He’s Overqualified, She’s Highly Committed
The Effect of Job Candidate Gender and Capability on Perceptions of Firm and Career Commitment
Elizabeth L. Campbell & Oliver Hahl (Tepper School of Business, Carnegie Mellon University)

A Mixed-Methods Approach: 2 Experiments and Qualitative Analysis
Participants rated 1 profile of a job candidate on perceived firm commitment, career commitment, and likelihood to hire. Qualitative analysis conducted on responses of why the hiring manager thought the candidate was applying for new positions.

Do hiring managers make gendered, pre-hire inferences about a job candidate’s firm and career commitment?

Study 1
2 (male, female) x 2 (capability: sufficiently, highly) between-subjects (n=215)

Qualitative Findings
• Signals of capability were also being used to make inferences about why a candidate was applying for new positions
• Highly capable women were assumed to be facing unfair barriers to their advancement

Study 2
2 (male, female) x 2 (capability: sufficiently, highly) x 2 (prior firm fairness: unfair, fair) between-subjects (n=424)

Conclusions
• Signals of high capability boosted women’s perceived firm and career commitment, which raised their chances of receiving a job offer (Study 1), except when it was clarified they received equal advancement opportunities in their prior firm (Study 2)
• These same signals of high capability lowered men’s perceived firm commitment and labor market outcomes, but never impacted men’s perceived career commitment (Study 1 & 2)

Elizabeth Campbell – elcampbe@andrew.cmu.edu – Funding to attend conference provided by CMU GSA/Provost Conference Funding – Please note: research is in progress and was presented at AOM 2020 as a presentation
Do Aggressive Questions Bring Better Questions?
Evidence From Stack Overflow

Zhaoqi Cheng, Dokyun Lee, Tridas Mukhopadhyay
Tepper School of Business, Carnegie Mellon University

Abstract
We investigate the effects of moderate-level aggressive comments over an individual’s content generation in the context of Q&A websites. Our empirical investigation suggests that the aggressive comments may affect both the volume and the quality of questions on the platform. Hurt new users’ future question output volume: (1) new users who receive aggressive comments may post fewer questions in the future; (2) after getting attacked by aggressive comments, users are found to write questions which have significant conciser code examples and more referral links but weakly lower topical relevance and information quantity, which suggests significant quality increases in truthfulness and manner, and weak quality decrease in quantity of information and relevance. We discuss the theoretical grounding of our method and implications for site managers.

Background: Aggressive Comments @ Stack Overflow
Q&A websites have become the fastest developing online platforms for sharing knowledge and expertise. The largest professional Q&A website, Stack Overflow, is not only an open knowledge-sharing platform for IT developers to solve daily questions, but also a pool for tech companies to hunt talents. Yet, this platform is often accused of having massive toxic comments by unfamiliar users, which typically target on the poor writing quality of the posts.

Research Questions

- How do aggressive influence individuals’ question post behavior?
- Do people most more or less after getting bullied?
- Do people post better questions after getting bullied?
- At the aggregate level, what impact will aggressive comments bring to the platform?
- How should managers make the strategy?

Research Context: Stack Overflow
Dataset is cleaned by the following criteria:
- Contents are posted in 2008-2017
- Questions are posted by active users
The cleaned dataset span the content and metadata of 25.6M questions by 300k users, which result in 10M comments
To aid further analysis, we use Louvain clustering algorithm to categorize the questions by their attached tags into 13 topic-based communities.

Feature Extraction: Measuring Comment Aggression and Question Quality
We use a Convolutional Neural Network pretrained on Wikipedia Detox dataset [1] to detect whether a comment is aggressive
The CNN contains 128 convolutional filters of different sizes and 4 max pooling layers, achieves an AUC score of 0.97 on the test set
Prediction show that 12% of the questions receive 1+ aggressive comments

Feature Extraction: Measuring the Writing Quality of Questions
To measure the writing quality of questions, we develop our quality metrics by operationalizing the famous linguistic theory of Grice’s Maxims.
- Quantity of Information: a question may discuss some topics at same time, but a question should have enough words to discuss them
- Truthfulness: the good question should use hyperlinks for citing references
- Relevance: the topic distribution of a good question should be similar to the topic distribution of the community in terms of KL divergence
- Manner: the questions should provide concise code examples

Estimation Methods and Results
Aggressive comments vs. beginners’ future question generation volume
- Linear model on user $l$

Result
- Aggressive comments may reduce question generation of new users
- We use propensity score matching to account for user-level covariates $X$ which may affect the outcome and cause selection bias
- e.g. registration year, user average frequency of posting, etc.

Main results

<table>
<thead>
<tr>
<th>Treatment Group</th>
<th>Word/topic (Quantity)</th>
<th>Hyperlinks (Trueness)</th>
<th>KL Divergence (Relevance)</th>
<th>Lines/Codeblock (Manner)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta Q$</td>
<td>0.25436</td>
<td>0.00234</td>
<td>0.00347</td>
<td>0.00575</td>
</tr>
<tr>
<td>$\Delta D$</td>
<td>0.39524</td>
<td>0.00523</td>
<td>0.00523</td>
<td>0.00285</td>
</tr>
<tr>
<td>$\Delta Q - \Delta D$</td>
<td>0.14092</td>
<td>0.00175</td>
<td>0.00175</td>
<td>0.00293</td>
</tr>
</tbody>
</table>

Managerial Implication & Conclusion
- Platform should provide more assistance to vulnerable groups
- Comments of moderate aggression may have a constructive role to the platform and to users
- Our contribution: propose theory-guided quality metrics for texts; bring a econ. framework to cyberbullying; focus on moderate-level aggression

Further work: sequential model of the bullying–posting process, affects of cyberbullying on the answers

Acknowledgments and References
Funding to attend this conference was provided by the CMU CSA/Provost Conference Funding. We thank Linda Argote, David Childers, Yan Huang, Hui Li, Emaad Manzoor, Michael D. Smith, Kannan Srinivasan for suggestions on the project.
The Importance of Transactive Memory Systems (TMS)

- TMS is often referred to as the “knowledge of who knows what”, and is crucial for efficiently accessing and using knowledge. (Lewis & Herndon, 2011; Lewis, 2004; Hollingshead, 1998; Liang, Moreland & Argote, 1995)
- TMS has been shown to increase:
  - Creativity (Gano, Argote, Minn-Spekter, & Todoro, 2010; Akgün, Byrne, Kaskin, Lynn, & Imamoglu, 2005)
  - Transfer of learning (Lewis, Lange, & Gillis, 2005)
  - Team performance (Forar & Sproull, 2000)
  - Relationship satisfaction (Wegner, Giuliano, & Hertal, 1985; for review, see Ren & Argote, 2011)

Why Examine the Role of Personality in TMS?

