An Overview of the NSF-ITR-Census Bureau Synthetic Data Project

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- SDC for Microdata

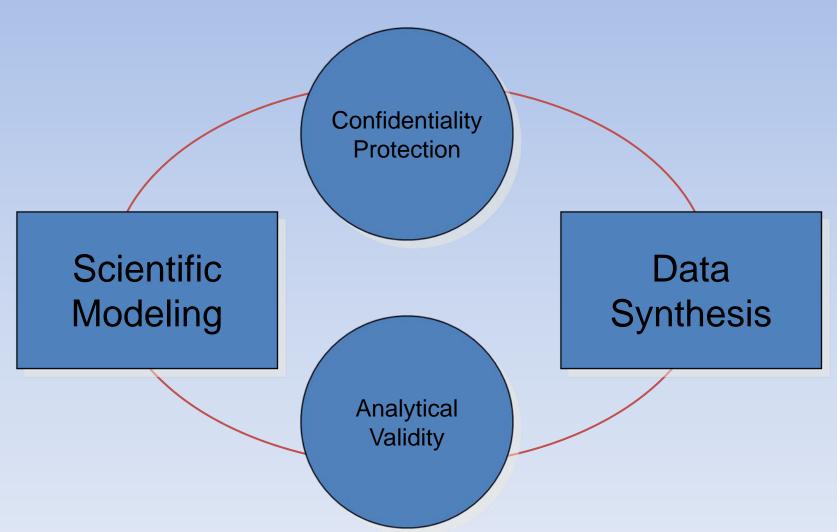
Acknowledgements and Disclaimer

- This work was partially supported by the National Science Foundation (grants SES-0339191, SES-0427889 and CNS-0627680) and the United States Census Bureau.
- All statistical materials in this presentation have been reviewed for disclosure avoidance.
- The opinions are those of the author and not the National Science Foundation nor the Census Bureau.

Outline

- Foundations of the NSF-ITR-Census Bureau project
- Criteria for "good" synthetic data
- Core projects
- The Cornell Virtual Research Data Center

The Research – Synthetic Data Feedback Cycle



Definition of Synthetic Data

 $X \equiv \text{confidential data}$

$$\Pr[\widetilde{X}|X] \equiv PPD \text{ of } \widetilde{X} \text{ given } X$$

Release data are samples of \tilde{X}

- Synthetic data are created by estimating the posterior predictive distribution (PPD) of the release data given the confidential data; then sampling release data from the PPD conditioning on the actual confidential values.
- The PPD is a parameter-free forecasting model for new values of the complete data matrix that conditions on all values of the underlying confidential data.

Connection to Randomized Sanitizers

 $X \equiv \text{confidential data}$ $U \equiv \text{random noise}$ $\operatorname{San}(X,U):(X,U)\to \widetilde{X}$ $\Pr[\widetilde{X}|X] \equiv \text{probability of } \widetilde{X} \text{ given } X$

- A randomized sanitizer creates a conditional probability distribution for the release data given the confidential data.
- The randomness in a sanitizer is induced by the properties of the distribution of *U*.
- The PPD is just a particular randomized sanitizer.

Disclosure Limitation Definitions

$$X = x^{(1)}$$
 and $X = x^{(2)}$

 $\tilde{X} = \tilde{x}$, realization of the synthesizer

- Consider two confidential data matrices that differ in only a single row, $x^{(1)}$ and $x^{(2)}$.
- Use the PPD to evaluate the probability of a particular release data set given the two different confidential data sets.

Synthetic Data Can Leak Information about a Single Entity

$$\Pr\big[\tilde{X} = \tilde{x} \big| X = x^{(1)}\big] \neq \Pr\big[\tilde{X} = \tilde{x} \big| X = x^{(2)}\big]$$

- Changing a single row of the confidential data matrix changes the PPD or the random sanitizer.
- The PPD or the random sanitizer define the transition probabilities from the confidential data to the release data.
- True for all SDL procedures that infuse noise.

Connection Between Synthetic Data and Differential Privacy

$$\frac{\Pr[X = x^{(1)} | \tilde{X} = \tilde{x}]}{\Pr[X = x^{(2)} | \tilde{X} = \tilde{x}]} = \frac{\Pr[\tilde{X} = \tilde{x} | X = x^{(1)}]}{\Pr[X = x^{(2)}]} = \frac{\Pr[\tilde{X} = \tilde{x} | X = x^{(1)}]}{\Pr[\tilde{X} = \tilde{x} | X = x^{(2)}]}$$

The posterior odds ratio for the gain in information about a single row of X is equal to the differential privacy from the randomized sanitizer that creates release data by sampling from the specified conditional distribution.

