Synthetic Data for Canadian LEAP

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Abstract

Statistics Canada collects data and creates databases based on administrative records on business establishments and enterprises, however, they only disseminate those business databases in highly aggregated forms. Since it is costly and inconvenient for researchers to get access to Canadian micro business databases, in this project, we implement the algorithm of the U.S. synthetic database for Longitudinal Business Database (LBD) to create the Canadian synthetic database for the Longitudinal Employment Analysis Program (LEAP). This Canadian synthetic database supports analytical validity for a wide range of statistical analyses which frequently use in the literature as well as provide evidence on confidentiality properties.

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1 Introduction

Statistics Canada collects data and creates databases based on administrative records (like T4 slip that is the annual statements of remuneration paid) on business establishments and enterprises, however, they only disseminate those business databases in highly aggregated forms into two-digit industry categories. The Canadian Center for Data Development and Economic Research (CDER) in Statistics Canada is responsible to protect the confidentiality of business data. CDER does not disseminate those business databases for two reasons. First, a confidentiality breach related to the business database is potentially more damaging to the statistical system because of the importance of key respondents that are more likely to be identifiable, e.g. Bombardier inc., a company mainly specializing in air and railway technology or Cavendish farm in Prince Edward Island (PEI). Second, the financial gains related to identifying a respondent are potentially greater, for example, people could make a profit by in investing stock markets through identifying Bombardier Inc.

To give access to business databases, CDER currently uses three measures in place to mitigate the higher risk to the statistical system when business microdata are accessed. First, a batch-submit system is used when accessing the actual data. Second, actual individual observations cannot be accessed without it being recorded. Third, "CDER version of synthetic data" is also provided to aid with programming.

Since it is costly and inconvenient for both researchers and Statistics Canada to get access to business databases, in this project, we create synthetic data[1] for Canadian LEAP database during the period of 1991 to 2014 using 2015 LEAP vintage. In this project, we have three objectives: i) evaluate to what extent synthetic code developed for the U.S. Longitudinal Business Database (LBD) can easily transferable to LEAP database with comparable structure; ii) examine whether the automated synthesis will generate useful datasets that offer

[1] Synthetic data are created by replacing sensitive values with repeated draws from a model fit to the original data (Little, 1993; Rubin, 1993). This approach is closely related to multiple imputations.

analytical validity for a wide range of statistical analyses; iii) provide evidence on confidentiality properties.

Synthetic code developed for the U.S. LBD can easily transferable to Canadian LEAP database with comparable structure, however, there are some issues raised to implement that the U.S. synthetic code in Canadian LEAP database. First, the U.S. synthetic LBD code does not converse for a group of industries for each time of implementation. Second, the U.S. synthetic LBD code does not properly approximate the last year information of firms. Third, the U.S. synthetic LBD code generates, in some cases, zero employment or payroll during the life cycles of firms.

Canadian synthetic database generates analytical validity for a wide range of statistical analysis which commonly uses in the literature. For example, we find that firm characteristics (gross employment, total payroll, the share of firms, the share of employment, the share of payroll) in the Canada synthetic data are very close to those in the LEAP, however, the manufacturing sector shows more close pattern than the private sector. In addition, we compare firm dynamics (entry and exit rates) and dynamics of job flows (job creation rate, and net job creation rate) between Canadian synthetic and LEAP database and find that those firm dynamics are similar. Furthermore, we assess how well Canadian database captures variability in economic growth due to industry and firm age using several dynamic panel data models and find that Canadian synthetic database provides similar predictions to LEAP database.

To provide evidence on confidentiality properties of Canadian synthetic database, we estimate the probability that the synthetic first year equals the true first year given the synthetic fist year and find that those probabilities are quite low except for the first year of LEAP database. This is because of censoring and lack of previous information.

This paper is organized as follows. Section 2 includes a detailed description of the LEAP database and usages of LEAP database. Section 3 provides a brief overview of the evolution of synthetic data and implementation in the Canadian context. In section 4, the analytical validity of synthetic database is discussed.

Finally, this paper concludes in Section 5. In addition, it includes a description to include other variables in Canadian synthetic database as an extension.

2 Data Description

2.1 LEAP database

The Longitudinal Employment Analysis Program (LEAP) is a database that contains annual employment information for each employer business in Canada. The LEAP covers incorporated and unincorporated businesses that issue at least one T4 slip–the annual statements of remuneration paid–in any given calendar year, but excludes self-employed individuals or partnerships where the participants do not draw salaries. The LEAP has the advantage of covering all sectors of the economy-though some of the information is more meaningful for the business sector than the public sector.

The LEAP is constructed using three sources of information: T4 administrative data received from Canada Revenue Agency, data from Statistics Canada's Business Register, and data from Statistics Canada's Survey of Employment, Payrolls and Hours (SEPH). In Canada, employing businesses are required to register with Canada Revenue Agency using the Business Number and issue to each of their employees a T4 slip that summarizes earnings received in the year. This process creates a link between the employee and the business through the Business Number. This link is the backbone of LEAP, and the reported payroll allows estimates of annual employment to be made. The payroll is converted to employment (called ALUs or Average Labour Units) using conversion factors derived from the SEPH.

- **Longitudinal Business Register Identifier (LBRID):** This is the unique identifier assigned to each enterprise. The LBRID tracks the enterprise across all years in which it has employees, for the period covered by the LEAP vintage. It is derived from the Business Register enterprise identifier (BRID). For various administrative reasons, an enterprise's identifier in the Business Register may sometimes change from year to year. This would lead to the appearance of false deaths and births in the LEAP file. To avoid this, a system of Labour Tracking is used to track the movements of workers between firms. This is used to detect false births and deaths and link firms by a common LBRID. Labour tracking can lead to many different types of linkages between firms. The simplest would be a one-to-one linkage between a death and a birth record. For example, if a business changes from incorporated to limited business, the Business Register may remove the original business from the register and create a new one. In this case, the only action necessary is to assign a common LBRID to the two businesses over time. A more complex case would be a merger between two firms, where most employees from the previous two firms are at a new firm. Here, all three entities are given the same LBRID, and the past records of the two merged firms would be combined into a single record. The employment of the two firms is added together, and the current NAICS code for the new firm is assigned to the combined, synthetic past record. In other words, it would be as if the newly merged firm already existed in the past. Similarly, acquisitions and spinoffs lead to the combination of firms and the creation of synthetic records.

- **Industry:** The 4-digit North American Industrial Classification System (NAICS) code that is assigned to a firm nationally. This is the most dominant NAICS code for firms that have activity in multiple industries. One of the characteristics of the LEAP is that the industry code for the most recent year that the firm is alive is pushed back in time, so that an enterprise has the same industry code each year within the same vintage.

- **Employment:** Employment of each firm is measured by its average labour units (ALUs). ALUs are the average employment an enterprise would have if it paid its workers the average annual earnings (AAE) of a typical worker in the enterprise's particular industry, province and enterprise size class. AAE are derived using information from the SEPH.