- There is a dearth of research on the influence of individual difference in TMS.
- There is increasing organizational relevance of ad hoc and non-permanent teams, which are often tasked with the highest-stakes teamwork (e.g. emergency room teams, flight teams, and anti-terrorism task forces). Individual differences (like individual well-being) are expected to play a stronger role on these teams, which cannot rely on interpersonal familiarity or shared work experience. (Lewis, 2004; Akgün, Byrne, & Kaskin, 2005; He, Butler, & King, 2007; Littpage, Robinson, & Reddington, 1997; Ren & Argote, 2011)

How TMS Emerges

- For TMS to emerge on a team, team members must:
  1. Accurately identify the expertise of their fellow team members (Brandon & Hollingshead, 2004; Karanawanachai & Yoo, 2007)
  2. Form positive relationships for knowledge sharing and coordination (Krackhardt, Nohria, & Eccles, 2003; McEvily, Peronne, & Zaheer, 2003; Uzzi, 1997; Hansen, 1999)

How is Expertise Identified?

- The accurate identification of expertise requires both judge accuracy and target transparency in terms of expertise.
- While the accurate identification of a target’s expertise is a relatively new concept in organizational science, accurate perception (in terms of personality traits) has been studied since the 1950s by social and personality psychologists.
- Accurate judgment depends on the accuracy of the cues provided by targets. (Funder, 1989; Rogers & Blesanz, 2018)

Well-being Facilitates Target Transparency

- Prior research has shown that people higher in well-being are more accurately judged for their personality traits because they provide more accurate, self-referential cues. (Human & Biesanz, 2011; Human, Biesanz, & Todorova, 2010)
- Individual well-being is a higher-order personality construct composed of elements of hedonic and eudemonic well-being (i.e. lower depression, higher self-esteem, higher satisfaction with life, higher positive relations with others) and are less likely to have overinflated or underinflated views of the self. (Funder, 1999; Human et al., 2014; Jahoda, 1958; Ryff, 1989; Waterman, 1993)

Well-being Facilitates Positive Relationships

- People with higher well-being have stronger, more positive relationships with others. (Colvin 1993a, 1993b; Human & Biesanz, 2011; Human et al., 2014)
- Strong, positive relationships support TMS by facilitating:
  - Increased coordination (Krackhardt, Nohria, & Eccles, 2003; Lewis, 2003; 2004; McEvily, Peronne, & Zaheer, 2003; Ryff 1989; Zinolnick, Kohn, and Della Grotta, 2000)
  - More complex knowledge-sharing and intensive problem solving (e.g. Uzzi, 1997; Hansen, 1999)
  - Greater trust and reciprocal information exchange (Krackhardt et al., 2003; McEvily et al., 2003)

Our Prediction

- Average team well-being will be positively associated with the transactive memory of teams.

Lab Experiment: Overview

- All aspects of this study are preregistered at AsPredicted.org.
- Participants completed an online personality questionnaire, assessing individual well-being, weeks or months before being recruited to participate in teams of three in the lab experiment.
- (n = 98 teams)
- Teams were randomly assigned to one of two conditions (high or low expertise explicitness) to further test our hypothesis in contexts where individual expertise is explicit (e.g. as in flight crews) versus those in which expertise is not explicit (e.g. as in sales teams).

Preliminary Results

- Average team well-being significantly predicted TMS in terms of credibility (trust) and coordination.
- Although all teams benefitted from high expertise explicitness, only team well-being was associated with greater trust and coordination

Conclusion

- While a team’s ability to identify expertise accurately can be improved relatively easily by making expertise information explicit, enhancing a team’s trust in that expertise and ability to coordinate may be more challenging, because it is influenced by the individual well-being of the team members, which may be difficult or time-resource-intensive to modify.
OVERVIEW

- Traditional methods to estimate the average treatment effect (ATE):
  - Collect deconfounded data
  - Run clinical trials
  - Assume underlying causal structure
- Baseline approach: estimate the ATE using deconfounded data only
- Reasons to consider confounded data:
  - Contains partial information on the ATE
  - Might be available with low costs
- We study the benefit of including confounded data alongside deconfounded data in estimating the ATE:
  - Analyze theoretically via
    - Sample complexity in the offline setting
  - Validate through both synthetic and real-world experiments
- Scope of the study:
  - Offline version: binary and categorical variables
  - Baseline approach: estimate the ATE using deconfounded data only
    - Might be available with low costs
  - Scope of the study:

PROBLEM SETUP

- Y: outcome (binary)
- T: treatment (binary)
- Z: confounder (categorical)
- \( \text{ATE} := P(Y=1|do(T=1)) - P(Y=0|do(T=0)) \)

THEOREMS

- Let \( C = \frac{12.5k^2}{\delta^2} \ln \left( \frac{3k^2}{\delta^2} \right) \) throughout.
- Baseline result: 
  \[ m_{\text{base}} := \max_{Y,T,Z}(y,t,z) \frac{4}{P_{Y,T,Z}(y,t,z)^2} C. \]
- Similarly, for outcome-weighted selection policy:
  \[ m_{\text{OWSP}} := \max_{y \in \{0,1\}, t \in \{0,1\}} \frac{2}{P_{Y,T}(y,t)^2} C. \]
- This allows us to construct a lower bound on the accuracy level
  \[ \text{deconfounded data required to estimate the ATE to within a desired accuracy level} \]

