Statistics Japan

Expanding the use of Big Data for CPI in Japan

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Outline

- Introduction
- Case of using Scanner data
- Case of using Web Scraping data
- Future Tasks

Introduction: History of using Big data in Japan

2000-base: Scanner data for “desktop computers” and “laptop computers”

2005-base: Added scanner data for “cameras”

2010-base: Included scanner data of “tablet computers” to “laptop computers”

2015-base: Separated “tablets computers” from “laptop computers”

2020-base: Web scraping data for “hotel charges”
“airplane fares”
“charges for package tours to overseas”

Scanner data for “video recorders”, “PC printers” and “TV sets”

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Contents example of scanner data: TV sets

Sales data
GTIN code (JAN code)
Vender
Model number
Product name
Sales quantity
Sales amount
Average unit price
etc.

Specifications	Examples
Release month	Year, Month
Tuner shape	Separate type, Integrated type, None
Screen size	3-inch type to 75-inch type
Number of pixels displayed	1366x768, 1920x1080, 3840x2160, etc.
D connector	D4x1, D5x1, None
PC input	D-Sub, None
Communication terminal	LAN, None
Card slot	SDXC, None
HDD capacity	0 GB to 2,000 GB
Internet	Capable, Incapable
Wireless function	IEEE802.11a/n, None
Audio output	10W+10W, 3W+3W, 5W+5W, etc.
HDMI connector	0 to 4
Link function	Available, Unavailable
Drive speed	Constant speed, Double speed
Recording media	HDD (external), HDD (internal/external)
High-definition capable	4K/2K, 8K, High-definition, Full high-definition, Incapable
Hybrid cast	Capable, Incapable

Using scanner data for CPI in Japan

Two methods for using scanner data to calculate price indices in Japan

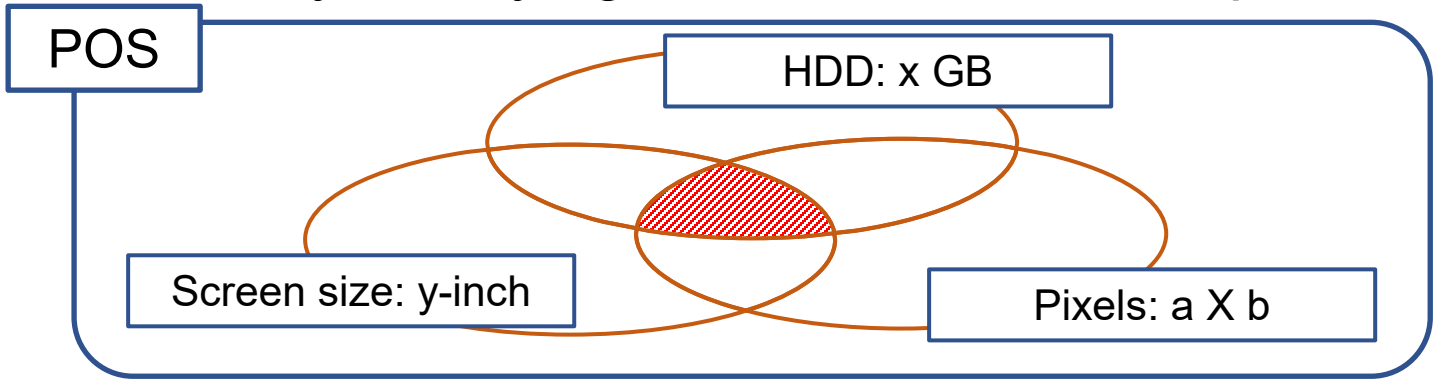
- Fixed specification method
- (Bilateral) Time dummy hedonic method

We get monthly scanner data in each month
→ Some new products appear and some old products disappear in two different month data (product replacement)

- For long lifecycle products (e.g. PC printers, Video recorders, etc.)
  Product replacement occurs **not frequently**
  → We use **Fixed specification method**
- For short lifecycle products (e.g. Laptop computers, TV sets, etc.)
  Product replacement occurs **frequently**
  → We use **Time dummy hedonic method**

Methods for using scanner data (1)

- Fixed-specification method
  1. Extract records only satisfying a fixed condition of specifications



  2. Calculate geometric mean of unit prices weighted by sales quantity

$$P_T = \left(\prod_i^N \left(p_{T,i}\right)^{q_{T,i}}\right)^{1/\sum_i q_{T,i}} = \exp\left[\frac{1}{\sum_i q_{T,i}} \sum_i^N \left(q_{T,i} \times \ln\left(p_{T,i}\right)\right)\right]$$

