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The Market For Data Privacy

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Data Privacy in the Internet Era

Firms collect, share and aggregate data about a wide range of consumers' online and offline activities

Varian, 2009; Krishnamurthy and Wills, 2009; FTC, 2014

Economics principles are subtle:

- Classical: Consumer data improves efficiency of allocations

  Stigler, 1980; Posner, 1981; Goldfarb and Tucker, 2011

- Second best: Concerns about insurance, price discrimination, negative externalities

  Hirshleifer, 1971; Taylor, 2004; Varian, 2009

How does the market for data privacy operate?

The Market for Data Privacy

Demand: Many consumers are passive, "consent fatigue"

Goldfarb and Tucker; 2012; Acquisti et al., 2015; Campbell et al., 2018

- Privacy paradox: stated preferences vs. behavior and WTP
- Reassurance by mere presence of legal text

  Norberg et al., 2007; Acquisti, 2016; Athey et al., 2017

Understanding *supply of privacy* is important in this context

This paper: What determines firms' privacy contracts and data sharing policies?

This Paper

Data collection: For a comprehensive set of US firms, we measure

1. What they say: Privacy policy text
2. What it means: Evaluation of these policies by a legal expert
3. What they do: Third party cookies on websites

Stylized facts using variation across firms:

- No standard industry-level boilerplate
- Detailed policies are **associated with more sharing** (fig leaves?)
- Systematic variation across firm characteristics
  - Size and technical sophistication