Connection Between Differential Privacy and Inferential Disclosure

$$\frac{\Pr[X = x^{(1)} | \tilde{X} = \tilde{x}]}{\Pr[X = x^{(2)} | \tilde{X} = \tilde{x}]} = \frac{\Pr[\tilde{X} = \tilde{x} | X = x^{(1)}]}{\Pr[X = x^{(2)}]} = \frac{\Pr[\tilde{X} = \tilde{x} | X = x^{(1)}]}{\Pr[\tilde{X} = \tilde{x} | X = x^{(2)}]}$$

The posterior odds ratio for the gain in information about a single row of X is the Dalenius (1977) definition of an inferential disclosure. Bounding the differential privacy therefore bounds the inferential disclosure.

Goals of Synthetic Data

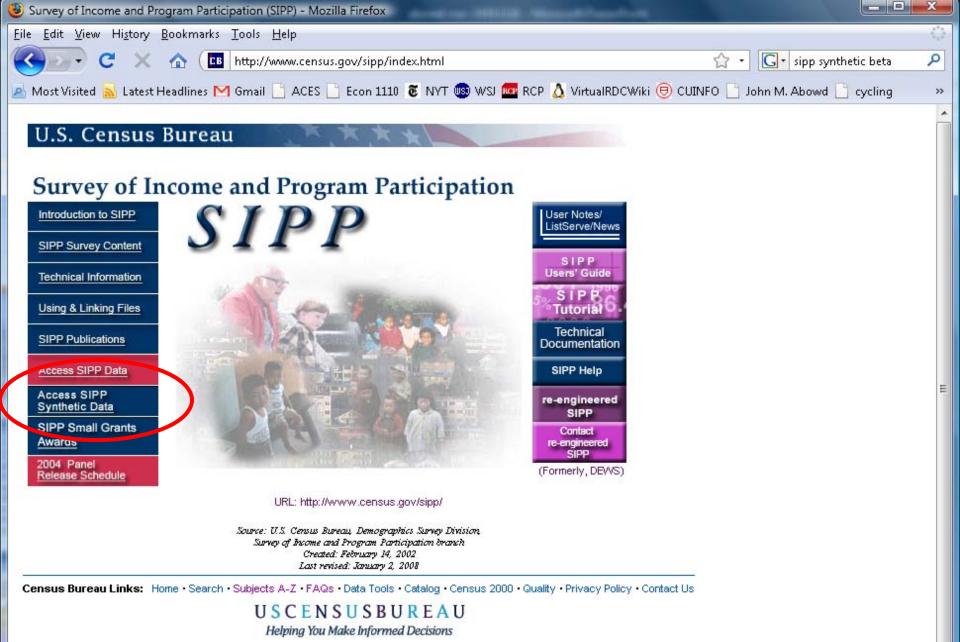
- Analytical validity
 - Statistical inferences based on the synthetic data should be "similar" to those based on the underlying confidential data.
- Confidentiality protection
 - The perturbation of the confidential data induced by replacing some, or all, of the values with draws from the PPD should be adequate to "protect" the confidential data.

Formal Models of Analytical Validity

- Unconditional analytical validity
 - The synthetic data process delivers the same inferences as the process that generated the confidential data. This property depends on both the synthesizer and the design of the confidential data
- Conditional analytical validity
 - The synthetic data process delivers the same inferences as the realized confidential data
- The Rubin (1993) inference validity was based on using multiple samples (implicates) from the PPD. It is an unconditional analytical validity model.