T: time, i: product, $p_{T,i}$: unit price, $q_{T,i}$: sales quantity

  3. Calculate mean prices for each two consecutive months and multiply the ratio of these prices by previous month index

$$I_t = I_{t-1} \times \frac{P_t}{P_{t-1}}$$

Methods for using scanner data (2)

- Bilateral Time dummy hedonic method
  1. Make a dataset of two consecutive month $(t, t-1)$ scanner data
  2. Estimate linear regression model for logarithmic prices by some specifications of products and time dummy

     $$\ln(P_{t,i}) = \beta_0 + \beta_1 D_{T,t} + \sum_a \beta_a x_{a,i} + \varepsilon_{T,i}$$

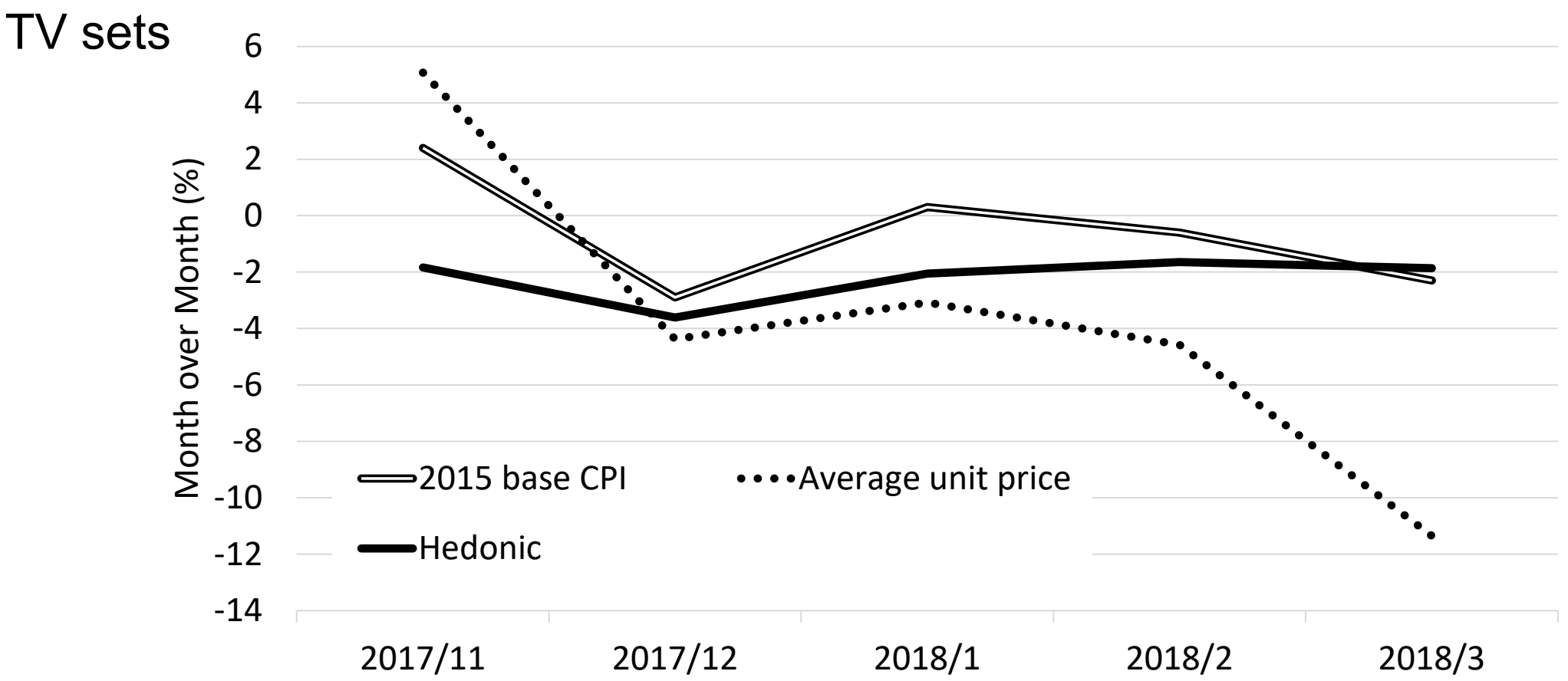
     t: time, $D_{T,t}$: dummy variable which is 1 for $T = t$ and 0 for $T = t-1$,
     i: product, $x_{a,i}$: specifications of products, $\beta_0, \beta_1, \beta_a$: regression coefficients,
     $\varepsilon_{T,i}$: error

  3. Multiplying exponential the coefficients of time dummy by the previous month index

     $$I_t = I_{t-1} \times \exp(\hat{\beta}_1)$$

Specifications of products as independent valuables in linear regression model can control the quality of products in scanner data (quality adjustment).

