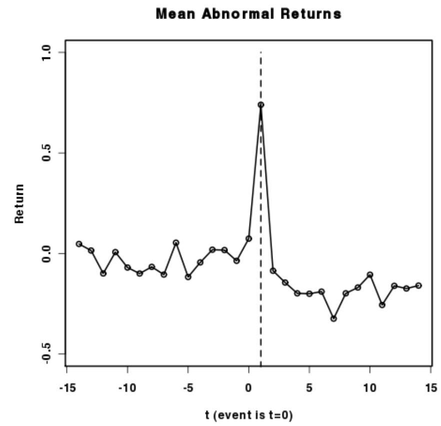
* NYU Stern School of Business and MIT

**NYU Stern School of Business

## The Cramer Effect

Cramer shifts the distribution of abnormal returns.




## Research Questions and Approach

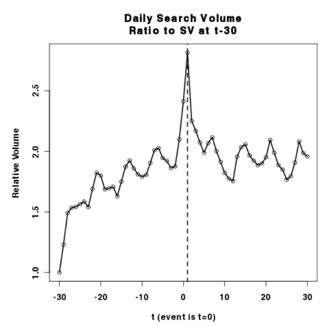
- Does Jim Cramer actually ***cause*** changes in market prices?
- Under what conditions is he more or less influential?
- We derive measures and characteristics of his discourse from transcripts of ***Mad Money***.
- Modeling Cramer’s selection process allows us to identify influence.
- Contribution: How different dimensions of information affect economic decisions and outcomes.

# Dimensions of Information

- Volume: number of words [significant, positive, quadratic effect]
- Uniqueness: log-likelihood of Cramer's text given his corpus word distribution [highly positive and significant]
- Topics: LDA estimated topic allocations for each recommendation [many topics significant, varying in magnitude and sign]
- Novelty (ongoing work): novelty of text in context of news leading up to the event using Reuters news and Spynn3r blogosphere data

# Identification & Cramer's Selection Process

- Cramer selects stocks which have had unusual run-ups in price.
- His picks tend to already be garnering attention in the form of Google searches.
- Strategy: For each stock recommended, match to a similar stock that was as likely to be recommended, but wasn't (matched sample).
- Heckman sample-selection model.



# Multiple Winner Award Rules In Buyer-determined Online Reverse Auctions

Juan Feng

City University of Hong Kong

University of Florida

With Qi Wang, Sandy Jap and Jinhong Xie

## e-Procurement Auctions

- Buyer-determined Auction:
  - buyer is free to choose the auction winner(s) on any basis
- Multiple Winner Rules:
  - Consideration set: winner will be chose from the lowest 3 bidders;
  - Allocation: 100%, 70/30, 50/30/20,…

**TABLE 1: MULTIPLE WINNER AWARD RULES**

| Award Allocation | Buyer Perspective | # win (nwin) | Average Award | Award Range | Winning Variance (vwin) |
|---|---|---|---|---|---|
| 100% | Max Holdup | 1 | 100 | 0 | 0 |
| 70/30 | Reward & foster | 2 | 50 | 40 | .08 |
| 60/30/10 | Test $H_2O$ | 3 | 35 | 50 | .13 |
| 50/30/20 | Distribute Risk | 3 | 35 | 30 | .05 |
| 40/30/20/10 | Min holdup; transaction costs | 4 | 25 | 30 | .05 |

## Research Questions

- How does the multiple-winner rules ---
  - Consideration set
  - # of winners
  - Allocation variance (50/50 vs 70/30)
- Affect bidder behavior (Experienced VS Inexperienced bidders)
  - Participation
  - Bidding responsiveness
  - Bid increment
- Affect the auctioneer's revenue

## Model

- A proprietary dataset
  - 54 industrial online auctions;
  - 192 suppliers, competing for over $73 million in purchase contracts;
  - 4456 bids;
  - three year period.
- Model
  - Estimation of parameters:
    - participation probability,
    - timing of initial bid,
    - bid responsiveness and increment.
  - Differentiate between experienced and inexperienced bidders;
  - Regression;

## SUMMARY ON BIDDING BEHAVIOR

| Bidder | Award Rule | Bidding Behavior | | |
|---|---|---|---|---|
| | | Participants | Responsiveness | Aggressiveness |
| All | Size of Consideration Set | No Influence | More | No Influence |
| | Proportion of Winners in the Consideration Set | More | More | Less |
| | Variance of Winning Order Allocation | No Influence | More | More |
| Experienced Bidder relative to Inexperienced Bidder | Size of Consideration Set | More | Less | Equally Less |
| | Proportion of Winners in the Consideration Set | More | More | More |
| | Variance of Winning Order Allocation | Less | Less | More |

