The Societal Impact of Big Data: A Transaction Cost and Information Economics Perspective

Bin Gu
W. P. Carey School of Business
Arizona State University

Texas Tech University 2016 Symposium on Big Data
Overview

- The societal impacts of big data
  - Informational – relational – structural (organizational and societal)
- Transaction cost and information economics
- Relevant studies from the past and current
Transaction cost economics

Coase (1937)
- Why do firms exist? What determines the boundary between firms and the market?
- Transaction costs
  - Search costs, bargaining costs, enforcement costs

Williams (1981)
- What determines transaction costs?
  - Asset specificity
  - Uncertainty
  - Frequency

Example: Uber
Information economics

- Asymmetry information leads to agency costs and potential market failures
- Adverse selection (before transaction)
  - The party with private information selectively participates in transactions
  - Market for lemons
- Moral hazard (after transaction)
  - The party with private information take actions that damage the welfare of the counterparty.
The role of big data

Studies from the trucking industry

- Transaction costs and agency costs

Hubbard (AER 2003)

- The diffusion of on-board monitoring system enabled 3-percent higher capacity utilization in the industry.

Baker and Hubbard (AER 2003, QJE 2004)

- How has truck ownership changed with diffusion of on-board computer with monitoring and real-time tracking features?
- Before the diffusion, driver ownership is greater for long than short hauls.
- After the diffusion of computers with monitoring features, driver ownership decreases, particularly for long hauls.
- After the diffusion of computers with resource allocation features, driver ownership increases.
Monitoring and moral hazard

 Française

Study 1: Does twitter make congressmen more representative of their constituents?

Study 2: How does better monitoring tool influence contract choice and performance in online labor markets?
Social Media: My Approach

Representing Silicon Valley, my office aggressively leverages technology and social networks to expand into new social networks, interact with my constituents, and inform the public on pressing issues.

Expanding into New Social Networks

Constituents want to be able to interact with my office on their terms, whether by email, Facebook, Twitter or another platform. My office meets the needs of constituents.

Google Plus

My office launched a Google Plus page earlier this year. As a supplement to our already robust followings on Facebook and Twitter, my Google Plus page has grown at an incredible rate. At more than 62,000 +1’s, it is already my largest social network. More importantly, it has allowed me to reach an entirely new audience, one especially important in our Silicon Valley district.
RESEARCH QUESTIONS

Does OSN adoption (Twitter) by politicians lead them voting more in line with the political ideology of their constituents?
RESEARCH MODELS

Model 1: *Fixed Effect Model*: \( y_{it} = \beta_1 x_{it} + i + t + \epsilon_{it} \)

Model 2: *OLS with clustered standard error at the Representative level*: \( y_{it} = \beta_0 + \beta_1 Q_i + \beta_2 Q_i \times x_{it} + B_3 Z_i + t + \epsilon_{it} \)

- \( i \): representative
- \( t \): month
- \( y_{it} \):
  - vote orientation
  - political misalignment
- \( x_{it} \): twitter adoption status (time varying)
- \( Q_i \): eventual twitter adopter
DATA

Panel data for Members of the 111th U.S. House of Representatives

- 24 months (January 2009- December 2010)

Dependent Variables

- Vote orientation (Weighted Nominal Three-Step Estimation WNOMINATE)
  - “a scaling procedure that performs parametric unfolding of binary choice data.” (Poole and Rosenthal 1985)
  - a spectrum of scores ranging from -1 to +1, with -1 representing the most Liberal Representative and +1 representing the most Conservative Representative
WNOMINATE: Vote Orientation

The 111th Congress Lifespan
DATA

Dependent Variables

- Political misalignment: absolute difference between vote orientation and constituents’ political ideology
- Constituents’ political ideology
  - A measure of constituents’ partisanship index from Tausanovitch and Warshaw (2013).
  - Measures the average policy preferences by estimating the extent to which a Congressional district leans toward Democrat or Republican parties.
  - Both constituents and Representatives’ scores were rescaled to vary from 0 to +1, with 0 representing the most Liberal district and +1 representing the most Conservative district.)
DATA

Independent variables

- Representatives’ twitter adoption status
  - The date each Representative created the Twitter account
  - API calls from Twitter API and Sunlight Foundation’s Congress API.
  - Out of 442 Representatives, 246 had Twitter accounts by the end of 111th Congress, 204 adopted Twitter during the 111th Congress.
DATA

Instrument variables (for twitter adoption)

- Name-mentions frequency: the number of tweets in which the Representatives’ first name & last name were mentioned on Twitter sphere in any given month (1.55 million twitters)

- Committee effect: the number of peers (other Representatives) who joined Twitter at each time period $t$ and who served at the same committees that Representative $i$ is a member of.