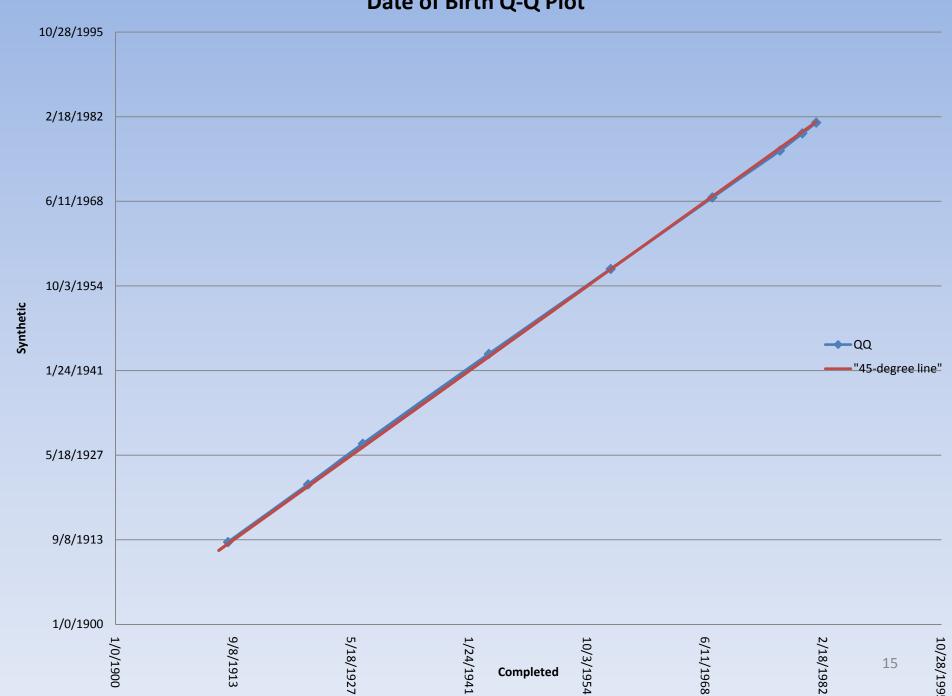
Project 1: Survey of Income and Program Participation Synthetic Beta

- Based on 1990-1993 and 1996 SIPP panels
- Linked to complete earnings and benefit histories from SSA (1950 to 2003)
- 16-implicate partially synthetic file with 633 variables released as Beta in November 2007
- Any beta user can have the analysis performed on the underlying confidential data by following the procedure outlined by the Census Bureau