Theory: Determinants of firms' data sharing and privacy policies

Data

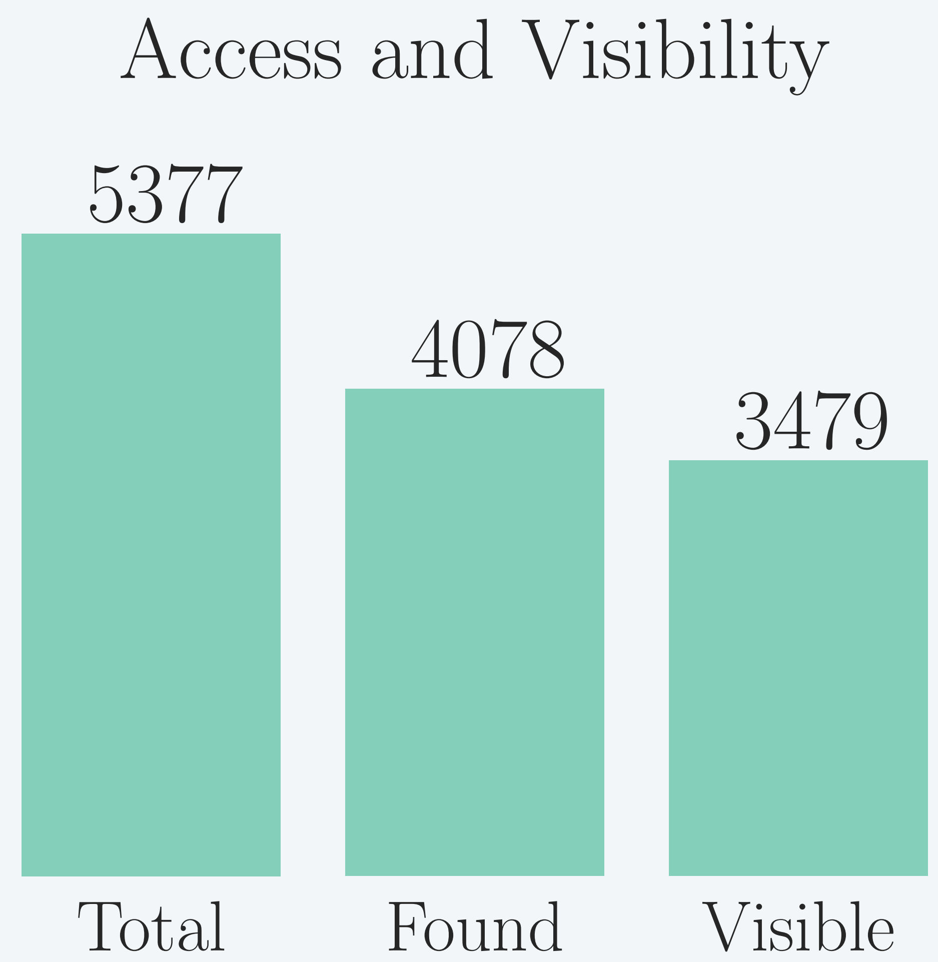
Privacy Policies

N =5377 firms in Compustat US

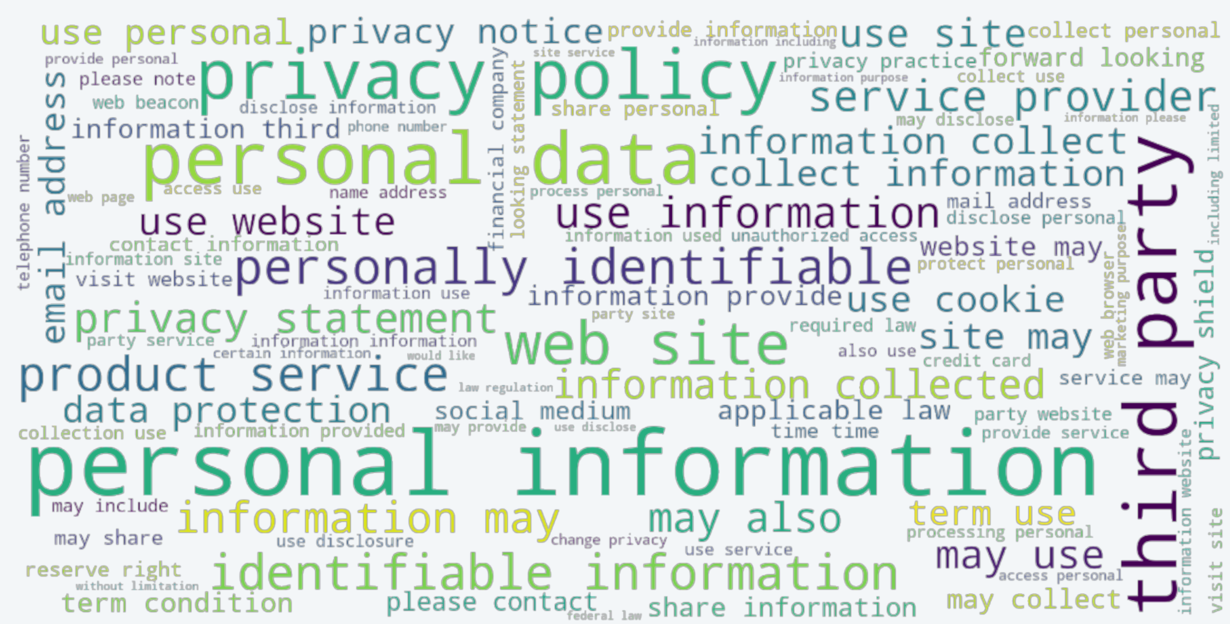
Finding privacy policies:

- Automated google search
- Web crawling
- Manual checking

Visibility: "Privacy" link on website

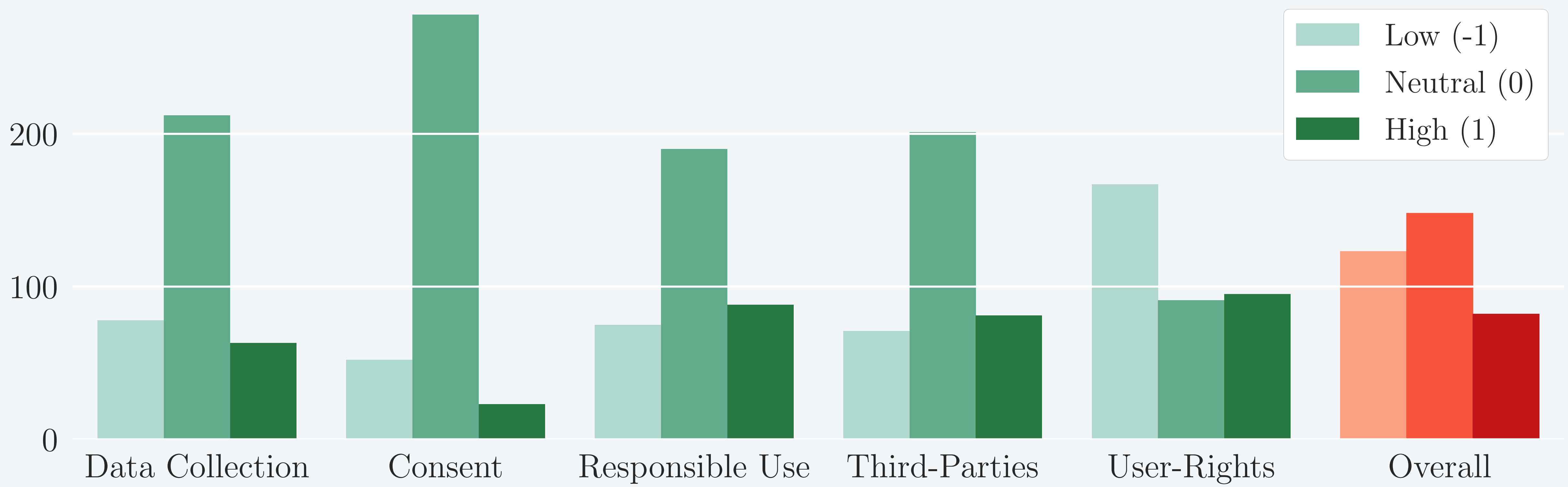


Word Cloud



Expert Evaluation

10% Sample of Policies

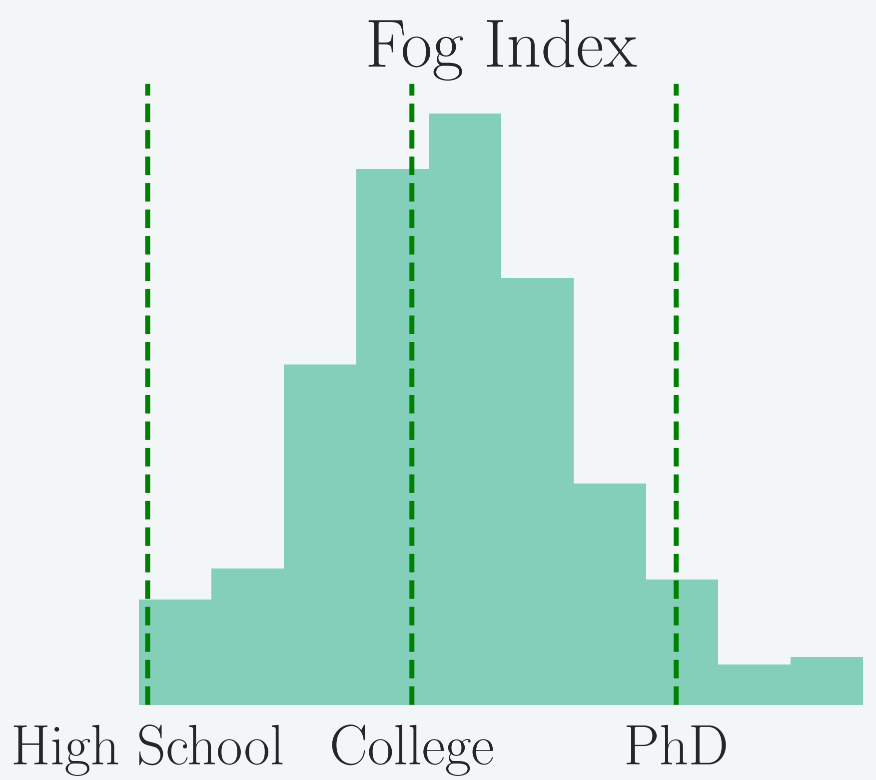


$$\begin{aligned} \textit{Legal Clarity Index} = &\ \text{Frequency of top 100 "High Overall" bigrams} \\ &- \text{Frequency of top 100 "Low Overall" bigrams} \end{aligned}$$

Readability and Third Party Data Sharing

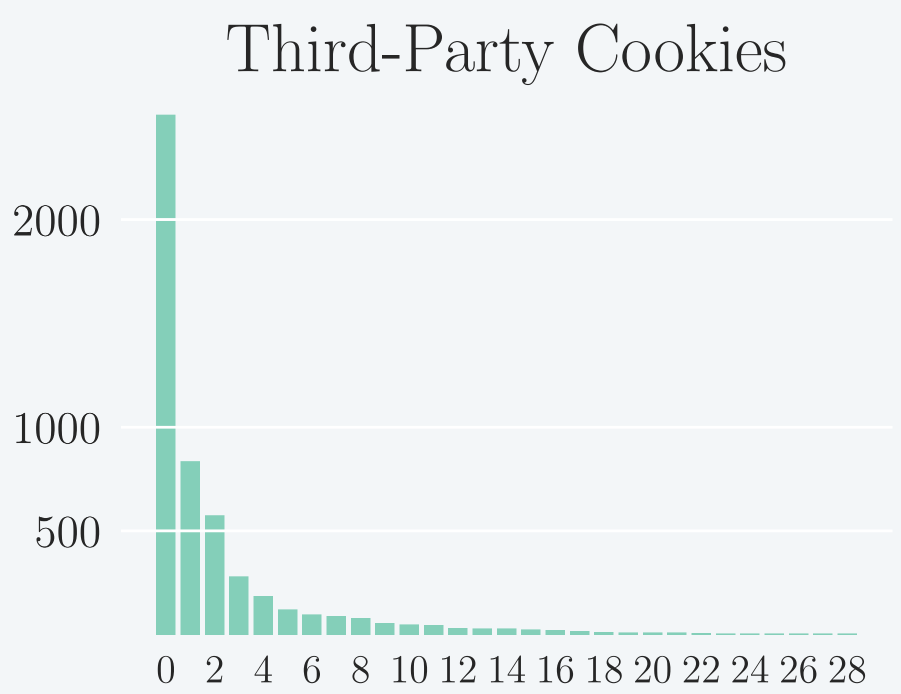
"Fog" readability index: Years of formal education needed to read a document

