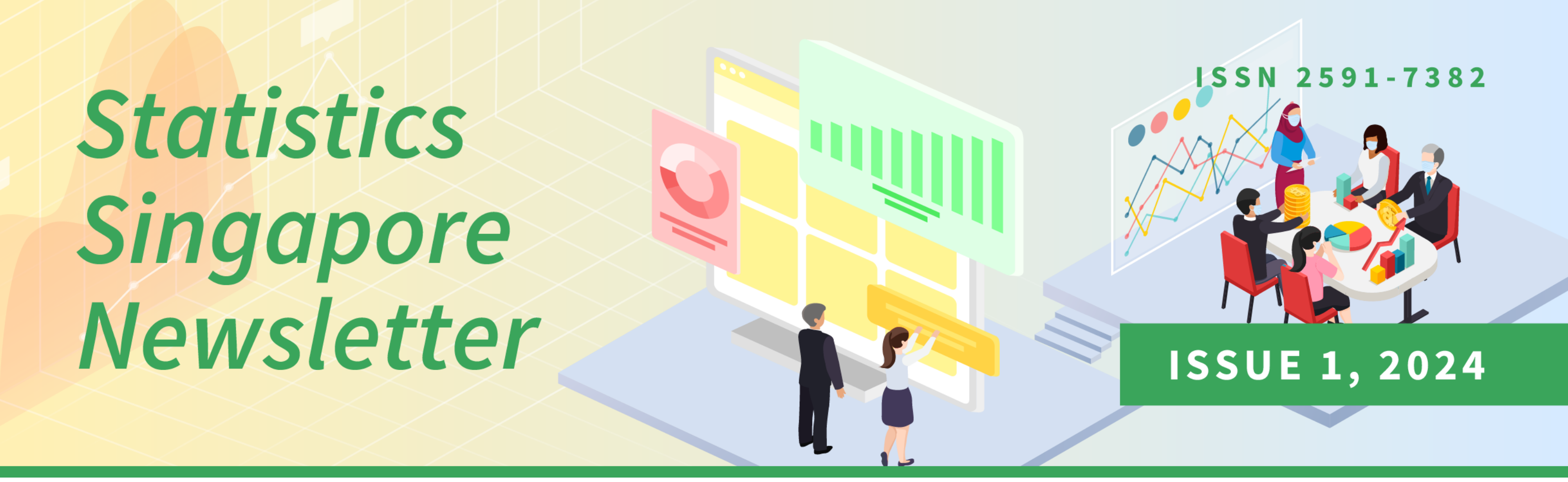

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Using Decomposed Total Fertility Rate (TFR) to Understand the Drivers for the Decline of TFR in Singapore

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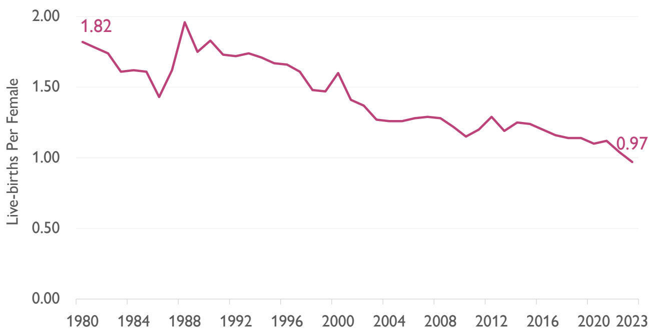
Introduction

Singapore's resident total fertility rate[1] (TFR) has been on a declining trend for the past three decades, falling to a historic low of 0.97 in 2023 (Chart 1). This is also the first time the resident TFR has dropped below 1.0, which means that on average, each female is having fewer than one child.

In Singapore's context, most births occur within marriage. One major reason for the decline in TFR is the increasing proportion of females in the prime child-bearing age groups choosing to remain single.

CHART 1

SINGAPORE'S RESIDENT TOTAL FERTILITY RATE



In addition to singlehood, this article aims to examine how the fertility patterns of married females in Singapore have contributed to this decline in TFR. Data analysed in this article are derived from administrative sources and annual household surveys[2].

Decomposition of TFR

The official TFR refers to the average number of live-births per female and is derived based on Equation (1)[3]. It can theoretically be decomposed into two components[4] : (i) Marital Fertility Rate and (ii) Proportion of Married Females.

In Singapore's context, it is reasonable to assume that all births are to married females as births to unmarried females are not common.

$$TFR = 5 \times \sum_{x=15-19}^{45-49} \frac{Live\ Births_x}{Female\ Population_x} \quad \text{—— EQUATION (1)}$$

$$= 5 \times \sum_{x=15-19}^{45-49} \left(\frac{Live\ Births_x}{Married\ Female\ Population_x} \times \frac{Married\ Female\ Population_x}{Female\ Population_x} \right)$$

$$= 5 \times \sum_{x=15-19}^{45-49} (Marital\ Fertility\ Rate_x \times Proportion\ of\ Married\ Females_x)$$

1 Refers to the average number of live-births each female would have during her reproductive years if she was subject to the prevailing age-specific fertility rates in the population in the given year.

2 Annual households surveys refer to the Census of Population, General Household Survey and Comprehensive Labour Force Survey.

3 For more information on how the official TFR is computed, refer to the infographic.

4 The method of decomposition into components is an established method used by researchers to allocate changes in population indicators over time into its components. See Lee-Jay Cho and Robert D. Retherford, 'Comparative analysis of recent fertility trends in East Asia', in International Population Conference, Liege, 1973, vol. 2, pp. 163-181; Evelyn M. Kitagawa, 'Components of a difference between two rates', Journal of the American Statistical Association, vol. 50, No. 272 (December 1955), pp. 1168-1174; and Shigesato Takahashi, 'Demographic Investigation of the Declining Fertility Process in Japan', The Japanese Journal of Population, vol. 2, No. 1 (March 2004), pp. 93-116.

Since 1990, data trends for the two time-periods - 1990 – 2005 and 2005 – 2023 were observed to be different.

From 1990 to 2005, there was a relatively large decline in the marital fertility rates, particularly among ages 25 – 34 years as illustrated by the gap between blue and orange lines in Chart 2.

In contrast, the marital fertility rates were higher in 2023 compared to 2005 for most age groups.

The drop in the proportion of married females among those in their 20s and 30s between 2005 and 2023 was also more pronounced than the drop between 1990 and 2005 (Chart 3).

CHART 2 AGE-SPECIFIC MARITAL FERTILITY RATES

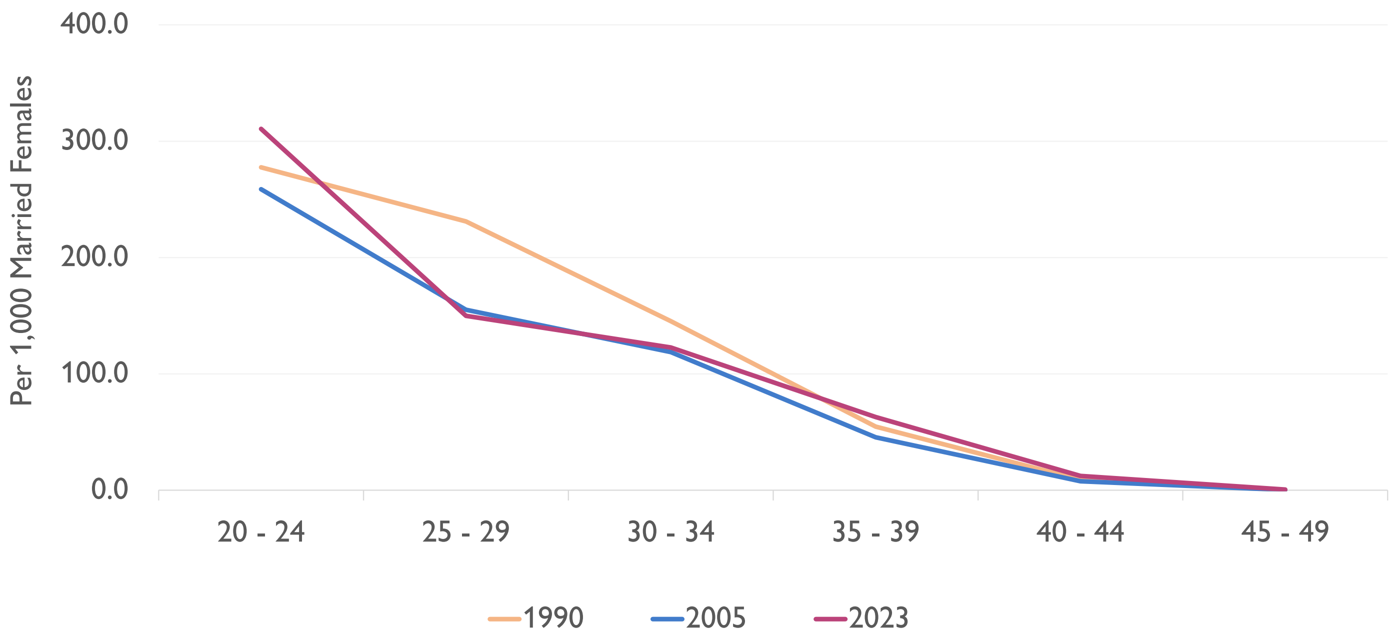
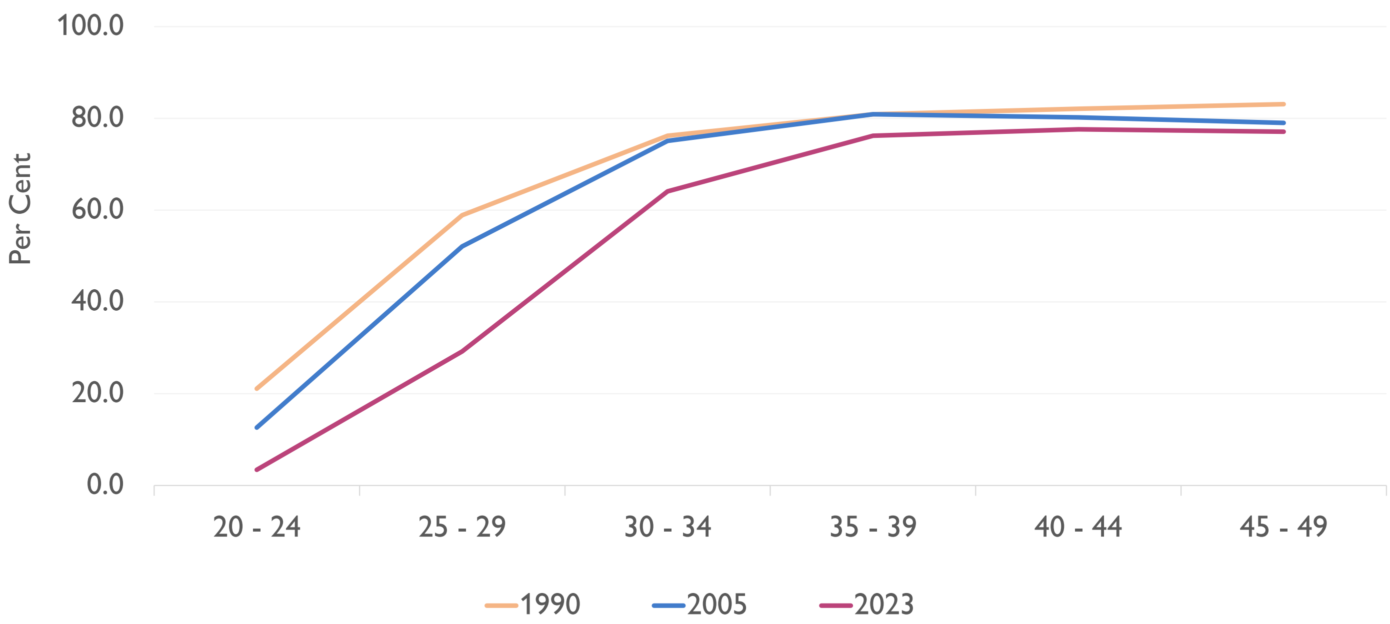


CHART 3 PROPORTION OF MARRIED FEMALES BY AGE GROUP



Note: Breakdowns in Charts 2 and 3 are not analysed for the 15-19 years age group as the married female population is small within this age group.

Key Findings

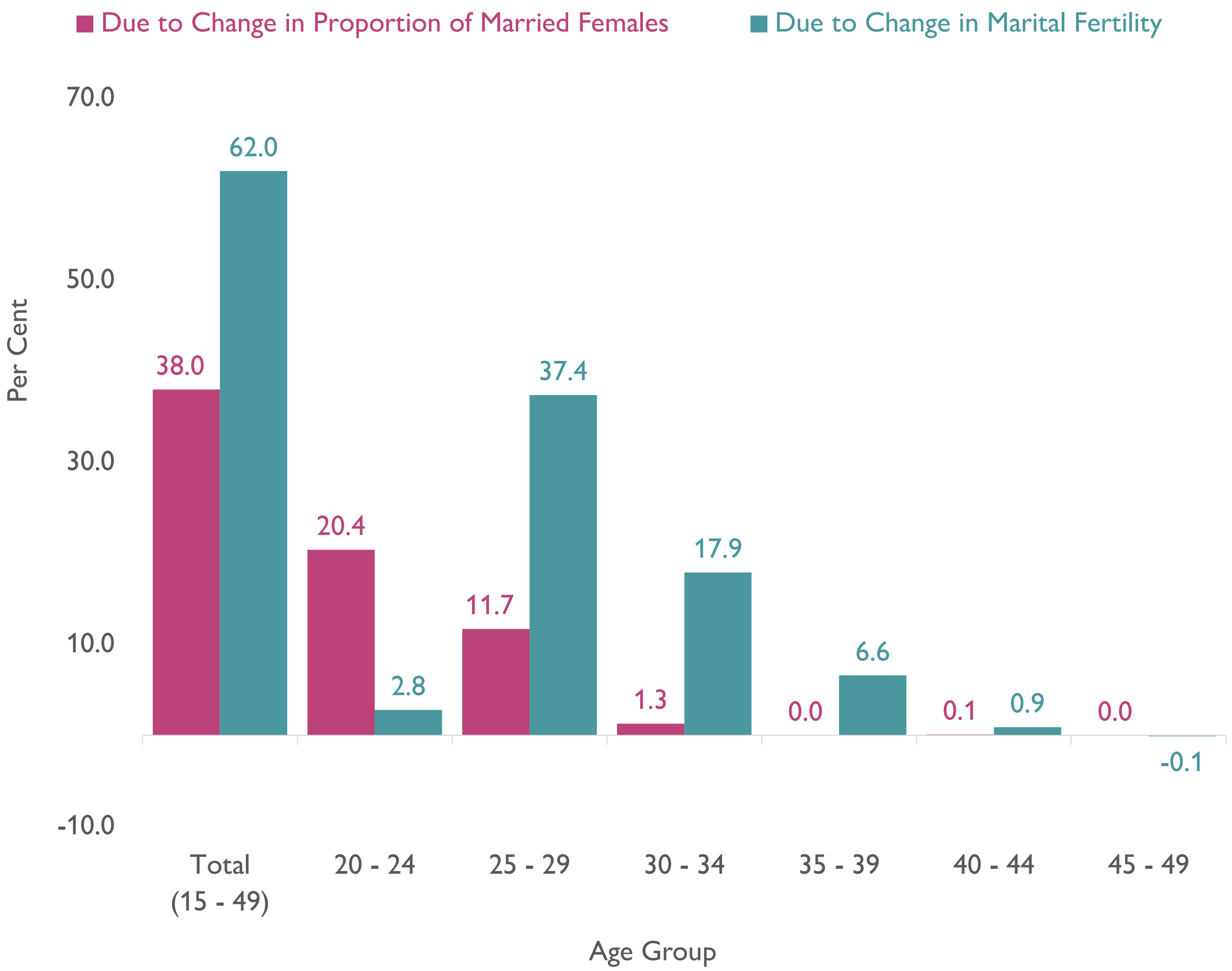
Period 1 - From 1990 to 2005: Decline in Marital Fertility was a Greater Contributor for the Drop in TFR

Applying the TFR decomposition formula, Chart 4 shows the decline in marital fertility contributed to 62 per cent of the decline in TFR, while the decline in the proportion of married females accounted for the remaining 38 per cent.