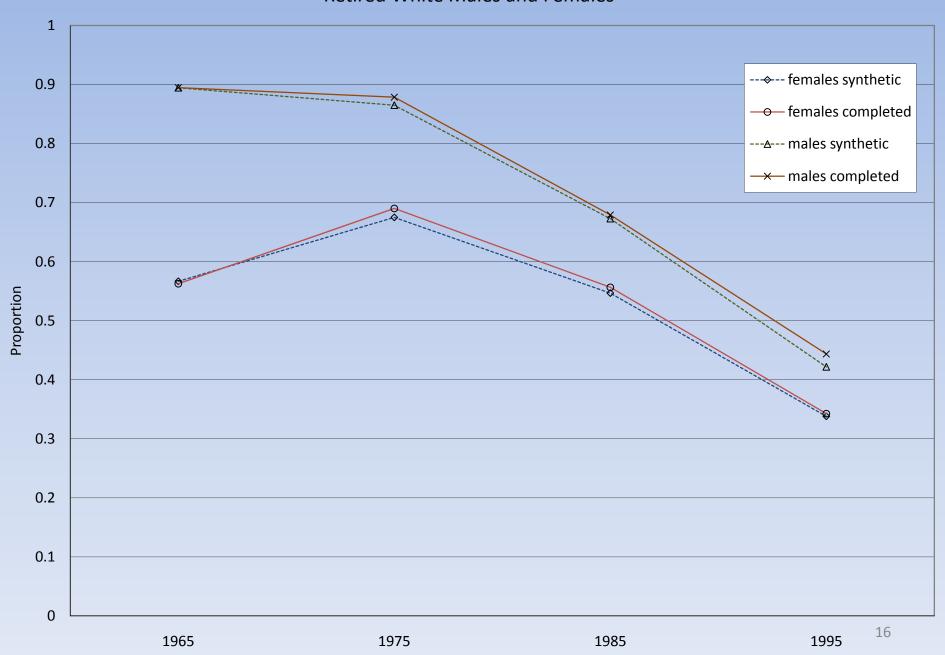


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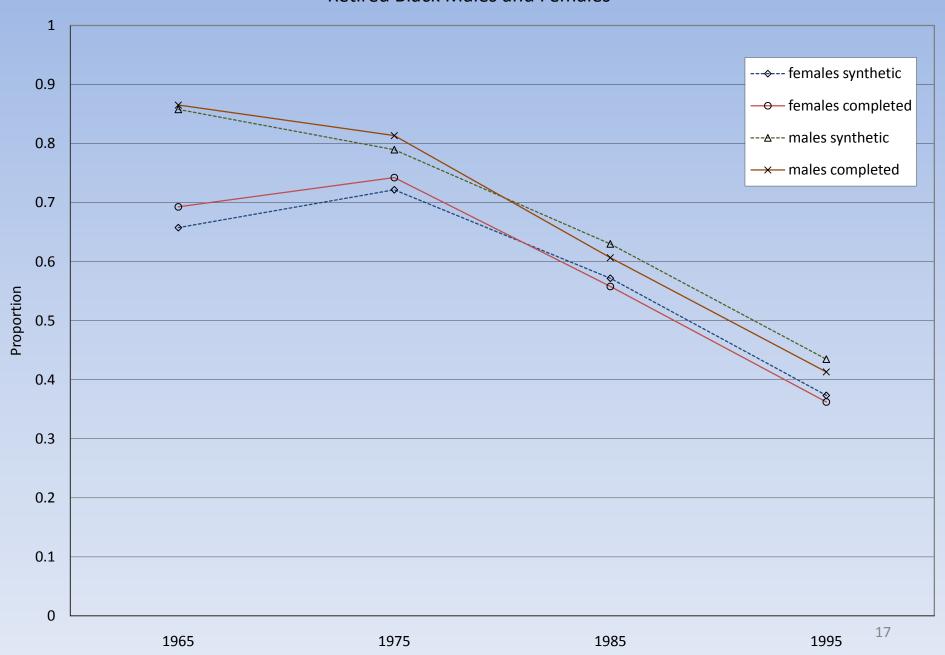
Date of Birth Q-Q Plot



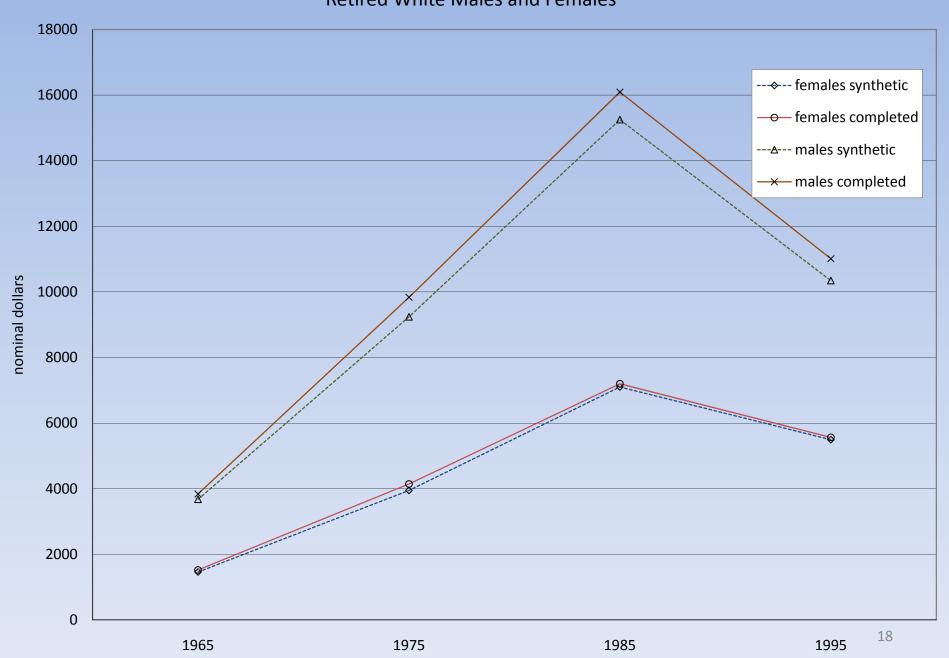
Comparison of Synthetic and Completed Annual Work Indicators Retired White Males and Females



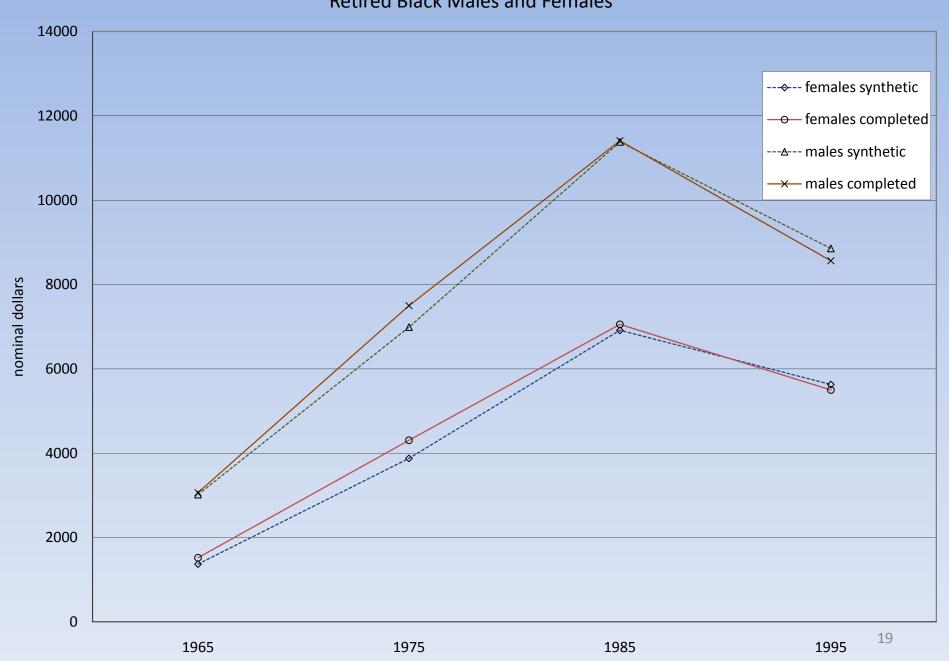
Comparison of Synthetic and Completed Annual Work Indicators Retired Black Males and Females