Comparison of the CPI and results from scanner data

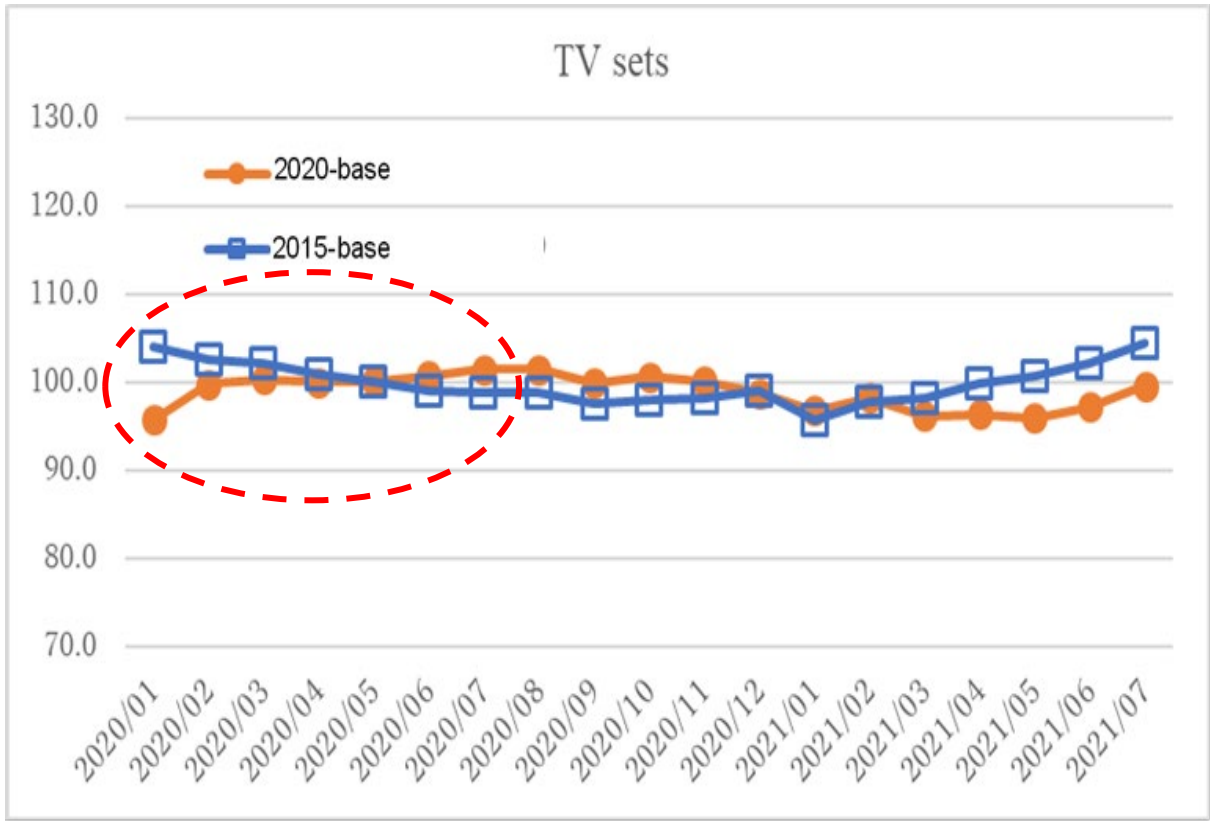


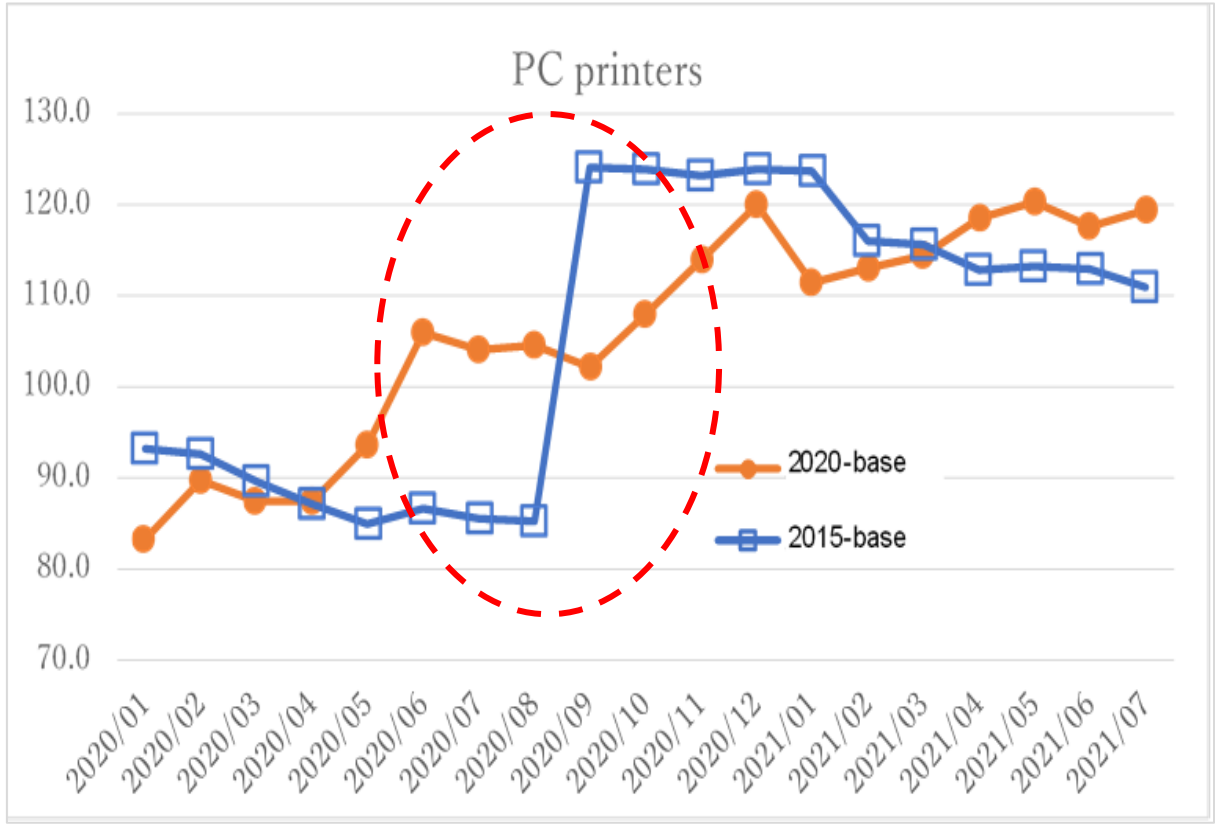
Hedonic regression model using scanner data enable stable quality adjustment and contribute to improving the accuracy of statistics.

Comparison of data sizes in 2015 and 2020 base CPI

	2015 Base (field collection)			2020 Base (Scanner data)		
Collection time and price	Price on any one of Wednesday, Thursday or Friday of the week including the 12th of each month			Prices from 1st to 31st of each month		
Item	Video recorders	PC printers	TV sets	Video recorders	PC printers	TV sets
Number of collected product models	6	1	8	23	46	600
Number of stores for collection	186	172	186	About 2,600	About 2,600	About 2,600
Number of collected prices	186	172	186	About 30,000	About 80,000	About 240,000

Comparison of price indices in 2015 and 2020 base CPI





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Study for using Web Scraping data: hotel charges

- A questionnaire survey to examine
  - ✓ trends in purchasing methods,
  - ✓ time to make reservations,
  - ✓ accommodation plans,
  - ✓ selection of collection websites, etc.