CONCLUSIONS

- The inclusion of confounded data can reduce the quantity of deconfounded data required to estimate the ATE to within a desired accuracy level.
- By carefully choosing these examples based upon the (already) observed treatment and outcome, we can reduce our data dependence further.
- The worst-case performance of our approach (vs. a natural benchmark) is bounded while our best-case gains are unbounded.
- Both theoretical and empirical results support our conclusions.
Funding to attend this conference was provided by the CMU GSA/Provost Conference Funding.
Investigating the Dynamic Relationship between Team Faultlines and Performance: A Multilevel and Latent Modeling Approach  
Ki-Won Haan (Tepper School of Business)

### Research Motivation

- **From diversity to faultlines**
  - Null main effect of team diversity (e.g., Roberson et al., 2017)
  - Consistent negative effects of faultlines (e.g., Thacher & Patel, 2011)
  - Regardless of activation (e.g., Zanetti et al., 2011)
- **Faultline types**
  - Identity vs. information-based faultlines (e.g., Bezrukova et al., 2009; Carton & Cummings, 2012; Chung et al., 2015)

### Research Questions

- **Average membership change**
  - Does average number of newcomers (a team-specific characteristic) affect the varying effects, if any, of faultlines across teams?
  - Testing old and new ideas with new methods
  - Hypotheses 1–4
- **Month-to-month membership change**
  - An examination of temporal effects of faultlines—immediate and long-term effects of faultlines on performance trajectories
  - Testing new ideas with new methods
  - Hypotheses 5, 6

### Data/Sample

- **19-month panel data**
- **Retail-banking sales teams**
- **Criteria**
  - Teams with at least 3 personnel, 3 months of data
- **Sample**
  - (H1 – H4) 26,582 observations from 1,800 teams
  - (H5, 6) 867 teams (month 1–10), 870 teams (month 11–19)

### Results

- **Average effects of faultlines across time**
  - H1: Identity-based faultlines (-) (supported)
  - H2: Information-based faultlines (non-monotonic) (supported)

- **Varying effects of faultlines and newcomers**
  - H3: Varying slopes of faultlines across teams (supported)
    - About 45% of teams showed significantly different slopes from the mean
  - H4: Greater team-specific effects when the average number of newcomers across time is higher (partial support)
    - Only for information-based faultlines
    - The main effect of average number of newcomers was negatively significant

### Methods

- **Multilevel theory**
  - Variance across different units (e.g., Kleins & Kozlowski, 2000)
    - For instance, in retail-banking, teams (branches) differ in terms of sales, operations, and governance (Mashell & et al., 2012)
    - Even if two teams have same faultlines, team-specific factors can influence the effects of faultlines
  - Hypothesis 3
  - There are variations in the effects of team faultlines across different teams within an organization on average across time.

### Dynamic Effects of Faultlines

- **Disruption to team development**
  - Impaired coordination (e.g., Argote et al., 2018)
  - Constant reversion to transition phase (Marks et al., 2001)
  - Increase in demand for newcomer socialization (e.g., Summers et al., 2012)
  - Hypothesis 4
  - Team-specific effects of team faultlines on performance will be greater when the average number of newcomers across time is higher, such that (a) the effects of identity-based faultlines become more negative and (b) the non-monotonic relationship between information-based faultlines and performance is stronger.

### Dynamic Effects of Identity-Based Faultlines

- **Near-term effects**
  - Value in diversity and attention to tasks
    - An external shock can divert team members’ attention away from relationship building (Spreitzer & Ellis, 2017)
    - Identity-related attributes can signal deep-level differences, which increases expectation for different information (e.g., Philips et al., 2004) and need for coordination (e.g., Loidl et al., 2013)
    - Hypothesis 5a
    - A time-lagged increase in identity-based faultlines is positively associated with team performance during the month of membership change.

- **Long-term effects**
  - Negative interpersonal processes tend to emerge over time
    - Misattribution of coordination failures (Srikanth et al., 2016)
    - People do not actively look for evidence that disconfirms their stereotypes (Fiske & Neuberg, 1990; Van Dijk et al., 2017)
    - Hypothesis 5b
    - Identity-based faultlines are negatively associated with time-lagged increase in team performance in the long-term.

### Dynamic Effects of Information-Based Faultlines

- **Near-term effects**
  - Task-focus and more coordination challenges
    - An external shock and reversion to the transition phase shift attention to re-establishing team structure and routines
    - Explanation of familiar resources
    - Re-framing of different thoughts and perspectives
    - Threats to task-related identities
    - Hypothesis 6a
    - A time-lagged increase in information-based faultlines is negatively associated with team performance during the month of membership change.

- **Long-term effects**
  - As reasons for conflicts are attributed more to identity-based characteristics, the initial negative effects are likely to wear off
  - Over time team members are more likely to appreciate the information-based resources of the newcomers
  - Hypothesis 6b
  - Information-based faultlines are positively associated with time-lagged increase in team performance in the long-term.

### Revisiting the Average Effects of Faultlines

- **Identity-based faultlines**
  - Social categorization process
    - Categorization based on multiple attributes (comparative fit)
    - An easier (instant) cognitive activation of differences (cognitive accessibility)
  - A few cross-sectional studies found negative relationship between identity-based faultlines and performance (e.g., Chung et al., 2015)
  - Hypothesis 3
  - Hypothesis 3: Identity-based team faultlines are negatively associated with team performance on average across time.

- **Information-based faultlines**
  - Mixed findings (e.g., Bezrukova et al., 2009; Bezrukova et al., 2012)
  - Information-elicitation vs coordination costs
    - Upside: access to diverse information, specialization, within-group support
    - Downside: divergent mental models (representation gap) (Cronin & Weingart, 2007), task-related identity categorization (Van Knippenberg et al., 2004)
  - Hypothesis 3
  - Hypothesis 3: Information-based team faultlines have a non-monotonic (inverted U-shaped) relationship with team performance on average across time.

