Disclosure Limitation

BLS Future in Disclosure Limitation

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Why Disclosure Limitation?

- Purpose of collecting data is to make data available for use.

- However, we promise to keep your responses confidential.

- Goal: Choose a method that protects the individual users responses from being known, while providing useful data.

QCEW

Provides employment and wage data in tabular form

NAICS	e20101	e20102	e20103	e20104	total
Series 1	2600	2899	3022	2599	11120
Sub1	1981	2256	2382	1957	8576
Sub2	32	33	37	33	135
Sub3	587	610	603	609	2409

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Need to protect sensitve cells

Sensitive Cells

$$T = X_1 + \ldots + X_n$$

where $X_i \geq X_{i+1}$

- Cell too small $n < 3$
- P% - Rule Fails

P%-Rule

$$R = X_3 + \ldots + X_n$$ remainder

$$T = X_1 + X_2 + R$$

Let $p \in (0, 1)$

Suppress if remainder is too small

$$R < pX_1$$

Motivation of P%-Rule

Suppose respondant 2, wants to know the value of respondent 1.

Estimate value $E_1 = T - X_2 = X_1 + R$

if $R < pX_1$

then $E_1 < (1+p)X_1$

so $E_1 \in \left(X_1, (1+p)X_1\right)$

Cell Suppression

	Q1	Q2	Q3	Q4	Annual Total
Industry 1	22	22	23	22	89
Industry 2	16	17	15	17	65
Industry 3	15	15	13	15	58
Total	53	54	51	54	212

sensitive cell

Remove Value

	Q1	Q2	Q3	Q4	Annual Total
Industry 1	22	[redacted]	23	22	89
Industry 2	16	17	15	17	65
Industry 3	15	15	13	15	58
Total	53	54	51	54	212

Can’t Remove Just One

	Q1	Q2	Q3	Q4	Annual Total
Industry 1	22	[redacted]	23	22	89
Industry 2	16	17	15	17	65
Industry 3	15	15	13	15	58
Total	53	54	51	54	212

Secondary Cell Suppression

	Q1	Q2	Q3	Q4	Annual Total
Industry 1	22	[redacted]	[redacted]	22	89
Industry 2	16	17	15	17	65
Industry 3	15	15	13	15	58
Total	53	54	51	54	212

Cox (1995) uses Complicated algorithm to find secondary suppressions

Quickly Looks Like "Swiss Cheese"

	Q1	Q2	Q3	Q4	Annual Total
Industry 1	22	[redacted]	[redacted]	22	89
Industry 2	16	17	15	17	65
Industry 3	15	[redacted]	[redacted]	15	58
Total	53	54	51	54	212

Suppression

Advantages

+ Provides accurate totals for cells that are published

Disadvantages

- No information for some cells
- QCEW suppresses over 60% of all possible cells
- No formal guarantee of protection
- Difficult to manage additional publications

Formal Privacy

Given the dataset D, let M(D) the released statistic after applying the disclosue limitaion method.

Example: The QCEW employment table with suppressed cells

Let be D^* a copy of the dataset with one of the observed values x, changed to $x^* = (1 \pm p)x$

A formally private method uses a ***stochastic mechanism*** M and its protection is guarteed by the fact that for all[‡] D^*

$$P(M(D^*) = M(D)) > 0$$

‡ or at least most of the relevant values in the range of M

Cell Suppression

Deterministic Method

$P(M(D^*) = M(D))=1$ or $P(M(D^*) = M(D))=0$

If value x is in a suppressed cell then

$$M(D^*) \quad = \quad M(D)$$

	Q1	Q2	Q3	Q4
Industry 1	22	[redacted]	23	22
Industry 2	16	17	15	17
Industry 3	15	15	13	15

	Q1	Q2	Q3	Q4
Industry 1	22	[redacted]	23	22
Industry 2	16	17	15	17
Industry 3	15	15	13	15

not true if we publish annual totals

Cell Suppression

Deterministic Method

$P(M(D^*) = M(D))=1$ or $P(M(D^*) = M(D))=0$

If value x is not in a suppressed cell then

$$M(D^*) \neq M(D)$$

	Q1	Q2	Q3	Q4
Industry 1	22	[redacted]	**27**	22
Industry 2	16	17	15	17
Industry 3	15	15	13	15

	Q1	Q2	Q3	Q4
Industry 1	22	[redacted]	23	22
Industry 2	16	17	15	17
Industry 3	15	15	13	15

Formal Privacy

Formally Private Method

$$P(M(D^*) = M(D)) > 0$$

If M adds random noise N(0, 1) to each cell value then rounds. Then with Probabity >> 0

D = M(D)