- Neighbor effect: the proportion of peers from Representative $i$’s state who joined Twitter at each time period $t$. 
## SUMMARY STATISTICS

<table>
<thead>
<tr>
<th>Variables</th>
<th>Observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representative’s voting orientation</td>
<td>10537</td>
<td>0.505</td>
<td>0.274</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>constituent’s political ideology</td>
<td>10680</td>
<td>0.614</td>
<td>0.184</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>political misalignment</td>
<td>10537</td>
<td>0.211</td>
<td>0.159</td>
<td>0</td>
<td>0.874</td>
</tr>
<tr>
<td>Eventual twitter adopter</td>
<td>10680</td>
<td>0.553</td>
<td>0.497</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>twitter status</td>
<td>10680</td>
<td>0.404</td>
<td>0.491</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>tweets frequency</td>
<td>10680</td>
<td>6.308</td>
<td>17.589</td>
<td>0</td>
<td>385</td>
</tr>
<tr>
<td>handle-mentions frequency</td>
<td>10680</td>
<td>36.928</td>
<td>124.78</td>
<td>0</td>
<td>1637</td>
</tr>
<tr>
<td>Instrumental Variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>name-mentions frequency</td>
<td>10632</td>
<td>146.11</td>
<td>226.02</td>
<td>0</td>
<td>1923</td>
</tr>
<tr>
<td>committee effect</td>
<td>10680</td>
<td>16.954</td>
<td>24.990</td>
<td>0</td>
<td>122</td>
</tr>
<tr>
<td>neighbor effect</td>
<td>10680</td>
<td>0.363</td>
<td>0.186</td>
<td>0</td>
<td>0.875</td>
</tr>
</tbody>
</table>
## MODEL-FREE EVIDENCE

<table>
<thead>
<tr>
<th>Variable</th>
<th>Period</th>
<th>adopter</th>
<th>Non-adopter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representatives’ voting orientation</td>
<td>Before adoption (twitter status=0)</td>
<td>0.386</td>
<td>0.484</td>
</tr>
<tr>
<td></td>
<td>After adoption (twitter status=1)</td>
<td>0.572</td>
<td></td>
</tr>
<tr>
<td>Constituents’ voting orientation</td>
<td>Throughout 111th Congress</td>
<td>0.606</td>
<td>0.624</td>
</tr>
<tr>
<td>Political misalignment</td>
<td>Before adoption (twitter status=0)</td>
<td>0.238</td>
<td>0.231</td>
</tr>
<tr>
<td></td>
<td>After adoption (twitter status=1)</td>
<td>0.179</td>
<td></td>
</tr>
</tbody>
</table>
# IMPACT OF TWITTER ADOPTION

<table>
<thead>
<tr>
<th></th>
<th>(DV= voting orientation)</th>
<th>(DV=political misalignment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1 (2SLS)</td>
<td>Model 4</td>
</tr>
<tr>
<td>adopter</td>
<td>-0.101*** (0.010)</td>
<td>-0.007 (0.679)</td>
</tr>
<tr>
<td></td>
<td>Model 2 (2SLS)</td>
<td>Model 5</td>
</tr>
<tr>
<td></td>
<td>-0.329*** (0.032)</td>
<td>0.027 (0.072)</td>
</tr>
<tr>
<td></td>
<td>Model 3 Coefficient</td>
<td>Model 6 Coefficient</td>
</tr>
<tr>
<td></td>
<td>Marginal Effect</td>
<td>Coefficient</td>
</tr>
<tr>
<td></td>
<td>Model 3</td>
<td>Marginal Effect</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td>Model 4</td>
</tr>
<tr>
<td>adopter × twitter status</td>
<td>0.091*** (0.007)</td>
<td>-0.010** (0.002)</td>
</tr>
<tr>
<td></td>
<td>0.188*** (0.012)</td>
<td>-0.039** (0.011)</td>
</tr>
<tr>
<td></td>
<td>0.630*** (0.034)</td>
<td>-0.278*** (0.059)</td>
</tr>
<tr>
<td></td>
<td>0.151*** (0.008)</td>
<td>-0.046*** (0.009)</td>
</tr>
<tr>
<td>Time-fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Representative fixed effect</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Clustered at Representative level</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Instruments</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>0.490</td>
<td>0.228</td>
</tr>
<tr>
<td>N</td>
<td>10537</td>
<td>10537</td>
</tr>
</tbody>
</table>
# IMPACT OF TWITTER USE