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What Factors Influence a Government’s Decision to Invest in the Community Rating System?
Caroline A. Hopkins (Tepper School of Business, Carnegie Mellon University)

Approach:
I build a theoretical model of a local government’s decision to invest in flood hazard mitigation and then test the implications of the model empirically using New Jersey municipality participation in the Community Rating System (CRS) from 2002-2015

Conclusions:
• Income, population, housing values, risk, value of amenity access, and if the local jurisdiction type is Mayor-Council are positively associated with flood hazard mitigation
• I argue that accountability is driving the mayor-council results and support that argument using an information shock
• Further show that the information shock has a significant effect on increasing participation
• Policy should focus on increasing information and incentivizing poorer high-risk areas.

Implications of the Model:
• Increase in the probability of flood shock increases investment
• Increase in housing values increases investment
• Increase in wealth increases investment
• Increase in population increases investment
• A representative homeowner with higher relative value of the amenity (i.e. coastal access) compared with other public goods (schools etc) will increase investment
• Higher accountability governments will increase investment

Table 1: Regression Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mayor-Council Indicator = 1</td>
<td>223.7***</td>
<td>0.394***</td>
</tr>
<tr>
<td>(0.155)</td>
<td>(0.0571)</td>
<td></td>
</tr>
<tr>
<td>Post Sandy</td>
<td>648.1***</td>
<td>1.188***</td>
</tr>
<tr>
<td>(184.7)</td>
<td>(0.347)</td>
<td></td>
</tr>
<tr>
<td>Post Sandy x Mayor Council</td>
<td>-129.2</td>
<td>-0.259</td>
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<tr>
<td>(79.35)</td>
<td>(0.148)</td>
<td></td>
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<tr>
<td>Percent Second Homeowners</td>
<td>8.405***</td>
<td>0.0152***</td>
</tr>
<tr>
<td>(0.793)</td>
<td>(0.00143)</td>
<td></td>
</tr>
<tr>
<td>Above Average Real Estate Campaign Contr. = 1</td>
<td>-61.19***</td>
<td>-0.114**</td>
</tr>
<tr>
<td>(27.40)</td>
<td>(0.0497)</td>
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<tr>
<td>Majority Democrat Voters = 1</td>
<td>157.7***</td>
<td>0.165**</td>
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<tr>
<td>(45.12)</td>
<td>(0.0812)</td>
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<tr>
<td>Percent Voter Turnout</td>
<td>3.610*</td>
<td>0.0051*</td>
</tr>
<tr>
<td>(1.883)</td>
<td>(0.0305)</td>
<td></td>
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<tr>
<td>Indicator for Large Government = 1</td>
<td>57.47</td>
<td>0.0781</td>
</tr>
<tr>
<td>(45.55)</td>
<td>(0.0867)</td>
<td></td>
</tr>
<tr>
<td>Log(Est. Population)</td>
<td>97.50***</td>
<td>0.174***</td>
</tr>
<tr>
<td>(11.30)</td>
<td>(0.0306)</td>
<td></td>
</tr>
<tr>
<td>Log(Per capita Tax from Property Value)</td>
<td>136.3***</td>
<td>0.244***</td>
</tr>
<tr>
<td>(17.44)</td>
<td>(0.0323)</td>
<td></td>
</tr>
<tr>
<td>Percent on SNAP</td>
<td>-23.06***</td>
<td>-0.0451***</td>
</tr>
<tr>
<td>(2.425)</td>
<td>(0.00439)</td>
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<tr>
<td>Indicator for Risk = 1</td>
<td>666.3***</td>
<td>1.157***</td>
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<tr>
<td>(41.09)</td>
<td>(0.0742)</td>
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<tr>
<td>Constant</td>
<td>-2.865***</td>
<td>-15.11***</td>
</tr>
<tr>
<td>(277.8)</td>
<td>(0.507)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,598</td>
<td>1,598</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.589</td>
<td>0.543</td>
</tr>
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</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: WHYY.org

Caroline A. Hopkins – chopkins@Andrew.cmu.edu – Funding to attend conference provided by CMU GSA/Provost Conference Funding – Please note: research is in progress and slides were presented at SEA 2019
Is structure all that matters?

- Brokerage gives access to non-redundant information (idea generation).
- Closure is associated with trust and consensus (idea acceptance).
- Taken together, these perspectives highlight a tradeoff.

“Bridging a structural hole can create value, but delivering the value requires the closed network of a cohesive team around the bridge” (Burt, 2005: 80).

- Past research has emphasized the importance of creating hybrid structures (Reagans & Zuckerman, 2001) but it has neglected the role of social perceptions in explaining unequal returns to brokerage.

- Idea: Alter’s perceptions of a focal actor’s brokerage opportunities can enrich our understanding of the link between network positions and performance.

A socio-cognitive approach to network advantage

- Having open networks enhances individuals’ performance by granting individuals informational and control benefits (Burt, 1992; Granovetter, 1973).
- Those that are being brokered may develop a belief that the broker is not “one of them,” thus triggering skepticism of the broker’s motives that can hinder brokers’ ability to get their ideas accepted (Coleman, 1988; Stovel & Shaw, 2012).
- Individuals are inaccurate in perceiving networks (Krackhardt, 1987). Actual and socially perceived brokerage can be decoupled.

Capturing actual and perceived brokerage

- Field data based on 191 employees in a consulting firm. Relational data collected through a web survey. Individual performance evaluations obtained directly from the organization.
- Performance (DV): Dummy variable capturing whether an employee is a high performer or not. Employees are assessed by their supervisor.
- Brokerage (IVs): Focus on advice networks. Actual brokerage is measured from an underlying network consisting only of ties that are confirmed by both parties. Perceived brokerage is measured using a novel approach relying on network visual scales (Mehra et al. 2014).

Measuring Alters’ Perceptions of a Focal Actor’s Network

- Trustworthiness: Count of how many people indicated that they trusted a given actor (Krackhardt & Hanson, 1993).
- I use Linear Probability Models with robust standard errors. Results are robust to other specifications.

Do social perceptions of brokerage matter?

The way in which others perceive your network configuration affects your ability to extract value from occupying bridging positions.

People who are perceived to have open networks are seen as less trustworthy. Trustworthiness is associated with performance.

Main takeaways

- Importance of decoupling actual and socially perceived network positions. Social cognitions can enrich our understanding of network advantage.
- Brokers do better, on average, especially when others perceive them to be embedded in cohesive groups.