Also

- Conducted price collection and index production by web scraping on a trial basis
- Compared with the index by conventional price surveys

- Capturing the price trend of internet sales grasped the price trend of hotel charges
- Web scraping can stably collect prices from each travel booking website
- A huge number of internet sales prices were accurately reflected in the indices

Web scraping contributes to the improvement of indices

Result of Questionnaire: Price collection sites

RESERVATION METHOD (N = 2,448)	RESERVATION TIME: Within a week	One to three weeks before	One month or more before	Unknown	Total
Called hotels directly	3%	4%	5%	1%	13%
Website of hotels	2%	7%	12%	1%	21%
Travel booking site	7%	21%	29%	2%	59%
Over the counter	0%	1%	2%	0%	3%
Others	0%	0%	1%	0%	1%
Unknown	0%	0%	1%	2%	3%
Total	12%	33%	50%	6%	100%

Result of Questionnaire: Accommodation plan

N = 2,448	Western-style rooms	Japanese-style rooms	Japanese-Western style rooms	Others	Total
No meals	24%	4%	1%	1%	29%
With breakfast	24%	3%	1%	0%	29%
With breakfast and dinner	11%	22%	7%	0%	40%
Breakfast, lunch and dinner included	1%	1%	0%	0%	2%
Others	0%	0%	0%	0%	0%
Total	60%	30%	9%	1%	100%