Analysing further by age group, the main factors for the drop in TFR were the decrease in marital fertility among females aged 25 – 34 years, which contributed to approximately 55 per cent of the decline in TFR, and the decrease in the proportion of married females among those aged 20 – 29 years, which contributed around 32 per cent of the decline.

These are consistent with the overall trends among females in Singapore who were delaying marriage or remaining single.

CHART 4 PERCENTAGE OF DECLINE IN TFR OVER 1990 - 2005 ATTRIBUTABLE TO CHANGES IN THE PROPORTION OF MARRIED FEMALES AND MARITAL FERTILITY



Note: Breakdowns in Chart 4 are not analysed for the 15-19 years age group as the married female population is small within this age group.

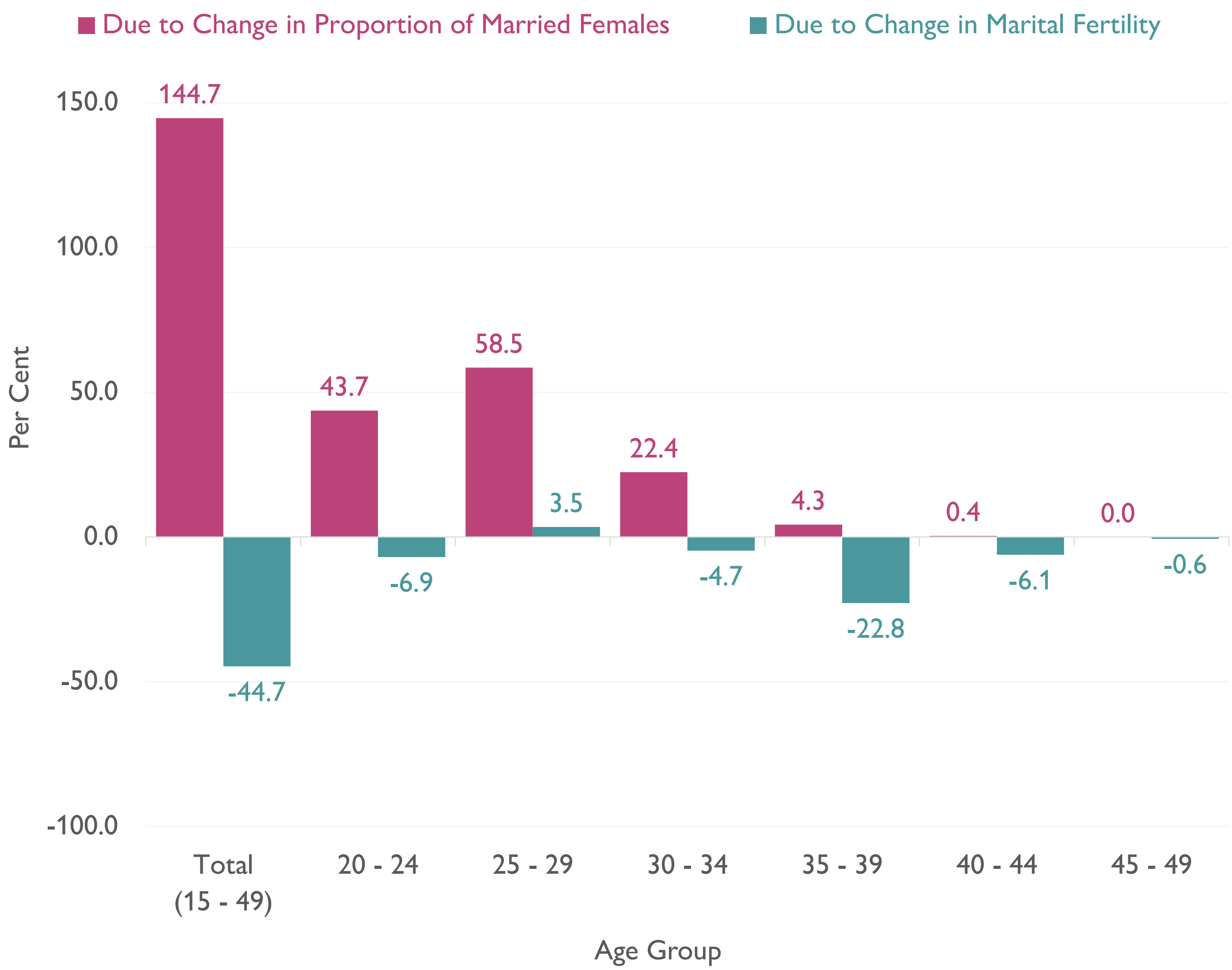
Period 2 - From 2005 to 2023: Decline in TFR was Mainly due to Decline in the Proportion of Married Females

Unlike the 1990 – 2005 period, marital fertility was higher in 2023 compared to 2005 across most age groups, except those aged 25 – 29 years. This had a positive effect (45 per cent) on the TFR but was more than offset by the larger drop in the proportion of married females, leading to an overall decline in the TFR (Chart 5).

Overall, the decline in TFR could be mainly attributed to the fall in the proportion of married females aged 20 – 34 years over the period.

The changes in marital fertility, which decreased for females aged 25 – 29 years but increased for females aged 35 – 39 years, reflect the trend of females marrying and giving birth at an older age. It does not necessarily represent an increase in the average number of children per married female at the end of their childbearing years – this number is still decreasing.

CHART 5 PERCENTAGE OF DECLINE IN TFR OVER 2005 - 2023 ATTRIBUTABLE TO CHANGES IN THE PROPORTION OF MARRIED FEMALES AND MARITAL FERTILITY



Note: Breakdowns in Chart 5 are not analysed for the 15-19 years age group as the married female population is small within this age group.

2005 – 2023

Why did the average number of children born to resident ever-married females aged 40 – 49 years decline (Chart 6) even though marital fertility rate increased (Chart 2)?

Average number of children born per ever-married female aged 40 – 49 years (i.e., at the end of their childbearing years) and age-specific marital fertility rate (ASMFR) are two distinct concepts.

Data on average number of children born per ever-married female aged 40 – 49 years are presented in Chart 6 and is derived **based on a stock concept.** It includes all the live-born children each ever-married female of the 40 – 49 years old cohort **has ever given birth to**, as at June of each reference year, including children born before the reference year. It includes children who are currently living with her, those who have set up their own homes and those who are no longer living.

On the other hand, the data on ASMFR presented in Chart 2 is **a period indicator derived based on a flow concept.** It only includes live-births **born in Jan—Dec of the reference year** to females within the specified age group, out of all married females in the same age group.

Due to their conceptual differences, period fertility trends (i.e., derived based on births within the reference year) can differ from trends observed based on a stock concept (i.e., derived based on cumulative births as at the reference year).

The following are observed when comparing the two constructs in 2005 and 2023.

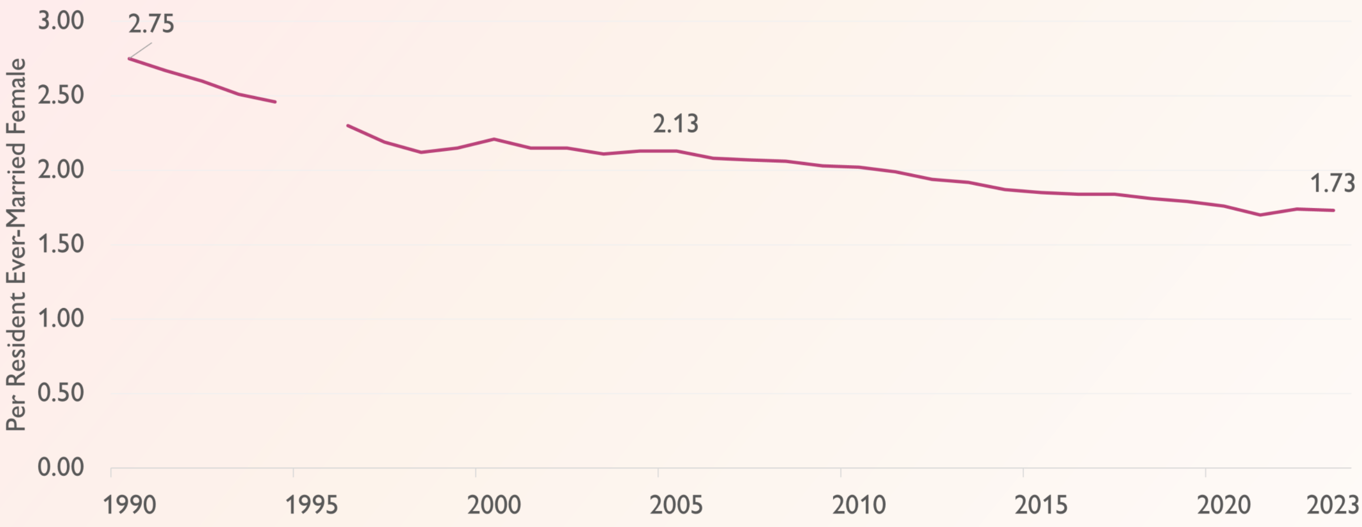
a. The ASMFR of females aged 40 – 44 and 45 – 49 years in 2023 were 12.4 and 0.7 live-births per 1,000 married females respectively. This was higher than the ASMFR of females in earlier cohorts, i.e., those aged 40 – 44 and 45 – 49 years in 2005 which were 7.8 and 0.3 live-births per 1,000 married females respectively.

b. On the other hand, the average number of children born to ever-married females aged 40 – 49 years in 2023 was 1.73, lower than the average number of children born to earlier cohorts of ever-married females who were aged 40 – 49 years in 2005 which was 2.13.

c. Taking the above together, while the more recent cohort of females experienced higher period marital fertility rates between the ages of 40 – 44 and 45 – 49 years compared to those from earlier cohorts, they had fewer children on average at the end of their child-bearing years, possibly due to them having fewer children on average in their earlier ages. This is in line with the trend of females having children later.

d. This explains why, even though the ASMFR of females at age 40 – 49 years might be higher in 2023, the average number of children born to ever-married females at age 40 – 49 years in 2023 is still lower.

CHART 6 AVERAGE NUMBER OF CHILDREN BORN TO RESIDENT EVER-MARRIED FEMALES AGED 40 - 49 YEARS



Note: Data for 1995 is not available.

'What If' Scenarios

The finding – decline in marital fertility rate had a greater impact on changes in TFR during 1990 to 2005 is supported by further simulations. If the proportion of married females in 2005 had remained at the 1990 level, simulations suggest that the TFR for 2005 may have been 1.47, higher than the actual TFR of 1.26 (Table 1). In another scenario, if marital fertility rate in 2005 had remained at the 1990 level, the simulations suggest that the TFR for 2005 may have been even higher at 1.60.

TABLE 1
'WHAT IF' SCENARIOS FOR 2005
(BASED ON 1990 LEVELS)

Scenario	1990	2005
Actual Resident TFR	1.83	1.26
If 1990 Proportion Married Prevailed	1.83	1.47
If 1990 Marital Fertility Rate Prevailed	1.83	1.60

In contrast, similar simulations for 2023 suggest that changes in the proportion of married females had a greater contribution to the decline in TFR than marital fertility between 2005 and 2023 (Table 2). If the proportion of married females in 2023 had remained at 2005 levels, simulations show that the TFR may have been 1.43, higher than the actual TFR of 0.97. On the other hand, if the 2005 marital fertility rate had prevailed, simulations show possibly an even lower TFR of 0.86.

TABLE 2
'WHAT IF' SCENARIOS FOR 2023
(BASED ON 2005 LEVELS)

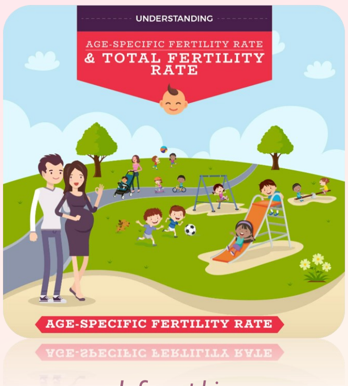
Scenario	2005	2023
Actual Resident TFR	1.26	0.97
If 2005 Proportion Married Prevailed	1.26	1.43
If 2005 Marital Fertility Rate Prevailed	1.26	0.86

Conclusion

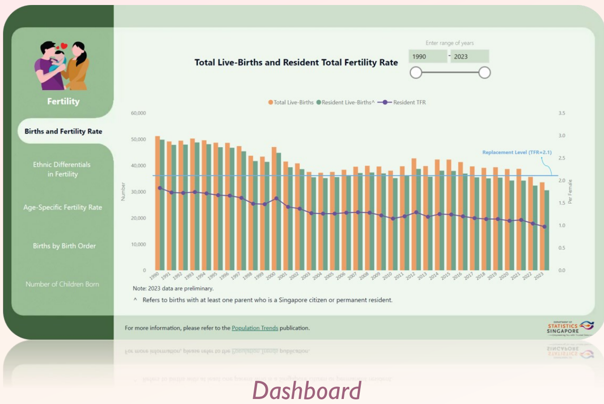
Like many developed societies, Singapore's TFR has been on a downward trend. By decomposing the TFR to isolate the impact from the changes in marital fertility and proportion of married females in Singapore, the drivers for the decline in TFR across the different periods can be better understood.