- **Payroll:** Sum of payroll from all T4 slips issued by the enterprise.

2.2 Usages of LEAP database

Using the LEAP database, we could conduct several research projects. For example, firm characteristics, firm dynamics (firm exit and firm entry), dynamics of job flows (job creation and job destruction), employment growth, changes in gross employment and payroll by firm size and firm age and industry. In addition, we could look at the distribution of employment growth rates and the variability in economic growth due to industry and firm age.

3 Methodology

3.1 Overview of method

Demand for firm-level data across countries and also within-country are increasing to study firm dynamics. For example, Bartelsman, Haltiwanger, and Scarpetta [3] use a cross-country dataset to study average post-entry behavior of young firms. Sedláček and Sterk [11] use the BDS to show the role of firm size in firm dynamics but also had access to the Synthetic LBD. However, due to limited access to firm-level data across countries and also within-country, it is difficult to identify the sources of the variation in firm dynamics across countries. To provide access to establishment data in the United States, Kinney et al. [10] describe an approach to release synthetic data for Longitudinal Business Database (LBD), which was created in the early 2000s (see Jarmin and Miranda [7] for details). The variables currently in the LBD are industry, annual payroll, employment, geography, birth year, death year, and firm structure.

Currently, there are two versions of the method to create the Synthetic database. The general approach to data synthesis is to generate a joint posterior predictive distribution of $Y|X$ where Y are variables to be synthesized and X are unsynthesized variables. In the Phase 1 version of the method to create synthetic data, variables are synthesized in a sequential fashion, generally categorical variables are processed first using a variant of Dirichlet-Multinomial and then continuous variables are synthesized using a normal linear regression model with kennel density-based transformation (Woodcock and Benedetto [13]). Phase 2 version has shifted to a Classification and Regression Trees (CART) model with Bayesian bootstrap. For the United States, the phase 2 version is currently in its final stages (Kinney, Reiter, and Miranda [9]). To evaluate whether synthetic data algorithms developed in the United States can easily be transferred to generate a similar synthetic data for other countries, Drechsler and Vilhuber [6] implement the Phase 1 version of the method to the German Longitudinal Business Database (GLBD).

3.2 Implementation in the Canadian context

To create a Canadian synthetic database, we use the 2015 LEAP vintage. As for the U.S. synthetic database for LBD, we synthesize categorical variables first, followed by continuous variables, controlling for the firm ID and the industry classification at 4-digit NAICS (see Table 1.)

Table 1: CanSynLEAP variable descriptions

Name	**Type**	**Description**	**Notation**	**Action**
synid	Identifier	Unique random number for enterprise		Created
NAICS	Categorical	4 digit industry code	x_1	Unmodified
Firstyear	Categorical	First year enterprise is observed	y_1	Synthesized
Lastyear	Categorical	Last year enterprise is observed	y_2	Synthesized
Year	Categorical	Year dating of annual variables		Created
ALU	Continuous	Average Labor Unit (annual)	y_3	Synthesized
Payroll	Continuous	Payroll (annual)	x_4	Synthesized

Note: Variables denoted with y_i are synthesized and variables denoted with x_i are not synthesized.

After implementing the U.S. synthetic LBD code, we follow four steps to create a Canadian synthetic database. First, we exclude the public sector (NAICS 61, 62, and 91) because Statistics Canada does not produce any statistics for this sector. Second, we exclude industries that are not converging for each time of implementation of the U.S. synthetic code for LBD. These industries are NAICS 4481, 4482, 4483, 4511, 4513, 4841, 4842, 5241, and 5242. Specifically, the SynLBD code does not converge around 7 percent observations as mentioned by "not synthesized" in Table 2. Third, we drop some industries, from the synthesized industries, which have sensitiveness information. Finally, we drop last year observation for each firm since the SynLBD code does not properly approximate the last year data. After the implementation of these steps, we have around 22 million observations in the CanSynLBD database during the period of 1991 - 2014.

Need to mention suppressed industries. Note presence of 0000 industries. Discuss.

Table 2: Synthesized observations

Category	**# of Observations (millions)**	**Percentage**
Synthesized	22.01	93.35
Not synthesized	1.57	6.65
Total	23.58	100.00

Note: Not synthesized industries are NAICS 4481, 4482, 4483, 4511, 4513, 4841, 4842, 5241, and 5242. These industries are not converging for each time of implementation We drop industries, from the synthesized industries, which have sensitiveness information. We do not synthesize the public sector (NAICS 61, 62, and 91).

4 Analytical validity

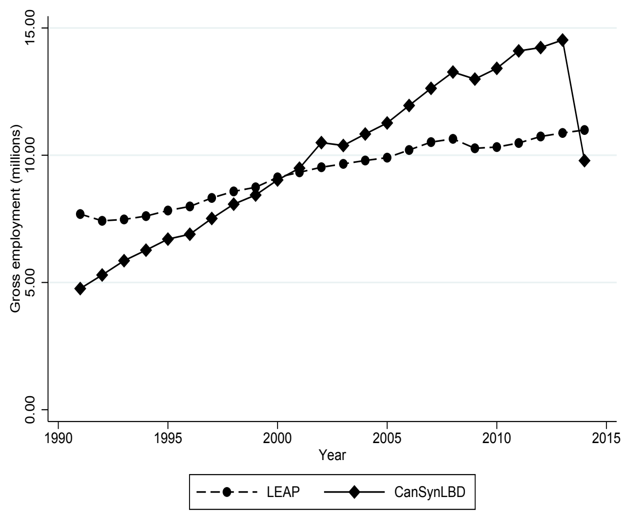
4.1 Firm Characteristics

The CanSynLBD and LEAP generally provide comparable inferences on aggregate means and correlations. For example, Figures 1 and 2 show gross employment levels for each year in the CanSynLBD are very close to those in the LEAP, however, manufacturing sector shows more close pattern than private sector. We find a similar comparison for total payroll (Figures 3 and 4) .

Redo Graph 1 omitting the last year

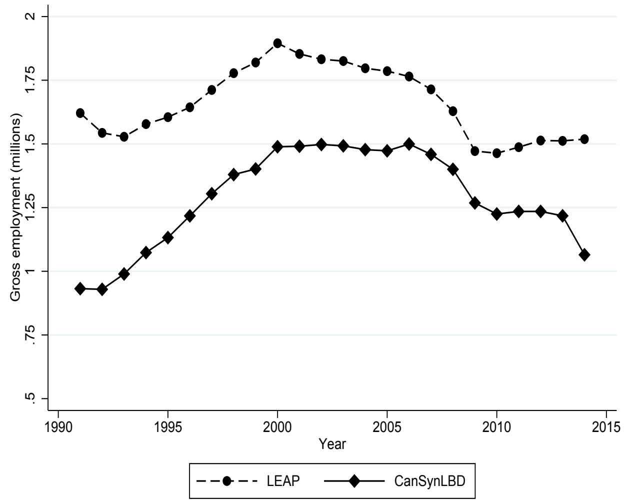
Why is manufacturing always below, but overall employment crosses? Which industries are driving that?