Web Scraping (hotel charges) : Price collection time

- Prices are collected, in principle, at the beginning of the month, two months before the accommodation date

As for one month before the accommodation date,

Some sites showed that the average price of some accommodations was abnormally high compared to that of the two-month prior collection

← due to the inability to collect low-priced plans because of full occupancy

Long-term web scraping conducted between August 2017 and March 2018

(for 30 accommodation facilities)

- Prices for about 10% of accommodations four months ahead and about half of accommodations six months ahead were not listed on the booking website
- Seasonal limit on the advanced reservation, a gap at the time of change of the fiscal year

Web Scraping (hotel charges) : Price collection time

	Reservation month										
Collection month	1 month ahead	2 month ahead	3 month ahead	4 month ahead	5 month ahead	6 month ahead	7 month ahead	8 month ahead	9 month ahead	10 month ahead	11 month ahead
2017 Aug	30	29	29	28	25	18	14	2	2	2	1
Sep	30	30	29	26	23	16	4	2	2	1	1
Oct	30	30	30	27	22	7	3	2	1	1	1
Nov	30	30	29	26	17	10	5	4	2	2	1
Dec	30	29	28	24	22	14	7	5	5	3	3
2018 Jan	29	29	27	26	26	14	9	6	5	5	5
Feb	29	28	28	27	26	18	12	5	5	5	3
Mar	29	29	28	27	26	17	10	6	6	3	2
Average	30	29	29	26	23	14	8	4	4	3	2
Collection percentage	100%	99%	96%	89%	79%	48%	27%	14%	12%	9%	7%

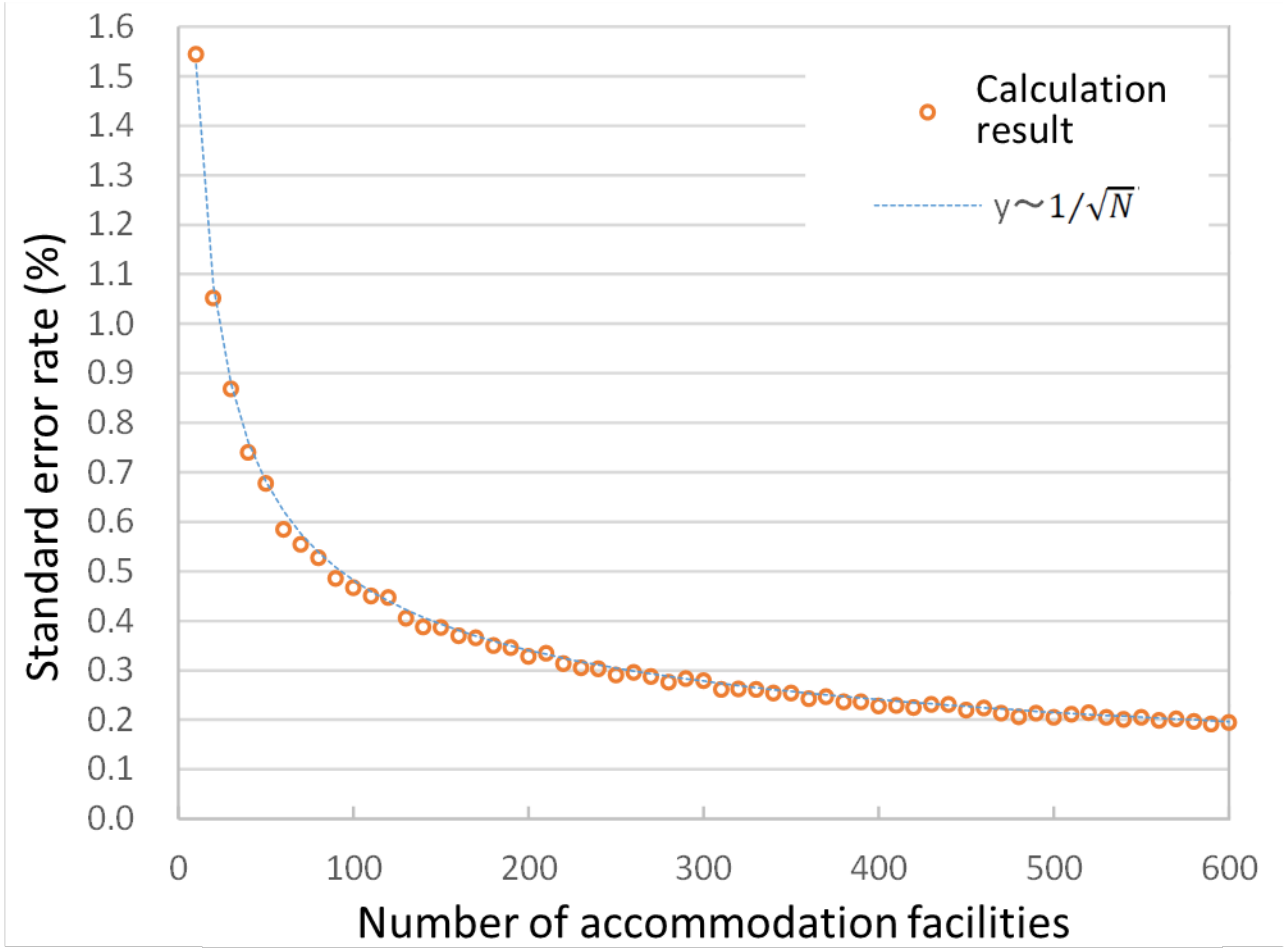
Yellow cells correspond to reservations of April 2018

