# Digitization, Privacy, and Fairness

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# Digitization and privacy

- Digital revolution reduces costs and increases capacity for large-scale collection, retention, distribution, analysis and use of personal data about individual people
- This includes:
  government records, business transactions, also
  tracking of online search, behavior and
  smartphone use, location and
  private and public surveillance devices

# What’s the problem?

- Data can reveal

    personal information - tastes, preferences, friendship, activity

    sensitive information - sex, politics, finances, health

    confidential information – used to verify identity
- Individuals can be harmed from data access, sharing and use
- Limiting data use can reduce privacy risks
- Suggests tradeoffs between harnessing gains from computing and protecting personal privacy
- How can individuals, organizations, governments balance them?

# Harms from lost privacy?

- Shame, embarrassment, social stigma
- Loss of freedom, autonomy
- Manipulation
- Identity theft – impersonation and fraud
- Market exclusion or higher prices

- These can be
  - subjective (disutility) or objective (financial)
  - direct or indirect, mediated through market
- Vary across individuals based on tastes and content of the information

# How do people express their privacy preferences?

- What choices do individuals have to protect their privacy?
- What factors controls those choices?
- Potential market failures in the marketplace for privacy
  - Limited information
  - Decision-making problems (behavioral)
  - Limited ability to enforce agreements
  - Data spillovers when information is also about friends, coworkers, neighbors, family members
- Limited private options in many markets, but that is an endogenous outcome

# Economics of privacy

- *Reading*: Acquisiti, Taylor and Wagman (JEL, 2016)

Key themes

1. No single unified theory of privacy; value depends in part on subjective, context-specific, contingent aspects
2. Mandated privacy protection rules can increase *or* decrease welfare
3. Limited consumer information about privacy risks is a potential source of market failure and under-provision

# Role for public policy in privacy protection

- Provide information, education
- Mandate information provision, disclosure
- Define, assign, enforce property rights
- Promote particular technologies, uses, behaviors
- Limit particular technologies, uses, behaviors

# Variation in privacy laws

- Can be targeted on certain types of data (health, financial, educational) or populations (children) or not
- Can mandate specific types of data protection, procedures after privacy loss events (e.g. reporting or compensation after data breaches; penalties for intentional violations)
- Can apply to collection, retention, sharing, use
  - Regulation of data use overlaps with second topic: fairness and discrimination
- Can apply to different entities – private sector companies, depending on relationship with individual and type of data; also government agencies

# Big new privacy policies

- GDPR EU General Data Protection Regulation of 2016; effective 2018
- CCPA CA Consumer Privacy Act of 2018; effective 2020

- Rules about data collection, disclosure, retention, distribution, security and protection, specifies individual rights to access, correct

- Note: policy variation is good for empirical research but control groups not obvious

# Privacy from the government

- My focus here is on business, but also important
- What data can government get directly? What can they compel from citizens? From companies operating in their boundaries?
- National security: What about foreign governments and companies with data on US citizens?
- Hacking and data theft across international boundaries

# Some effects of privacy policy

- Finding of economics cost:
  - Slow technology adoption
  - Make new technologies less effective
- But also benefits:
  - Could enhance adoption, depending on what people do in absence

- Could also shift future innovation and development of technology

# Privacy and digital advertising

- Digital tracking is extensive, evolving, often obscure to consumers
  - Cookies and webpage interactions, phones, connected devices
- Data is essential for targeted advertising
  - Advertising main revenue source for major internet, media companies
- Privacy protection can reduce the impact, value of digital ads
  - Goldfarb and Tucker (2011): Privacy protection in EU lowered advertising effectiveness

# Privacy and healthcare

- Healthcare is an area of heightened privacy concern in population and among policymakers. My research with Catherine Tucker highlights tradeoffs.
- Miller and Tucker (2009) asks if legal protection of health data increases or decreases adoption of digital health records
  - Does legal reassurance increase willingness of patients to share data? Or do restrictions on data flow reduce the value of digitization?
  - We find the latter; hospitals usually increase adoption in response to adoption by other local hospitals, but this is eliminated by strict privacy laws
- Miller and Tucker (2011) confirms this on longer sample and shows impact on infant mortality (digitization saved lives)

# Privacy and personalized medicine

- More recent paper addresses genetic testing for cancer risk
- Genetic data are unique because:
  - Reveal a lot about a person – current and *future* health status, other traits
  - Can also reveal a lot about family members
  - Are persistently informative
  - Have potential implications and meanings that are likely to increase
- Miller and Tucker (2017) studies 3 policy approaches to protecting genetic data: privacy risk notification; consent requirement for re-disclosure; limits on data use. Find different effects on genetic testing:
  - Notification lowers rates, consent (ownership) increases it, no effect of use.