## WISE 2009
## December 14-15, 2009, Phoenix, AZ

# Linking Real-Time Information to Actions: Optimal Collection of Credit-Card Debt

**Naveed Chehrazi and Thomas A. Weber**

**Stanford University**
**Department of Management Science and Engineering**

## Motivation & Research Question

- Outstanding consumer debt in U.S. is large (>$900 billion)
  - Credit card debt is a large fraction
  - Less than half is paid back
- Despite large exposure banks have only poor understanding of analytical tools to improve predictions & actions
  - Bayesian updating poorly understood – collectability scores often pre-computed and updated with data-mining techniques
  - Imperfect integration between bank and collection agency
- Question: Find optimal settlement offer and timing
  - Based on actual real-time data, predict repayment behavior and reaction to account interventions (identification problem)
  - Find optimal timing and magnitude of interventions (control problem)

## Modeling a Payment Process

- Account parameters P (fixed)
  - Outstanding balance, type (revolving/charge), credit limit, FICO score, mortgage status
- State of economy $X_t$ (variable)
  - Continuous-time Markov process (e.g., interest rate)
- Collector actions $A_t$ (decisions)
  - Discrete interventions (e.g., contact, settlement)

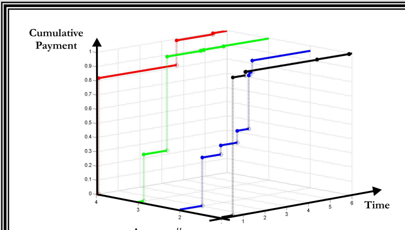
Raw Data:

| Fico Distribution | stlflag | |
|---|---|---|
| rndfico | not settled | settled |
| 350-400 | 0.07% | 0.02% |
| 400-450 | 4.49% | 2.11% |
| 450-500 | 23.41% | 16.85% |
| 500-550 | 30.70% | 30.29% |
| 550-600 | 19.16% | 21.44% |
| 600-650 | 12.74% | 16.12% |
| 650-700 | 5.44% | 7.47% |
| 700-750 | 2.29% | 3.47% |
| 750-800 | 1.19% | 1.50% |
| 800-850 | 0.50% | 0.73% |
| Grand Total | 100.00% | 100.00% |

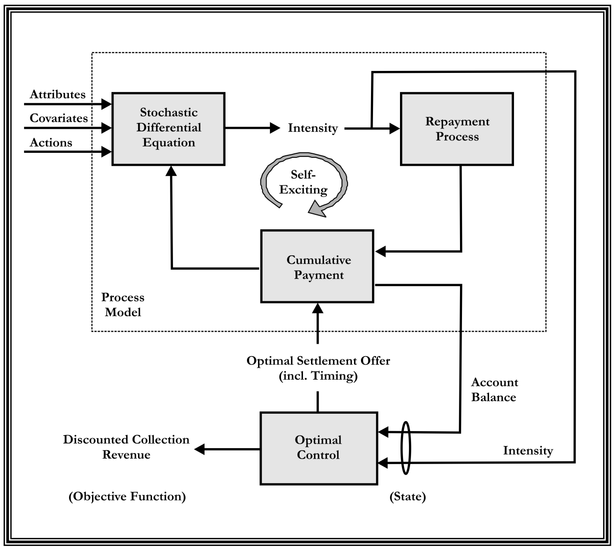
| Ability Distribution | stlflag | |
|---|---|---|
| ABILITY | not settled | settled |
| 0 | 65.95% | 50.40% |
| 1 | 34.05% | 49.60% |

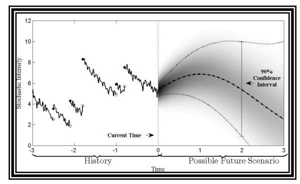
(…)

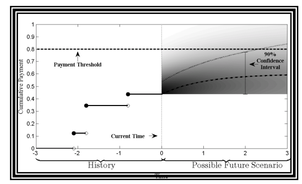
| First in line distribution | stlflag | |
|---|---|---|
| FRSTINLINE | not settled | settled |
| 0 | 43.61% | 35.39% |
| 1 | 56.39% | 64.61% |

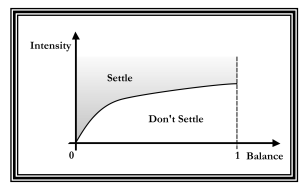


## Model & Results




## Summary

1. Estimation of dynamic arrival process (payment timing) together with process for payments (payment amounts)

   * Main technique = self-exciting point process

   * Key step = change of measure to simulate as Poisson process

2. Procedure allows for attributes, covariates, and planned actions, which produce linear weights in the stochastic differential equation (identified via maximum likelihood estimation)

3. Optimal stopping, together with optimal action (settlement) at stopping point

4. Method can be applied to identify and control other monotone stochastic processes such as for innovation or exhaustible-resource extraction