Next steps

- What are some of the possible antecedents of the mismatch between actual brokerage and socially perceived brokerage?
- To what extent can brokers alter others’ perceptions?
- Are these results influenced by the type of culture surrounding individuals (e.g., collectivist or individualistic)?
Market Shifts the Sharing Economy: The Impact of Airbnb on Housing Rentals

Yijin Kim, Hui Li, and Kannan Srinivasan (Tepper School of Business, Carnegie Mellon University)

Introduction & Data

Background
- Airbnb provides landlords an alternative opportunity to rent to short-term tourists, potentially causing some of the property owners to switch away from long-term rental for local residents.
- Airbnb’s impact on rental supply and affordability has been a topic of heated debate, especially in cities with tight housing markets like New York and San Francisco.
- Current short-term rental regulations such as occupancy tax and limits on how often hosts can rent out on Airbnb are not empirically supported.

Research Question
1. How does Airbnb affect rental housing supply and affordability?
   - Supply: how many units
   - Affordability: type of properties/demographics/city
2. What is the impact of potential policies or regulations on short-term rental?
   - Occupancy tax
   - Night limits

Data
- American Housing Survey (AHS) 2015
  - Representative units in 25 metropolitan areas
  - Tenure (renter- or owner-occupied) & rent
  - Property characteristics
  - Householder demographics
  - 342,873 unique properties across the US
  - Number of days listed/booked & price
  - Property characteristics
  - Host demographics (imputed from zip code level data)

Model

Model Overview
- Property owners make two decisions that maximize their profit, namely, revenue and cost.
- We do know the revenue from data, but not the cost.
- Our goal is to back out the heterogeneous costs by building a structural model of property owners’ decision.

2nd Stage: Continuous Decision of Listing on Airbnb
- Profit function
  \[ \Pi_i^A(s) = p_i^A \phi_i^A s_i^A - c_i^A \exp \left( \frac{p_i^A}{c_i^A} \right) - 1 \]
- Optimal number of days to list
  \[ s_i^A = \min \left\{ \gamma \cdot \ln \left( \frac{p_i^A \phi_i^A}{c_i^A} \right), 1 \right\} \]

1st Stage: Discrete Decision of Where to List
- Profit function
  - Airbnb: \[ \Pi_i^A = \sum \Psi_i^A \Pi_i^A \]
  - Rental: \[ \Pi_i^R = p_i^R - c_i^R \]
  - Outside option: \[ \Pi_i^O = 0 \]
- Optimal choice
  \[ d_i^* = \arg \max_{d_i(A,R,O)} \Pi_i^d \]

Results & Conclusion

Cannibalization and Market Expansion
- Airbnb mildly cannibalizes the long-term rental supply but creates market expansion effect.
- The percentage of switchers varies across metro area.
- Switcher Profiles
  - The cannibalization impact is largely concentrated on affordable units.

Short-term Rental Regulations
- Short-term rental regulations help reduce the cannibalization, but also reduce the market expansion effect.
- Limiting the number of months and imposing concave tax are more desirable than imposing linear tax.
Will Your New Customers Buy Again? When? What?

- Predicting and understanding when and what customers will buy is crucial for marketing managers who allocate marketing efforts in a timely and effective manner. We propose a new approach to predict when and what customers of non-subscription companies will buy.
- Customers place orders on a more regular basis, while others do so at sparser intervals: difficult to predict customer activity using traditional approaches based on transaction data.
- We augment transaction data with clickstream data through a Bayesian model to predict what product category customers will purchase and when purchases will take place. Our model is "multi-view" (view 1: transaction history; view 2: browsing history).
- Our clusters customers into transaction and clickstream topics, which depicts profiles of customers and their relative economic potential, and relates these topics to how long customers wait to buy.
- The profiles of topics and customers are directly interpretable and are of use to marketing managers engaging in promotional activities for customers.

Main Findings

- We find that clickstream data contains leading indicators about the next purchase timing and churn characterization.
- The discovered topics are understandable in both their content and their purchase timing distribution.
- We also find that while some topics have similar purchase timing distribution, they differ in their content.
- On the methodological side, we build a correlated topic model over time, with distributed representation of correlation, supervised by the purchase timing at the individual level, and allow the label to be right censored.

Summary

- Question: How to predict churn or customer activity in a non-subscription company?
- Solution: We build a probabilistic machine learning model that uses purchased product categories and parsed pieces of visited URLs from customers, and reduce them into purchasing and browsing topics. Then, we use topics to train our label variable, the next purchase timing, at the individual level. Finally, we predict the label on our test set (when will they buy?) and interpret the topics (what will they buy?).

Limitations and Future Research

- Our model can incorporate more than two "views" of the customer.
- We do not claim any causal effects.
- We do not model purchase quantities in addition to purchase timing.
- Dynamics could arise in terms of topic evolution.
- Future work will extend our model and include a stochastic process governing the evolution of topic proportions over time.
Group Brainstorming: The Effects of Collective Intelligence, Individual Ability, and Task Structure

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Tepper School of Business, Carnegie Mellon University

Overview

Are structural interventions beneficial for all brainstorming groups? We use a measure of CI along with a measure of individual ability to predict brainstorming performance in small groups using either a hybrid or collective task structure.

Collective Intelligence & Production Blocking

Woolley et al. (2010) found that, like an individual intelligence factor, a collective intelligence factor (CI) emerges based on group performance on a variety of tasks. Across multiple samples and contexts, high CI groups tend to communicate more effectively than low CI groups.

Production blocking (PB) is among the strongest inhibitors of group brainstorming. Monitoring group speaking patterns increases members’ cognitive loads, which disrupts mental image activation, resulting in low idea category variety in groups’ brainstorming performance.

Due to their enhanced communication ability, high CI groups may naturally experience low PB, resulting in greater category variety, which is a more proximal outcome than total ideas (quantity) or judged overall creativity (quality).

H1: Category variety mediates the positive relationship between group CI and group brainstorming quantity/quality.