Comparison of Synthetic and Completed Earnings Retired White Males and Females



Comparison of Synthetic and Completed Earnings Retired Black Males and Females



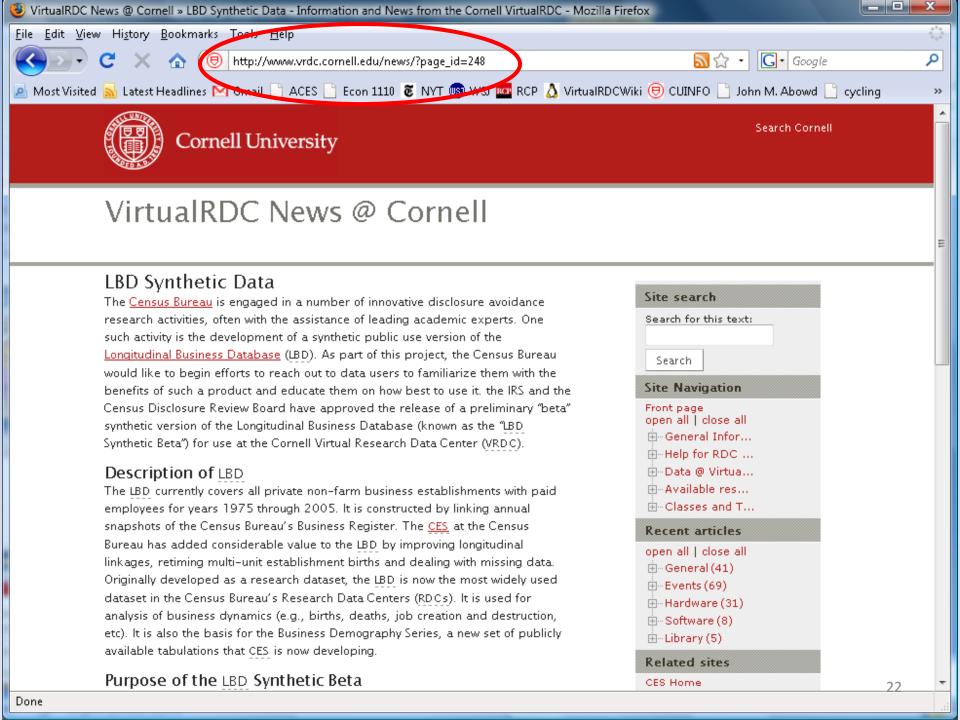
Disclosure Avoidance Review

 Done by probabilistic record linking and distance-based record linking to the source SIPP public use file

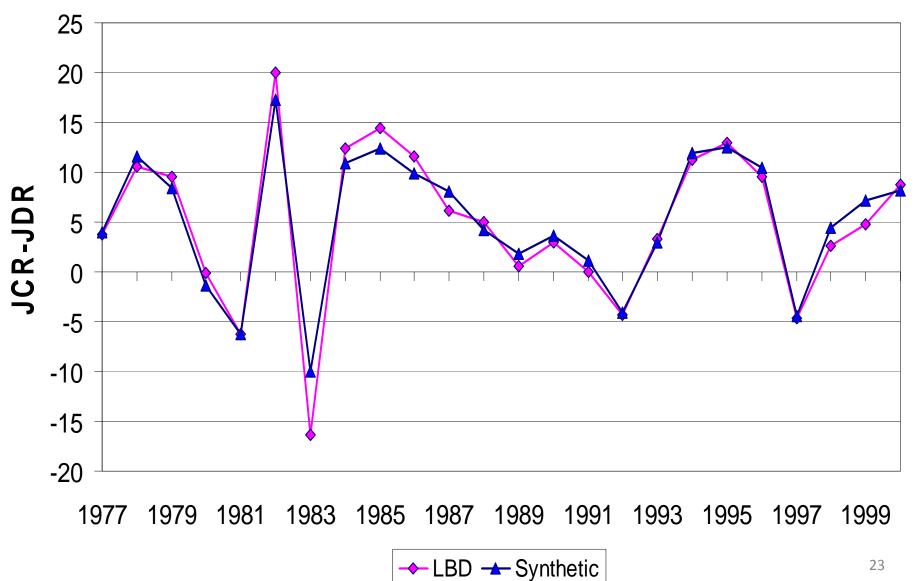
Decile of Distance Distr.	True Matches	False Matches	% True
1	181	26199	0.686%
2	193	26186	0.732%
3	193	26186	0.732%
4	184	26196	0.697%
5	207	26172	0.785%
6	231	26148	0.876%
7	243	26137	0.921%
8	267	26112	1.012%
9	368	26011	1.395%
10	612	25767	2.320%
Overall	2679	261114	1.016%