Between 1990 and 2005, the decline in TFR was largely due to a fall in the marital fertility rate. However, between 2005 and 2023, while marital fertility was higher in 2023 compared to 2005 across most age groups, this was more than offset by the larger decline in the proportion of married females, or relatedly increasing prevalence of singlehood.

Check out the Total Fertility Rate Infographic and Fertility Dashboard available on the SingStat Website!



Infographic



Dashboard

The Use of Artificial Intelligence and Machine Learning in DOS

By Malcolm Cai, Jun Wen Tay and Nicholas Chin
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Introduction

The world is in a transformative era fuelled by the rapid development of new Artificial Intelligence (AI) and Machine Learning (ML) technologies. They have the ability to revolutionise operations, products, and services in many domains, such as statistics, from smart automation and data capabilities, to hyper-personalised customer experiences. To thrive in an AI-driven world, organisations have to embrace change and transform the way they operate. They would also need to be aware of the growing need for better governance to tackle ethical, privacy and accountability issues associated with AI deployment.

The Singapore Department of Statistics (DOS) has embarked on a transformation journey in the past years to deploy AI/ ML technologies in statistical processes. This article discusses three key areas critical to AI/ ML implementation – business processes, human capital, and governance framework.

Tapping Ever-Evolving Technologies Requires a Focused and Agile Approach

DOS adopted a focused and agile approach to embed AI/ ML and automation technologies in business processes. The Digital Transformation Unit was formed to work closely with various divisions in DOS and acts as a coordinator to identify synergies between existing and potential AI/ ML projects across the data value chain – from data collection to analysis and dissemination. Another role of the Unit was to identify and prioritise projects with well-defined use cases[1] to operate within resource capacities. AI was only utilised when it is best suited in meeting user needs. Once the value of the AI/ ML method is established via proof-of-concept[2] experiments, the Unit would then optimise and productionise it for use, roll it out across DOS and offer it to Research and Statistics Units (RSUs), and agencies within the Whole of Government (WOG).

Creating a Vibrant Talent Ecosystem

The quality of manpower is critical for successful AI/ ML adoption. Within DOS, statisticians' expertise in statistical theory and computer programming placed them in a good stead to pick up advanced AI/ ML skillsets. Beyond training courses to upskill staff, the Unit created communities of practices and various channels to facilitate information exchange and ideation, and promote cross-collaboration within DOS, RSUs, and WOG agencies. Secondment of staff to private companies with strong data science and AI/ ML capabilities allowed DOS to glean best practices from the private sector and benchmark against industry standards. Thematic sharing on data science and analytics between RSUs, government agencies and industry leaders have helped to create a conducive exploration environment for innovation, and opened new possibilities in using AI to address business challenges.

Data Stewardship and Governance as a Cornerstone for AI/ ML Adoption

As the National Statistical Office, the advocation of statistical best practices and robust data management by DOS have ensured that quality data are produced within DOS and across the WOG. DOS's experience in data stewardship and governance has laid a strong foundation for AI/ ML adoption. Key principles of responsible and ethical AI, such as transparency, interpretability and accountability, are part of the broader framework of statistical best practices. DOS's track record of data management, privacy, security,

1 Well-defined use cases refer to projects where the problem statement, objectives, and expected outcomes are clearly described. The area where AI/ ML is used should be mentioned and the benefits should be measurable.

2 Proof-of-concept measures the feasibility of a project by gathering evidence to support or through a demonstration.

and accountability maintains public's trust in DOS's data products and services, and contribute towards the building of a digital government through the government data architecture[3] initiative.

DOS's efforts have led to successful outcomes. Over the years, DOS has developed many in-house solutions that optimise statistical operations, ranging from data collection, compilation, analyses, and dissemination. Examples include finding a novel way of updating the Statistical Business Register[4], automating statistical processes such as the classification coding in Census 2020[5], and providing new statistical insights[6].

The following sections elaborate two of DOS's latest AI initiatives - the DOS Intelligent Classification Engine (DICE) to process natural language text into Singapore Standard Classification codes and the ML Toolkit to simplify complexity surrounding ML projects.

DOS Intelligent Classification Engine (DICE)

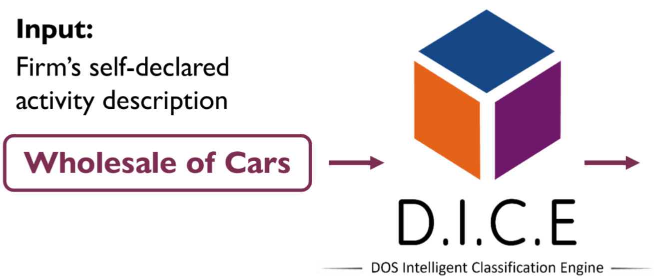
The Singapore Standard Industrial Classification (SSIC) is used to classify firms according to their principal economic activity. As data on the SSIC are widely used by public agencies in many aspects (e.g., compilation of economic statistics, research studies, and policy implementation), it is crucial to ensure the accuracy of SSIC data. However, firms may find it challenging to select the most appropriate SSIC code when registering with the Accounting and Corporate Regulatory Authority (ACRA). Agencies surveying firms may also find it difficult to classify firms into sectors based on activity descriptions of the firms. The effort to ensure the correct classification of firms is significant, involving coordination between agencies, manual verification of SSIC codes, as well as training staff to be well-versed in SSIC knowledge.

Thus, DICE was developed for users (e.g., firm registrants and public officers) to automatically identify the most relevant SSIC codes through ML. DICE takes a text description of a firm's economic activity as an input and recommends suitable SSIC codes[7] as an output, along with a score on how confident the engine is on the predictions (Figure 1).

To train DICE, the team acquired large quantities of data on the descriptions of principal activity and the corresponding SSIC codes from sources such as administrative data from ACRA, survey returns from DOS and RSUs, and official SSIC definitions. However, curating clean training data with the correct SSIC labels is challenging, since a proportion of firms from the raw data sources are expected to have wrong SSIC labels. The time and effort required to manually verify voluminous number of records is impractical. Hence, an in-house solution was developed to automatically detect wrongly labelled data for correction.

In addition, the team tapped on BERT[8] to enhance DICE's capabilities. BERT is a large language model developed by Google and trained on a large corpus of

FIGURE 1 USING DICE TO RECOMMEND SSIC CODES



Prediction	Score
SSIC 46561: Wholesale of motor vehicles except motorcycles and scooters	92%
SSIC 46563: Wholesale of parts and accessories for vehicles	5%
SSIC 47311: Retail sale of motor vehicles except motorcycles and scooters	2%

3 More details on government data architecture are available from the Digital Government Blueprint.

4 DOS (2023), 'Experimental Uses of Machine Learning and New Data Sources in Updating the Statistical Business Register' in Statistics Singapore Newsletter (SSN), Issue 1, 2023.

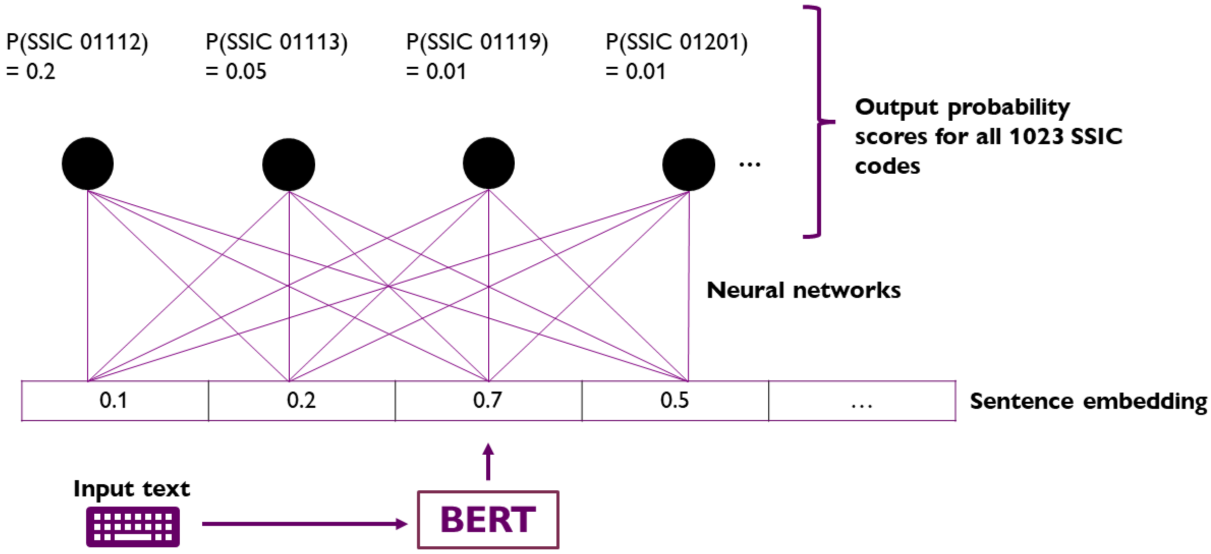
5 DOS (2021), 'Coding of SSOC/ SSIC in Census 2020 using Machine Learning' in Statistics Singapore Newsletter (SSN), Issue 2, 2021.

6 DOS (2022), 'Using Big Data to Profile Singapore's Internet Economy' in Statistics Singapore Newsletter (SSN), Issue 2, 2022.

7 DICE can generate recommendations at various levels of SSIC granularity, e.g., 5-digit and 2-digit.

8 Bidirectional Encoder Representations from Transformers. Read more in: Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018), 'BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding'.

FIGURE 2 SIMPLIFIED ARCHITECTURE OF DICE



text including 2.5 billion words from the English Wikipedia. BERT models utilise sentence embeddings to support various downstream tasks such as predicting SSIC codes, by adding a neural network layer on top of them (Figure 2). The entire network is then fine-tuned by training on the task-specific data (i.e., descriptions of firm activities and corresponding SSIC codes).

DICE has fared well across several performance metrics, like having an accuracy score of around 86%. With DICE, large volumes of data are now more efficiently and accurately classified within a shorter time frame as compared to manual labelling.

The project team continues to enhance DICE by working closely with partner agencies such as the Economic Development Board, Maritime and Port Authority of Singapore, and ACRA, on their use cases to ensure that DICE's functionality aligns with their operational needs. The team is also working with the Ministry of Manpower for DICE to support the Singapore Standard Occupational Classification (SSOC) code prediction. Moving forward, DICE is envisaged to be a WOG productivity tool for Singapore Standard Classification use cases in classifying codes related to expenditure, commodities, education, etc., beyond industry and occupation codes.

Machine Learning Toolkit

Increasingly, ML is being used in data analysis and business decision-making. However, the complexity of ML models and its steep learning curve make it challenging for those with limited data science background to implement ML projects efficiently in DOS. Furthermore, building ML models is time-consuming and often requires trial-and-error for the model's hyperparameters.

While commercialised automated ML (AutoML) products can offer comprehensive end-to-end ML capabilities, they come at a premium price. With the aim to empower and support DOS statisticians in adopting ML for their work, acquiring commercial products at a large scale would not be cost effective.

As such, the Unit conducted extensive research on various popular open-source AutoML libraries and curated a selection of suitable ones to develop DOS's own toolkit. This helps to lower the barriers to entry for data science exploration and makes it easier for officers to build ML models. Figure 3 details the end-to-end process from data cleaning to model training and diagnostics. It also reinforces best practices in ML ethics such as evaluating fairness of a model and providing transparency in managing ML projects.

Statisticians in DOS can now easily conduct their ML modelling process by answering simple questions for the toolkit to determine the best approach for the data and task. Thereafter, the toolkit will train and build different ML models and provide relevant model information such as performance metric, fairness metrics, and interpretability plots. With these outputs, DOS officers can select the better-performing models

FIGURE 3 FEATURES OF THE MACHINE LEARNING TOOLKIT

Data Cleaning, Feature Engineering and Selection

- Automatically finds and fixes errors in ML dataset.
- Performs automatic feature selection based on feature's importance.
- Contains common pre-processing functionalities (e.g., imputes missing values, fixes data imbalances, normalises data).

Model Training and Diagnostic

- Automates hyperparameter tuning and neural architecture search for various models to achieve the best set of results with minimal human intervention.
- Explains a model's predictions with easy-to-interpret plots
- Measures data and concept drifts to monitor model's performance
- Uses bias-aware modelling approach to ensure fairness across different populations.

Guiding Principle in Machine Learning Ethics

- Promotes the responsible use of data science techniques.
- Benchmarks against best practices from NSOs (e.g., UK Statistics Authority), government agencies (e.g., Monetary Authority of Singapore) and private sector.

to further explore or fine-tune for their use case. This increases efficiency significantly without having to build the ML model from scratch and the officer will only have to focus on a smaller subset of models output from the toolkit.

As ML models are increasingly being used to make decisions that can have significant impact on individuals and the society, it is important to ensure that the model developed is fair. The toolkit is able to compute fairness metrics and generate fairness plots to highlight unfair models, while providing sample codes to utilise techniques such as resampling and reweighting to improve the model's fairness. This ensures that the developed model will not discriminate against certain groups.

Overall, the ML toolkit encourages a hands-on approach to experimentation and to test and refine predictive models and analytical techniques. It helps statisticians streamline ML processes, therefore enhancing DOS's overall capability.

Conclusion

The gradual but fundamental shift in adopting AI/ ML technologies evolves DOS's business processes, upskills manpower, and updates governance framework. It enables DOS to harness AI productively, which in turn enhances the data products and statistical services offered to various user groups.

DOS will continue to invest in AI training for staff, such as developing an internal AI playbook to keep abreast of the latest advancements in both AI and generative AI spaces, as well as practical applications of AI in the statistical and data analytical fields.

Moving forward, other AI initiatives in areas such as data collection (e.g., web-scraping as a new key data source, document intelligence) and data dissemination (e.g., seamless user experience in searching for relevant information and data) are actively explored, as part of DOS's efforts to continually enhance the process of collecting, producing and consuming statistical data.

Hawker Food Price Trends Across Cooked Food Establishment Types (2019 as Base Year)

by Ruth Lee, Ryan Lee and Chau Wun
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Singapore Department of Statistics

Introduction

Meals at Hawker Centres and Food Courts & Coffee Shops (collectively termed 'hawker food') accounted for 7.9% of the total weights in the 2019-based Consumer Price Index (CPI) basket. In 2023, overall prices of hawker food increased 6.1%, the highest since 2008.