Brainstorming Task Structure

Hybrid brainstorming structures, which incorporate individual and collective work portions, have been utilized in attempts to mitigate the effects of group inhibitors like PB, and have been shown to enhance group brainstorming performance on average.

However, since they reduce the time when cognitive stimulation can occur between group members, hybrid structures might do so at the expense of inhibiting well-coordinated groups, where members inspire each other through interaction, from reaching their full creative potential.

Since high CI groups experience low PB, they may not be helped by, and may even be limited by, hybrid task structures. Such groups may benefit from more group interaction when inspiration can occur.

H2: High CI groups perform better in a collective brainstorming structure, while low CI groups perform better in a hybrid brainstorming structure.

Method

99 3-person groups (65% = Female; $M_{age}$=22.02, $SD_{age}$= 5.04)

Participants completed an individual brainstorming task, a CI task battery, and a group brainstorming task.

Manipulation and Measures

- **Brainstorming task structure manipulation**
  - Collective (n=50, group only) or Hybrid (n=49, individual then group)

- **Collective intelligence**
  - The test for collective intelligence uses a variety of group tasks including typing, matrix puzzles, Sudokus, and word unscrambles
  - Akin to a g factor in tests for individual intelligence, a c factor emerges in this test for collective intelligence

- **Average brainstorming ability**
  - Average group member performance on the individual brainstorming task

- **Group brainstorming performance**
  - Category variety; Total ideas; Judged creativity

- **Group conversation audio**

Results

CI had an indirect effect through category variety on group total ideas (95% ci: 0.35, 2.92) and judged overall creativity (95% ci: 0.09, 0.37), above and beyond the effect of the individual creative ability of the group members.

Conclusion

We conducted a laboratory experiment to investigate the effects of collective intelligence, individual brainstorming ability, and task structure on group brainstorming performance.

While theory on group creativity holds that groups can be synergistically creative in idea generation, existing research has generally found them to be ineffective brainstormers, often performing even worse than the sums of their parts.

We hope to contribute to both brainstorming and CI literature by highlighting the conditions under which brainstorming groups can capture creative synergy, proposing that CI allows groups to reduce production blocking, enhance knowledge combination, and capitalize on the resources they have available to them (i.e., member ability).

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Research Questions

- Do individuals learn equally from all others’ failures in organizations?
- How does seniority hierarchies influence learning from seniors’ vs. juniors’ failures?

Introduction

- The effectiveness of learning from failures depends on the ability, motivation, and information available to learn [1].
- In organizations with seniority hierarchies created based on professional tenure, individuals with longer tenure (‘seniors’) are expected to perform better than individuals with shorter tenure (‘juniors’).[1]
- The different performance expectations create the variance in learning from seniors’ and juniors’ failures, by affecting the motivation and information available to learn.

Hypotheses

In organizations with seniority hierarchies:

**H1** Individuals learn from seniors’ failures but not from juniors’ failures. … due to three possible mechanisms:

**Attention:** Individuals attend more to seniors’ failures, expecting the information to be more useful.

**H2** Individuals will learn less from seniors’ failures when they have low attention capacity, than when they do not.

**Ability:** Seniors are better at providing others with more accurate interpretations of own failures.

**H3** Individuals will learn more from own failures as their professional tenure increases.

**Self-enhancement:** Juniors are more likely to hoard or distort information of own failures, providing less information available for others to learn from.

**H4** Individuals will learn more from juniors’ failures in psychologically safe environments, than in others.

Empirical Setting, Data, Methods

- 288 California-based cardiothoracic (CT) surgeons in 127 hospitals from 2003 to 2016 (1,491 observations)

Appropriateness of the Research Context:

1. Performance outcomes can be reliably linked to an individual.
2. Clear and objective measures of failures and learning from failures exist.
3. Hospitals are exemplar settings in which seniority hierarchies based on professional tenure are likely to exist.

Econometric Model

Fixed effects OLS regression with surgeon-hospital dyad and period fixed effects. Standard errors are clustered by surgeon-hospital dyad.

Variables

- **DV. Learning from Others’ Failures**
  - A decrease in surgeons’ patient risk-adjusted mortality rate (RAMR) within each hospital

**IV (H1). Seniors’ and Juniors’ Failures**

- **Seniors:** surgeons who finished CT training earlier than a focal surgeon
- **Failures:** no. of deaths caused by a surgeon

**IV (H2). Surgeon Low Attention Dummy**

- Periods a surgeon dealt with public sanctions

**IV (H3). Surgeon’s Professional Tenure**

- Years since completing one’s CT training

**IV (H4). Hospital Psych. Safe Dummy**

- Nonteaching & Nongovernment-owned hospitals

Results

**Individuals learned from seniors’ failures but not from juniors’ failures (H1). The mechanisms are:**

**H2. Attention** (supported)

“Because we’re hierarchical in our training, it’s beneath me to listen to a junior. Frequently seen where nobody wants to hear what the junior person has to say.” (CT surgeon, Apr’ 19)

**H3. Ability** (supported)

“Having more experience base allows you to see a pattern. A person with less experience might have a hard time seeing a pattern.” (CT surgeon, May’ 19)

**H4. Self-enhancement** (weakly supported)

“Do failure cases travel across hospital? Sure Can. Absolutely. Certainly when you are a junior, you really think about that. You do not want to be labeled as a bad surgeon.” (CT surgeon, May’ 19)

<table>
<thead>
<tr>
<th>DV: Surgeons’ risk-adjusted mortality rate (t+1)</th>
<th>Test of Prediction</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seniors’ failures in focal hospital (t)</td>
<td>H1</td>
<td>-0.139* (0.067)</td>
<td>-0.142* (0.067)</td>
<td>-0.150* (0.069)</td>
<td>-0.152* (0.067)</td>
</tr>
<tr>
<td>Juniors’ failures in focal hospital (t)</td>
<td>H1</td>
<td>n.s.</td>
<td>-0.116 (0.093)</td>
<td>-0.115 (0.093)</td>
<td>-0.112 (0.093)</td>
</tr>
<tr>
<td>Seniors’ failures x Surgeon low attention dummy (t)</td>
<td>H2</td>
<td>+</td>
<td>0.864* (0.353)</td>
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<td></td>
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<tr>
<td>Own failures x Surgeon’s professional tenure (t)</td>
<td>H3</td>
<td>-</td>
<td>-0.020* (0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Juniors’ failures x Hospital psych. safe dummy (t)</td>
<td>H4</td>
<td>-</td>
<td>-0.207+ (0.119)</td>
<td></td>
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</tbody>
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Intra-Organizational Competition Decreases Knowledge Sharing