<table>
<thead>
<tr>
<th></th>
<th>(DV= voting orientation)</th>
<th>(DV=political misalignment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 7</td>
<td>Model 8</td>
</tr>
<tr>
<td>tweets frequency (logged)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.010* (0.004)</td>
<td>-0.006* (0.002)</td>
</tr>
<tr>
<td>Robust</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Time-fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Individual-fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>R-squared (within)</td>
<td>0.471</td>
<td>0.198</td>
</tr>
<tr>
<td>N</td>
<td>10537</td>
<td>10537</td>
</tr>
</tbody>
</table>

* Significant at the 0.05 level.
## IMPACT OF TWITTER MENTION

<table>
<thead>
<tr>
<th></th>
<th>(DV= voting orientation)</th>
<th>(DV=political misalignment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 9</td>
<td>Model 10</td>
</tr>
<tr>
<td>handle-mentions frequency (logged)</td>
<td>0.012*** (0.001)</td>
<td>-0.005*** (&lt;0.001)</td>
</tr>
<tr>
<td>Robust</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Time-fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Representative fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>R-squared (within)</td>
<td>0.008</td>
<td>0.001</td>
</tr>
<tr>
<td>N</td>
<td>10537</td>
<td>10537</td>
</tr>
<tr>
<td>F-statistic</td>
<td>72.18</td>
<td>15.96</td>
</tr>
<tr>
<td>Prob &gt; F</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Specification</td>
<td>FE</td>
<td>FE</td>
</tr>
</tbody>
</table>
FURTHER ADDRESSING THE SELECTION BIAS

- Propensity Score Matching
  - For each adopter, find a similar non-adopter and compare the change in $y$ ($\Delta y_i = y_{i}^{post} - y_{i}^{pre}$) between them.

- External Events
  - In May/19/2010 Twitter launched Twitter for iPhone and iPod for free on the iTunes App Store

- Twitter Usage & political misalignment
  - In geographic regions where citizens use Twitter more often the magnitude of the influence should be larger
Matching variables:

- Age
- Gender
- Seniority in Congress
- Percentage of party-favored votes
- Number of sponsored bills
- Number of co-sponsored bills
- Percent of missed votes
- Prior voting orientation
- Constituent’s mean household income
- Percent of high school graduates
- Percent of white population
# PROPENSITY SCORE MATCHING

<table>
<thead>
<tr>
<th>Calendar Month</th>
<th>Model 13 $\Delta y_i =$ Changes in voting orientation</th>
<th>Model 14 $\Delta y_i =$ Changes in political misalignment</th>
<th>Number of adopters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feb-09</td>
<td>0.075** (0.021)</td>
<td>-0.045** (0.009)</td>
<td>23</td>
</tr>
<tr>
<td>Mar-09</td>
<td>0.067* (0.20)</td>
<td>-0.062** (0.018)</td>
<td>27</td>
</tr>
<tr>
<td>Apr-09</td>
<td>0.031* (0.013)</td>
<td>-0.031* (0.011)</td>
<td>19</td>
</tr>
<tr>
<td>May-09</td>
<td>0.0003 (0.019)</td>
<td>-0.069* (0.026)</td>
<td>13</td>
</tr>
<tr>
<td>Jun-09</td>
<td>0.063** (0.018)</td>
<td>0.058 (0.067)</td>
<td>11</td>
</tr>
<tr>
<td>Sep-09</td>
<td>0.052** (0.015)</td>
<td>-0.055** (0.011)</td>
<td>11</td>
</tr>
<tr>
<td>Jun-10</td>
<td>0.034* (0.017)</td>
<td>-0.137*** (0.018)</td>
<td>13</td>
</tr>
</tbody>
</table>
EXTERNAL EVENT