# Privacy and discrimination

- Discrimination is related to privacy as it applies to data use
  - Some privacy rules about data use are anti-discrimination rules for protected categories of information or groups
- Major example is GINA 2008 (genetic information), where the privacy concept works well
  - If you don’t collect or obtain the data, you can’t use it for discrimination
- The problem with this conception is that discrimination can also happen from data that does not contain the protected category
  - In the wild, many variables are correlated with protected categories
  - Possible to infer membership without having it in the data or to inadvertently generate outcomes that differ by category because of the correlations

# Fairness and discrimination

# Discrimination and fairness

- What is legal? What is fair?
- Legal standards are about group differences and name particular categories as protected
  - Fairness is broader and can be about non-protected categories and about differences in treatment across individuals within groups
- Fairness is not about equal outcomes for everyone or even equal outcomes across groups
  - Some differentiation is legitimate (legal), some is suspect (illegal)
- As with privacy, standards depend on type of decision, type of data

# Digitization and discrimination: not so simple

# Why do people discriminate?

- Preferences = taste-based, willing to sacrifice profits (Becker, 1957)
- Statistical = proxy for some other variable that matters for profits that itself is imperfectly observable (Phelps, 1972; Arrow, 1973)
  - Can be "rational" = correct on average and profitable because groups differ
  - Can be that groups are judged same on average, but treated differently because evaluators draw less precise inference about members of other groups
  - Can involve "bias" in average prediction = this can be implicit bias (aversion but not intentional as in taste-based) or it can be error in computing conditional probabilities

# Why do algorithms discriminate?

Tucker and Cowgill (2019)

- Unrepresentative training data
  - Sample selection bias
- Improper outcomes
  - E.g., mislabeling of data on outcomes or missing payoffs
- Feedback loops = self-fulfilling prophecies
- Biased programmers
- Spillovers and composition
  - Market forces like price or demand

# Digitization and discrimination

- Data can increase the prevalence of taste-based discrimination
  - If information about protected class (like disability or health status or even race or ethnicity) becomes more observable
  - People who wanted to discriminate before but were limited in identifying targets are now better able to do that
  - Or they can identify targets earlier in the process when it’s less costly or when they are less likely to get caught (recall that overt discrimination the basis of protected categories is often illegal)

# Digitization and discrimination

- If discrimination is statistical, it could decrease if better data or proxies are available
  - Conditional on more observables, protected category should matter less
- Note, if the discrimination was rational, that this doesn't imply better average outcomes for the protected group
  - Why not? Average group differences lined up with average differences in underlying variable
- If discrimination came from some bias against the group (in the statistical sense), then group average outcomes for protected group would improve with better measures of underlying variables

# Data and learning

- If there was bias with limited data, more data and “learning” could improve models and reduce the bias
- Expectations were wrong, but more data moves closer to truth
- But that depends on sample including data from the range of outcomes (enough variation) to actually learn
- E.g., if the minority worker is never hired (female candidate is never promoted), we can’t learn about their productivity

# Evidence from a few settings

# Judicial determinations of pre-trial detention

Kleinberg et al. (2018)

- Simulation suggests that ML can improve prediction, thereby reduce crime at current jail rates or reduce jail population without increasing crime
- Algorithm does not include information on race
- Their model would have the same minority share in jail population (as it turns out)
- Could also explicitly code race into algorithm – keep racial disparities at current level or enforce neutrality – with no loss to

# Screening of job applicants

Cowgill (2018)

- Field experiment using ML algorithms for resume screening of applicants for white-collar jobs.
- Theory: AI can reduce impact of human biases (if present) if there is enough noise in the “training” (pre-AI) data to see outcomes for unusual decisions
  - Otherwise algorithms encode existing biases
- Finds: AI does better on several outcomes; comes from candidates who are evaluated in noisy, biased way by humans
- Does not relate to protected categories, but shows:
  - Promise of AI in setting, potential to reduce bias (or encode it)
  - Side point about weights on factors not being the same as treatment effect

# Mortgage lending

Bartlett et al. (2019)

- Compare loans originating from lenders using FinTech platforms versus face-to-face
- Context: fair lending law only allows lenders to consider creditworthiness, not profit
- Find: racial/ethnic disparities in interest rates, conditional on creditworthiness
- These are smaller but still present for FinTech
  - Speculate that gaps remain because of geography and WTP (lower demand elasticity from less shopping around)
  - Suggests a conflict between “allowed” discrimination and profits

# Online ad delivery

- Sweeney (2013) does online searches on matching names and finds more ads from Instant Checkmate with the word “arrest” in them for black-identifying first names
- Lambrecht and Tucker (2019) find that STEM job was shown to more men than women
  - But the reason was that female “eyeballs” were more expensive because of greater demand for them from consumer products
  - Raises challenging issues about whether we want to address this type of disparate impact and what tools would be needed to do so

# What can you do?

- Recent growing interest from economists
- This is good for policy and science
- Theory models are useful for thinking about incentives, about tradeoffs, social welfare and distributional effects
- Empirical work can assess ground reality as it unfolds, guide policy