Gunning, 1952



OpenWPM scraper counts cookies on firm's website

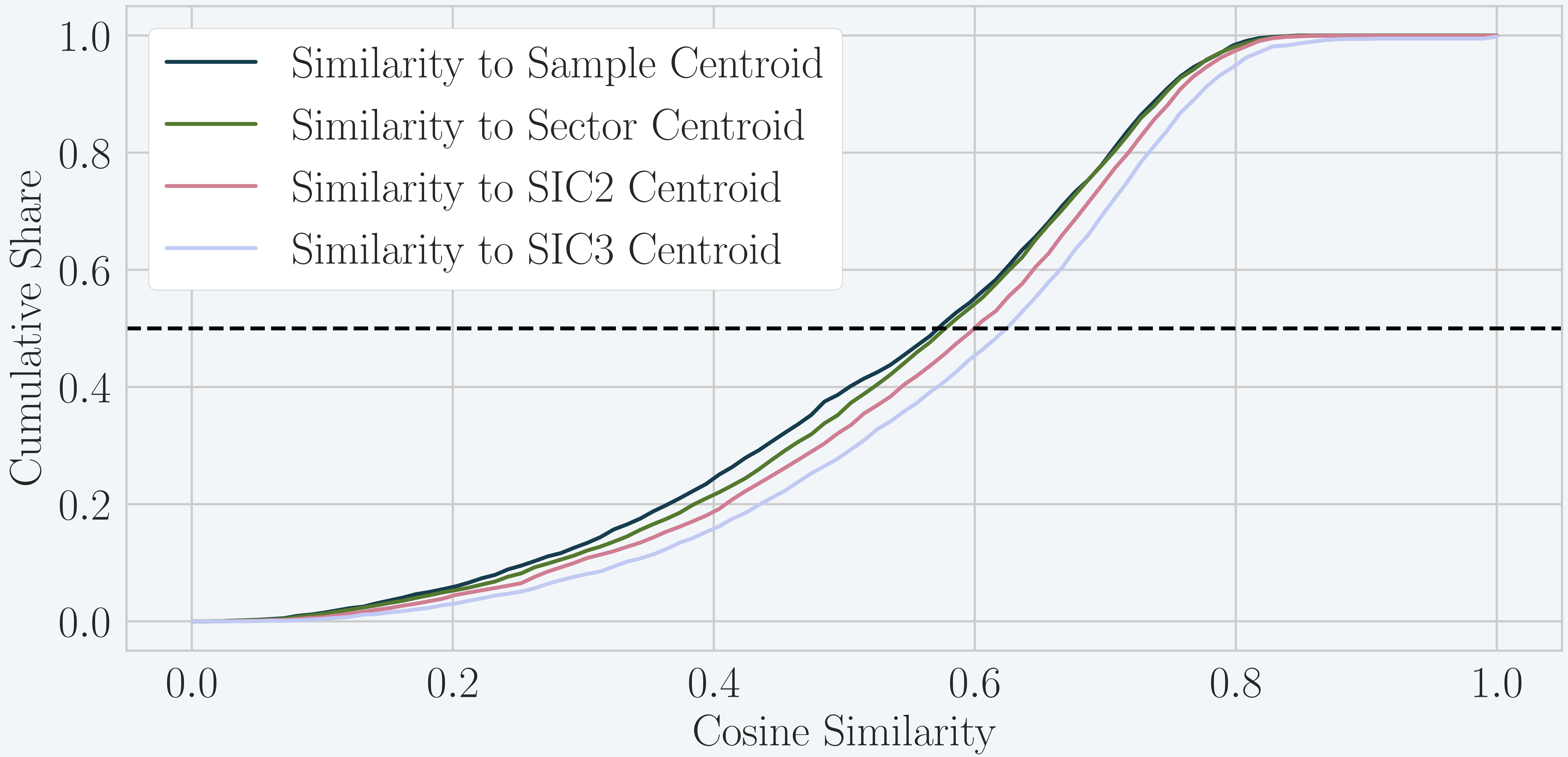
Englehardt and Narayanan, 2016



Stylized Facts

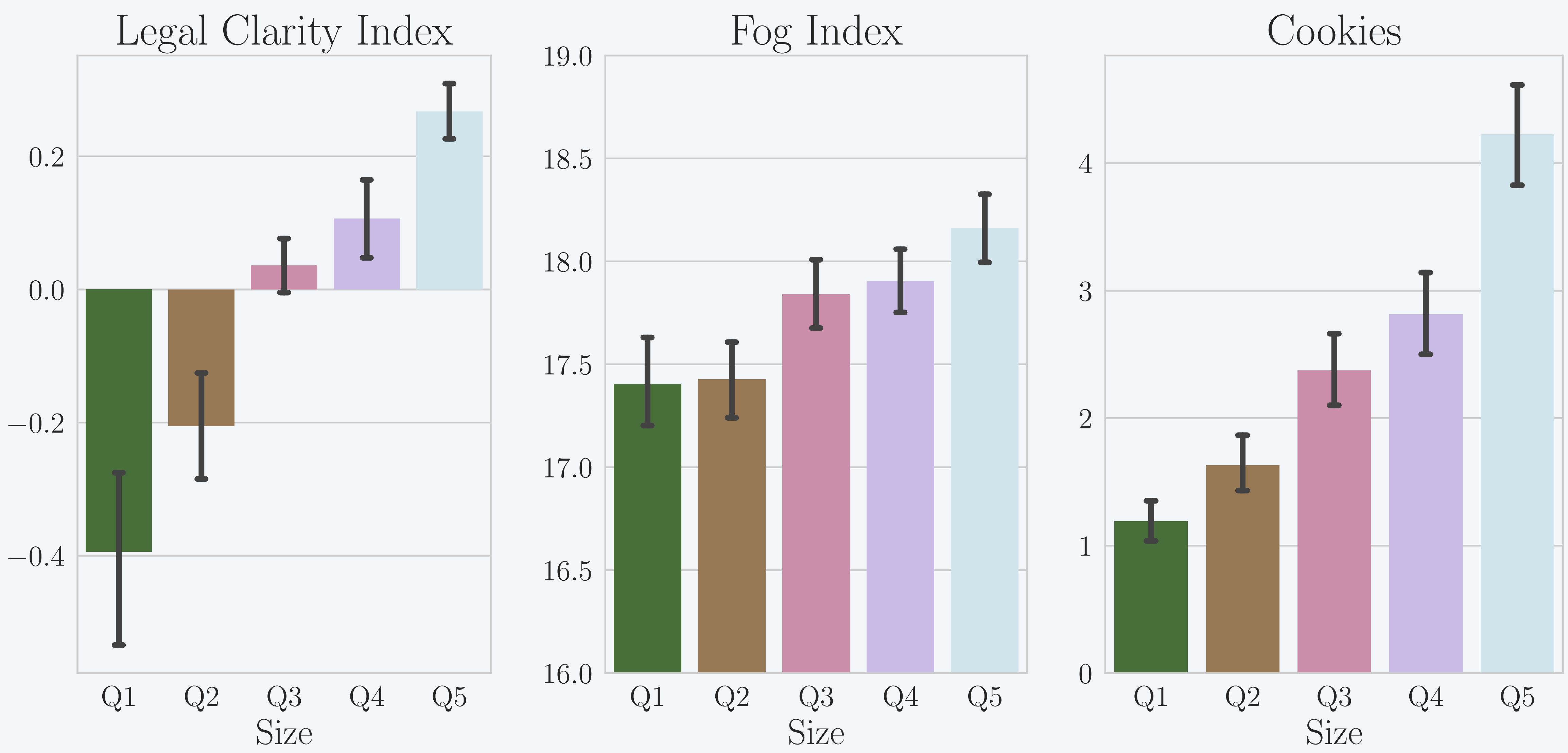
Variation: No Industry Boilerplates

Similarity of Word Frequency Vectors Across Policies



Only slight increase in similarity in latent "topic" space

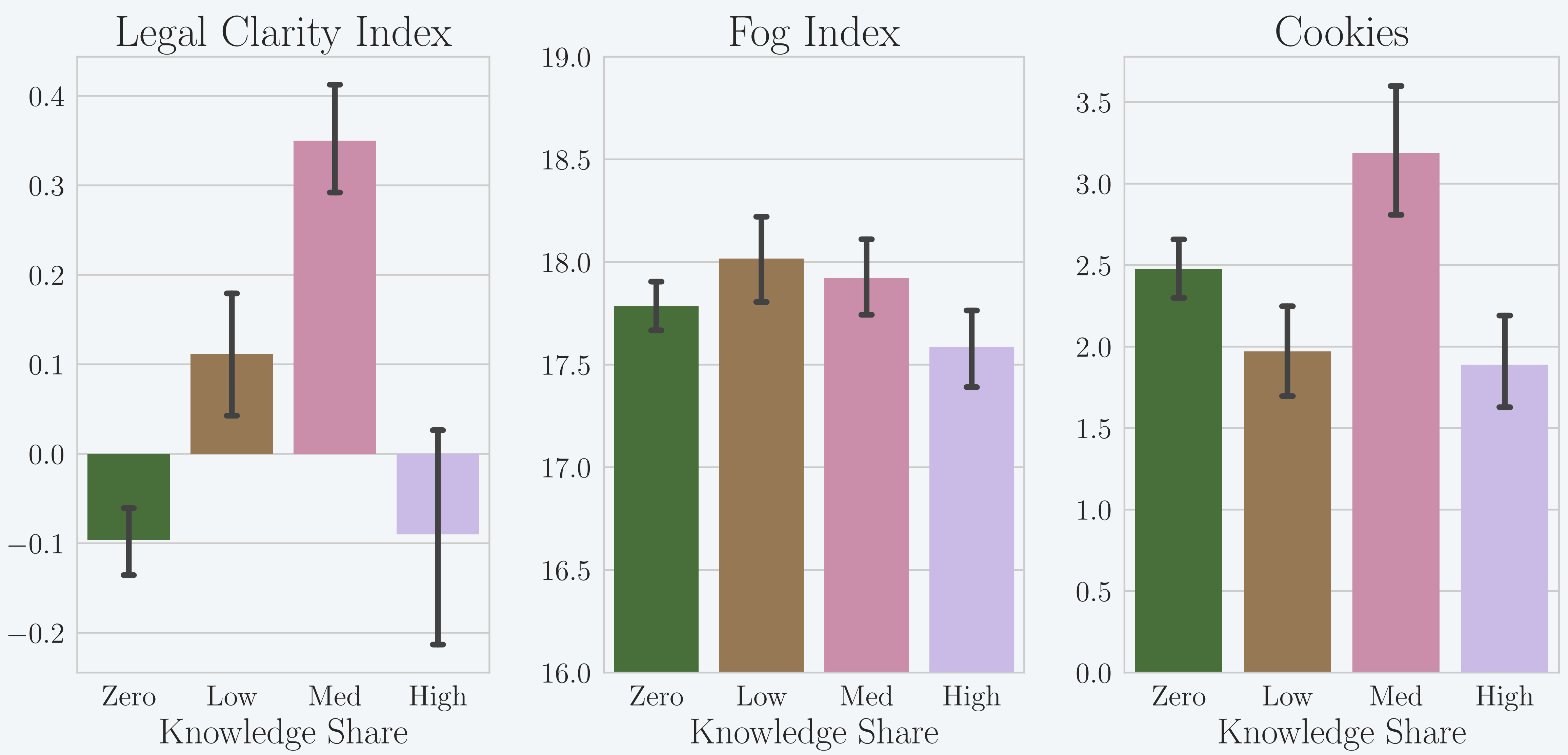
Firm Size, Policies and Behavior



Large firms also have longer policies which are easier to find

Knowledge Share, Policies and Behavior