Figure 1: Gross employment level by year (private)



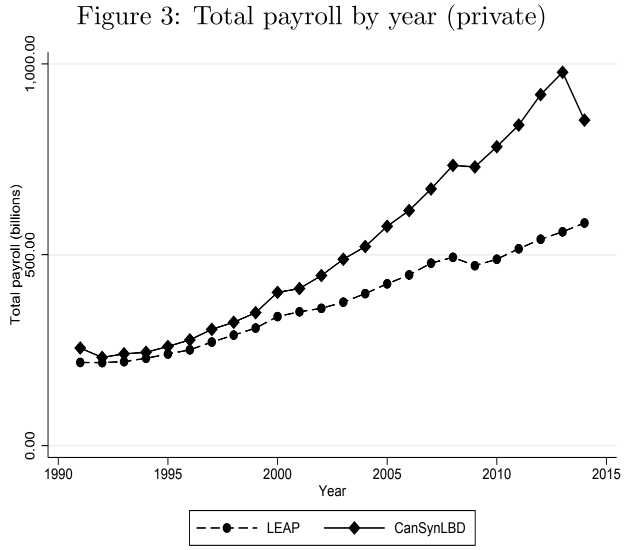
Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm.

Figure 2: Gross employment level by year (manufacturing)



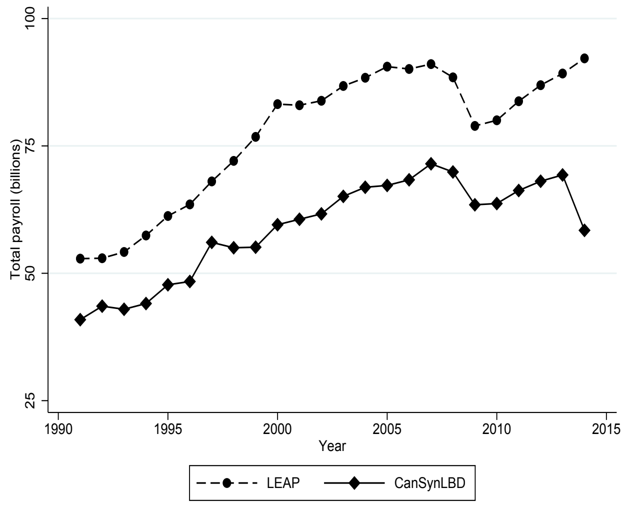
Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for manufacturing sector and drop last year observation of each firm.

Figure 3: Total payroll by year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm.

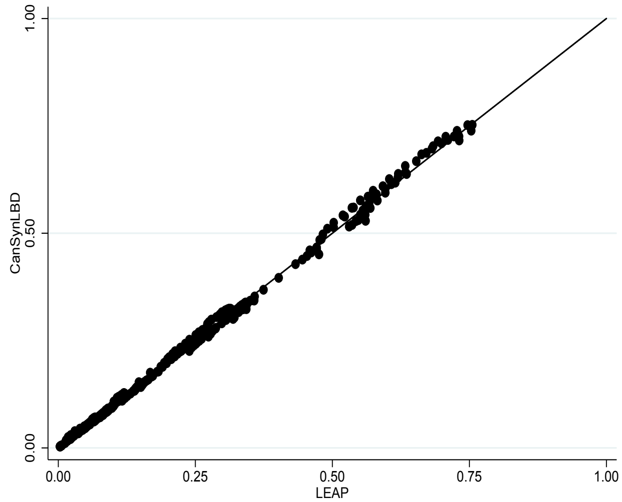
Figure 4: Total payroll by year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for manufacturing sector and drop last year observation of each firm.

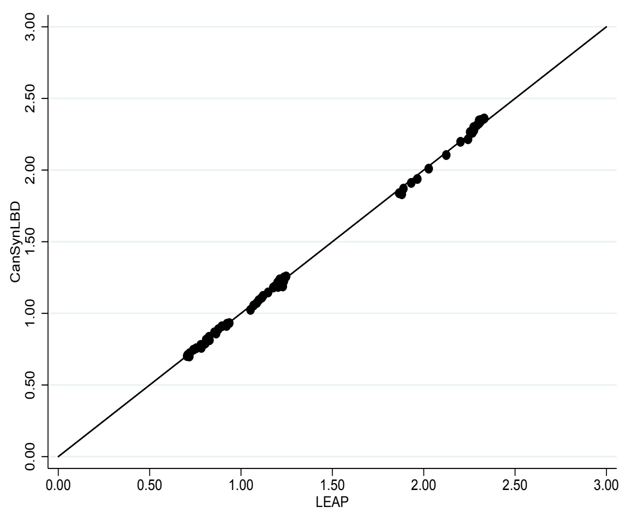
Figures 5 and 6 plot the share of firms by two-digit industry and year for both CanSynLBD and LEAP database and show that the shares cluster along the 45-degree line.

Figure 5: Share of firms by NAICS two-digit and year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm.

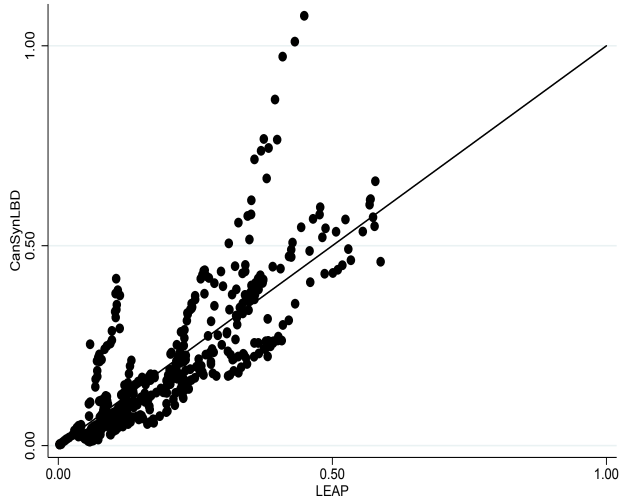
Figure 6: Share of firms by NAICS two-digit and year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for manufacturing sector and drop last year observation of each firm.

Figures 7 and 8 plot the share of employment by two-digit industry and year for both CanSynLBD and LEAP database [2] and show that those shares do not cluster along the 45-degree line. However, the share of employment for manufacturing sector more cluster along the 45-degree line than private sector.

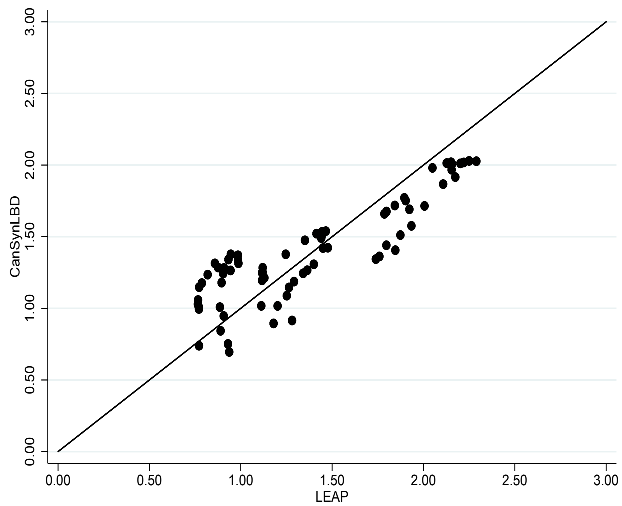
Figure 7: Share of employment by NAICS two-digit and year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm.