Project 2: Synthetic Longitudinal Business Database

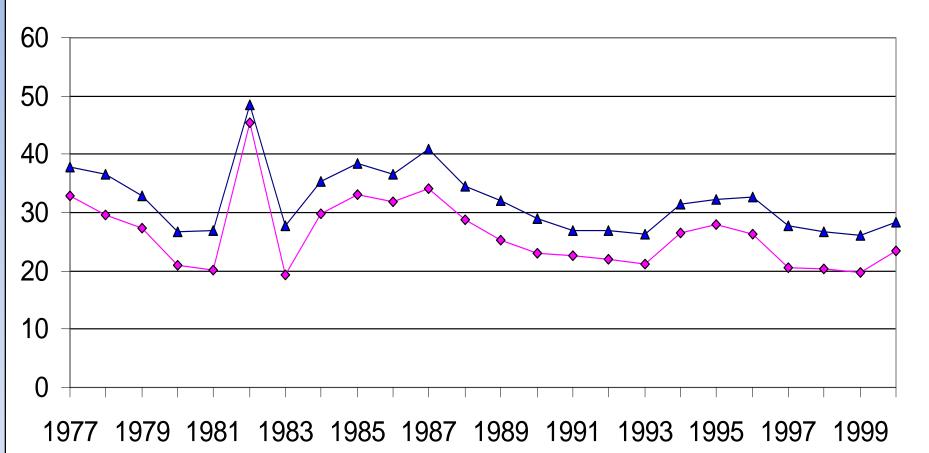
- Census Bureau establishment universe from 1976 to 2001
- Partially synthetic microdata file released in beta for a single industry (SIC 573) in May 2007
- Complete partially synthetic microdata file currently undergoing disclosure avoidance review
- Beta users of the synthetic LBD will be able to have their analyses run on the confidential LBD, as in the SIPP example



Net Job Flow Rate



Job Creation Rates: LBD and Implicates by Year



Year

Pearson Correlation Coefficients										
SIC 573										
Year: 2000										
	Synthetic Synthetic									
	Employment	Employment	Payroll	Payroll						
Employment	1									
	41000									
Synthetic	0.003	1								
Employment	21100	41000								
Payroll	0.712	-0.012	1							
	41000	21100	41000							
Synthetic	0.007	0.444	0.004	1						

Payroll

Application to Synthetic LBD

- Categorize each of employment and payroll so that
 - 100 represents observation in 0-90th percentiles
 - 010 represents obs in 90-99th percentiles
 - 001 represents obs in 99+ percentiles
- Construct transition matrix so that
 - 100100 represents point in 0-90 %ile of both employment and payroll
 - 100010 represents point in 0-90th %ile of employment and 90-99th %ile of payroll
 - Etc.

	Synthetic								
Actual	100100	100010	100001	010100	010010	010001	001100	001010	001001
100100	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100010	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100001	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
010100	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250
010010	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250
010001	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250
001100	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250
001010	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250
001001	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000

Application Synthetic LBD

- When one obs on one variable changes, it could affect the frequencies in any of the cells of the synthetic data.
- For each of the cells in the synthetic data (columns), calculate the relative probability that two observed data sets could have generated slightly different synthetic data sets.
- Compare only all possible "neighboring" cells in the observed data that could be the source of the difference. These cells differ only by employment or payroll (not both)

Example (Artificial Data)

- Transition matrix (artificial data)
 - Rows represent actual (confidential) data, columns represent synthetic (released) data
 - Rows are the conditional probability of releasing the column value, given the row value
 - The example has been simplified to illustrate the method