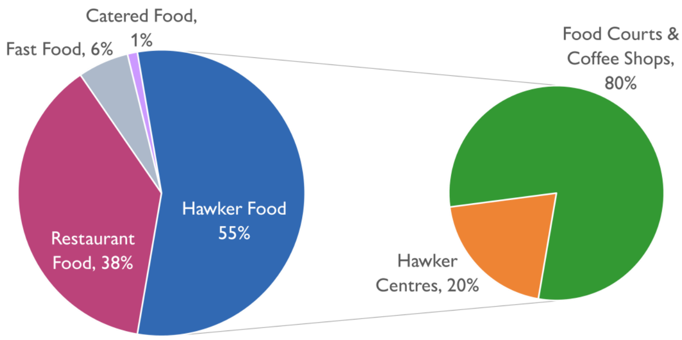
This article provides an overview of the coverage of hawker food in the CPI, examines the key factors driving hawker food inflation in 2023, as well as analyses and compares the price trends of hawker food across Hawker Centres and Food Courts & Coffee Shops.

Expenditure Share and Coverage of Hawker Food in the CPI

The expenditure share in the CPI refers to the proportion of total household expenditure that is allocated to a specific category of goods or services. It reflects the relative importance of each category in the overall spending patterns of consumers.

The expenditure share of hawker food declined over time, from 10.3% in the 2004-based CPI to 7.9% in the 2019-based CPI. Nonetheless, hawker food remains the predominant expenditure group within the Food Serving Services expenditure division, which includes Restaurant Food, Fast Food and Catered Food.

CHART 1 THE 2019-BASED CPI WEIGHTS BY TYPE OF FOOD SERVING SERVICES



Within the hawker food group, meals sold at Food Courts & Coffee Shops currently constitute 80% of its weight share, while those at Hawker Centres make up the remaining 20% (Chart 1).

For the compilation of the CPI for hawker food, prices of over 100 common hawker food items are collected from some 1,700 stalls across the various types of cooked food establishments. Examples of items monitored include coffee/ tea with milk, mee rebus, fishball noodles, chicken rice, economical rice, chicken nasi briyani and ice kachang.

Watch the video on '[How are Prices Collected for the Compilation of Consumer Price Index]' for an introduction to how price data are gathered for the compilation of the CPI by the Singapore Department of Statistics (DOS).

DID YOU KNOW? The CPI represents the average price changes across various items and outlets

- Prices used for compilation of the CPI are gathered from a *large number* of outlets for a *wide variety* of items.
- Outlets *revise their prices at different times and in differing magnitude.*

EXAMPLE There are 4 stalls that sell coffee. Each charges $1.10 per cup of coffee.
In Jan 2023, 2 stalls raised their prices.

JAN 2023	Stall 1	Stall 2	Stall 3	Stall 4
	$1.30 (↑18%)	$1.20 (↑9%)	$1.10 (-)	$1.10 (-)

The average price increase for coffee in Jan 2023 was 7%.

Hence, for consumers who frequent Stall 1 in Jan 2023, the price change they faced was 18%.
However, the change in the average price of coffee as measured by the CPI was smaller at 7%.

Main Drivers of Hawker Food Inflation in 2023

Hawker food prices rose 6.1% in 2023, up from 5.7% in 2022 and exceeded the average increase of 2.2% per annum observed during the 2012 – 2022 period.

Within the hawker food group, prices of meals sold at Food Courts & Coffee Shops increased 6.1%, a tick higher than the 6.0% rise at Hawker Centres.

Common food items driving the price increases at these establishments were economical rice, chicken rice, fishball noodles and coffee/ tea.

The broad-based increase in hawker food prices was partly driven by higher input costs, including pricier raw food ingredients[1] due to supply chain disruptions triggered by the COVID-19 pandemic and compounded by other events such as the Russia-Ukraine war.

Nevertheless, hawker food inflation has since eased significantly to 4.1% in December 2023, down from a peak of 8.3% in January/ February 2023 (Chart 2).

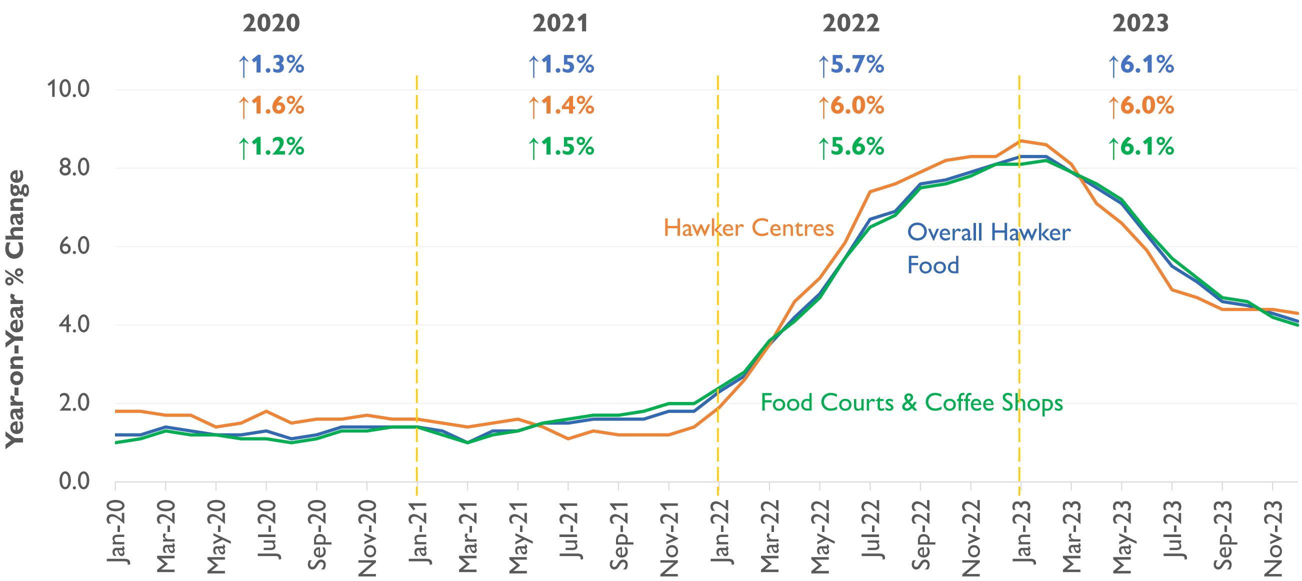
Price Trends of Cooked Food Items[2] Across Cooked Food Establishment Types

While the CPI for hawker food is compiled from a comprehensive range of representative food items[3], 16 cooked food items commonly sold at Hawker Centres and Food Courts & Coffee Shops are selected for detailed analysis. To facilitate price comparisons, these cooked food items are further classified into three primary categories, namely noodle-based, rice-based and beverage items.

Among these food categories, noodle-based cooked food items exhibited the most substantial average price increase of 7.6% in 2023. This was closely followed by beverages at 7.0% and rice-based cooked food items at 6.3%.

At Hawker Centres, beverages recorded the largest price increase of 6.9% in 2023, rising faster than noodle-based (6.2%) and rice-based (5.4%) cooked food prices. In contrast, at Food Courts & Coffee Shops, prices of beverages (6.3%) increased more gradually compared to noodle-based (8.0%) and rice-based (6.5%) cooked food items.

CHART 2 YEAR-ON-YEAR PERCENTAGE CHANGE IN THE 2019-BASED CPI FOR HAWKER FOOD, 2020 – 2023



1 See Speech by Minister for Trade and Industry Gan Kim Yong at Ministry of Trade and Industry (MTI's) Committee of Supply Debate 2023 and Macroeconomic Review Volume XXII Issue 1, Apr 2023

2 The 16 cooked food items include char kway teow, fishball noodles, mee rebus, mee siam, sliced fish bee hoon, wanton noodles, chicken rice, chicken nasi briyani, char siew rice, duck rice, economical rice (1 meat & 2 vegetables), saba fish set with rice, coffee/ tea without milk, coffee/ tea with milk, canned drinks and milo with milk. These items from the 2019-based CPI have been specially selected for this analysis. They are widely available across Hawker Centres and Food Courts & Coffee Shops and there are adequate consistent quotations for these items to establish meaningful and reliable average prices.

3 Explore the interactive dashboard on 'Average Retail Prices of Selected Consumer Items' for the average retail prices of selected consumer items monitored in the CPI basket.

CHART 3 AVERAGE RETAIL PRICES FOR NOODLE-BASED COOKED FOOD ITEMS ($), 2019 – 2023

NOODLE-BASED	2019	2020	2021	2022	2023
Char Kway Teow	3.80	3.88	3.91	4.18	4.52
Hawker Centres	3.48	3.55	3.65	3.88	4.05
Food Courts & Coffee Shops	3.91	3.99	4.00	4.28	4.68
Fishball Noodles	3.46	3.50	3.56	3.77	4.13
Hawker Centres	2.98	3.03	3.05	3.28	3.52
Food Courts & Coffee Shops	3.54	3.59	3.65	3.86	4.24
Mee Rebus	3.26	3.30	3.32	3.55	3.79
Hawker Centres	2.97	3.01	3.03	3.25	3.45
Food Courts & Coffee Shops	3.36	3.40	3.42	3.65	3.92
Mee Siam	3.13	3.17	3.20	3.43	3.65
Hawker Centres	2.88	2.92	2.96	3.21	3.42
Food Courts & Coffee Shops	3.25	3.29	3.32	3.54	3.76
Sliced Fish Bee Hoon	4.45	4.56	4.61	4.97	5.35
Hawker Centres	3.98	4.14	4.18	4.43	4.68
Food Courts & Coffee Shops	4.62	4.70	4.76	5.15	5.58
Wanton Noodles	3.42	3.51	3.55	3.85	4.12
Hawker Centres	3.18	3.28	3.28	3.56	3.82
Food Courts & Coffee Shops	3.52	3.61	3.66	3.96	4.24

Noodle-based Cooked Food Items

The noodle-based cooked food items used for analysis and comparison of price trends between the cooked food establishment types were char kway teow, fishball noodles, mee rebus, mee siam, sliced fish bee hoon and wanton noodles.

Notably, sliced fish bee hoon had the highest average price of $5.35 while mee siam had the lowest average price of $3.65 (Chart 3).

In terms of price changes, Chart 4 details the prices registered for all six noodle-based cooked food items in 2023, with increases ranging from 6.4% to 9.5%.

At Hawker Centres, prices of the noodle-based cooked food items rose between 4.4% and 7.3%. In particular, fishball noodles and wanton noodles saw the most significant price increases while char kway teow was the most gradual. Nonetheless, more pronounced price increases were observed at Food Courts & Coffee Shops (ranging from 6.2% to 9.8%), with a bowl of fishball noodles costing almost 10% more in 2023 compared to 2022.

CHART 4
YEAR-ON-YEAR PERCENTAGE CHANGE IN AVERAGE RETAIL PRICES OF NOODLE-BASED COOKED FOOD ITEMS BY COOKED FOOD ESTABLISHMENT TYPE (%), 2023

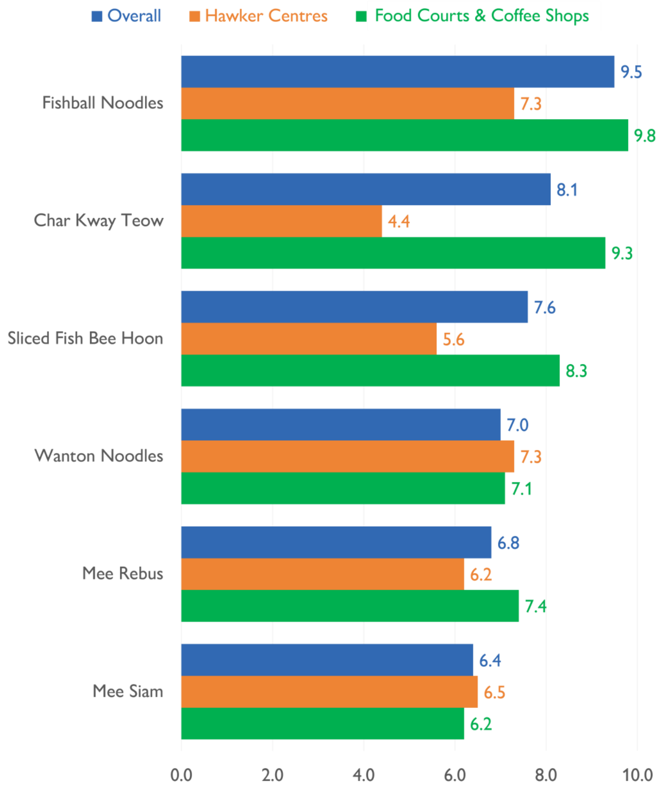


CHART 5 AVERAGE RETAIL PRICES FOR RICE-BASED COOKED FOOD ITEMS ($), 2019 – 2023

RICE-BASED	2019	2020	2021	2022	2023
Chicken Rice	3.40	3.47	3.54	3.86	4.15
Hawker Centres	2.98	3.03	3.04	3.38	3.61
Food Courts & Coffee Shops	3.51	3.58	3.67	3.98	4.28
Chicken Nasi Briyani	5.58	5.65	5.79	6.22	6.52
Hawker Centres	5.20	5.29	5.33	5.86	6.35
Food Courts & Coffee Shops	5.65	5.71	5.87	6.29	6.55
Char Siew Rice	3.31	3.39	3.44	3.73	4.04
Hawker Centres	2.98	3.04	3.11	3.32	3.49
Food Courts & Coffee Shops	3.44	3.52	3.56	3.89	4.26
Duck Rice	3.90	3.96	4.03	4.30	4.55
Hawker Centres	3.24	3.27	3.31	3.60	3.82
Food Courts & Coffee Shops	4.14	4.21	4.29	4.55	4.80
Economical Rice (1 Meat & 2 Vegetables)	3.34	3.37	3.40	3.58	3.82
Hawker Centres	2.98	3.03	3.06	3.20	3.36
Food Courts & Coffee Shops	3.42	3.45	3.48	3.67	3.93
Saba Fish Set with Rice	5.99	6.03	6.09	6.22	6.52
Hawker Centres	5.30	5.45	5.45	5.64	5.70
Food Courts & Coffee Shops	6.02	6.06	6.12	6.25	6.56

Rice-based Cooked Food Items

Among the rice-based cooked food items sold at Hawker Centres and Food Courts & Coffee Shops, chicken rice, chicken nasi briyani, char siew rice, duck rice, economical rice (1 meat & 2 vegetables), and saba fish set with rice were selected for analysis. Chicken nasi briyani and saba fish set with rice cost the most at an average price of $6.52 each, while economical rice recorded the lowest average price of $3.82 across all cooked food establishment types (Chart 5).