Number of Adopters

Calendar Month

ASU®
W. P. CAREY
SCHOOL of BUSINESS
ARIZONA STATE UNIVERSITY
## EXTERNAL EVENT

<table>
<thead>
<tr>
<th>(DV= voting orientation)</th>
<th>(DV=political misalignment)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 15</strong></td>
<td><strong>Model 16</strong></td>
</tr>
<tr>
<td><strong>Coefficient</strong></td>
<td><strong>Marginal Effect</strong></td>
</tr>
<tr>
<td>adopter</td>
<td>-0.139*** (0.015)</td>
</tr>
<tr>
<td>adopter × twitter status</td>
<td>0.062*** (0.013)</td>
</tr>
</tbody>
</table>

| Time-fixed effects | √ | √ | √ | √ | √ | √ |
| Representative fixed effects | √ | | | | | |
| Clustered at Representative level | | √ | | | | |
| Adj. R-squared | 0.534 | 0.156 | 0.333 | 0.142 |
| N | 312 | 4920 | 4920 | 312 | 4920 | 4920 |
ADDRESSING SERIAL CORRELATION

- Ignoring Time Series Information
  - Collapsing the time series information into a “pre” and “post” period produces consistent standard errors

- Randomization Inference
  - Generate a distribution of DiD estimates for 10,000 simulated data sets, then compare with the actual estimate.
  - Randomization across Representatives and across calendar months
IGNORING TIME SERIES INFORMATION

<table>
<thead>
<tr>
<th></th>
<th>(DV=Mean voting orientation) Model 21</th>
<th>(DV=Mean political misalignment) Model 22</th>
</tr>
</thead>
<tbody>
<tr>
<td>adopter × twitter status</td>
<td>0.071*** (&lt;0.001)</td>
<td>-0.039*** (&lt;0.001)</td>
</tr>
<tr>
<td>Robust</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Time-fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Representative fixed effects</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>R-squared (within)</td>
<td>0.449</td>
<td>0.207</td>
</tr>
<tr>
<td>N</td>
<td>10537</td>
<td>10537</td>
</tr>
<tr>
<td>F-statistic</td>
<td>331.11</td>
<td>106.57</td>
</tr>
<tr>
<td>Prob &gt; F</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Specification</td>
<td>FE</td>
<td>FE</td>
</tr>
</tbody>
</table>
The difference-in-difference estimates for a large number of randomly generated placebo events are estimated first. Then the empirical distribution of the estimated effects for these placebo events are used to form significance test for the true event.
## RANDOMIZATION INFERENC3E

<table>
<thead>
<tr>
<th></th>
<th>(DV= voting orientation)</th>
<th>(DV=political misalignment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual Estimate</td>
<td>95% Lower Bound Estimate</td>
</tr>
<tr>
<td>adopter × twitter status</td>
<td>0.022</td>
<td>-0.012</td>
</tr>
<tr>
<td>Time-fixed effects</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Representative fixed effects</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Specification</td>
<td>OLS</td>
<td>OLS</td>
</tr>
</tbody>
</table>
## MODERATING FACTOR

<table>
<thead>
<tr>
<th>Factor</th>
<th>Adoption effect on Voting orientation</th>
<th>Adoption effect on political misalignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representative &amp; constituent party match =1</td>
<td>N</td>
<td>+</td>
</tr>
<tr>
<td>party affiliation = Republican</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>age</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>seniority</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>sponsorship</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>co-sponsorship</td>
<td>+</td>
<td>N</td>
</tr>
<tr>
<td>missed votes (%)</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>party votes (%)</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>white (%)</td>
<td>-</td>
<td>N</td>
</tr>
<tr>
<td>highschool graduates (%)</td>
<td>-</td>
<td>N</td>
</tr>
<tr>
<td>household income (logged)</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>unemployment rate (%)</td>
<td>+</td>
<td>N</td>
</tr>
</tbody>
</table>
EXAMPLE (STEPHANIE SANDLIN)

The diagram illustrates the changes in voting orientation over time, with two lines representing different aspects:
- **Constituent’s Political Ideology**
- **Representative’s Voting Orientation**

The graph shows a period labeled "Before Adoption" and another labeled "After Adoption," indicating a shift in voting orientation over time. The x-axis represents the calendar month, and the y-axis represents the voting orientation (normalized).