[2] $x_{its} = X_{its}/\sum_i \sum_t X_{its}$, where i are two-digit NAICS industries, t are the years in-sample, and s indicates whether it is in the synthetic or confidential data.

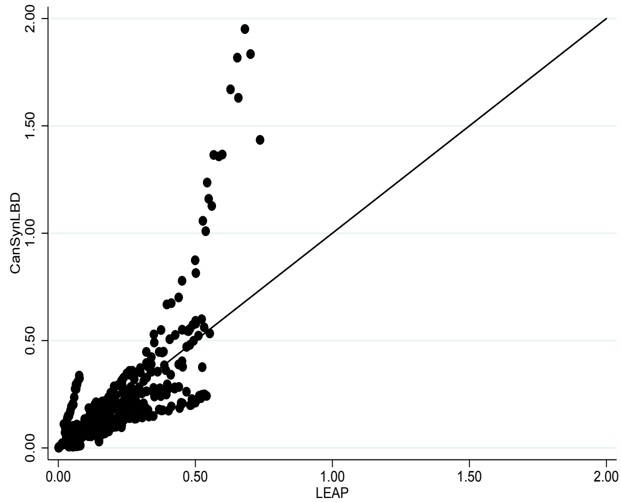
Figure 8: Share of employment by NAICS two-digit and year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for manufacturing sector and drop last year observation of each firm.

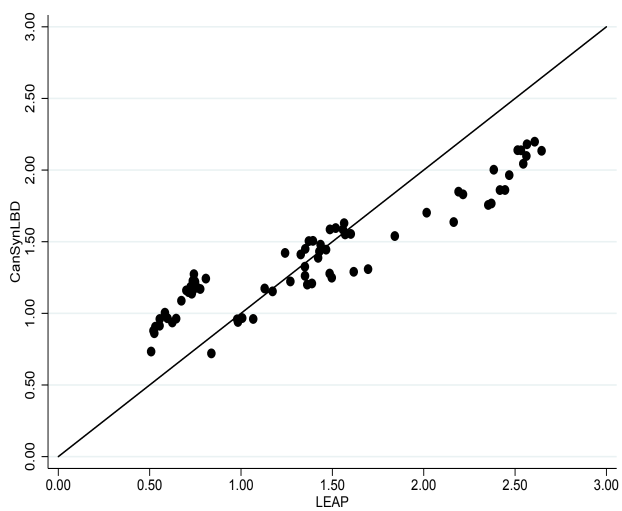
Figures 9 and 10 plot the share of payroll by two-digit industry and year for both CanSynLBD and LEAP database and show that those shares do not cluster along the 45-degree line. However, the share of payroll for manufacturing sector more cluster along the 45-degree line than private sector.

Figure 9: Share of payroll by NAICS two-digit and year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm.

Figure 10: Share of payroll by NAICS two-digit and year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for manufacturing sector and drop last year observation of each firm.

4.2 Firm Dynamics

To assess how well the CanSynLBD captures firm dynamics, we calculate entry and exit rates of the private sector by year. Table 3 shows that those rates for CanSynLBD are similar to LEAP database. In addition, we calculate the divergence of entry rate as the entry rate of CanSynLBD net the entry rate of LEAP and the divergence of exit rate as the exit rate of CanSynLBD net the exit rate of LEAP (see Table 3).

LV Reformat table, compute divergence

Table 3: Entry and exit rates by year

	LEAP		CanSynLBD		Divergence	
Year	**Entry Rate**	**Exit Rate**	**Entry Rate**	**Exit Rate**	**Entry Rate**	**Exit Rate**
1992	11.77	11.72	11.16	11.71	-0.60	-0.00
1993	11.81	11.61	10.84	12.18	-0.97	0.57
1994	12.04	11.79	11.57	12.01	-0.47	0.22
1995	11.94	12.09	11.69	12.26	-0.25	0.17
1996	12.91	10.31	12.62	10.64	-0.29	0.32
1997	13.18	9.75	13.03	10.21	-0.15	0.47
1998	12.48	10.89	12.97	10.13	0.50	-0.75
1999	12.00	10.66	12.16	9.97	0.16	-0.69
2000	11.80	10.51	11.59	9.70	-0.20	-0.82
2001	11.44	10.20	11.33	9.52	-0.12	-0.68
2002	11.39	9.91	11.10	9.03	-0.29	-0.89
2003	11.17	10.21	10.52	9.37	-0.65	-0.84
2004	12.13	9.76	10.94	9.57	-1.20	-0.20
2005	11.92	10.07	11.07	9.86	-0.84	-0.21
2006	11.81	9.96	11.15	9.34	-0.66	-0.62
2007	12.28	9.80	10.99	9.31	-1.29	-0.49
2008	11.60	10.14	10.78	9.75	-0.82	-0.40
2009	10.77	9.93	9.99	9.81	-0.78	-0.12
2010	10.80	9.75	9.91	9.65	-0.89	-0.10
2011	10.62	9.79	9.73	10.00	-0.89	0.21
2012	10.60	9.76	10.02	10.20	-0.58	0.44
2013	10.16	9.71	9.95	10.32	-0.21	0.62
2014	9.93	10.11	9.26	10.70	-0.67	0.59

Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for the manufacturing sector and drop last year observation of each firm. We calculate the divergence of entry rate as the entry rate of CanSynLBD net the entry rate of LEAP and the divergence of exit rate as the exit rate of CanSynLBD net the exit rate of LEAP.

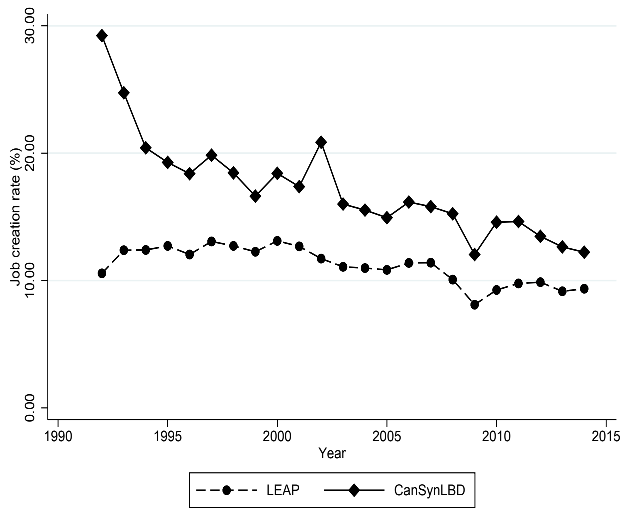
Figure 11: Divergence of exit and entry rate between LEAP and CanSynLBD

Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for private sector and drop last year observation of each firm. We calculate the divergence of entry rate as the entry rate of CanSynLBD net the entry rate of LEAP and the divergence of exit rate as the exit rate of CanSynLBD net the exit rate of LEAP.