Web Scraping (hotel charges) : Accommodation Facility

- About 400 representative accommodations facilities are selected

- While price collection by web scraping does not require consideration of the upper limit of the number of target facilities caused by resource constraints, unrestricted access to websites to obtain prices is not possible in light of the load on the website.
  ➔ It is necessary to set an appropriate number of target facilities.

- In the pilot study, the standard error rate of the average price for the increase in the number of facilities almost stopped decreasing and leveled off when the number of facilities exceeded 400



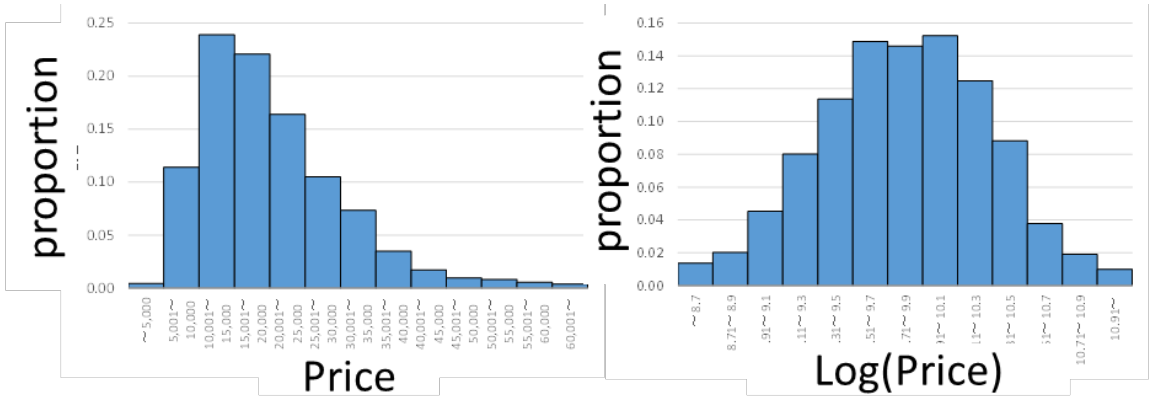
Web Scraping (hotel charges) : Calculation of indices

- Using a two-month data set for the current month (t) and the previous month ($t-1$) the price indices are calculated according to the following procedures (1) to (4)

(1) Exclusions of outliers

$P_{s,a,b,c}$ s: booking website,
a : accommodation date,
b : accommodation facility,
c : plan

$Y_{s,a,b,c} = \log(P_{s,a,b,c})$



$$Y_{s,a,b} = \frac{1}{N_{s,a,b}} \sum_{c=1}^{N_{s,a,b}} Y_{s,a,b,c}$$

$$\sigma_{s,a,b} = \sqrt{\frac{1}{N_{s,a,b}-1} \sum_{c=1}^{N_{s,a,b}} \left(Y_{s,a,b,c} - Y_{s,a,b}\right)^2}$$

➡ $Y_{s,a,b,c}$ is considered as an outlier if $\left|Y_{s,a,b,c} - Y_{s,a,b}\right| > 3\sigma_{s,a,b}$

Web Scraping (hotel charges) : Calculation of indices

(2) Creation of a data table

- Average prices for each booking website(s), accommodation date(a), and accommodation facility(b) are calculated,
- Data table with these as attributions is created

$$Y'_{s,a,b} = \frac{1}{N'_{s,a,b}} \sum_{c=1}^{N'_{s,a,b}} Y_{s,a,b,c}$$

(3) Missing value imputation : Next Slide

(4) Calculation of index

- Data set after imputation is used to calculate average prices for the current month (t) and the previous month ($t-1$), respectively.
- Ratio of these prices are multiplied by the price index for the previous month to calculate the price index for the current month.