**ASU**
**W. P. CAREY SCHOOL OF BUSINESS**
**ARIZONA STATE UNIVERSITY**
RESULTS

- Representatives who adopt Twitter become more conservative.
- Representatives who adopt Twitter vote closer to their constituents’ political ideology.
- Representatives who post more content on Twitter vote closer to their constituents’ political ideology.
- Representatives who are mentioned more often on Twitter vote closer to their constituents’ political ideology.
Politicians could use constituents’ data available in OSN platforms to gauge their political decisions. (RTs, Favorites, content analysis)

Constituents could use OSN platforms to influence their Representatives in Congress.
New report shows regional universities R&D trending down, needs critical attention @eric swalwell @RepMikeHonda #svlg
LIMITATIONS

- Unique research context
- Information effects vs monitoring effects
- Need better measure of constituents’ political ideology
Thank you!
CONCLUSION

- Twitter makes Congressmen more representative their constituents!
Study 2

MONITORING AND ONLINE LABOR MARKETS
MOTIVATION

Online talent platforms could increase global GDP by $2.7 trillion by 2025 and raise employment by 72 million FTEs.

Global GDP impact of online talent platforms by 2025, $ billion

<table>
<thead>
<tr>
<th>Component</th>
<th>2025 Impact</th>
<th>Higher participation</th>
<th>Reduced unemployment</th>
<th>Higher productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total impact</td>
<td>2,700</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher participation</td>
<td>1,270</td>
<td>0.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced unemployment</td>
<td>805</td>
<td></td>
<td>105</td>
<td></td>
</tr>
<tr>
<td>New matches</td>
<td>700</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Faster matches</td>
<td></td>
<td></td>
<td></td>
<td>625</td>
</tr>
<tr>
<td>Reduced informality</td>
<td></td>
<td></td>
<td></td>
<td>290</td>
</tr>
<tr>
<td>Better matches</td>
<td></td>
<td></td>
<td></td>
<td>335</td>
</tr>
<tr>
<td>Higher productivity</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component</th>
<th>Percentage</th>
<th>Million FTE</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP increase</td>
<td>2.0%</td>
<td></td>
</tr>
<tr>
<td>Employment increase</td>
<td>72</td>
<td>47</td>
</tr>
</tbody>
</table>

1 Includes increasing participation among people who currently do not work and increasing hours among part-time workers.
2 Full-time equivalents.
NOTE: Numbers may not sum due to rounding.
MOTIVATION

Adverse Selection and Moral Hazard

Unlike the traditional temporary employment, the control mechanism of online labor market is weaker and indirect, such as emails, virtual meeting technologies (Horton et al. 2015). It’s easier for the contractors to hold their private information about the actual need of efforts and time from employers.
RESEARCH CONTEXT

Enhanced online tracking feature introduced

- Supply side
  - Number of bids
  - Average bid price
- Demand side
  - Employers’ preference
  - Employer surplus

Hourly projects

Fixed-price projects
RESEARCH CONTEXT

Differences between fixed price contracts and hourly (time-and-materials) contracts

<table>
<thead>
<tr>
<th></th>
<th>fixed-price contracts</th>
<th>time-and-materials contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>risk allocation</td>
<td>mainly on contractors</td>
<td>mainly on employers</td>
</tr>
<tr>
<td>ex ante costs of contract design</td>
<td>Higher</td>
<td>Lower</td>
</tr>
<tr>
<td>ex post costs of monitoring and auditing</td>
<td>Lower</td>
<td>higher</td>
</tr>
<tr>
<td>ex post costs of maladaptation</td>
<td>Higher</td>
<td>Lower</td>
</tr>
<tr>
<td>ex post costs of renegotiation costs</td>
<td>Higher</td>
<td>Lower</td>
</tr>
<tr>
<td>incentives for quality performance</td>
<td>Lower</td>
<td>Higher</td>
</tr>
<tr>
<td>incentives for cost performance</td>
<td>higher</td>
<td>Lower</td>
</tr>
</tbody>
</table>
- *Freelancer*, one of the largest online labor outsourcing markets. This year, it was awarded as 2015 Best Employment Website and 2015 Best Professional Services Website.

