Outline

1. The CE data and top-coding for skewed continuous data
2. The synthetic data approach
3. Proposed risk-adjusted synthesizer
   - Overview
   - The synthesizer
   - Evaluation of identification disclosure risks
   - A risk-adjusted synthesizer
4. Results of CE family income synthesis
5. Implications and references
The CE data at the BLS

- Conducted by the U.S. Census Bureau for the BLS.
- Contains data on expenditures, income, and tax statistics about consumer units (CU) across the country.
- Provides information on the buying habits of U.S. consumers.
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- Data users would like to access to more detailed versions of the CU’s family income, however BLS is not releasing the original values of family income due to confidentiality concerns (Title 13).
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- How to make it happen?
The Consumer Expenditure Surveys data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Gender of the reference person; 2 categories</td>
</tr>
<tr>
<td>Age</td>
<td>Age of the reference person; 5 categories</td>
</tr>
<tr>
<td>Education Level</td>
<td>Education level of the reference person; 8 categories</td>
</tr>
<tr>
<td>Region</td>
<td>Region of the CU; 4 categories</td>
</tr>
<tr>
<td>Urban</td>
<td>Urban status of the CU; 2 categories</td>
</tr>
<tr>
<td>Marital Status</td>
<td>Marital status of the reference person; 5 categories</td>
</tr>
<tr>
<td>Urban Type</td>
<td>Urban area type of the CU; 3 categories</td>
</tr>
<tr>
<td>CBSA</td>
<td>2010 core-based statistical area (CBSA) status; 3 categories</td>
</tr>
<tr>
<td>Family Size</td>
<td>Size of the CU; 11 categories</td>
</tr>
<tr>
<td>Earner</td>
<td>Earner status of the reference person; 2 categories</td>
</tr>
<tr>
<td>Family Income</td>
<td>Imputed and reported income before tax of the CU; approximate range: (-7K, 1,800K)</td>
</tr>
</tbody>
</table>

**Table:** Variables used in the CE sample. Data taken from the 2017 Q1 Consumer Expenditure Survey.
The CE data and top-coding for skewed continuous data

The CE data: highly skewed family income

- Family income: imputed and reported income before tax of the CU.

![Graph showing skewed distribution of family income]
The CE data and top-coding for skewed continuous data

The CE data: highly skewed family income

- Family income: imputed and reported income before tax of the CU.
- Record with high risks: assumed to be in the tail, i.e. CUs with extremely high family income.
- What to do?
The CE data and top-coding for skewed continuous data

The CE data: highly skewed family income

- Family income: imputed and reported income before tax of the CU.
- Record with high risks: assumed to be in the tail, i.e. CUs with extremely high family income.
- What to do? Topcoding (statistical disclosure control).
Protection for highly skewed family income: topcoding

- Topcoding affects observations in the tail.
- Reduction in data utility (An and Little, 2007).
- Reduction in disclosure risks?

**Figure**: Range (250K, 500K)

**Figure**: Range (500K, 3,000K)
Rubin (1993) and Little (1993) proposed the synthetic data.

- Simulate records from statistical models that are estimated from the original confidential data.

- Balance of data utility and disclosure risks
  - preserve relationships of variables
  - low disclosure risks

- Allow data analysts to make valid inference for a wide class of analyses.
Protection for highly skewed data: synthetic data

- Census Bureau’s synthetic data products:
  - Survey of Income and Program Participation (SIPP)
  - Longitudinal Business Databases (LBD)
  - OnTheMap
The synthetic data approach

Protection for highly skewed data: synthetic data

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- Ongoing research at the Census
  - Economic Census microdata synthesis
  - Joint collaboration between the Census Bureau and Dr. Hang Kim (University of Cincinnati and ASA/NSF/Census Fellow)
  - Contact: Jenny Thompson (katherine.j.thompson@census.gov)

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Bayesian Pseudo Posterior Synthesis for Data Privacy Protection
Protection for highly skewed data: proposed approach

- Typically, statistical agencies will
  - Develop a synthesizer, and simulate synthetic data.
  - Evaluate the data utility and disclosure risks of the synthetic data.
  - Make decision on the synthetic data release based on utility and risks profiles.