Motivations for Individual Knowledge Acquisition and Learning

If the amount of knowledge received decreases, individuals may shift to 'impersonal' sources of knowledge (e.g., KMS)
- Performance-based incentives increase not only agents' knowledge acquisition, but also individual learning
- In the absence of competition, individuals can rely on others' expertise (e.g., TMS)
- When experts are competitors, individuals must retain knowledge for themselves to respond to pressures for performance

H2: Intra-organizational competition positively influences the extent to which an individual seeks knowledge from impersonal sources.

H3: Intra-organizational competition positively influences individual learning (i.e., retention of the knowledge acquired by the individual).

Does the KS-Individual Knowledge Activities “Trade-Off” Affect Organizational Learning?

Tournament incentives reveal a potential trade-off between knowledge sharing with others (helping) and individual learning through self-acquisition and retention of knowledge.

Why would overall organizational learning continue despite intra-organizational competition?

Organizational learning curves can have different ‘portfolios’ of individual-, group- and org-level knowledge activities

The net effect on org learning might not change even if constituent knowledge activities change

Productivity (one of the key measures of org learning) will increase, or at least remain the same, at the aggregate level of the organization

H4: Intra-organizational competition has a non-negative effect on overall organizational learning.

Intra-Organizational Competition Decreases Knowledge Sharing

Related Topics in Past Literature

- Incentive Theory
  - Performance-based incentives increase individuals’ task-related efforts but reduce helping
- Knowledge Management
  - Institutionalizing and rewarding knowledge sharing does not guarantee individual participation
  - Linking an agent’s pay to imperfect measures of output will undercut motivations to engage in helping behaviors—such as informal knowledge sharing.
  - Competitive dynamics within the firm may amplify indivduals’ concern over losing advantage and status.
  - Agents have a smaller capacity in their individual knowledge repositories, making it difficult to share only selective knowledge.
  - If the amount of knowledge received decreases, individuals may shift to ‘impersonal’ sources of knowledge (e.g., KMS)
  - Performance-based incentives increase not only agents’ knowledge acquisition, but also individual learning
  - In the absence of competition, individuals can rely on others’ expertise (e.g., TMS)
  - When experts are competitors, individuals must retain knowledge for themselves to respond to pressures for performance

Knowledge Sharing in Knowledge Management Systems (KMS) is often assumed to be positively related to organizational performance. However, this assumption is often based on observations that relate knowledge sharing to increased productivity or other learning outcomes. For instance, in tournaments, agents compete for an “optimal” prize that maximizes productive output of all contestants. In this context, knowledge sharing is assumed to be an important factor for achieving high performance.

The Effect of Intra-Organizational Competition on Knowledge Sharing and Learning

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Tepper School of Business at Carnegie Mellon University

ROMBA Leadership Summit
Out & Allied (80 members)

TOP PRIORITIES
• Provide a supportive environment for LGBTQ students, allies, and partners.
• Establish relationships and foster dialogue with employers and alumni
• Equip future business leaders to be LGBTQ advocates in the workplace and in their communities.

ACHIEVEMENTS:
• Shared 3 Coming Out stories to 200+ students and faculty.
• Hosted a Pink Party raising $1,000+ for the Susan G Komen Breast Cancer foundation.
• Sponsored a dinner for an organization that serves patients and families seeking medical care.
• Created Tepper’s Fantasy Drag Race League for RuPaul’s Drag Race All Stars 4 and Season 11.

CHALLENGES:
• Increase ally engagement.
• Develop a partnership with a Pittsburgh LGBTQ organization.

Funding to attend the ROMBA Leadership Summit was provided by the CMU GSA / Provost Conference Funding
Nitzan Sherman
Prospanica is an organization whose mission is to empower and enable Hispanic professionals to achieve their full educational, economic and social potential.

The Conference provides an opportunity to attend workshops that help build leadership and networking skills.

In addition, the conference provides a forum to network with representatives from companies such as Microsoft, Nintendo, Medtronic and Google as well as students from other MBA programs.

This year’s conference was in Orlando Florida.

What did I get out of attending?
- Exposure to companies that do not visit Carnegie Mellon
- Network with other MBA students who I wouldn’t normally interact with
- Strategies on how to be inclusive
- Strategies on how to infuse my personal brand into my professional career and the recruiting process
- Network with Tepper Alumni and other Tepper Students from other programs
- An internship offer

The conference provided an opportunity to hone in on the networking skills taught through clubs, the Masters Career Center, as well as other students.
Unlike commercial ridesharing, non-commercial peer-to-peer (P2P) ridesharing has been subject to limited research—although it can promote viable solutions in non-urban communities. This paper focuses on the core problem in P2P ridesharing: the matching of riders and drivers. We elevate users’ preferences as a first-order concern and introduce novel notions of fairness and stability in P2P ridesharing. We propose algorithms for efficient matching while considering user-centric factors, including users’ preferred departure time, fairness, and stability. Results suggest that fair and stable solutions can be obtained in reasonable computational times and can improve baseline outcomes based on system-wide efficiency exclusively. In this paper, we address these limitations and study matching in P2P ridesharing without payment from a user-centric perspective, with the objective to balance system-wide efficiency and user satisfaction. To our knowledge, we are the first to study the efficiency-fairness-stability tradeoff in P2P ridesharing. We make the following contributions. 1) We propose a new algorithm that reduces computational times and can improve baseline outcomes based on system-wide efficiency exclusively. Unlike commercial ridesharing, non-commercial peer-to-peer (P2P) ridesharing can be the set of users’ origins and destinations. We consider a finite, continuous time window, with each rider shown up in at most one driver-schedule. Let $S$ be the subset of riders that driver $i$ is matched to. For short, is a collection of driver-schedules, one for each driver, with each rider shown up in at most one driver-schedule. Let $M$ be the set of users’ origins and destinations. We consider a finite, continuous time window, with each rider shown up in at most one driver-schedule. Let $S$ be the subset of riders that driver $i$ is matched to.