	Q1	Q2	Q3	Q4
Industry 1	22	22	23	22
Industry 2	16	17	15	17
Industry 3	15	15	13	15

	Q1	Q2	Q3	Q4
Industry 1	23	21	23	21
Industry 2	16	19	13	17
Industry 3	15	15	14	15

Formal Privacy

Advantages

+ Allows publication of most cells with small relative error
+ Guaranteed protection under very weak assumptions
+ Provides an easy way to manage new publications of data
+ Protection of one response is independent of others

Disadvantages

- Cell totals will have error
- Must use for other non-optimized applications

Randomized Response

- Warner (1965) proposed using random mechanism to change responses with known probability.
- Fuller (1993) proposed using additive noise to mask true values.

$$\tilde{y}_i = y_i + \epsilon_i$$

- Dwork (2008) developes differentially private definition

$$\mathbb{P}(M(D) \in S) \quad \leq \quad e^{\varepsilon}\, \mathbb{P}(M(D') \in S)$$

and framework for choosing noise level and protection guarantees.

- Wasserman & Zhou (2010) relates protection guarantee of ε-δ

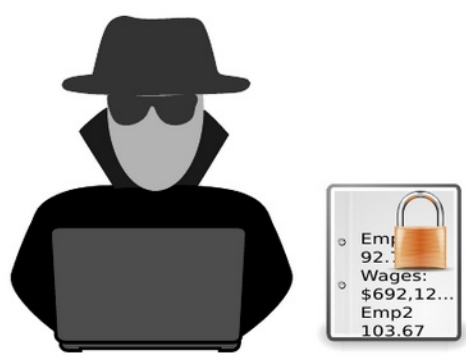
$$\mathbb{P}(M(D) \in S) \quad \leq \quad e^{\varepsilon}\, \mathbb{P}(M(D') \in S) + \delta$$

to hypothesis testing.

Protection Guarantee

- Difficulty of inference is expressed as point hypothesis test. E.g
  - Null: employment = 100 (reported value)
  - Alternate: employment = 110
  - Evidence: published confidentiality protected data 

100 vs. 110



BLS Approach in Development

- M(Employment by Establishment)
  - Noise is added to each establishment's employee data independently.
  - Uncertainty interval parameter β.
  - Privacy budget to spend: μ

- Establishment i:
  - M adds additive noise $N(0, \sigma^2)$ with $\sigma = \beta/\mu$ to $\sqrt{\text{employment}}$.
  - This is converted to unbiased employment estimate: $(\sqrt{employment} + N(0, \sigma^2))^2 - \sigma^2$
  - Attacker sees noisy employment: $\widetilde{E}$.
  - Can attacker distinguish between whether noise was added to E_1 vs. E_1'?
    - For any given significance level α, power in deciding E_1 vs. E_1' has slightly less than power in deciding between $N(0, 1)$ vs. $N(\mu, 1)$.

Protection vs Accuracy

Protection and accuracy is decided by choice of parameters

- Level of protection $|\sqrt{E_1} - \sqrt{E_1'}| \leq \beta$
- Variance of noise added to value $\sigma = \beta/\mu$
- Power of test deciding between $N(0,1)$ vs. $N(\mu,1)$ is $\leq \Phi(\Phi^{-1}(\alpha) + \mu)$

Protection vs Accuracy

Let $|\sqrt{E_1} - \sqrt{E_1'}| \leq \beta = 1$

	sqrt ± 1	
E_1	**Uncertainty Interval for E_1'**	**Relative Size**
1	[0, 4]	400.0%
100	[81, 121]	40.0%
1,000	[937, 1065]	12.7%
10,000	[9801, 10201]	4.0%
100,000	[99368, 100634]	1.3%