					Synthetic				
Actual	100100	100010	100001	010100	010010	010001	001100	001010	001001
100100	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100010	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100001	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
010100	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250
010010	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250
010001	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250
001100	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250
001010	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250
001001	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000

Example, Part II

- Differential Privacy Calculation
 - Consider the column 100010
 - Entry highlighted in yellow is the maximum numerator (row value 100010)
 - Entries highlighted in green have row values that differ from the row value for only a single variable (employment or payroll, not both)

	Synthetic								
Actual	100100	100010	100001	010100	010010	010001	001100	001010	001001
100100	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100010	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100001	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
010100	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250
010010	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250
010001	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250
001100	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250
001010	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250
001001	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000

Example, Part III

Differential Privacy Calculation

- Repeat the calculation for every column of the transition matrix
- In each column, the yellow entry is the maximum numerator and the green entries are the relevant rows for comparison
- Differential privacy for this synthesizer is 3.4657
- The inferential disclosure odds ratio has been bounded at 32

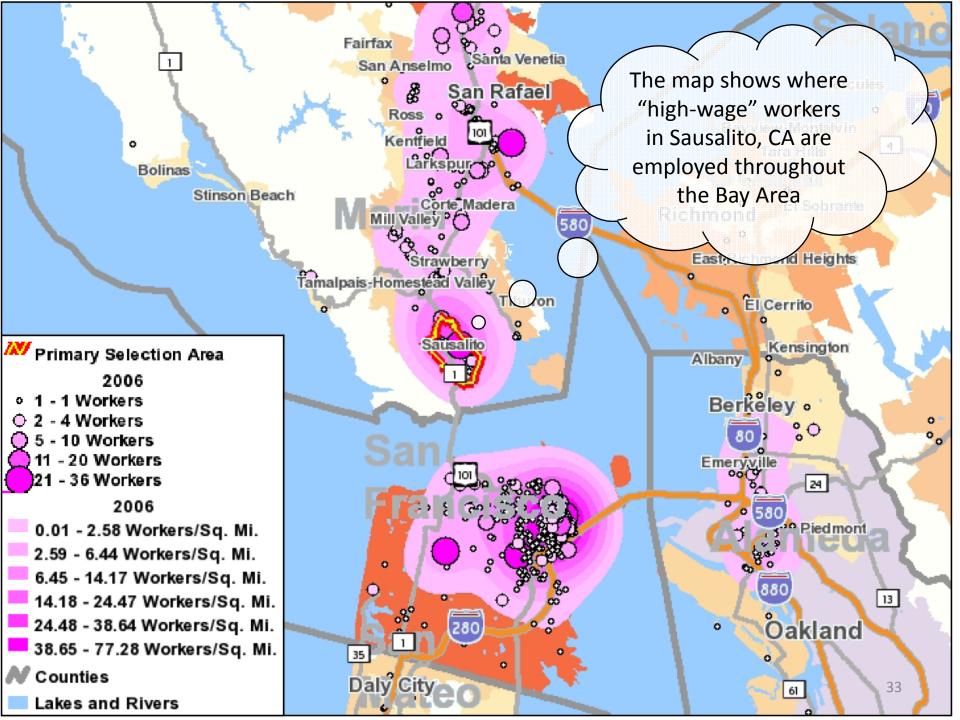
	Synthetic								
Actual	100100	100010	100001	010100	010010	010001	001100	001010	001001
100100	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100010	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
100001	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250
010100	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250	0.0250
010010	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250	0.0250
010001	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250	0.0250
001100	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250	0.0250
001010	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000	0.0250
001001	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.0250	0.8000