<table>
<thead>
<tr>
<th>Bids</th>
<th>Avg Bid (USD)</th>
<th>Project Budget (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>$122</td>
<td>$30 - $250</td>
</tr>
</tbody>
</table>

**Figure 1** A fixed-price project

I am re-branding my business and looking for a creative way to get people back on board. Looking for logo animation is what I believe it’s called. Or my logo made into a video.

**About the employer**

- **4.8** (2 Reviews)
- **VERIFIED**

**Skills required**

- Adobe Flash, After Effects, Animation

**Post a Project like this**

---

<table>
<thead>
<tr>
<th>Bids</th>
<th>Avg Bid (USD)</th>
<th>Project Budget (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>$11/hr</td>
<td>$8 - $15/hr</td>
</tr>
</tbody>
</table>

**Figure 2** A hourly project with a time and materials contract
### Research Context

Freelancer, one of the largest online labor outsourcing markets. This year, it was awarded as 2015 Best Employment Website and 2015 Best Professional Services Website.

### Data

<table>
<thead>
<tr>
<th>Freelancers Awarded</th>
<th>Reputation</th>
<th>Bid (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>loveamlan</td>
<td>4.8</td>
<td>$65</td>
</tr>
<tr>
<td></td>
<td></td>
<td>In 2 days</td>
</tr>
<tr>
<td></td>
<td>76 Reviews</td>
<td></td>
</tr>
<tr>
<td></td>
<td>88% Completion Rate</td>
<td></td>
</tr>
</tbody>
</table>

- Completed - Freelancer rated

<table>
<thead>
<tr>
<th>Freelancers Bidding (0)</th>
<th>Reputation</th>
<th>Bid (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>acejudger</td>
<td>5.0</td>
<td>$300</td>
</tr>
<tr>
<td></td>
<td></td>
<td>In 2 days</td>
</tr>
<tr>
<td></td>
<td>22 Reviews</td>
<td></td>
</tr>
<tr>
<td></td>
<td>95% Completion Rate</td>
<td></td>
</tr>
</tbody>
</table>

- Completed - Freelancer rated

<table>
<thead>
<tr>
<th>Freelancers Bidding (0)</th>
<th>Reputation</th>
<th>Bid (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>swsindia</td>
<td>4.4</td>
<td>$123</td>
</tr>
<tr>
<td></td>
<td></td>
<td>In 1 days</td>
</tr>
<tr>
<td></td>
<td>15 Reviews</td>
<td></td>
</tr>
<tr>
<td></td>
<td>88% Completion Rate</td>
<td></td>
</tr>
</tbody>
</table>

- Completed - Freelancer rated
Research Context

- **Enhanced online tracking feature**

On August 2\textsuperscript{nd} 2015, Freelancer provides a new offline tracking feature.

Advantages:
1. keep a record of the project process even with an unstable Internet connection
2. employers do not need to keep checking the project process frequently and the monitoring record will be automatically archived
3. remarkably increase the precision of monitoring result

all of the above => lower monitoring cost
RESEARCH HYPOTHESES

Offline tracking feature in Freelancer app

- Supply side
  - Number of bids
  - Average bid price
- Demand side
  - Employers’ preference
  - Employer surplus

Because the fixed-price projects in the control group can well capture the effect of economy circle, platform characteristics, the expertise level of bidder population, unemployment rate etc., we can identify the treatment effect of offline tracking feature.
Reduced transactions costs

- **H1:** Ceteris paribus, compared to fixed-price projects, the number of bidders of hourly projects will be higher, after the introduction of the monitoring tool. (more bidders of high-quality work bid for the hourly projects)
RESEARCH HYPOTHESES