An optimal driver-schedule where the driver only waits at the pickup location of a rider (to satisfy the rider’s request before and adapt to the rider’s preferred departure time) and always takes the shortest path to reach the next stop. Therefore it is sufficient to only determine the departure time at each stop. We use variables $a_i$ to represent the departure time at stop $v \in \{i, j \mid i \in D, S\}$ and get TripLP:

\[
\begin{align*}
\min_{x, y} & \sum_{s, t} c_{s, t}x_{s, t} + \sum_{i} a_i \\
\text{s.t.} & \quad x_{s, t} \leq \text{capacity} \quad \forall s, t \\
& \quad \sum_{s, t} x_{s, t} = 1 \quad \forall i \\
& \quad a_i \leq \Delta_v \quad \forall v
\end{align*}
\]

Algorithm 1 (Alg 1) is a depth-first search-based algorithm that solves a linear program TripLP at each leaf node. It first finds a heuristic driver-schedule $a_i$ and its cost $c_i$, (Line 1). To do so, it shuffles the pickup and drop-off order of the riders to get a driver-schedule without time (referred to as route $\omega$) and solves a linear program TripLP, which finds the best time to visit each stop. Then it calls TripSearch to build a search tree. Each node of the search tree corresponds to a stop in a driver-schedule, with the root representing an empty node. The path from the root to a node represents a partial route. When reaching a leaf node during the tree search, we get a complete route and call TripLP again to determine when to visit each stop. For intermediate nodes, we expand the node by appending a feasible unvisited stop to the current partial route.

TripLP is built upon the following observation. There exists an optimal driver-schedule where the driver only waits at the pickup location of a rider (to satisfy the rider’s request before and adapt to the rider’s preferred departure time) and always takes the shortest path to reach the next stop. Therefore it is sufficient to only determine the departure time at each stop. We use variables $a_i$ to represent the departure time at stop $v \in \{i, j \mid i \in D, S\}$ and get TripLP:

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& \quad \sum_{s, t} x_{s, t} = 1 \quad \forall i \\
& \quad a_i \leq \Delta_v \quad \forall v
\end{align*}
\]

The Efficiency Algorithm

Definition 1. A probabilistic matching $M$ is $\theta$-fair if $\forall r \in R$.

Definition 2. A matching satisfies individually rationality (IR) for a user if he does not get a worse utility by participating in the P2P system.

Definition 3. A $(d, S)$ is a blocking pair of a matching $M$ if $(d, S)$ is currently not matched in $M$ but $U_{d, S} > U_{d, S}$ and $U_{d, S} > U_{d, S}$ for all $r \in S$, where $S'$ is the set of the riders that are matched to $i$ under $M$, $d_i$ is the driver that rider $r$ is matched to in $M$, and $S''$ is a subset of riders that are matched to the same driver with $r$ (including $r$) in $M$.

Definition 4. A matching $M$ is stable if it has no blocking pair.

The following LP computes a min-cost probabilistic matching subject to the $\theta$-fairness constraint.

\[
\begin{align*}
\min & \quad \sum_{r \in R} \sum_{(s, t) \in S} c_{s, t}P_{s, t}(r) \\
\text{s.t.} & \quad \sum_{s, t \in S} P_{s, t}(r) = 1 \\
& \quad P_{s, t}(r) \geq 0 \\
& \quad \forall r \in R
\end{align*}
\]

Numerical Results

We evaluate our algorithms with three sets of experiments. First, we experimented with problem instances that simulate a typical neighborhood in a morning rush hour. In addition to our small scale baseline experimental setting (which mimics a typical morning rush hour situation), we also test our algorithms in a large-sized setting (which captures suburbs and rural areas). Moreover, we also experimented with real-world data collected from a survey to residents living in subsidized, low-rent apartments in a suburban area in the US.

Acknowledgements

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References

1. Research Questions

- How do bank mergers shape the lending relationships in the credit market?
- Does the merged bank make relationship loans to the target bank’s pre-merger borrowers?
- Do bank mergers affect the real economy through the relationship credit channel?

So What?

- Evaluating the costs and benefits of the regulatory changes fostering bank consolidations in the U.S.
- Understanding the real effects of lending relationships as an information transmission mechanism in the credit market.

2. Key Takeaways

I. Bank mergers disrupt relationship lending to target banks’ pre-merger borrowers.
II. The relationship disruptions are due to informational frictions since bank mergers are likely to bring about loss of soft information.
III. Target banks’ borrowers suffer when their pre-merger loans come due: they exhibit more constrained investment and are more likely to lay off employees.

3. Research Design

Staggered Event Study (Event-Bank Merger)
- U.S. loan-level data
- Manually-linked data on bank mergers
- SNL-DealScan-Capital IQ
- Cross-sectional variation in borrower exposure to merger partners

Pr (Continue) = \( a + b R_{Target} + \text{Bank FE} + \text{Firm-Year FE} + \text{Controls} + e \)

- Firms having pre-merger relationships with both types of merger partners

4. Robustness

- Staggered event study with different windows
- Generalized DiD with pre-trend analysis
- Propensity weighting (targets’ vs. acquirers’)

5. Real Effects

Consistent with the regulators’ concerns over inefficient credit rationing and the real consequences.

- Intensified financing frictions
- Sorely restricted investments
- Significant crisis layoff

Raising concern over the potential loss of bank merger efficiency.

6. Limitation

Internal Validity vs. External Validity

- Targets’ pre-merger borrowers
- Quartile rankings are based on the level of soft information used in loan decisions

Measurement of Soft Information

- Soft information used in loan decisions
- Loan Spreads = \( a + b \text{ Hard Information} + \text{ Loan Type FE} + \text{ Bank FE} + e \)
- Hard Information: size, profitability, tangibility, M/B, leverage, credit ratings
- # Repeated firm-bank interactions
- Length of firm-bank relationship