Capital Accumulated through R&D / Total Assets



Firm Characteristics

Theory of Data Sharing

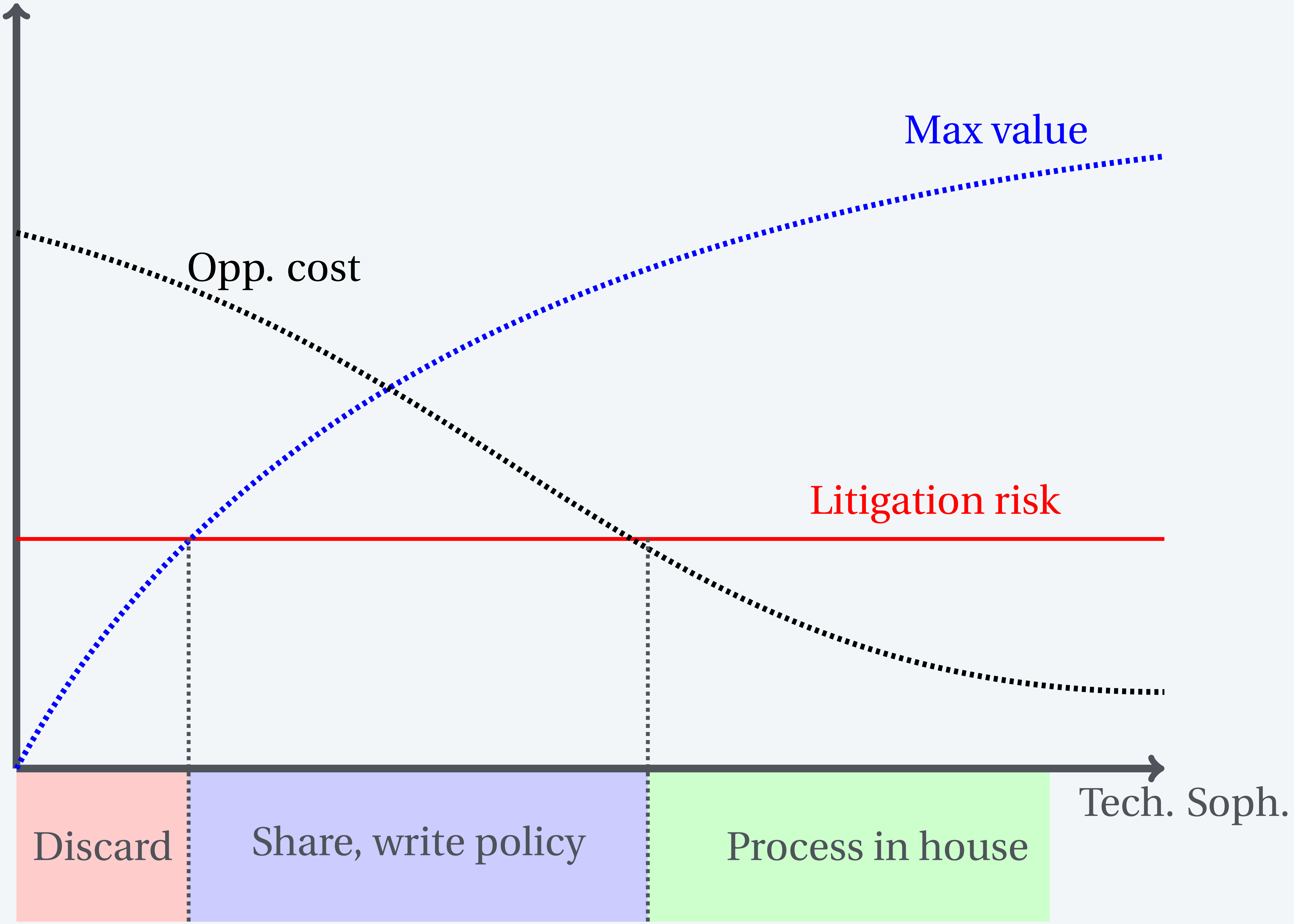
Model

Firm can monetize its data by:

1. Processing in-house
2. Sharing with a specialist **data intermediary**

Sufficient statistics:

- Max value of data
- Opportunity cost of in-house processing
- Litigation risk (alleviated by costly privacy policy)


Max value
Opp. cost
Litigation risk
Tech. Soph.
Discard
Share, write policy
Process in house

Partial Effects of Knowledge Capital

Controlling for firm size, market share, industry FE:

	(1) Policy Found	(2) Policy Visible	(3) Log Words	(4) Overall Score	(5) Fog Index	(6) 3^{rd}-Party Trackers
Log Market Value	0.0421***	0.0484***	-0.00597	0.0426***	0.0296	0.330***
	(12.22)	(12.13)	(-0.61)	(4.44)	(1.14)	(8.20)
Knowledge Share	0.847***	0.695***	2.405***	2.605***	0.501	4.447***
	(8.33)	(5.89)	(8.80)	(9.78)	(0.69)	(3.76)
Knowledge Share^2	-0.813***	-0.793***	-2.821***	-3.811***	-0.264	-7.114***
	(-4.90)	(-4.12)	(-6.30)	(-8.74)	(-0.22)	(-3.69)
Log Market Share	0.0157***	-0.0105***	0.0874***	0.0615***	0.100***	0.119***
	(5.41)	(-3.11)	(10.49)	(7.57)	(4.54)	(3.52)
Observations	5140	5140	3918	3918	3918	4951

Conclusions

- We assemble comprehensive data for studying the market for privacy, focusing on the supply side
- Stylized facts on cross-firm variation
  - Clear policies $\Rightarrow$ more sharing
- Simple testable theory of data sharing

Public Resources

www.github.com/ansgarw/privacy

- All our data for work with Compustat US firms
- Python code, demos and documentation
- Get policies and their attributes for *any* sample of firms or websites