$$P_t = \left(\prod_{s,a,b} P_{t,s,a,b}\right)^{\frac{1}{N_t}} = \exp\left[\frac{1}{N_t}\sum_{s,a,b}\log\left(P_{t,s,a,b}\right)\right] = \exp\left[\frac{1}{N_t}\sum_{s,a,b} Y'_{t,s,a,b}\right]$$

$$I_t = I_{t-1} \times \frac{P_t}{P_{t-1}}$$

Web Scraping (hotel charges) : Missing value imputation

Accommodation date (X_a)	Booking site (X_s)	Facility (X_b)	Log Average Price (y)
2018/12/1	A	X	9.51
2018/12/1	A	Y	9.61
2018/12/1	A	Z	9.75
2018/12/1	B	X	
2018/12/1	B	Y	
2018/12/1	B	Z	
2018/12/1	C	X	9.58
2018/12/1	C	Y	9.69
2018/12/1	C	Z	9.85
2018/12/2	A	X	9.65
2018/12/2	A	Y	9.66
2018/12/2	A	Z	
2018/12/2	B	X	9.49
……	…	…	……

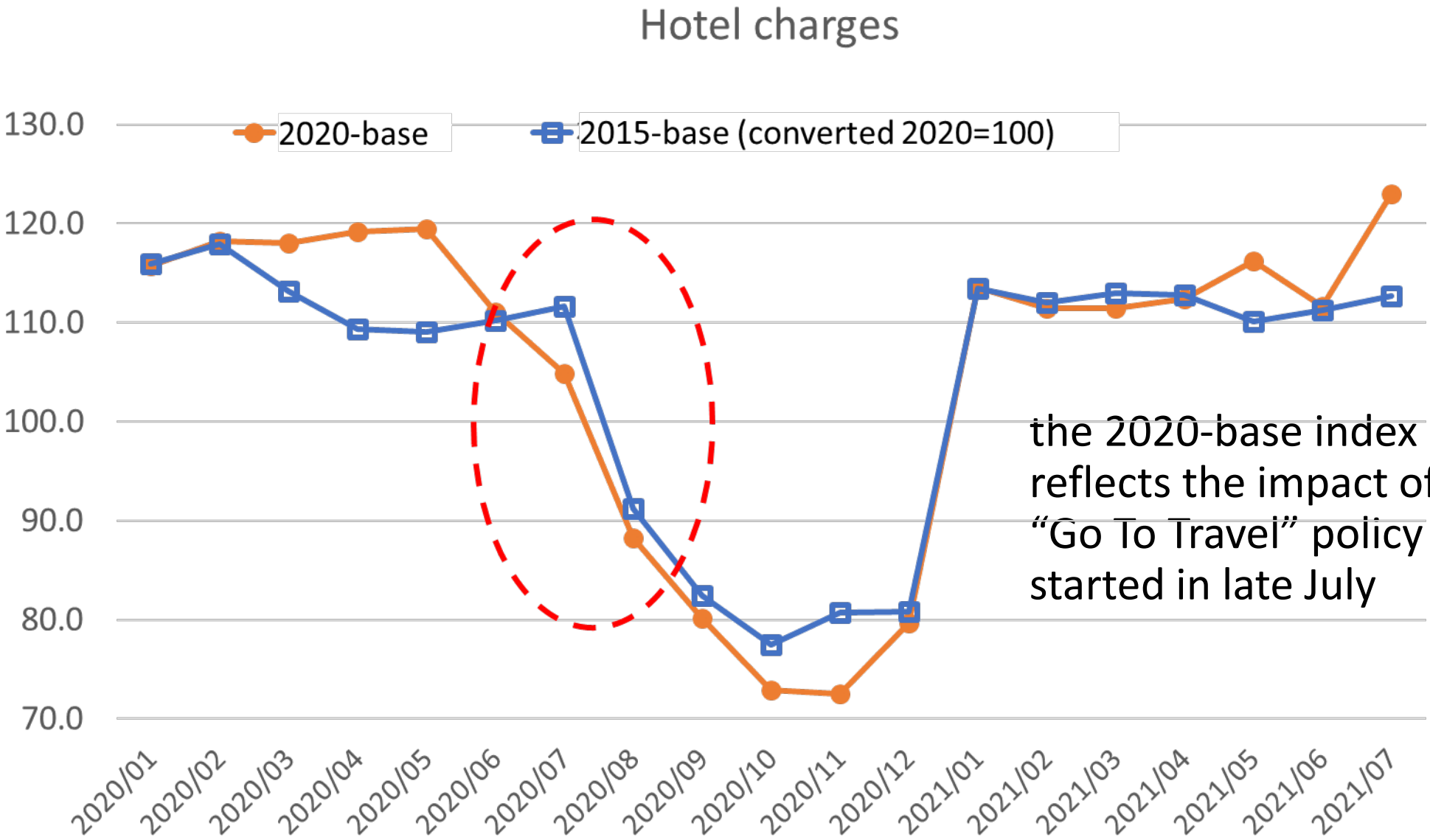
Accommodation date (X_a)	Booking site (X_s)	Facility (X_b)	Log Average Price(y)
2018/12/1	A	X	9.51
2018/12/1	A	Y	9.61
2018/12/1	A	Z	9.75
2018/12/1	C	X	9.58
2018/12/1	C	Y	9.69
2018/12/1	C	Z	9.85
2018/12/2	A	X	9.65
2018/12/2	A	Y	9.66
2018/12/2	B	X	9.49
……	…	…	……