What if the disclosure risks are deemed too high?
- Option 1: develop a new synthesizer, or many new synthesizers if necessary.
- Option 2: use the evaluated disclosure risks to create a risk-adjusted synthesizer, which induces further disclosure protection on high risk records.
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- We will illustrate proposed Option 2 for the CE family income data synthesis.
Protection for highly skewed data: proposed approach

Our CE family income data synthesis methods involve:

- Develop a nonparametric mixture synthesizer, and simulate synthetic family income.
- Evaluate the identification disclosure risks of the synthetic family income.
- Create a new risk-adjusted synthesizer.
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Our CE family income data synthesis methods involve:

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- Synthesize family income from the new risk-adjusted synthesizer, and evaluate the identification disclosure risks.
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- Create a new risk-adjusted synthesizer.
- Synthesize family income from the new risk-adjusted synthesizer, and evaluate the identification disclosure risks.
- Evaluate and compare risk profiles of:
  - Synthetic data from original synthesizer.
  - Synthetic data from risk-adjusted synthesizer.
  - Topcoded microdata.
A nonparametric mixture synthesizer

\[
y_i \mid X_i, z_i, \beta, \sigma \sim \text{Normal}(y_i \mid x'_i\beta^*_z, \sigma^*_z) \quad (1)
\]
\[
z_i \mid \pi \sim \text{Multinomial}(1; \pi_1, \cdots, \pi_K) \quad (2)
\]

- \(y_i\) is the family income of CU \(i\).
- \(x'_i\) includes 10 predictors of CU \(i\).
- \(y_i \mid X_i, z_i, \beta_i, \sigma_i \sim \text{Normal}(y_i \mid x'_i\beta_i, \sigma_i)\), where \(\beta_i = \beta^*_z\) and \(\sigma_i = \sigma^*_z\) given \(z_i\).  
- The nonparametric mixture synthesizer could model the long tail better with several mixture components.
A nonparametric mixture synthesizer

Proposed risk-adjusted synthesizer

The synthesizer

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Bayesian Pseudo Posterior Synthesis for Data Privacy Protection
A nonparametric mixture synthesizer

\[ y_i \mid X_i, z_i, \beta, \sigma \sim \text{Normal}(y_i \mid x_i' \beta_{z_i}^*, \sigma_{z_i}^*) \]  
\[ z_i \mid \pi \sim \text{Multinomial}(1; \pi_1, \cdots, \pi_K) \]

To generate synthetic family income, \( y_i^* \), for CU \( i \):

- Generate \( z_i \) from Equation (4).
- Generate \( y_i^* \) given \( x_i' \) and estimated \( \beta_{z_i}^*, \sigma_{z_i}^* \) from Equation (3).
- Do this for every CU, and obtain one partially synthetic dataset \( Z^{(l)} \).
- Repeat the above steps for \( m \) times, and obtain \( m \) independent partially synthetic datasets \( Z = (Z^{(1)}, \cdots, Z^{(m)}) \).
Record-level identification disclosure

- Focus on record-level identification disclosure risks.
- As opposed to file-level identification disclosure risk summary.
- Want to surgically target high risk records.
Assumptions about intruder’s knowledge

- **Available information known by the intruder about CU \(i\):**
  - A known pattern of the un-synthesized categorical variables, \(X^p_i \subseteq X_i\), e.g. (Gender, Age, Education Level, Marital, Earner).
  - The true value of synthesized family income \(y_i\).
  - A name or identity of interest.

- **Successful identification allows the intruder to learn other information of CU \(i\) in the released microdata.**
Identification risks based on notion of isolation

- Define radius $r$ of synthetic data $y^*$ in pattern $p$ around the truth $y$.
- Use percentage radius, e.g. $r = 20\%$.
  - e.g. For a CU $i$ with $50,000$ family income, the interval/ball is: $[$40,000, $60,000]$.

Outside of radius $\rightarrow$ isolation.

- Do this for each record $y_i$: all $y_j^*$’s in pattern $p$.
- Identification risk (IR) for each record is a probability.
Evaluation of identification disclosure risks

- Fewer synthetic values inside the interval/ball $\rightarrow$ the intruder has a higher probability of guessing the record of the name they seek.
Evaluation of identification disclosure risks

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Scenario 1:

\[ IR_i = \frac{10}{13} \times 1 = \frac{10}{13}. \]
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Scenario 1:
\[ IR_i = \frac{10}{13} \times 1 = \frac{10}{13}. \]

Scenario 2:
\[ IR_i = \frac{10}{13} \times 0 = 0. \]
Evaluation of identification disclosure risks

More synthetic values inside the interval/ball → the intruder has a lower probability of guessing the record of the name they seek.

Scenario 3:

\[ IR_i = \frac{5}{13} \times 1 = \frac{5}{13}. \]
Evaluation of identification disclosure risks

- More synthetic values inside the interval/ball $\rightarrow$ the intruder has a lower probability of guessing the record of the name they seek.