Reduced moral hazard

- **H2**: Ceteris paribus, compared to fixed-price projects, the average bid price of hourly projects will be higher, after the introduction of the monitoring tool. (better monitoring ensures effort level; higher average quality work)
- **H3**: After the introduction of the monitoring tool, employers of hourly projects will have a weaker preference for bidders with high-reputation contractors after IT-enabled monitoring tool is available. (“slumming” problem, low-reputation bidders might lead to better trade-off between outcome value and price)
- **H4b**: After the introduction of the monitoring tool, the employer surplus will be higher
## RESULTS

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Num_Bids</td>
<td>Num_Bids</td>
<td>Num_Bids</td>
<td>Num_Bids</td>
</tr>
<tr>
<td><strong>Hourly_i</strong></td>
<td>0.310***</td>
<td>0.367***</td>
<td>0.197***</td>
<td>0.201***</td>
</tr>
<tr>
<td></td>
<td>(3.39)</td>
<td>(4.07)</td>
<td>(4.88)</td>
<td>(5.13)</td>
</tr>
<tr>
<td><strong>After_i</strong></td>
<td>0.229***</td>
<td>0.211***</td>
<td>0.187***</td>
<td>0.179***</td>
</tr>
<tr>
<td></td>
<td>(4.37)</td>
<td>(4.11)</td>
<td>(16.45)</td>
<td>(15.89)</td>
</tr>
<tr>
<td><strong>After_i × Hourly_i</strong></td>
<td>0.271**</td>
<td>0.239*</td>
<td>0.168***</td>
<td>0.157***</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(1.83)</td>
<td>(3.64)</td>
<td>(3.51)</td>
</tr>
<tr>
<td><strong>Budget_Max</strong></td>
<td>0.152***</td>
<td>0.142***</td>
<td>0.139***</td>
<td>0.126***</td>
</tr>
<tr>
<td></td>
<td>(8.09)</td>
<td>(7.59)</td>
<td>(37.21)</td>
<td>(34.64)</td>
</tr>
<tr>
<td><strong>Desc_Length</strong></td>
<td>-0.118***</td>
<td>-0.113***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.13)</td>
<td></td>
<td>(-16.83)</td>
<td></td>
</tr>
<tr>
<td><strong>SkillsNum</strong></td>
<td>0.273***</td>
<td></td>
<td>0.387***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.86)</td>
<td></td>
<td>(40.67)</td>
<td></td>
</tr>
<tr>
<td><strong>Employer_Developed</strong></td>
<td>0.275***</td>
<td></td>
<td>0.304***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.42)</td>
<td></td>
<td>(27.19)</td>
<td></td>
</tr>
<tr>
<td><strong>_cons</strong></td>
<td>1.745***</td>
<td>1.832***</td>
<td>1.882***</td>
<td>1.840***</td>
</tr>
<tr>
<td></td>
<td>(17.60)</td>
<td>(12.76)</td>
<td>(86.31)</td>
<td>(55.46)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1620.000</td>
<td>1620.000</td>
<td>3.5e+04</td>
<td>3.5e+04</td>
</tr>
<tr>
<td><strong>r2_a</strong></td>
<td>0.056</td>
<td>0.098</td>
<td>0.049</td>
<td>0.108</td>
</tr>
</tbody>
</table>
# RESULTS