Protection vs Accuracy

Let $|\sqrt{E_1} - \sqrt{E_1'}| \leq \beta = 1$ and $\alpha = 0.05$

μ	σ	power
0.5	2	0.1261
1.0	1	0.2595
1.5	0.67	0.4424
2.0	0.5	0.6387

$\sqrt{E_1}| \leq \beta$

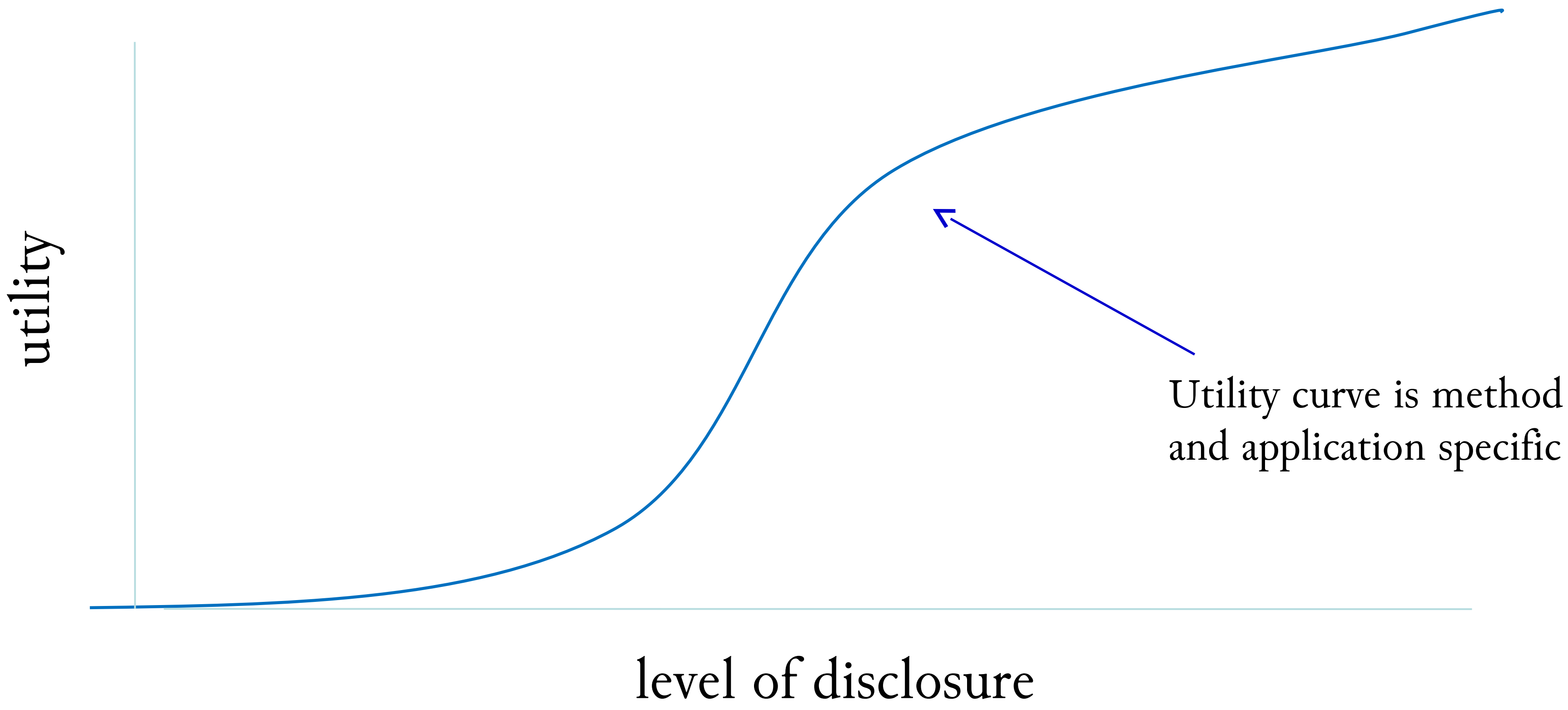
Protection vs Accuracy

Let $|\sqrt{E_1} - \sqrt{E'_1}| \leq \beta = 1$ and $\alpha = 0.05$

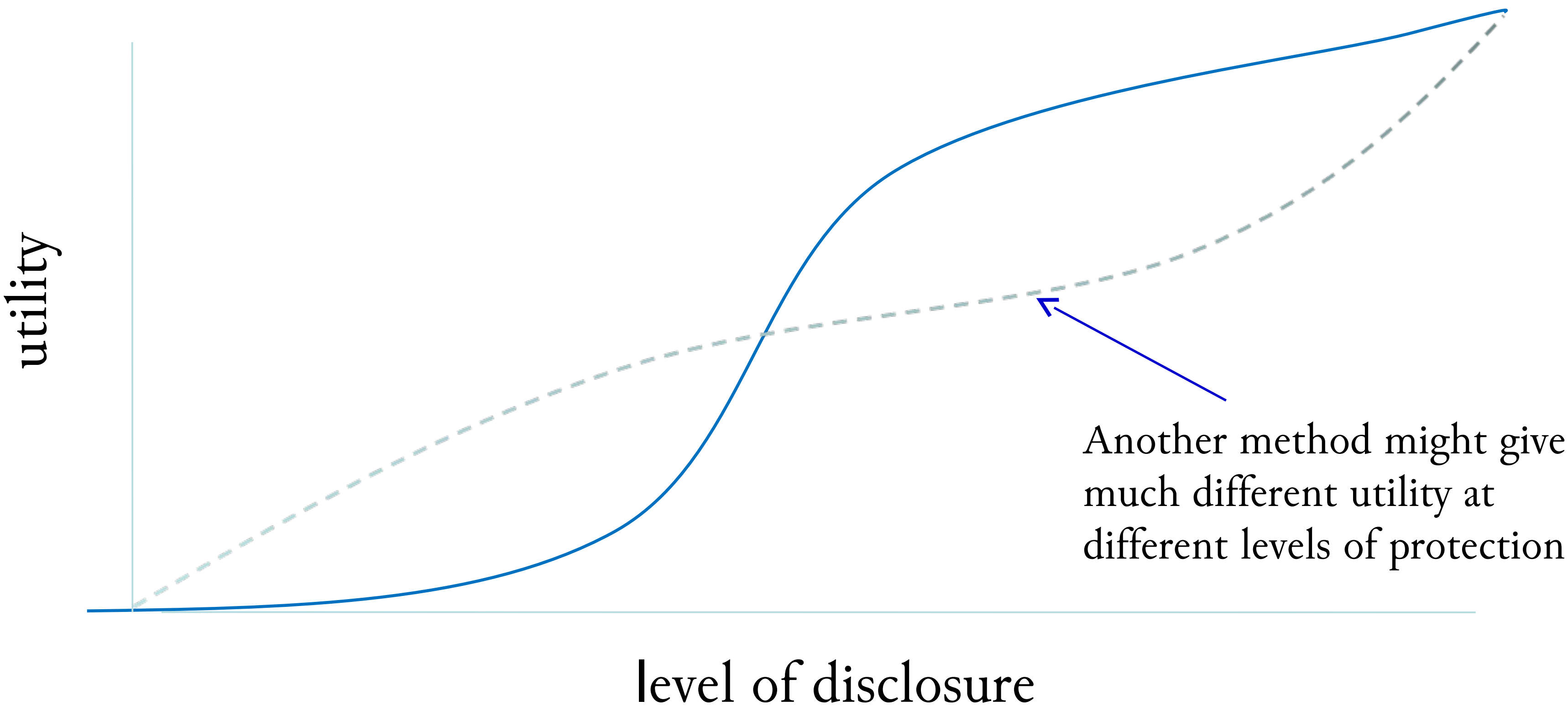
μ	σ	power
0.5	2	0.1261
1.0	1	0.2595
1.5	0.67	0.4424
2.0	0.5	0.6387

How to use privacy budget effectively?

Utility / Protection Tradeoff



Different Method = Different Utility



Splitting the Budget

Use budget μ_1 for protection of individual establishment values

Use budget μ_2 for protection of cell totals

Then the overall budget as far as the accuary/protection tradeoff is

$$\mu \leq \sqrt{\mu_1^2 + \mu_2^2}$$

Examples: $\mu_1 = 1$, $\mu_2 = 1.5$ then $\mu \leq 1.80$

$\mu_1 = .75$, $\mu_2 = 1.9$ then $\mu \leq 2.04$

Example

- Original:

Total Employment

📈 👷‍♀️ 🥦 🏗️ 🍎 $=$ 1,000,000

Employment by County

A	B	C
📈 $= 1,000$	👷‍♀️ 🥦 $= 639,000$	🏗️ 🍎 $= 360,000$

- Add noise
  - $\beta = 1$,
  - $\mu_1 = 0.3$ for total, $\mu_2 = 0.4$ for county