Price increases between 4.8% and 8.3% year-on-year were observed for all six rice-based cooked food items, with char siew rice recording the sharpest increase of 8.3% in 2023 as shown in Chart 6.

The prices of rice-based cooked food items rose between 4.1% and 9.5% at Food Courts & Coffee Shops in 2023, outpacing the price increases of 1.1% to 8.4% observed at Hawker Centres. Among the food items, chicken rice, char siew rice, economical rice and saba fish set with rice at Food Courts & Coffee Shops saw greater price increases compared to those sold at hawker centres. Interestingly, chicken nasi briyani registered the largest price increase at Hawker Centres (8.4%) but the smallest increase at Food Courts & Coffee Shops (4.1%).

CHART 6
YEAR-ON-YEAR PERCENTAGE CHANGE IN AVERAGE RETAIL PRICES OF RICE-BASED COOKED FOOD ITEMS BY COOKED FOOD ESTABLISHMENT TYPE (%), 2023

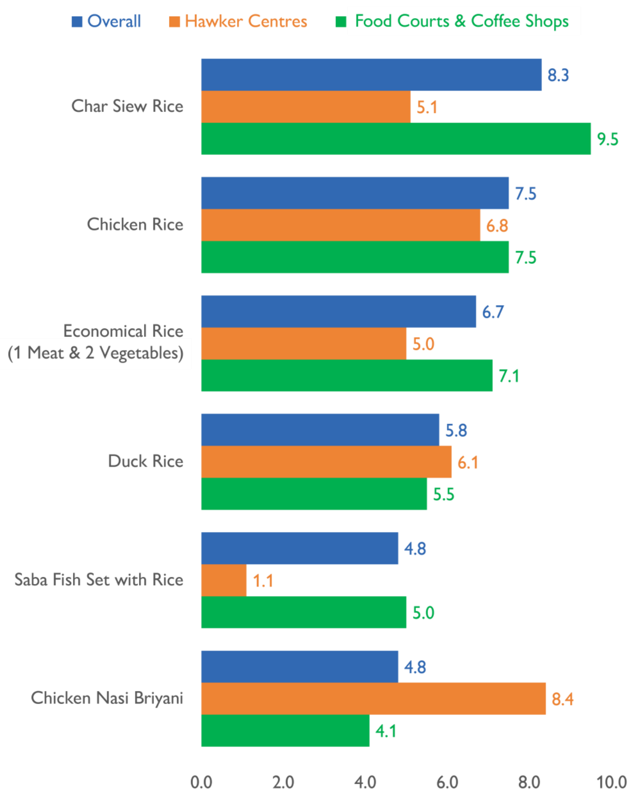


CHART 7 AVERAGE RETAIL PRICES FOR BEVERAGE ITEMS ($), 2019 – 2023

BEVERAGE	2019	2020	2021	2022	2023
Coffee/ Tea without Milk	1.06	1.07	1.08	1.14	1.22
Hawker Centres	0.84	0.85	0.85	0.92	0.99
Food Courts & Coffee Shops	1.12	1.13	1.14	1.21	1.28
Coffee/ Tea with Milk	1.17	1.17	1.19	1.26	1.34
Hawker Centres	0.95	0.96	0.97	1.03	1.10
Food Courts & Coffee Shops	1.22	1.22	1.24	1.31	1.39
Canned Drinks	1.52	1.53	1.54	1.59	1.71
Hawker Centres	1.24	1.25	1.25	1.31	1.37
Food Courts & Coffee Shops	1.56	1.57	1.58	1.64	1.75
Milo with Milk	1.34	1.35	1.37	1.43	1.53
Hawker Centres	1.10	1.10	1.11	1.16	1.26
Food Courts & Coffee Shops	1.43	1.44	1.47	1.53	1.63

Beverage Items

The beverages chosen for price analysis between Hawker Centres and Food Courts & Coffee Shops were coffee/ tea without milk, coffee/ tea with milk, canned drinks and milo with milk. Canned drinks had the highest average price of $1.71, while coffee/ tea without milk recorded the lowest average price of $1.22 (Chart 7).

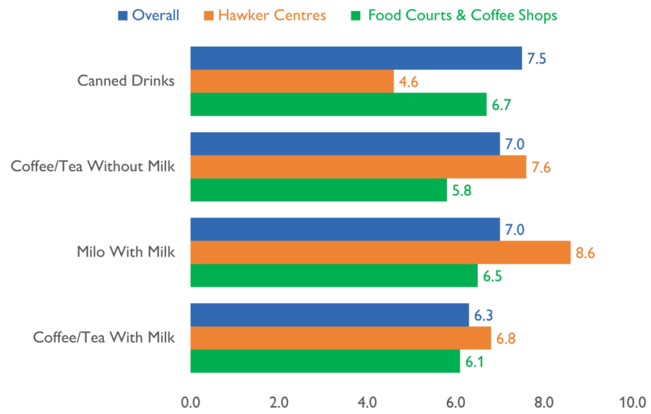
In 2023, all four beverage items experienced price increases ranging from 6.3% to 7.5% (Chart 8). Canned drinks, which recorded the highest average price level, rose at the fastest pace during the period.

Beverages registered price increases of between 5.8% (coffee/ tea without milk) and 6.7% (canned drinks) at Food Courts & Coffee Shops.

In comparison, the increases in beverage prices at Hawker Centres ranged from 4.6% (canned drinks) to 8.6% (milo with milk).

While canned drinks sold at Food Courts & Coffee Shops saw larger price increases relative to those sold at Hawker Centres, the increase in prices of coffee/ tea and milo with milk were higher at Hawker Centres.

CHART 8
YEAR-ON-YEAR PERCENTAGE CHANGE IN AVERAGE RETAIL PRICES OF BEVERAGE ITEMS BY COOKED FOOD ESTABLISHMENT TYPE (%), 2023



Conclusion

Hawker food inflation has risen in recent years amidst higher global food commodity prices and elevated cost pressures. Comparing hawker food prices between cooked food establishment types, the average price levels of cooked food items sold at Food Courts & Coffee Shops tend to be higher than those sold at Hawker Centres. In addition, some items, especially beverages, saw larger price increases at Hawker Centres (partly due to a lower price base) whereas the noodle-based and rice-based cooked food prices generally rose faster at Food Courts & Coffee Shops.

Experimental Use of New Data Sources for Prompt Identification of Changes in Firms' Status

by Peh Li Lin, Seng Li Cheng and Cui Hui Min
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Introduction

Significant changes in business activities of firms, especially those of large firms, may have a sizeable impact on Singapore's business, National Accounts and Balance of Payments statistics. It is important that such changes are promptly detected and captured to ensure consistent and reliable statistics across subject domains.

To promptly identify significant changes in business activities of firms, the Singapore Department of Statistics (DOS) initiated the 'Early Triggering[1]' pilot project. The project aims to detect entries and exits of large firms or those with substantial revenue and/ or employment changes. Identified firms are then assessed by the relevant subject domain teams to gauge the potential impact of their changes on short-term surveys and economic indicators for consistent statistical treatment.

This article shares DOS's efforts in the pilot project on 'Early Triggering' which leverages the Statistical Business Register (SBR) and higher frequency data that includes qualitative data from online sources.

Coverage and Maintenance of the SBR

The SBR serves as the foundational statistical database for compiling business and economic statistics. The SBR, managed by DOS, is primarily updated using administrative data and supplemented with statistical survey returns from DOS and Research & Statistics Units (RSUs) in government ministries and statutory boards.

The SBR encompasses all entities registered in Singapore. Basic identification [e.g., Unique Entity Number (UEN)[2], enterprise name] and firm characteristics (e.g., registration date and status) are readily available from the various registration authorities. In the SBR, firms are uniquely identified by their UENs, which are issued to firms upon their registration in Singapore. UENs are used by firms in their interactions with the Government such as the application of business licenses and permits or the filing of tax returns. Therefore, the UEN enables DOS to process and integrate firm-level data from various sources efficiently and accurately.

The primary data sources for the SBR are administrative data which have comprehensive coverage and good data quality. However, some administrative data are filed annually and are only available more than one year after the firm's financial year ending.

Increasingly, users are seeking indicators with more recent data to detect economic changes early and facilitate timely policy responses. This urges DOS to explore new data sources to update the SBR and develop more timely economic indicators.

Early Triggering with Employment and Goods & Services Tax (GST) Data

The primary administrative data sources for the Early Triggering project are higher frequency administrative data sources of employment from the Central Provident Fund Board (CPFB) and Ministry of Manpower (MOM), as well as GST data from the Inland Revenue Authority of Singapore (IRAS).

Employment Data

The Central Provident Fund (CPF) is a mandatory social security savings scheme in Singapore, funded by contributions from employers and employees. Employers of local workers[3] are required to declare wage information and pay CPF contributions to them

1 Also known as Early Warning Systems (EWS) in other countries, as explained in the 'European Business Profiling Recommendations Manual'.
2 For more information, please refer to the UEN website.
3 Refer to Citizens and Permanent Residents of Singapore.

monthly. Conversely, firms employing foreign workers must apply for relevant work passes from the MOM. Employers of foreign employees are also required to inform MOM of changes such as revisions in employee's salary and updates to personal particulars. Therefore, data from CPFB and MOM provide timely information on local and foreign employment and wages which can be used to update the SBR.

GST Data

GST is a broad-based consumption tax levied on the purchases of goods and services in Singapore[4]. Firms with annual taxable turnover exceeding S$1 million must register for GST, while those under S$1 million can voluntarily register for GST. GST data are timely as firms are required to file GST on a quarterly basis, within one month after the end of the accounting period. Data collected on GST returns comprise information such as firms' revenue and taxable purchases, serving as a reliable and timely data source to update their economic status and performance in the SBR.

Early Triggering with Employment and GST Data

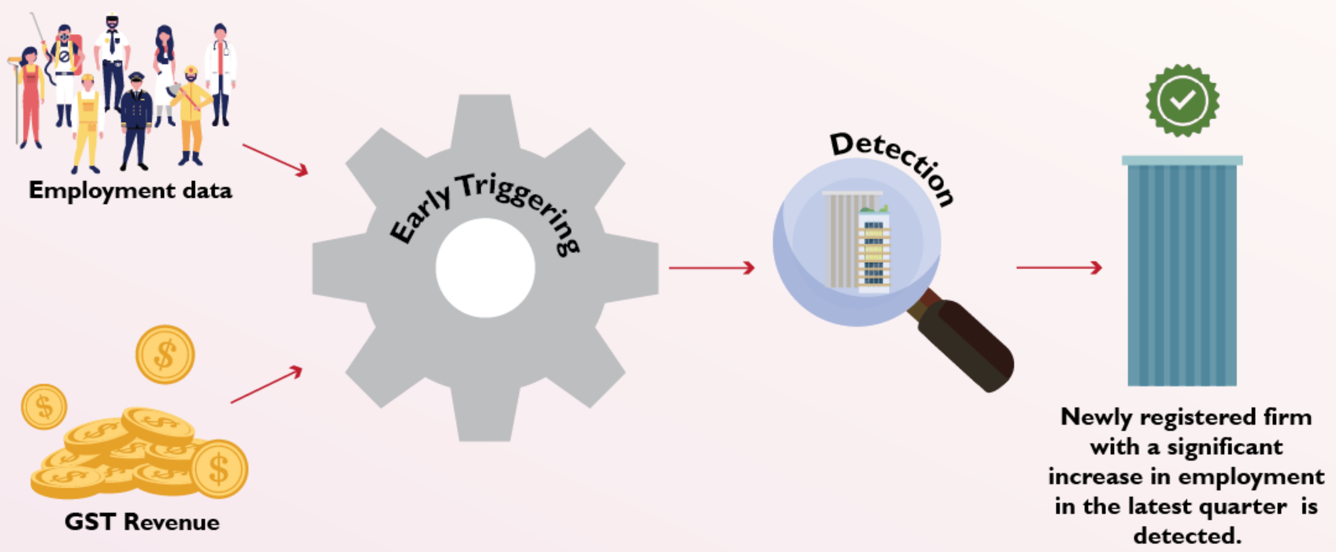
Early Triggering is more effective when the triggering criteria is tailored to industry characteristics. Quantitative thresholds specific to the sector are adopted instead of having a single quantitative threshold to cover all industries. The sector-specific quantitative thresholds are developed in consultation with the relevant subject domain experts, based on the revenue and employment percentile distribution of firms by industry.

Figure 1 illustrates the detection of the entry of a large firm using employment data in the Early Triggering project. The newly registered firm recorded a significant increase in employment in the latest quarter but did not report any GST revenue. This could occur when a firm is at the pre-production phase, where recruitment and training of employees precede the actual production activities.

The increase in employment activities serves as an early indication of impending production, with its revenue expected to be reported after the commencement of sales.

The project team provides the firm's information such as characteristics (e.g., registration date and economic sector), quarterly employment and/ or revenue data over available time periods to the relevant subject domains teams for developing of timely economic indicators.

FIGURE 1 DETECT THE ENTRY OF A LARGE FIRM IN EARLY TRIGGERING



4 GST is also known as the Value-Added Tax (VAT) in other countries. For more information, please refer to the IRAS website.

Use of Qualitative Data as Supplementary Indicators

Business Outlook

DOS collects qualitative information on changes in firms' business activities, to supplement quantitative data on employment and GST. DOS's Quarterly Business Expectations Survey[5] collects information from larger firms about their business outlook and major restructuring plans in the next six months.

Weekly Economic Brief

DOS has access to a curation of business news from major media outlets based on keywords covering a range of topics such as firms' expansion and restructuring plans, mergers and acquisitions, as well as business headwinds and tailwinds.

The selected news articles are categorised into pre-defined topics such as retail trade, tourism, and internationalization for easy reference.

Indicator on Firm's Internet Presence

DOS utilises text mining to extract keywords such as 'Shop', 'Cart' and 'Price' from corporate websites. Using these keywords and their frequency, DOS leverages supervised machine learning to classify the firms' websites into different categories (i.e., those with websites and generate revenue directly from their website, or those with websites but do not generate revenue from them) and derive an indicator on firms' internet presence.

This indicator is integrated with firms' characteristics in the SBR to provide new insights for further analyses. For instance, the identification of firms with corporate websites are early indications of business activities to be included in the sampling frame for business surveys.

Experimental Use of Electricity Consumption and Property Stamp Duty Data in Early Triggering

Most administrative sources are available at the enterprise level, such as the employment and GST data used for the Early Triggering project. DOS has been exploring new data sources of electricity consumption and property stamp duty which provide information at the establishment level, to be incorporated into the SBR and used as supplementary indicators in the Early Triggering project.