Scenario 3:
$$IR_i = \frac{5}{13} \times 1 = \frac{5}{13}.$$  

Scenario 4:
$$IR_i = \frac{5}{13} \times 0 = 0.$$
More formally, for CU $i$ with pattern $p$:

\[
IR_i := \Pr (\text{identification disclosure of } i) = \frac{\sum_{j \in M_i} \mathbb{I} \left( y_j^* \notin B(y_i, r) \right)}{|M_i|} \times T_i.
\] (5)

- $B(y_i, r)$: a ball of radius $r$ around true value, $y_i$.
- $T_i = 1$ if the true value, $y_i$ is among those records, $j \in M_i$ whose $y_j^* \in B(y_i, r)$; $T_i = 0$ otherwise.
A new risk-adjusted synthesizer

- Use weight $\alpha_i \in (0, 1)$ for CU $i$.
- $\alpha_i \propto \frac{1}{IR_i}$.
- Selectively downweight to defeat the likelihood principle:
  \[
  \prod_{i=1}^{n} p(y_i \mid (\pi_k, \beta_k^*, \sigma_k^*)_{k=1}^{K})^{\alpha_i} \prod_{k=1}^{K} p(\pi_k, \beta_k^*, \sigma_k^* \mid \theta).
  \]
- Surgical distortion: scalar $\alpha$ vs vector $\alpha_i$. 
Results of CE family income synthesis

Data utility results

Figure: Range (-10K, 250K)

Figure: Range (250K, 3,000K)

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Bayesian Pseudo Posterior Synthesis for Data Privacy Protection
Data utility results

Figure: Synthesizer  Figure: Vector Weights  Figure: Topcoding
Violin plots of identification risks
### Table of identification risks for top 10 size/magnitude records

<table>
<thead>
<tr>
<th>Data Value</th>
<th>Synthesizer</th>
<th>Weights_V</th>
<th>TC 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0000</td>
<td>0.0486</td>
<td>0.0000</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0482</td>
<td>0.1446</td>
<td>0.0000</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0000</td>
<td>0.2473</td>
<td>0.0000</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0000</td>
<td>0.1440</td>
<td>0.0000</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0496</td>
<td>0.0987</td>
<td>0.0000</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0967</td>
<td>0.0000</td>
<td>0.9565</td>
</tr>
<tr>
<td>(250K, 3,000K)</td>
<td>0.0986</td>
<td>0.0989</td>
<td>0.0000</td>
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# Results of CE family income synthesis

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</tr>
</thead>
<tbody>
<tr>
<td>(-10K, 50K)</td>
<td>0.6258</td>
<td>0.0925</td>
<td>0.9762</td>
</tr>
<tr>
<td>(50K, 100K)</td>
<td>0.5318</td>
<td>0.1717</td>
<td>0.8312</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5725</td>
<td>0.1635</td>
<td>0.8108</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5274</td>
<td>0.2261</td>
<td>0.8889</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5369</td>
<td>0.1560</td>
<td>0.7738</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5258</td>
<td>0.1348</td>
<td>0.8788</td>
</tr>
<tr>
<td>(-10K, 50K)</td>
<td>0.5270</td>
<td>0.3250</td>
<td>0.9400</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5310</td>
<td>0.1708</td>
<td>0.8214</td>
</tr>
<tr>
<td>(100K, 250K)</td>
<td>0.5925</td>
<td>0.0460</td>
<td>0.9080</td>
</tr>
<tr>
<td>(50K, 100K)</td>
<td>0.5351</td>
<td>0.2629</td>
<td>0.7113</td>
</tr>
</tbody>
</table>
### Results of CE family income synthesis

#### Risky records are unique

<table>
<thead>
<tr>
<th>Variable</th>
<th>Record A</th>
<th>Record B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>Male</td>
</tr>
<tr>
<td>Age</td>
<td>20 - 40</td>
<td>60 - 80</td>
</tr>
<tr>
<td>Education Level</td>
<td>Bachelor’s degree</td>
<td>Some college, no degree</td>
</tr>
<tr>
<td>Region</td>
<td>South</td>
<td>South</td>
</tr>
<tr>
<td>Urban</td>
<td>Urban</td>
<td>Urban</td>
</tr>
<tr>
<td>Marital</td>
<td>Married</td>
<td>Married</td>
</tr>
<tr>
<td>Uatype</td>
<td>Urbanized area</td>
<td>Urbanized area</td>
</tr>
<tr>
<td>Cbsastat</td>
<td>In a CBSA not in the Principal City</td>
<td>In a CBSA in the Principal City</td>
</tr>
<tr>
<td>Family Size</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Earner</td>
<td>Member Earns Income (-10K, 50K)</td>
<td>Member Earns Income (-10K, 50K)</td>
</tr>
<tr>
<td>Family Income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IR: Synthesizer</td>
<td>0.6258</td>
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Implications

- Our proposal is for agencies to release respondent-level synthetic data.
  - Users never see real data.

- We may directly interrogate the disclosure risks of the synthetic records.
  - As contrasted with dynamic queries of the real data.

- We should directly measure the disclosure risks of the synthetic data.
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- The use of topcoding incorrectly assumes which records express high risks.
References