  - overall $\mu = \sqrt{0.3^2 + 0.4^2} = 0.5$

Total Employment

📈 👷‍♀️ 🥦 🏗️ 🍎 $= 1,002,394.88$

Employment by County

A	B	C
📈 $= 1,226.92$	👷‍♀️ 🥦 $= 640,506.56$	🏗️ 🍎 $= 359,329.31$

Calibrate Protected Values

Total Employment

📈 👷‍♀️ 🥦 🏗️ 🍎 $= 1,002,394.88$

Employment by County

A	B	C
📈 $= 1,226.92$	👷‍♀️ 🥦 $= 640,506.56$	🏗️ 🍎 $= 359,329.31$

- Find values for 📈 👷‍♀️ 🥦 🏗️ 🍎 that minimize

$$\frac{(\text{📈} + \text{👷‍♀️} + \text{🥦} + \text{🏗️} + \text{🍎} - 1,002,394.88)^2}{\text{variance(Total Employment)}}$$

$$+\frac{(\text{📈} - 1,226.92)^2}{\text{variance(County A)}} + \frac{(\text{👷‍♀️} + \text{🥦} - 640,506.56)^2}{\text{variance(County B)}}$$

$$+\frac{(\text{🏗️} + \text{🍎} - 359,329.31)^2}{\text{variance(County C)}}$$

Advantages of Protected Micro-Data

- Just use the protected data to produce tables
- No need for cell suppressions
- Users can define areas of interest
- Use protected micro-data for new publication/analysis (no disclosue review needed!)

Selected References

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Thank You

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