4.3 Dynamics of Job Flows

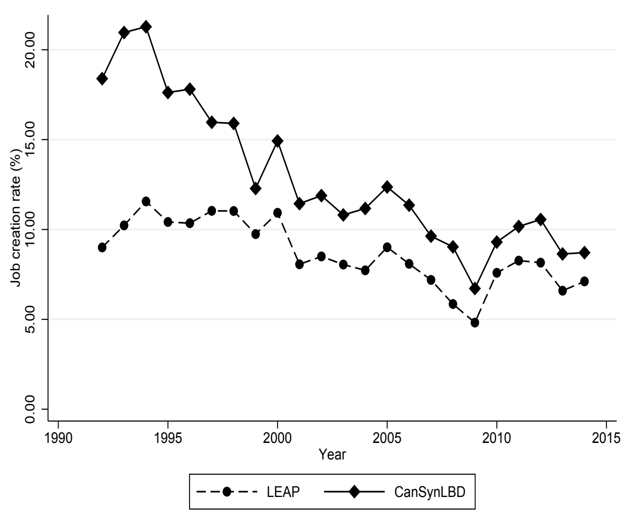
One of the most important applications of LEAP is to generate statistics that describe job flows. To measure job creation and job destruction, we follow the method developed by [5]. The job creation is the sum of all employment gains from expanding firms from year $t-1$ to year t including entry firms and the job destruction is the sum of all employment losses from contracted firms from year $t-1$ to year t including exiting firms. Net job creation is the job creation rate minus the job destruction rate. Figures 12 and 13 show the job creation rates from the CanSynLBD and compares them against the LEAP. These figures show that the manufacturing sector has more close pattern than the private sector. We find a similar pattern for net job creation rates (Figures 14 and 15).

Figure 12: Job creation rate by year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for the private sector and drop last year observation of each firm.

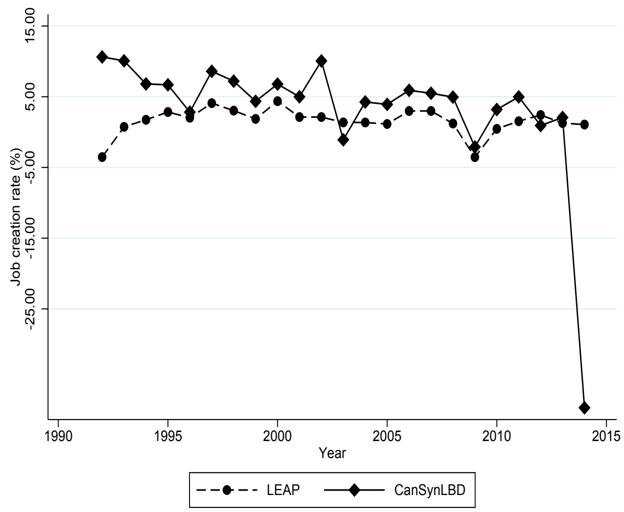
Figure 13: Job creation rate by year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for the manufacturing sector and drop last year observation of each firm.

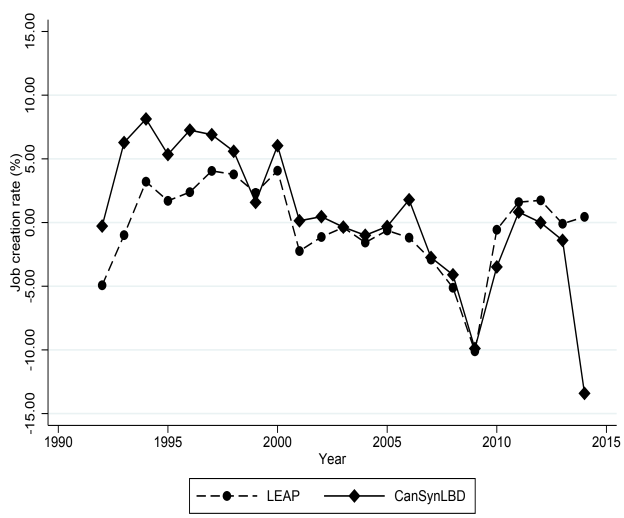
LV regraph, dropping last year (net job creation not defined)

Figure 14: Net job creation rate by year (private)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for the private sector and drop last year observation of each firm.

Figure 15: Net job creation rate by year (manufacturing)



Note: *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP for the manufacturing sector and drop last year observation of each firm.

4.4 pMSE

To compare the quality of the synthetic data relative to the confidential data, we compute $pMSE$, which is the mean-squared error of the predicted probabilities (i.e., propensity scores) for those two databases. Specifically, $pMSE$ is a metric to assess how well we are able to discern between synthetic data and confidential data. This means that these two databases have high distributional similar if we are unable to discern.

We follow the method by Snoke and Slavkovic [12] to calculate the $pMSE$. Here is the steps we follow to calculate the $pMSE$.

1. append the n_1 rows of the confidential database X to the n_2 rows of the synthetic database X^s to create X^{comb} with $N = n_1 + n_2$ rows

2. create an indicator variable, I, to X^{comb} subject to $I = \{1 : X^{comb} \in X^s\}$. This means that we create an indicator variable of 1 for the synthetic database and 0 for the confidential database.

3. fit the following model to predict I

$$I = \alpha + ALU_{it} + \lambda Pay_{it} + Age_{it}^T \beta + \lambda_t + \alpha_s + \epsilon_{it} \quad (1)$$

   where ALU_{it} is the logarithm of average labour unit (ALU) of firm i in year t, Pay_{it} is the logarithm of payroll of firm i in year t, Age_{it} is a vector of dummy variables for age of firm i in year t, λ_t is the year fixed effect, α_s is an unobserved time-invariant industry-specific effect, and ϵ_{it} is the disturbance term of firm i in year t.

4. calculate the predicted probabilities, $\hat{p}_i$ for each row of X^{comb}

5. compute the $pMSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{p}_i - 0.5)^2$

A $pMSE = 0$ means every $\hat{p}_i = 0.5$. This implies the highest utility.

To compute the $pMSE$, we estimate the regression equation 1 using both Logistic Regression and Probit Regression. Table 4 shows the calculated value of $pMSE$, which is lower for the manufacturing sector than the public sector in both regressions. This is because, as we explained before, the manufacturing sector shows more close pattern than the private sector.