Electricity Consumption Data

Experiences from other National Statistical Offices demonstrated that electricity meter data can be used in the production of statistics on the electricity consumption of businesses and households[6]. In Singapore, meters are installed in all households and establishments to measure electricity usage, hence monthly consumption data for households and business accounts are available. Business accounts data includes details like UEN, establishment address and the electricity consumed in kilowatt-hours (kWh) for the billing month. Therefore, electricity consumption data offers the advantage of data timeliness and establishment details, which could be useful for the project.

Property Stamp Duty Data

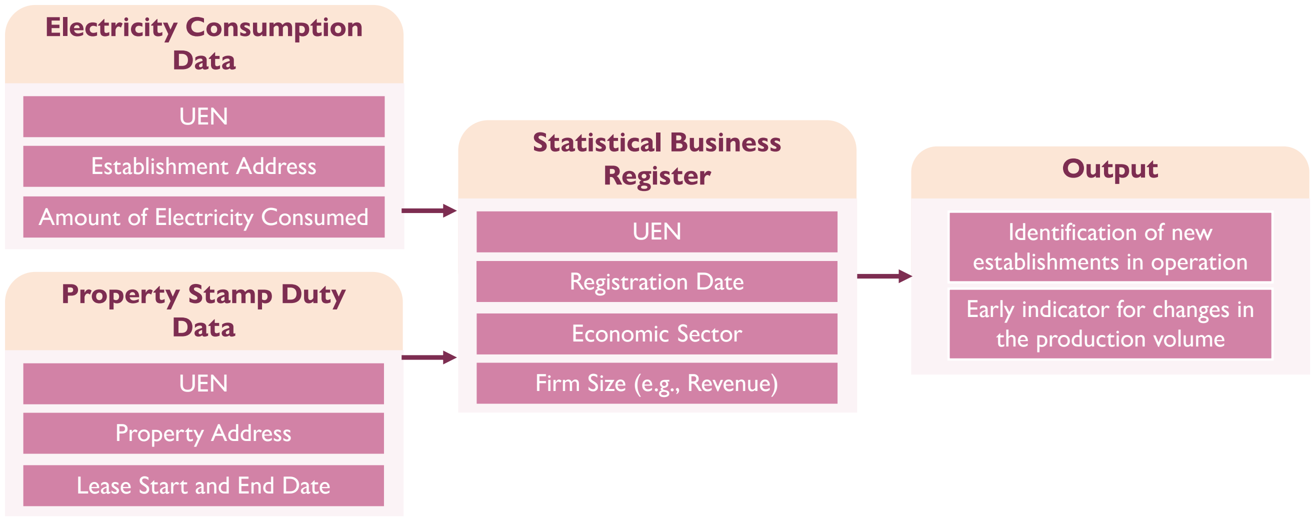
Property stamp duty refers to the tax on documents relating to the transactions of properties in Singapore. Parties involved in property transactions are required to e-stamp the documents of sales and purchase agreement or tenancy agreement and pay stamp duty[7]. Stamp duty data from IRAS contains sales and purchase information such as UEN, property address, the selling price of the property, as well as tenancy information like monthly rents and the start and end date of leases.

5 For more information on the Business Expectations Survey, please refer to the SingStat Website.

6 For more information, please refer to EuroStat's report on "Implementation of Smart Meter Data in the Production of Official Statistics".

7 For more information, please refer to the IRAS website.

FIGURE 2 USE OF ELECTRICITY CONSUMPTION AND PROPERTY STAMP DUTY DATA IN EARLY TRIGGERING



Experimental Use in the Early Triggering Project

Integrating electricity consumption and stamp duty data at the establishment level with firm characteristics in the SBR (e.g., registration date, economic sector and firm size) could be additional sources for Early Triggering.

Specifically, information on firms' new electricity meter accounts and leases or purchases of commercial properties could facilitate identification of new establishments or outlets in operation. Furthermore, significant changes in electricity consumption can be an early indicator for changes in production volume (Figure 2).

Conclusion

The SBR plays an important role in the data collection, compilation and analyses of economic and business statistics. It aids in early detection of significant changes in firm's business activities using higher frequency data. Additionally, qualitative data can provide an early sensing of events that may impact the firm's performance and could be used as supplementary indicators where available.

The experimental use of electricity consumption and property stamp duty data showed the possibility of using them to update establishment information in the SBR. DOS will continue exploring new data sources to update the SBR and produce comprehensive statistics.

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Analysis of Revisions to Gross Domestic Product Estimates

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Introduction

The compilation of statistics generally involves a trade-off between timeliness and accuracy. This is observed in the compilation of Singapore's Gross Domestic Product (GDP) estimates.

Assessing real-time economic conditions is challenging due to the limited availability of timely economic data which may be subsequently revised as more information becomes available. Timely estimates are used to paint a short-term picture of the current economic situation for macroeconomic policymakers and analysts, even before all information is available.

Hence, it is normal and inevitable for GDP estimates to be regularly revised and refined by incorporating previously unavailable data. Revisions can also arise from improvements in compilation methodology. This article explains and analyses these revisions to the quarterly and annual GDP growth estimates.

Why are GDP Estimates Revised?

The recent-period quarterly GDP estimates[1] are compiled using an extensive number of timely short-term indicators of economic activities in each industry. This is prior to the availability of comprehensive annual survey benchmarks. Sources of these indicators include high frequency administrative data and short-term survey data obtained from a relatively small number of companies or establishments.

Revisions to Incorporate Newer Data in Recent-period Estimates

Singapore's advance GDP estimates are released no later than two weeks after the end of each reference quarter. The advance GDP estimates are largely computed from data for the first two months of the reference quarter and are intended as an early indicator of GDP growth for that quarter. More comprehensive data on the full quarter's performance become available after this advance release and are incorporated in the subsequent updates. For example, the preliminary GDP estimates of the quarter are released no later than eight weeks after the end of the reference quarter and are published in the Economic Survey of Singapore (ESS).

Did You Know?

United States and United Kingdom were the first few economies to release advance GDP estimates, in addition to the preliminary GDP estimates. Within Southeast Asia, Singapore was the first to release advance GDP estimates. In recent years, an increasing number of economies such as India and Malaysia have started releasing advance GDP estimates.

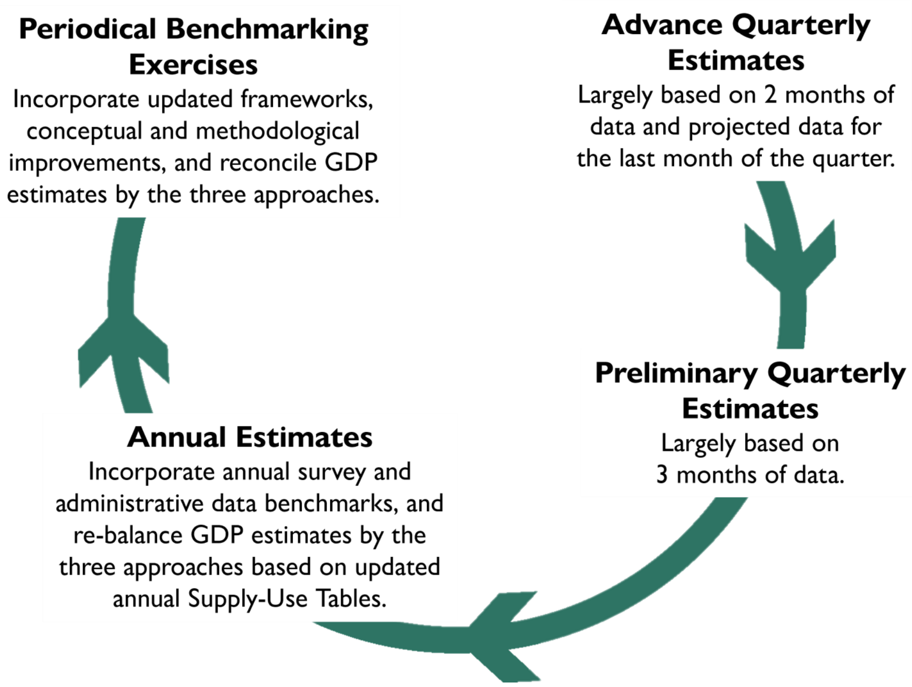
Revisions to Incorporate Annual Survey Benchmarks and Updated Annual Supply and Use Tables

A comprehensive review of the GDP estimates occurs annually during which annual survey benchmarks and up-to-date administrative data are incorporated into the estimates. Survey benchmarks are a comprehensive set of data compiled from aggregated survey returns from establishments.

Survey returns are usually only available 9 to 15 months after the reference period as detailed survey results follow after companies have compiled full financial details from their operations and filed statement of accounts. GDP estimates compiled by the three approaches (i.e., production, expenditure and income approaches) are also re-balanced on the basis of updated annual supply and use tables[2].

1 More details are available in the information paper 'Quarterly Estimates of Output-Based GDP' dated Jul 2023
2 Learn more about Supply and Use tables from the video and infographic.

FIGURE 1 REVISION CYCLE OF GDP ESTIMATES



Revisions to Incorporate Conceptual and Methodological Improvements During Periodical Benchmarking Exercises

Besides revising the GDP estimates to incorporate updated annual survey benchmarks, the estimates are also revised during periodical benchmarking exercises. The periodical benchmarking exercises reconcile the three GDP estimates from the production, expenditure and income approaches and allow for the inclusion of conceptual and methodological improvements, as well as updated international frameworks.

Did You Know?

In the latest periodical benchmarking exercise, annually reweighted chain volume measures of GDP were adopted, replacing the previous five-yearly reweighted volume measures. Other conceptual and methodological improvements included the refined estimation of insurance service charges and revised conceptual treatment of goods for processing.

The revisions from periodical benchmarking exercises[3] are applied to past data where applicable, to ensure comparability of the estimates over time. The incorporation of latest and more complete data is in line with international best practices. Figure 1 illustrates how GDP estimates are revised over time.

Revisions to Real GDP Growth Estimates

The following sections discuss the revisions to real GDP estimates with reference to both shorter-term revisions (advance to preliminary GDP estimates revisions) and longer-term revisions (preliminary GDP estimates revisions).

Advance to Preliminary GDP Revisions

First released in 4Q 2002, advance GDP estimates act as early estimates of economic activities to facilitate timely policy and business decision making.

The mean absolute revision[4] is 0.5 percentage points over the periods between 4Q 2002 to 4Q 2023. Most revisions to the year-on-year GDP growth estimates

3 Read more about the benchmarking exercise from the information paper 'Benchmarking of Singapore's National Accounts to Reference Year 2015' dated May 2019.

4 The mean absolute revision (MAR) statistic is a widely used measure of the size of the revisions and is defined as the simple average of the absolute value of revisions.

were small, at less than 1.0 percentage point absolute revision (Chart 1). Larger revisions were generally observed near the start of economic booms and downturns, as business cycle turning points[5] may not be apparent in real time.

For example, 4Q 2008 and 1Q 2020 saw revisions of -1.6 percentage points and 1.5 percentage points respectively. The large revision of 2.4 percentage points observed in 1Q 2010 was due to the benchmarking of GDP from reference year 2000 to 2005.

Revisions to Preliminary GDP Estimates

Year-on-year (y-o-y) preliminary GDP growth estimates are revised due to the incorporation of data updates, annual survey benchmarks and periodical benchmarking exercises.

The following evaluation is based on the differences between the first-available quarterly or annual preliminary GDP growth estimates and the growth estimates as at the Annual Economic Survey of Singapore (AES) one or two years later.

Figure 2 illustrates the timeline on the availability of the first-available quarterly and annual GDP estimates as at the AES one and two years later.

The mean absolute revision to the overall annual GDP growth for the reference period of 2002 to 2023 as at the AES one year later is relatively small, at around

CHART 1 ADVANCE TO PRELIMINARY QUARTERLY GDP GROWTH RATES AND REVISIONS

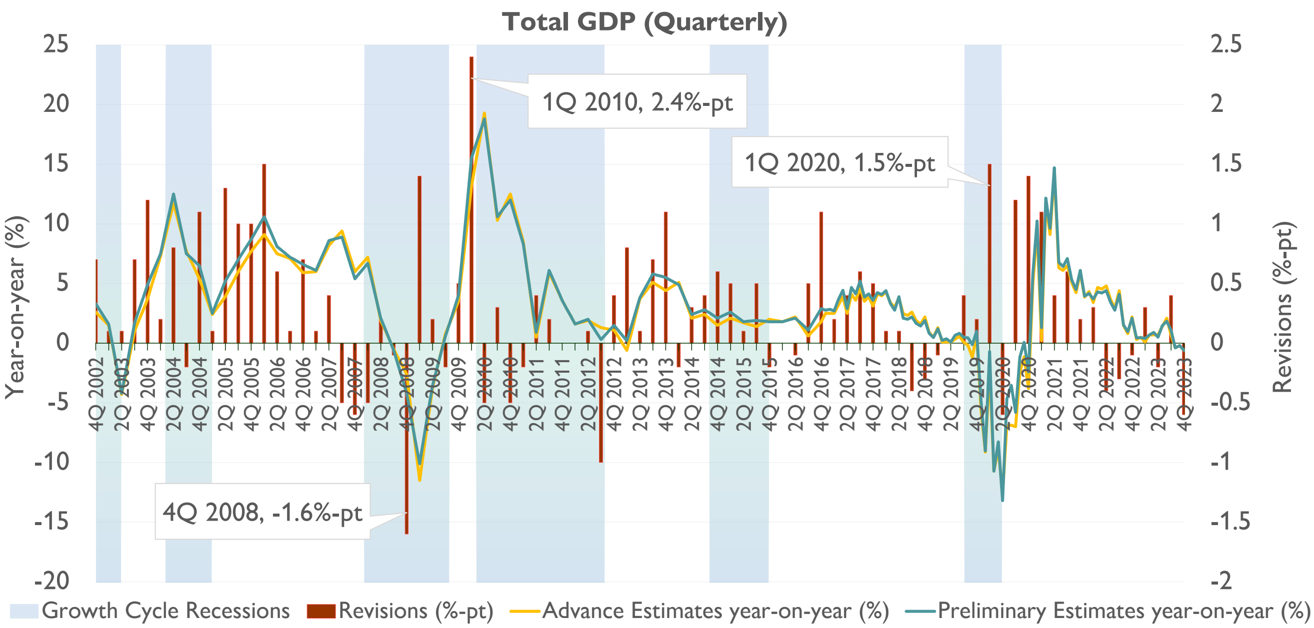
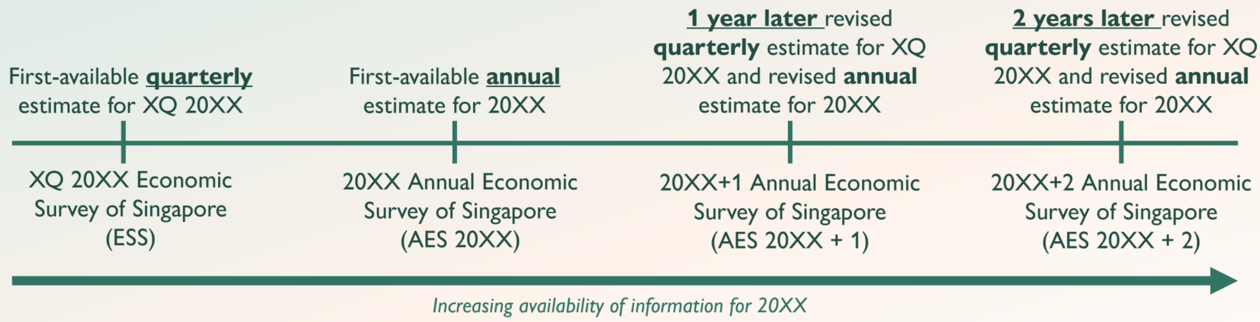


FIGURE 2 TIMELINE ON FIRST-AVAILABLE, 1 YEAR LATER AND 2 YEARS LATER ESTIMATES



5 More information on business cycle turning points are available from the article '[Singapore's Growth Cycle Chronology, Coincident and Leading Indicators]'.