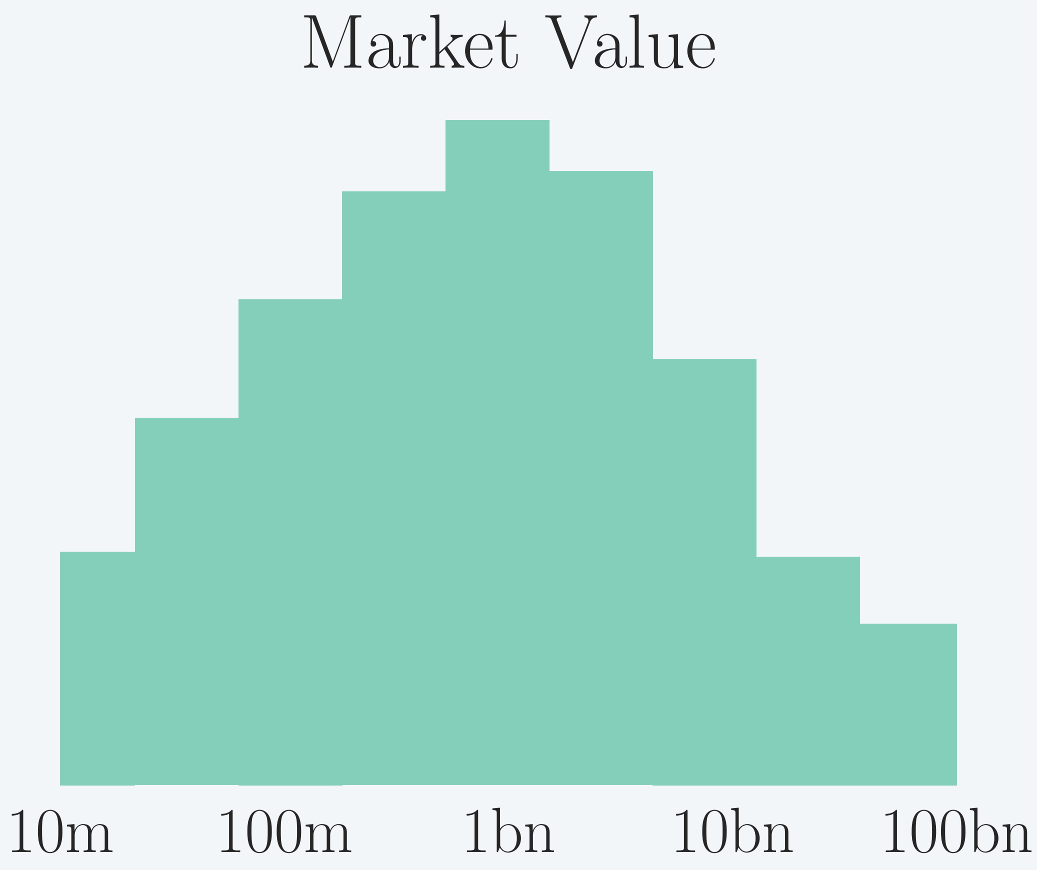
Simplest Example

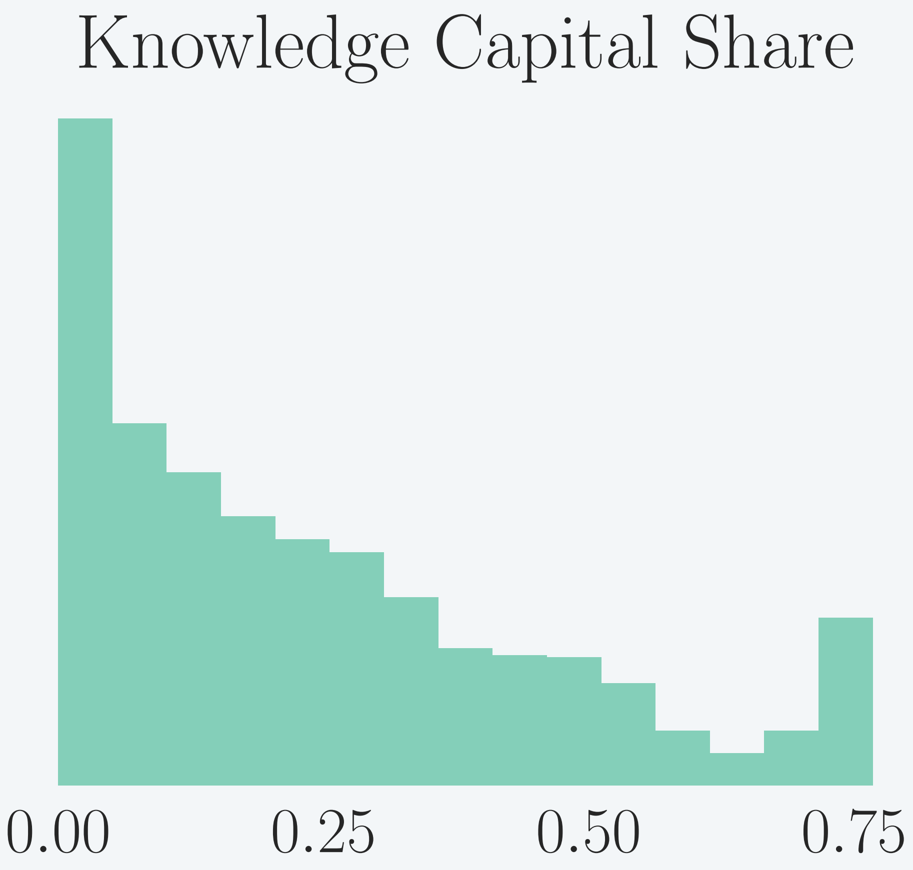
Here are 5 lines of code that find the policy for American Airlines:

```
from src.urls import crawlPrivacy, filterPrivacy
from src.text import findPolicy
status, urls = crawlPrivacy('www.aa.com',clicks=2) # crawls candidate URLs
ranked = filterPrivacy(sum(urls,[])) # filter and rank by likelihood of being privacy policy
status, policy, url = findPolicy(ranked) # scrape highest ranked page that contains 'privacy'
```


```
Legal clarity of www.aa.com: 1.136
Legal clarity of www.ba.com: 1.691
```

Firm Characteristics





$$\text{Knowledge Share} = \frac{\text{Capital accumulated through R\&D}}{\text{Total Assets}}$$

Peters and Taylor, 2017 Back to sorts

Legal Clarity Index

High and low score policies look different, so we construct:

$$\textit{Legal Clarity Index} = \text{Frequency of top 100 "High" bigrams}$$
$$- \text{Frequency of top 100 "Low" bigrams}$$

Similar results with an index that uses supervised machine learning

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