Table 4: pMSE estimates

Independent Variables	Logistic Regression		Probit Regression	
	Manufacturing	Private	Manufacturing	Private
Ln ALU	0.1580***	0.7138***	0.1003***	0.4390***
	(0.0039)	(0.0010)	(0.0024)	(0.0006)
Ln Pay	0.0039	-0.4426***	0.0012	-0.2691***
	(0.0037)	(0.0010)	(0.0023)	(0.0006)
Age 3-4	0.0392***	0.0972***	0.0252***	0.0618***
	(0.0078)	(0.0017)	(0.0049)	(0.0010)
Age 5-7	-0.0382***	0.0477***	-0.0233***	0.0309***
	(0.0073)	(0.0016)	(0.0045)	(0.0010)
Age 8-12	-0.1258***	-0.0263***	-0.0781***	-0.0152***
	(0.0071)	(0.0015)	(0.0044)	(0.0009)
Age 13 or more	-0.2190***	-0.1024***	-0.1365***	-0.0627***
	(0.0074)	(0.0016)	(0.0046)	(0.0010)
N	2243011	34638723	2243011	34638723
pseudo R^2	0.0112	0.0318	0.0112	0.0320
pMSE	0.0041	0.0121	0.0041	0.0124

Note: An observation is a firm and a year of both synthetic and original databases. In all specifications, we include both time and industry fixed effects. Standard errors are in parentheses. In this table, we use 2015 vintage of LEAP to create the synthetic database and drop last year observation of each firm. ***, **, and * indicate statistically significant coefficients at 1%, 5%, and 10% percent levels, respectively.

4.5 Regression Analysis

To assess how well the CanSynLBD captures variability in economic growth due to industry and firm age, we estimate the following dynamic panel data model:

$$ALU_{it} = \alpha + \theta ALU_{i,t-1} + \lambda Pay_{it} + Age_{it}^{T}\beta + \lambda_t + \alpha_s + \epsilon_{it} \quad (2)$$

where ALU_{it} is the logarithm of average labour unit (ALU) of firm i in year t, $ALU_{i,t-1}$ is the logarithm of last year's average labour unit (ALU) of firm i, Pay_{it} is the logarithm of payroll of firm i in year t, Age_{it} is a vector of dummy variables for age of firm i in year t, λ_t is the year fixed effect, α_s is an unobserved time-invariant industry-specific effect, and ϵ_{it} is the disturbance term of firm i in year t.

Table 5: Regression coefficients (OLS)

Independent Variables	**LEAP**		**CanSynLBD**	
	Private	Manufacturing	Private	Manufacturing
AR(1) Coefficient	0.2031***	0.2481***	0.3970***	0.4405***
	(0.0001)	(0.0005)	(0.0002)	(0.0007)
Ln Pay	0.7847***	0.7300***	0.5481***	0.5228***
	(0.0001)	(0.0005)	(0.0002)	(0.0006)
Age 3-4	-0.1202***	-0.1717***	-0.1223***	-0.2340***
	(0.0003)	(0.0014)	(0.0004)	(0.0016)
Age 5-7	-0.1260***	-0.1891***	-0.1235***	-0.2507***
	(0.0003)	(0.0014)	(0.0004)	(0.0016)
Age 8-12	-0.1268***	-0.1973***	-0.1169***	-0.2551***
	(0.0003)	(0.0013)	(0.0004)	(0.0016)
Age 13 or more	-0.1246***	-0.1992***	-0.1101***	-0.2577***
	(0.0003)	(0.0014)	(0.0004)	(0.0017)
N	15708195	1015293	13573225	959764
R^2	0.9696	0.9743	0.9444	0.9523

Note: An observation is a firm and a year. In all specifications, we include both time and industry fixed effects. Standard errors are in parentheses. *LEAP* is the Longitudinal Employment Analysis Program and *CanSynLBD* is the Canadian synthetic database based on LEAP. In this table, we use 2015 vintage of LEAP and drop last year observation of each firm. ***, **, and * indicate statistically significant coefficients at 1%, 5%, and 10% percent levels, respectively.

We estimate the model separately on LEAP and CanSynLBD database for the private and manufacturing sector and find that the CansynLBD database provides similar predictions to LEAP database (Tables 5).

compute overlap interval

Table 6: Regression coefficients (Dynamic)

Independent Variables	**LEAP**		**CanSynLBD**	
	Private	Manufacturing	Private	Manufacturing
AR(1) Coefficient	0.0805***	0.1189***	0.5722***	0.5425***
	(0.0003)	(0.0018)	(0.0024)	(0.0084)
Ln Pay	0.8991***	0.8523***	0.4101***	0.4302***
	(0.0002)	(0.0015)	(0.0018)	(0.0067)
Age 3-4	-0.0450***	-0.0797***	-0.2075***	-0.2972***
	(0.0002)	(0.0014)	(0.0010)	(0.0051)
Age 5-7	-0.0438***	-0.0860***	-0.2129***	-0.3162***
	(0.0002)	(0.0015)	(0.0011)	(0.0059)
Age 8-12	-0.0418***	-0.0923***	-0.2187***	-0.3294***
	(0.0003)	(0.0017)	(0.0013)	(0.0070)
Age 13 or more	-0.0379***	-0.0898***	-0.2318***	-0.3414***
	(0.0003)	(0.0019)	(0.0015)	(0.0080)
N	15708195	1015293	13573225	959764
m2	-14.5000	-2.2200	-27.5400	-9.4400
Sargan test	6.9e+04	4.6e+03	1.5e+04	1.5e+03
df of Sargan Test	252.0000	252.0000	252.0000	252.0000
P value of Sargan test	0.0000	0.0000	0.0000	0.0000

Note: An observation is a firm and a year. In this table, $m2$ is the Arellano-Bond test for zero autocorrelation in first-differenced errors for order two. $LEAP$ is the Longitudinal Employment Analysis Program and $CanSynLBD$ is the Canadian synthetic database based on LEAP. In this graph, we use 2015 vintage of LEAP and drop last year observation of each firm. Standard errors are in parentheses. ***, **, and * indicate statistically significant coefficients at 1%, 5%, and 10% percent levels, respectively.

As ALU_{st-1} is correlated with α_s because ALU_{st-1} is a function of α_s, OLS estimators are biased and inconsistent. Due to this endogeneity, we estimate this model using the method in Arellano and Bond [1] and find similar prediction (Table 6). To check the validity of the model, I use two tests. First, to test for autocorrelation, I use the test $m2$ by Arellano and Bond [1]. In the table, I report z test statistic for $m2$ test for zero autocorrelation in first-differenced errors for order two. Second, I use the Sargan test to verify the validity of instrument subsets (shows in the last three rows in the table).

We furthermore estimate the model using the system GMM method proposed by Arellano and Bover [2] and Blundell and Bond [4] and find similar predictions as before (Table 7).