TABLE 1

MEAN ABSOLUTE REVISIONS TO GDP GROWTH ESTIMATES (Y-O-Y)

Real GDP Growth (year-on-year)	Mean Absolute Revisions (%)			
	Annual Series		Quarterly Series	
Reference Period	Year 1	Year 2	Year 1	Year 2
2002 to 2019*	0.31	0.79	0.44	0.79
2002 to 2023#	0.41	0.84	0.44	0.88

** Quarterly periods from 1Q 2002 to 4Q 2019*
 # Quarterly periods from 1Q 2002 to 4Q 2023

0.41 percentage points (Table 1). At the AES two years later, the mean absolute revision is larger at 0.84 percentage points, mainly due to the incorporation of more complete and updated annual survey benchmarks.

Growth magnitudes of the quarterly GDP series are generally more pronounced than the annual series, leading to larger revisions in the quarterly series compared to the annual series. The mean absolute revision to quarterly overall GDP growth for the reference period of 2002 to 2023 after a year is 0.44 percentage points (higher than the 0.41 percentage points for the annual series) and around 0.88 percentage points after two years (higher than the 0.84 percentage points for the annual series).

Larger Revisions in Recent Years Due to Greater Uncertainties

Revisions to quarterly GDP growths for COVID-impacted periods are comparatively more significant than periods without. For instance, the mean absolute revision to annual overall GDP growth for the reference period of 2002 to 2019 as at the AES one year later stands at 0.31 percentage points, compared to the 0.41 percentage points for the reference period 2002-2023 (Table 1).

The onset of COVID-19 had significantly disrupted business operations and impacted firms' responses to some short-term surveys and administrative filing, as many were adjusting to new modes of operations. This resulted in greater revisions when more up-to-date data were provided in the annual survey returns and administrative records.

The growth revisions as at the AES two years later showed that GDP growths were revised up to 2.6 percentage points for reference quarters in 2020 and 2021 (COVID-impacted periods), as compared to the largest growth revision of around 1.3 percentage points for reference quarters from 2017 to 2019. The relatively larger revision of 2.6 percentage points registered for reference quarters 1Q 2021 and 2Q 2021 can be attributed to the Construction, Wholesale Trade and Transportation & Storage industries (Chart 2).

CHART 2 PRELIMINARY GDP GROWTH RATES AND REVISIONS 2 YEARS LATER

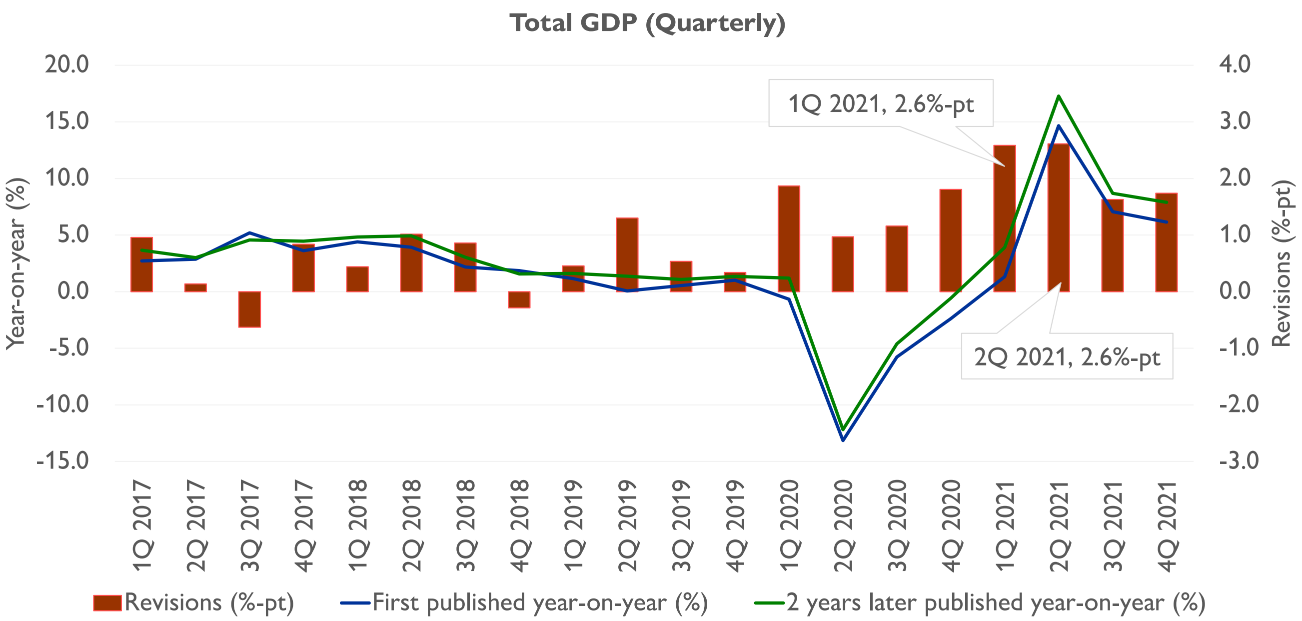
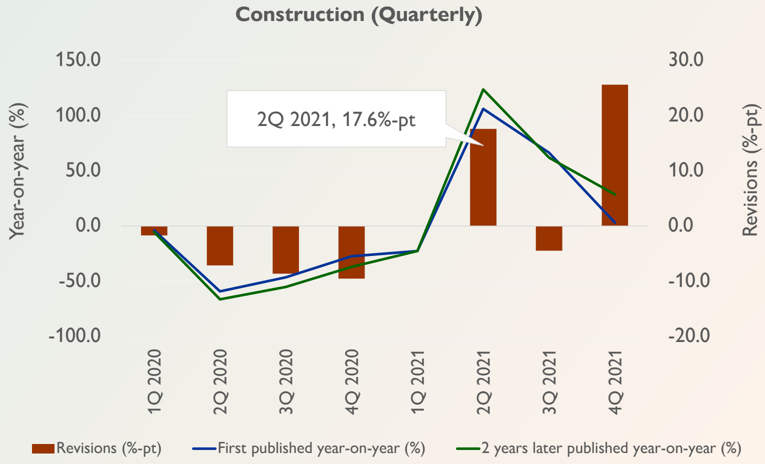


CHART 2 PRELIMINARY GDP GROWTH RATES AND REVISIONS 2 YEARS LATER (CONT'D)

For reference quarters in 2020 and 2021, growths for the Construction industry were revised following the incorporation of annual survey benchmarks. The survey showed that the level of construction activities in 2020 was lower than estimated with stoppage of works due to the tightening of COVID-related restrictions. On the other hand, the level of activities in 2021 was generally higher than estimated with the resumption of works after the relaxation of restrictions.

CHART 2A
PRELIMINARY GROWTH RATES AND REVISIONS 2 YEARS LATER FOR CONSTRUCTION

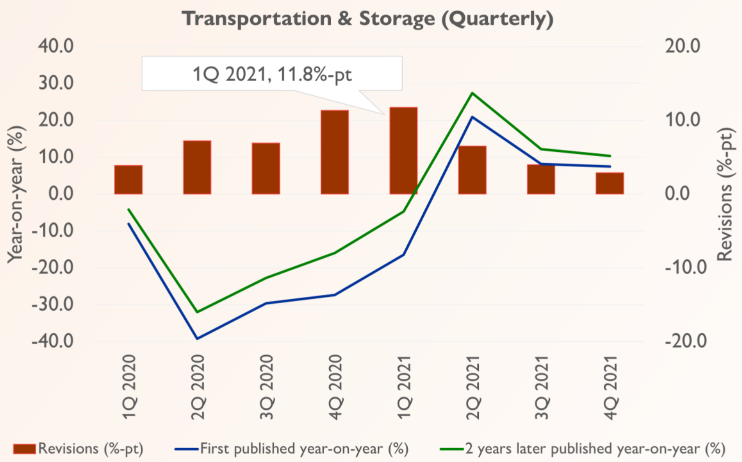


For reference quarters in 2021, the annual survey benchmark showed that wholesalers trading in machinery, equipment and supplies expanded more strongly than estimated, following the surge in telecommuting since 2020.

CHART 2B
PRELIMINARY GROWTH RATES AND REVISIONS 2 YEARS LATER FOR WHOLESALE TRADE

Growth revisions to the Transportation & Storage industry in 2021 were largely attributed to better performance of water transport as the annual survey returns showed that demand for shipping services was stronger than estimated.

CHART 2C
PRELIMINARY GROWTH RATES AND REVISIONS 2 YEARS LATER FOR TRANSPORTATION & STORAGE



Revisions to the seasonally-adjusted (SA) quarter-on-quarter (q-o-q) GDP growth for the reference period 4Q 2008 to 4Q 2023 are presented in Table 2[6]. The mean absolute revision recorded as at the AES one year and two years later are 0.46 and 0.62 percentage points respectively. The SA q-o-q GDP growth are used as the basis of comparison with other countries.

TABLE 2

MEAN ABSOLUTE REVISIONS TO SEASONALLY-ADJUSTED QUARTERLY GDP GROWTH ESTIMATES (Q-O-Q)

Real GDP SA Growth (quarter-on-quarter)	Mean Absolute Revisions (%)	
Reference Period	Year 1	Year 2
4Q 2008 to 4Q 2023	0.46	0.62

International Comparison

Revision practices and policies, including when comprehensive benchmarking exercises are conducted, vary across countries.

Chart 3 shows the relative mean absolute revisions (RMAR)[7] to the SA q-o-q real GDP growth, two years after the release of preliminary data for Singapore and selected countries.

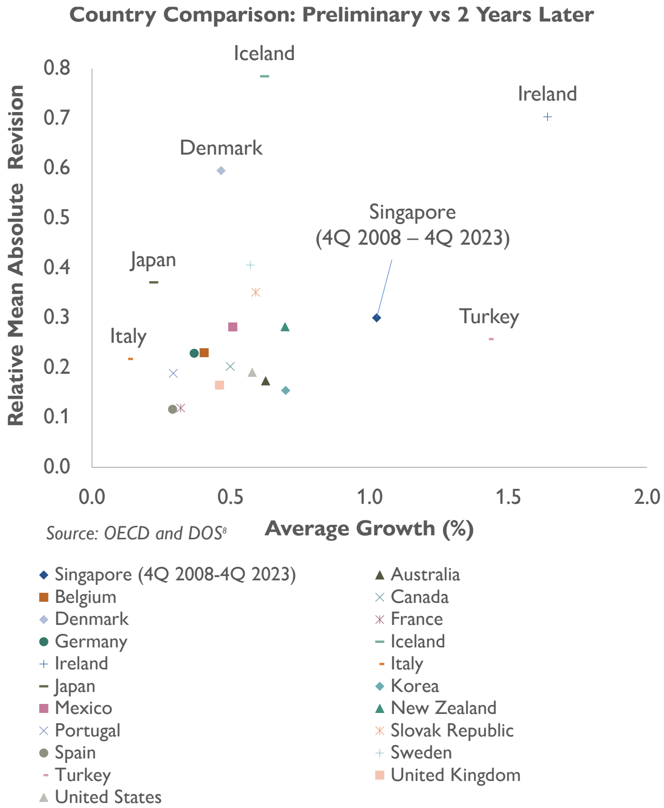
Most of the countries recorded an average SA q-o-q real GDP growths of between 0.3 to 0.7 per cent, with RMAR under 0.4. Italy and Japan experienced the slowest average growths of 0.13 and 0.22 per cent respectively, while Turkey and Ireland registered the fastest average growths of more than 1.4 per cent.

Despite having a similar average growth with most countries, Iceland recorded an exceptionally high RMAR of close to 0.8, which was more than double that of most other countries.

With an average growth of 1.0 per cent, Singapore's RMAR is comparable to that of most other developed countries.

CHART 3

COUNTRY COMPARISON OF RELATIVE MEAN ABSOLUTE REVISIONS TO SEASONALLY-ADJUSTED QUARTERLY GDP GROWTH ESTIMATES (QUARTER-ON-QUARTER, %)



Source: OECD and DOS[8]

Concluding Remarks

Singapore's GDP estimates are regularly revised to refine the initial estimates, incorporating new and more complete data and improvements to compilation methodology. These revisions make the GDP estimates more reliable and ensure that they can be compared across different time periods, helping users make better economic judgments based on consistent and reliable data.

The Singapore Department of Statistics (DOS) regularly updates GDP estimates by including the latest and most comprehensive data, consistent with international best practices. Singapore's RMAR is comparable to that of other developed countries. Revisions may become larger with greater global economic and political uncertainties. DOS will continue to monitor these revisions to the GDP estimates as part of its quality assurance process.

6 Real GDP SA data are only available from reference period 4Q 2008.

7 Relative mean absolute revision (RMAR) statistic corrects the mean absolute revision by the size of the growth rates. This measure facilitates comparability across countries as revisions are expected to be larger in periods of high growths than in periods of slow growths, and vice-versa.

8 The countries' revisions are compiled based on published data for reference period 1Q 2010 to 3Q 2023, subject to data availability. Only seasonally-adjusted data are available for comparison. For Singapore, RMAR and average growth remain unchanged at 0.30 and 1.0% respectively if the reference period is shortened to only cover from 1Q 2010 to 3Q 2023.