$$Y'_{s,a,b} = \alpha + \boldsymbol{\beta}_a \cdot \boldsymbol{x}_a + \boldsymbol{\beta}_s \cdot \boldsymbol{x}_s + \boldsymbol{\beta}_b \cdot \boldsymbol{x}_b + \varepsilon$$

Use of web Scraping data : hotel charges

	2015-Base method (field collection)	2020-Base method (web scraping)
Collection conditions	Prices on Friday and Saturday of the week including the 5th of every month	Prices of 1st to 31st of every month purchased two months in advance of accommodation
Number of collected prices	640	About 1 million

Use of web Scraping data : hotel charges



the 2020-base index in July reflects the impact of the "Go To Travel" policy that started in late July

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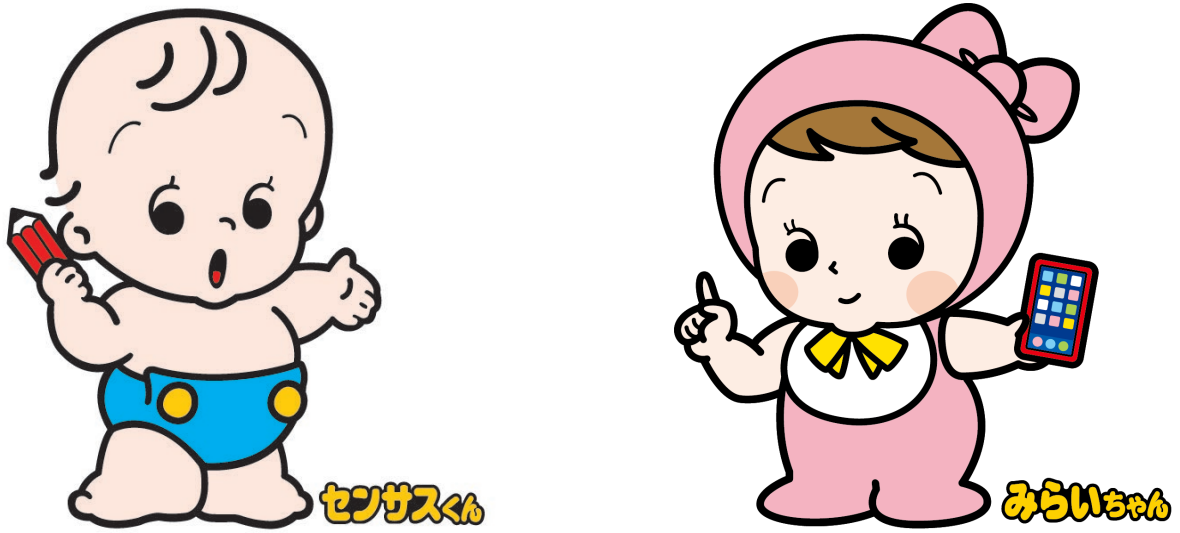
Future Tasks

- Expansion in usage of big data for the CPI
  - White goods, foods, medical supplies, daily necessities, and clothing
- Handling of items for which price collection has been missing for a long period of time
  - Package holidays abroad
- New initiatives / areas
  - Using machine learning to classify web scraping data
  - Exploring methodologies to integrate scanner data in CPI
    → Using multilateral method (GEKS), multilateral time dummy hedonic, …
  - Other data sources (Tax data, Transaction data, …)

Thank you



Mascot of Statistics Bureau of Japan

"*Census-Kun*" and "*Mirai-chan*"

(Master. Census) (Miss. Future)