Table 7: Regression coefficients (Dynamic - system GMM)

Independent Variables	**LEAP**		**CanSynLBD**	
	Private	Manufacturing	Private	Manufacturing
AR(1) Coefficient	0.0978***	0.1614***	0.5111***	0.5780***
	(0.0002)	(0.0014)	(0.0008)	(0.0041)
Ln Pay	0.8854***	0.8161***	0.4562***	0.4022***
	(0.0002)	(0.0012)	(0.0006)	(0.0033)
Age 3-4	-0.0555***	-0.1097***	-0.1828***	-0.3177***
	(0.0002)	(0.0012)	(0.0004)	(0.0028)
Age 5-7	-0.0558***	-0.1201***	-0.1860***	-0.3408***
	(0.0002)	(0.0013)	(0.0005)	(0.0031)
Age 8-12	-0.0548***	-0.1298***	-0.1875***	-0.3583***
	(0.0002)	(0.0014)	(0.0005)	(0.0036)
Age 13 or more	-0.0524***	-0.1317***	-0.1943***	-0.3747***
	(0.0002)	(0.0016)	(0.0006)	(0.0041)
N	15708195	1015293	13573225	959764
m2	-11.4300	1.3900	-41.6000	-7.6700
Sargan test	7.7e+04	6.3e+03	1.8e+04	1.7e+03
df of Sargan Test	274.0000	274.0000	274.0000	274.0000
P value of Sargan test	0.0000	0.0000	0.0000	0.0000

Note: An observation is a firm and a year. In this table, $m2$ is the Arellano-Bond test for zero autocorrelation in first-differenced errors for order two. $LEAP$ is the Longitudinal Employment Analysis Program and $CanSynLBD$ is the Canadian synthetic database based on LEAP. In this table, we use 2015 vintage of LEAP and drop last year observation of each firm. Standard errors are in parentheses. ***, **, and * indicate statistically significant coefficients at 1%, 5%, and 10% percent levels, respectively.

We also estimate above dynamic panel data model with a first-order moving average using appropriate instruments for both level and difference equation as proposed by Arellano and Bover [2] and Blundell and Bond [4]:

$$ALU_{it} = \alpha + \theta ALU_{i,t-1} + \lambda Pay_{it} + Age_{it}^T\beta + \lambda_t + \alpha_s + \epsilon_{it} + \gamma\epsilon_{it-1} \quad (3)$$

Table 8 shows that the CansynLBD provides similar predictions to LEAP database.

Table 8: Regression coefficients (Dynamic - system GMM with MA(1))

Independent Variables	**LEAP**		**CanSynLBD**	
	Private	Manufacturing	Private	Manufacturing
AR(1) Coefficient	0.2005***	0.2821***	0.4850***	0.5737***
	(0.0007)	(0.0040)	(0.0012)	(0.0059)
Ln Pay	0.8044***	0.7135***	0.4760***	0.4056***
	(0.0005)	(0.0034)	(0.0009)	(0.0046)
Age 3-4	-0.1245***	-0.2033***	-0.1716***	-0.3158***
	(0.0005)	(0.0032)	(0.0006)	(0.0037)
Age 5-7	-0.1328***	-0.2264***	-0.1733***	-0.3389***
	(0.0005)	(0.0035)	(0.0006)	(0.0043)
Age 8-12	-0.1383***	-0.2454***	-0.1731***	-0.3560***
	(0.0006)	(0.0039)	(0.0007)	(0.0051)
Age 13 or more	-0.1441***	-0.2586***	-0.1774***	-0.3717***
	(0.0006)	(0.0042)	(0.0008)	(0.0058)
N	15708195	1015293	13573225	959764
m2	8.2000	7.0600	-40.0300	-6.6400
Sargan test	2.8e+04	2.3e+03	1.7e+04	1.3e+03
df of Sargan Test	251.0000	251.0000	251.0000	251.0000
P value of Sargan test	0.0000	0.0000	0.0000	0.0000

Note: An observation is a firm and a year. In this table, $m2$ is the Arellano-Bond test for zero autocorrelation in first-differenced errors for order two. $LEAP$ is the Longitudinal Employment Analysis Program and $CanSynLBD$ is the Canadian synthetic database based on LEAP. In this table, we use 2015 vintage of LEAP and drop last year observation of each firm. Standard errors are in parentheses. ***, **, and * indicate statistically significant coefficients at 1%, 5%, and 10% percent levels, respectively.

4.6 Confidentiality protection

In this section, we estimate the probability that the synthetic first year equals the true first year, given the synthetic first year. Tables 9 and 10 show that these probabilities are quite low except for the first year. This is because of censoring and lack of previous information.

Table 9: Observed firm births given synthetic births (private)

First (Birth) Year		**% of Births over NAICS**		
Synthetic	**Actual**	**Minimum**	**Mean**	**Maximum**
1991	1991	0.00	27.69	83.02
1992	1992	0.00	3.37	11.11
1993	1993	0.00	3.79	33.33
1994	1994	0.00	3.73	33.33
1995	1995	0.00	3.86	20.00
1996	1996	0.00	4.25	33.33
1997	1997	0.00	4.10	16.94
1998	1998	0.00	4.41	25.00
1999	1999	0.00	4.23	33.33
2000	2000	0.00	3.41	25.00
2001	2001	0.00	2.73	22.22
2002	2002	0.00	2.65	25.00
2003	2003	0.00	2.22	10.00
2004	2004	0.00	2.60	17.86
2005	2005	0.00	2.71	20.00
2006	2006	0.00	2.83	50.00
2007	2007	0.00	2.90	33.33
2008	2008	0.00	2.38	20.00
2009	2009	0.00	2.47	50.00
2010	2010	0.00	2.12	33.33
2011	2011	0.00	2.65	50.00
2012	2012	0.00	2.41	20.00
2013	2013	0.00	2.48	25.00
2014	2014	0.00	2.23	20.00
2015	2015	0.00	2.15	33.33

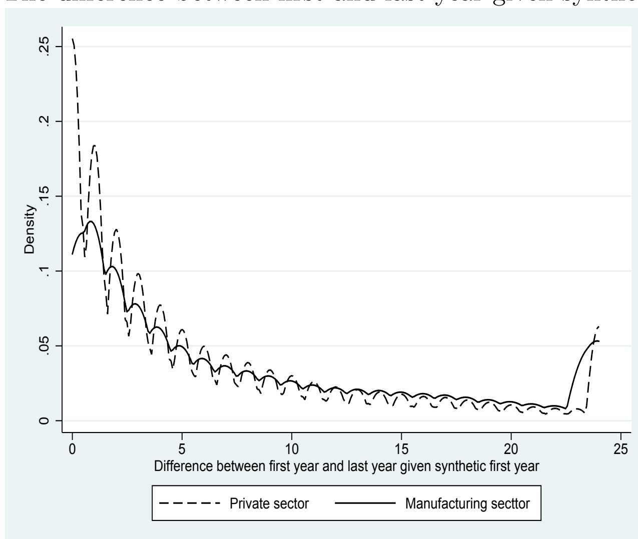
Note:

Table 10: Observed firm births given synthetic births (manufacturing)