Project 3: Synthetic Longitudinal Employer-Household Dynamics Data

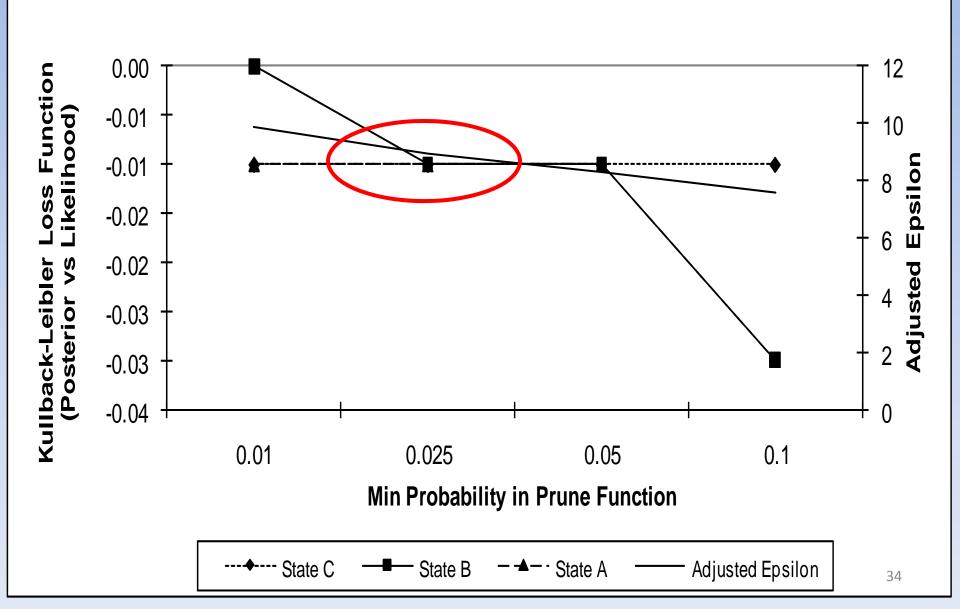
- You saw the presentation yesterday by Simon
- Longitudinally integrated relational database of individuals, employers, jobs
- Complete realized mobility graph (who ever worked for whom) not synthesized.

Related Projects: OnTheMap

- Residential location-workplace location mapping application developed from the Census Bureau's Longitudinal Employer-Household Dynamics infrastructure file system
- Block-level data for 2002 through 2006
- Complete origin-destination matrix stratified by age group, income group, and industry protected by synthetic data methods



Analytical Validity v. Confidentiality Protection in on the Map



Taking Account of Formal Privacy Models

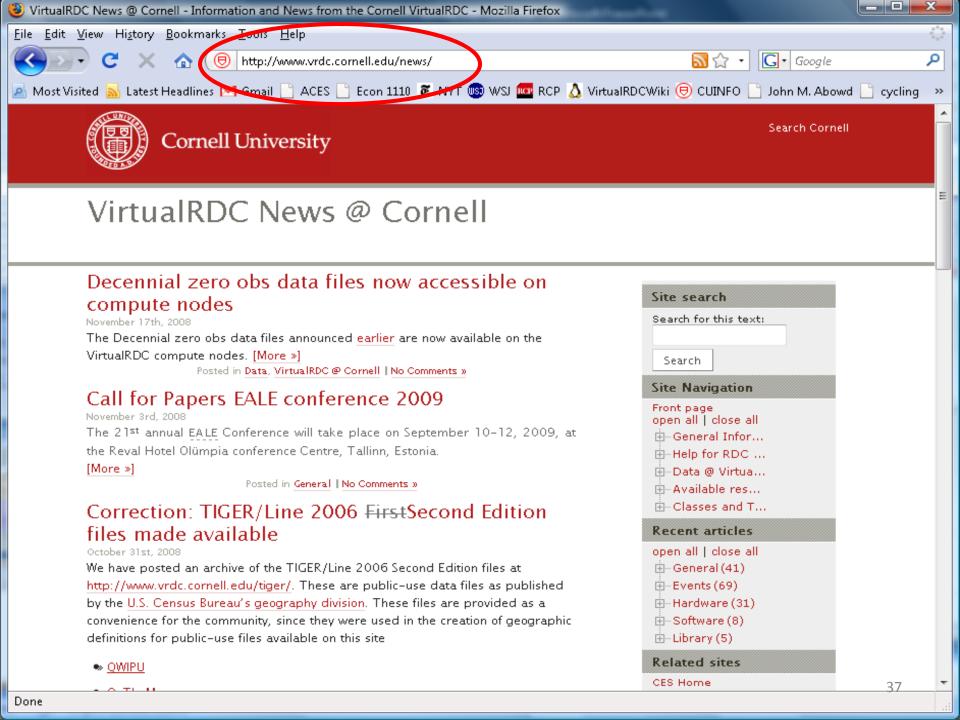
- It is now known from a variety of papers in the cryptographic data privacy literature (Dwork, Nissim and their many collaborators, Gehrke and his collaborators, and others) that the confidentiality protection afforded by synthetic data depends upon properties of the transition probabilities that relate the confidential data to the release data.
- Not surprising since

$$\Pr[\tilde{X}|X] = I$$

implies that the PPD leaves the confidential data unchanged by the synthesizer.

The Virtual Research Data Center

- Web-based application that allows complete access to all synthetic data products developed by the NSF-ITR collaborators with the Census Bureau
- Full access from anywhere
- Simulates the Census RDC operation to facilitate developing models on synthetic data that can be estimated on the underlying confidential data



Contacts

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Thank you