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>hourlyPrice</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Hourly_i$</td>
<td>-0.153***</td>
<td>-0.538***</td>
<td>-0.558***</td>
</tr>
<tr>
<td></td>
<td>(-5.65)</td>
<td>(-20.05)</td>
<td>(-21.00)</td>
</tr>
<tr>
<td>$After_i$</td>
<td>-0.058***</td>
<td>-0.035***</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(-7.48)</td>
<td>(-4.69)</td>
<td>(0.99)</td>
</tr>
<tr>
<td>$After_i \times Hourly_i$</td>
<td>0.069**</td>
<td>0.065**</td>
<td>0.051*</td>
</tr>
<tr>
<td></td>
<td>(2.15)</td>
<td>(2.13)</td>
<td>(1.70)</td>
</tr>
<tr>
<td>$Budget_Max$</td>
<td></td>
<td>-0.136***</td>
<td>-0.137***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-55.12)</td>
<td>(-54.94)</td>
</tr>
<tr>
<td>$Desc_Length$</td>
<td></td>
<td></td>
<td>0.069***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(15.23)</td>
</tr>
<tr>
<td>$SkillsNum$</td>
<td></td>
<td></td>
<td>0.103***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(15.89)</td>
</tr>
<tr>
<td>$Employer_Developed$</td>
<td></td>
<td></td>
<td>0.036***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.73)</td>
</tr>
<tr>
<td>$Num_Bids$</td>
<td></td>
<td></td>
<td>-0.045***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-12.50)</td>
</tr>
<tr>
<td>_cons</td>
<td>0.988***</td>
<td>1.721***</td>
<td>1.428***</td>
</tr>
<tr>
<td></td>
<td>(172.44)</td>
<td>(119.70)</td>
<td>(61.51)</td>
</tr>
<tr>
<td>N</td>
<td>3.3e+04</td>
<td>3.3e+04</td>
<td>3.3e+04</td>
</tr>
<tr>
<td>r2_a</td>
<td>0.003</td>
<td>0.087</td>
<td>0.108</td>
</tr>
</tbody>
</table>
### RESULTS

Conditional (fixed-effects) Logistic regression  
Number of obs = 4781  

<table>
<thead>
<tr>
<th>LR chi2(20) = 266.91</th>
<th>Prob &gt; chi2 = 0.0000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood = -1140.2975</td>
<td>Pseudo R2 = 0.1048</td>
</tr>
</tbody>
</table>

| Project awarded | Coef. | Std.Err. | Z   | P>|z| | 95% Conf. | Interval |
|-----------------|-------|----------|-----|------|---------|-----------|
| **after#hourly*capability** |       |          |     |      |         |           |
| After Hourly    |       |          |     |      |         |           |
| 0 0             | 0.0761 | 0.0374   | 2.040 | 0.0410 | 0.00294 | 0.149     |
| 0 1             | 0.0953 | 0.0830   | 1.150 | 0.251  | -0.0673 | 0.258     |
| 1 0             | 0.0832 | 0.0419   | 1.990 | 0.0470 | 0.00112 | 0.165     |
| 1 1             | 0.158  | 0.167    | 0.940 | 0.346  | -0.170  | 0.485     |

| **after#hourly#c.reputation** |       |          |     |      |         |           |
| After Hourly    |       |          |     |      |         |           |
| 0 0             | 0.393  | 0.0622   | 6.310 | 0     | 0.271   | 0.515     |
| 0 1             | 0.326  | 0.132    | 2.470 | 0.0130 | 0.0676  | 0.584     |
| 1 0             | 0.249  | 0.0826   | 3.020 | 0.00300 | 0.0873 | 0.411     |
| 1 1             | 0.155  | 0.232    | 0.670 | 0.506  | -0.301  | 0.610     |
## RESULTS

<table>
<thead>
<tr>
<th>Employer Surplus</th>
<th>Fixed-price</th>
<th>Hourly</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Before</strong> mean</td>
<td>0.315921</td>
<td>0.284902</td>
<td>0.311184</td>
</tr>
<tr>
<td>S sd</td>
<td>0.45114</td>
<td>0.325262</td>
<td>0.434299</td>
</tr>
<tr>
<td>N</td>
<td>910</td>
<td>164</td>
<td>1074</td>
</tr>
<tr>
<td><strong>After</strong> mean</td>
<td>0.273344</td>
<td>0.343961</td>
<td>0.284338</td>
</tr>
<tr>
<td>S sd</td>
<td>0.574913</td>
<td>0.330858</td>
<td>0.544522</td>
</tr>
<tr>
<td>N</td>
<td>461</td>
<td>85</td>
<td>546</td>
</tr>
<tr>
<td><strong>Total</strong> mean</td>
<td>0.301605</td>
<td>0.305062</td>
<td>0.302136</td>
</tr>
<tr>
<td>S sd</td>
<td>0.496412</td>
<td>0.327719</td>
<td>0.474319</td>
</tr>
<tr>
<td>N</td>
<td>1371</td>
<td>249</td>
<td>1620</td>
</tr>
</tbody>
</table>
CONCLUSION

- The societal impacts of big data
  - Informational
  - Relational
  - structural (organizational and societal)
THANK YOU!