First (Birth) Year		% of Births over NAICS		
Synthetic	**Actual**	**Minimum**	**Mean**	**Maximum**
1991	1991	4.76	31.64	52.03
1992	1992	0.00	3.32	10.53
1993	1993	0.00	3.97	33.33
1994	1994	0.00	4.21	33.33
1995	1995	0.00	4.41	20.00
1996	1996	0.00	5.36	33.33
1997	1997	0.00	4.09	16.94
1998	1998	0.00	5.46	25.00
1999	1999	0.00	5.27	33.33
2000	2000	0.00	3.39	25.00
2001	2001	0.00	2.19	10.00
2002	2002	0.00	2.45	25.00
2003	2003	0.00	1.71	10.00
2004	2004	0.00	2.07	17.86
2005	2005	0.00	1.92	16.67
2006	2006	0.00	2.49	50.00
2007	2007	0.00	1.74	14.29
2008	2008	0.00	1.60	20.00
2009	2009	0.00	1.60	20.00
2010	2010	0.00	1.34	33.33
2011	2011	0.00	2.43	50.00
2012	2012	0.00	1.93	20.00
2013	2013	0.00	1.61	20.00
2014	2014	0.00	1.71	14.29
2015	2015	0.00	1.41	14.29

Note:

Figure 16: The difference between first and last year given synthetic first year



Note:

5 Conclusion and Extensions

Statistics Canada disseminates business data in highly aggregated forms. To get access to Canadian micro business databases, in this paper, we implement the algorithm of the U.S. synthetic data for LBD to create Canadian synthetic data for LEAP. This Canadian synthetic database supports analytical validity for a wide range of statistical analyses as well as provide evidence on confidentiality properties.

5.1 Addition of variables that are not analytically valid

5.2 Addition of analytically valid variables

Capital stock or revenue for incorporated

Supplementary Graphs

A Analytical validity

A.1 Confidence interval for gross employment and other measures

We compute the standard error for gross employment as follows. We consider gross employment E to be the sum of firm employments E_j:

$$E = \sum_j E_j \tag{4}$$

Average firm employment $\bar{E} = \frac{E}{N_j}$ is assumed to be normally distributed, with standard deviation $\sigma_{\bar{E}}$. We compare the synthetic and the confidential data for gross employment, including error bands.

A.2 Confidence interval overlap measures

More generally, the question as to the statistical precision of the results obtained from the synthetic data can be assessed. For this purpose, we computed the overlap of parameter estimates as suggested by [8]. We compute the *interval overlap measure* $J_{k,m}$ for parameter k in model m. Consider the overlap of confidence intervals (L, U) for $\beta_{k,m}$ (estimated from the confidential data) and (L^*, U^*) for $\beta^*_{k,m}$ (from the synthetic data). Let $L^{over} = \max(L, L^*)$ and $U^{over} = \min(U, U^*)$. Then the average overlap in confidence intervals is

$$J^*_{k,m} = \frac{1}{2}\left[\frac{U^{over} - L^{over}}{U - L} + \frac{U^{over} - L^{over}}{U^* - L^*}\right]$$

We then average $J^*_{k,m}$ over all estimated models and parameters, by validation request. The correct counterfactual is running these validation requests against synthetic data that does not claim analytical validity, such as synthetic data generated from unidimensional distributions of variables. Results are pending.

A.3 Other models

Possible papers:

-
- Bartelsman, Haltiwanger, and Scarpetta [3] use a cross-country dataset to study average post-entry behavior of young firms.

References

[1] Manuel Arellano and Stephen Bond. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations". In: *Review of Economic Studies* 58.2 (1991), pp. 277–297. URL: `https://EconPapers.repec.org/RePEc:oup:restud:v:58:y:1991:i:2:p:277-297.`.

[2] Manuel Arellano and Olympia Bover. "Another look at the instrumental variable estimation of error-components models". In: *Journal of Econometrics* 68.1 (1995), pp. 29–51. URL: `https://EconPapers.repec.org/RePEc:eee:econom:v:68:y:1995:i:1:p:29-51`.

[3] Eric Bartelsman, John Haltiwanger, and Stefano Scarpetta. "Measuring and Analyzing Cross-country Differences in Firm Dynamics". In: Timothy Dunne, J. Bradford Jensen, and Mark J. Roberts. *Producer Dynamics: New Evidence from Micro Data*. University of Chicago Press, Jan. 2009, pp. 15–76. URL: `http://www.nber.org/chapters/c0480`.

[4] Richard Blundell and Stephen Bond. "Initial conditions and moment restrictions in dynamic panel data models". In: *Journal of Econometrics* 87.1 (Aug. 1998), pp. 115–143. URL: `https://ideas.repec.org/a/eee/econom/v87y1998i1p115-143.html`.

[5] Steven J. Davis, John C. Haltiwanger, and Scott Schuh. *Job creation and destruction*. Cambridge, MA: MIT Press, 1996.

[6] Jorg Drechsler and Lars Vilhuber. *A First Step Towards A German Synlbd: Constructing A German Longitudinal Business Database*. Working Papers 14-13. Center for Economic Studies, U.S. Census Bureau, Feb. 2014. URL: https://ideas.repec.org/p/cen/wpaper/14-13.html.

[7] Ron S Jarmin and Javier Miranda. *The Longitudinal Business Database*. Working Papers 02-17. Center for Economic Studies, U.S. Census Bureau, July 2002. URL: https://ideas.repec.org/p/cen/wpaper/02-17.html.

[8] A. F. Karr et al. "A Framework for Evaluating the Utility of Data Altered to Protect Confidentiality". In: *The American Statistician* 60.3 (2006), pp. 1–9. DOI: 10.1198/000313006X124640.

[9] Satkartar K. Kinney, Jerome P. Reiter, and Javier Miranda. *Improving The Synthetic Longitudinal Business Database*. Working Papers 14-12. Center for Economic Studies, U.S. Census Bureau, Feb. 2014. URL: https://ideas.repec.org/p/cen/wpaper/14-12.html.

[10] Satkartar K. Kinney et al. "Towards Unrestricted Public Use Business Microdata: The Synthetic Longitudinal Business Database". In: *International Statistical Review* 79.3 (Dec. 2011), pp. 362–384. DOI: j.1751-5823.2011.00152.x. URL: https://ideas.repec.org/a/bla/istatr/v79y2011i3p362-384.html.

[11] Petr Sedláček and Vincent Sterk. "The Growth Potential of Startups over the Business Cycle". In: *American Economic Review* 107.10 (Oct. 2017), pp. 3182–3210. DOI: 10.1257/aer.20141280. URL: http://www.aeaweb.org/articles?id=10.1257/aer.20141280.

[12] Joshua Snoke and Aleksandra Slavkovic. "pMSE Mechanism: Differentially Private Synthetic Data with Maximal Distributional Similarity: UNESCO Chair in Data Privacy, International Conference, PSD 2018, Valencia, Spain, September 26-28, 2018, Proceedings". In: Jan. 2018, pp. 138–159. ISBN: 978-3-319-99770-4. DOI: 10.1007/978-3-319-99771-1_10.

[13] Simon D. Woodcock and Gary Benedetto. "Distribution-preserving statistical disclosure limitation". In: *Computational Statistics & Data Analysis* 53.12 (2009), pp. 4228–4242. ISSN: 0167-9473. DOI: https://doi.org/10.1016/j.csda.2009.05.020. URL: http://www.sciencedirect.com/science/article/pii/S0167947309002011.