Rebasing of the Import, Export, Singapore Manufactured Products and Domestic Supply Price Indices (2023 = 100)

by Toh Wei Jun, Tan Bing Xiang and Li Pei Pei
Prices Division
Singapore Department of Statistics

Introduction

The Import Price Index (IPI), Export Price Index (EPI), Singapore Manufactured Products Price Index (SMPPI) and Domestic Supply Price Index (DSPI) compiled by the Singapore Department of Statistics (DOS) are used to track price movements of goods and measure the real value of the trade and manufacturing sectors as well as domestic supply of goods.

Periodic rebasing of the indices ensures that the commodities used in the computation of the price indices account for changes to the latest trade, manufacturing and supply patterns. In the latest exercise, these producer price indices were rebased from base year 2018 to 2023.

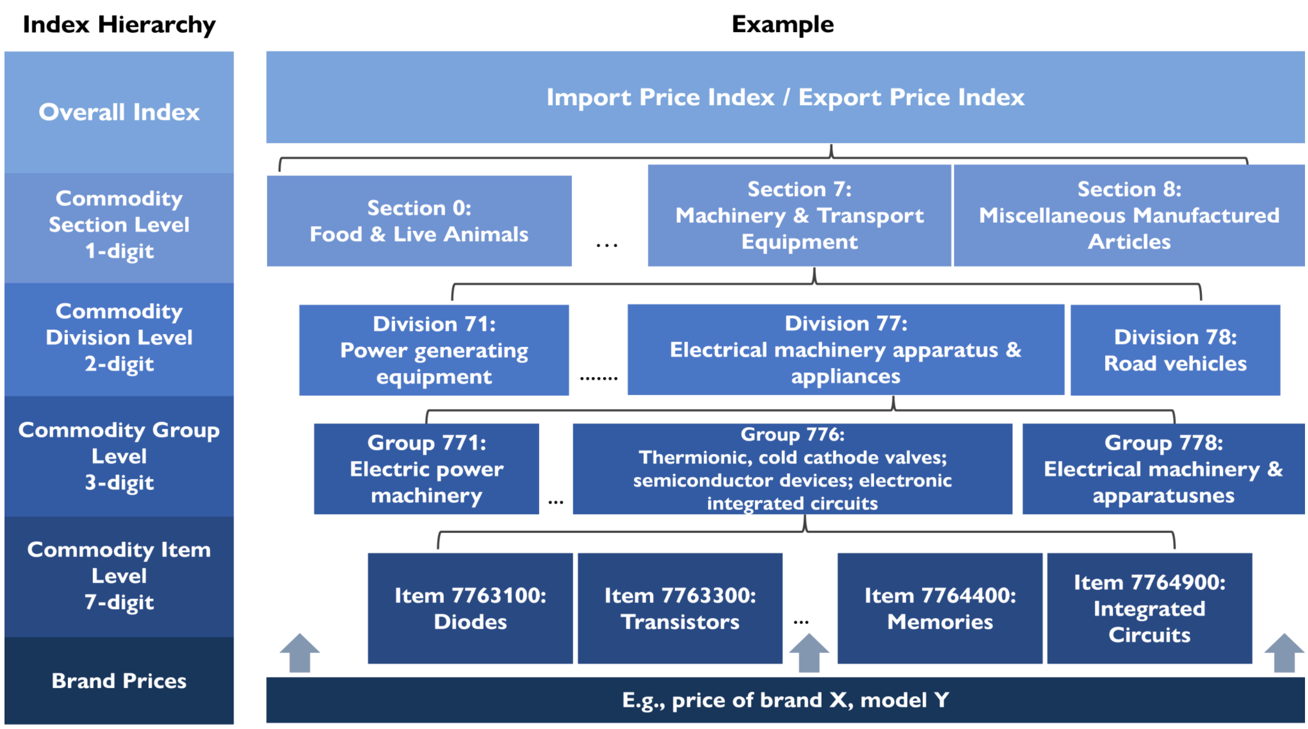
This article provides an overview of the rebasing exercise for the four prices indices, highlighting the changes in the weighting patterns and trends between the 2023-based and 2018-based indices.

Definition and Index Structure

The IPI, EPI and SMPPI measure the price changes of merchandise imports, merchandise exports and Singapore manufactured products respectively. The DSPI is an index derived from the IPI and SMPPI, which measures the price changes of commodities used in the domestic economy.

The price indices are structured in accordance with the Standard International Trade Classification, Revision 4.1 (SITC Rev 4.1)[1]. The most detailed level of this classification is the 7-digit commodity item level (e.g., Integrated Circuits). Higher or broader levels include:

- 3-digit group level (e.g., Semi-conductor Devices, Electronic Integrated Circuits)
- 2-digit division level (e.g., Electrical Machinery Apparatus & Appliances)
- 1-digit section level (e.g., Machinery & Transport Equipment)



1 The Standard International Trade Classification (SITC) is a product classification of the United Nations used for the publication of statistics on export and import values and volumes of goods. Classifying products based on the SITC allows for international comparisons of commodities and manufactured goods.

Survey Coverage and Products Selection

In the 2023 rebasing exercise, purposive sampling was used in the selection of commodity items with (7-digit SITC codes); only commodity items that were significant in their respective sections were selected.

Thereafter, the selected major importers, exporters and manufacturers of the chosen commodity items provided details on the product, model or brand specifications during the preliminary survey of the rebasing exercise. The surveys involved about 2,700 importers, 1,600 exporters and 1,200 local manufacturers.

Only products that were available on a frequent and regular basis and of significance to each selected company were then chosen to be included in the respective basket of goods of each price index.

Table 1 lists the final selection of the baskets of goods for the respective indices and the number of businesses covered.

TABLE 1

NUMBER OF SELECTED COMPANIES, COMMODITY ITEMS AND PRODUCTS COVERED UNDER THE 2023-BASED PRICE INDICES

	Number of Companies Covered	Number of Commodity Items	Number of Products[2] Selected
IPI	843	546	2,521
EPI	527	315	1,590
SMPPI	329	158	851
DSPI	-	591	-

Weights Distributions

Up-to-date data sources were used to derive the weights distribution for the 2023-based price indices.

The weights at the 1-, 2-, 3- and 7-digit levels for the IPI and EPI were compiled from the 2023 merchandise import and export values[3] while the weights for the SMPPI were derived using the 2022 production values[4]. For the DSPI, the weights were based on the 2022 retained imports[5] and domestic production sales[6] values.

Chart 1 compares the weight distribution between the 2023-based and 2018-based price indices.

The Machinery & Transport Equipment section remained the leading section for all indices base year 2023. The Machinery & Transport Equipment, Oil (Mineral Fuels) and Chemicals & Chemical Products sections continued to be the top three sections across all four price indices.

Together, these sections represented at least 80% of the total weight of each 2023-based index.

Trend Comparison: 2023-based vs 2018-based Price Indices

Chart 2 provides a comparison of the trends observed in the 2023-based and the 2018-based indices over the period of January to December 2023.

For all four indices, the overall trends of the 2023-based series were less volatile as compared to those of the 2018-based series, with a smaller increase registered in the third quarter of 2023 for the IPI and DSPI.

Similarly, a smaller decrease was observed in the fourth quarter of 2023 for the IPI, SMPPI and DSPI.

2 The product level is the level at which prices are collected e.g., Brand AA Integrated Circuit Type Model ABC123.

3 Import and Export values are obtained from the International Merchandise Trade Statistics compiled by Enterprise Singapore (ESG).

4 Production values are obtained from the Census of Manufacturing Activities conducted by the Singapore Economic Development Board (EDB)

5 Retained imports refer to the values of imports less re-exports.

6 Domestic production sales refer to the total production value of local producers less exports.

CHART 1 COMPARISION OF WEIGHTS DISTRIBUTION BETWEEN 2023-BASED AND 2018-BASED PRICE INDICES

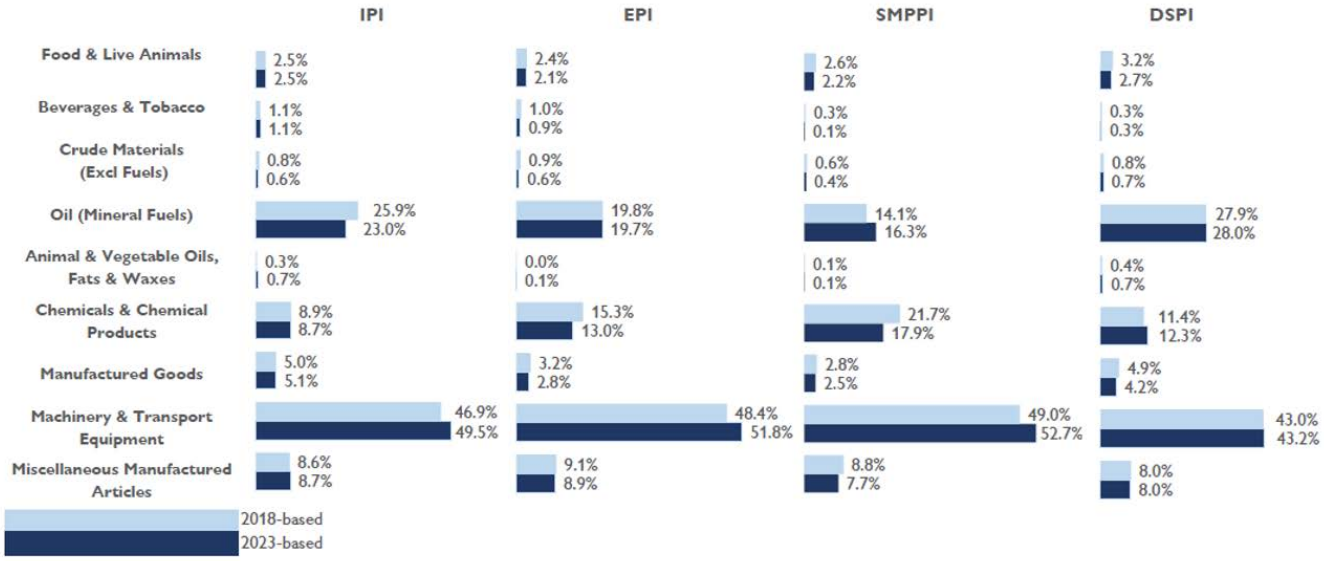
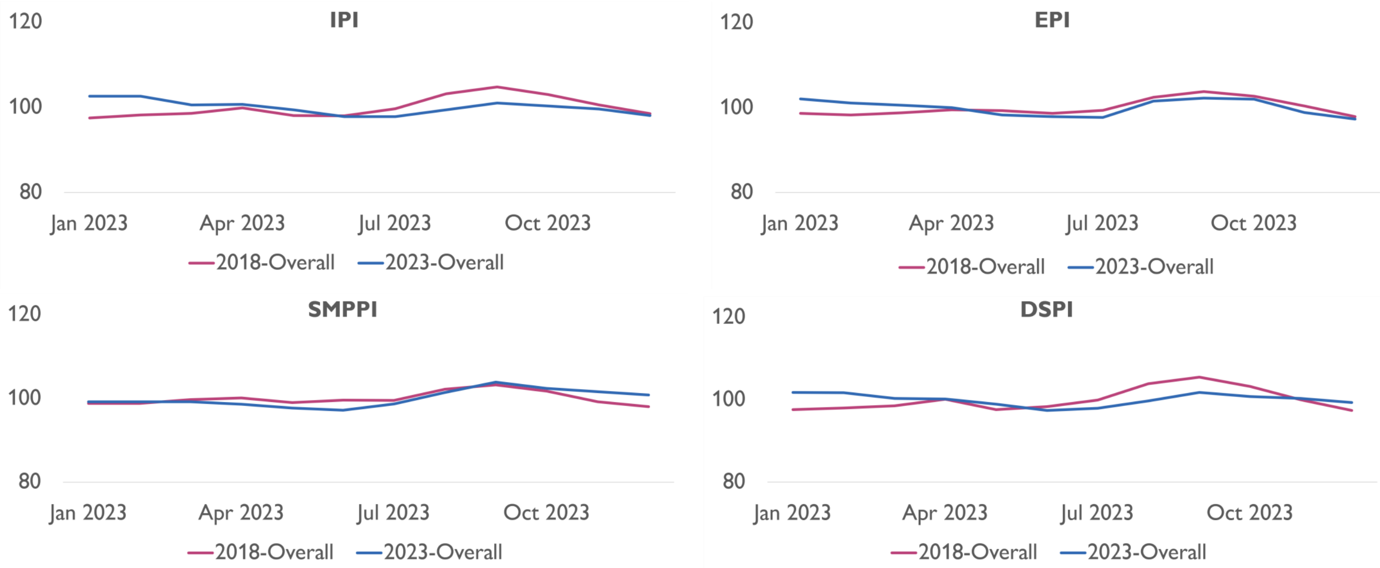


CHART 2 COMPARISION OF 2023-BASED AND 2018-BASED PRICE INDICES



Conclusion

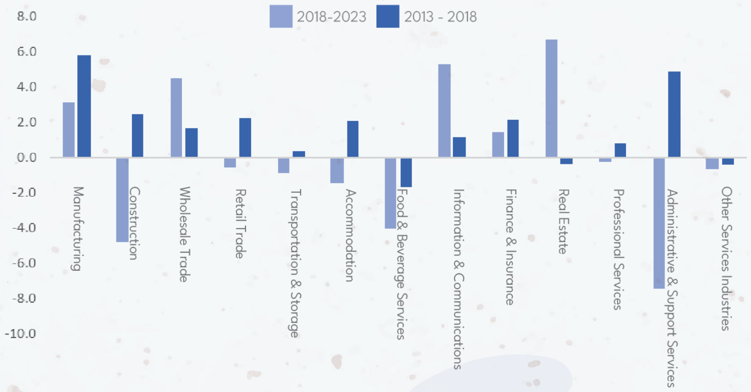
In the 2023 rebasing exercise, the baskets of goods used for the compilation of the IPI, EPI, SMPPI and DSPI, along with their respective weights have been refreshed, consequently improving the quality and representativity of the indices. The next rebasing exercise will be carried out in the next five to six years, in accordance with international guidelines for the rebasing of producer price indices.

For more details on the latest rebasing exercise of the four price indices, please refer to the Information Papers 'Rebasing of the Import and Export Price Indices (2023=100)' and 'Rebasing of Singapore Manufactured Products and Domestic Supply Price Indices (2023=100)'.

Monthly reports on the latest IPI, EPI, SMPPI and DSPI are released on the SingStat Website. Data on the indices are available on the SingStat Table Builder.

Recent Trends in Labour Productivity

Compound Annual Growth rate (%) of Real Productivity[1]



The Wholesale Trade, Information & Communications and Real Estate industries registered higher compound annual growth rate (CAGR) of real productivity during the five-year period from 2018 to 2023 compared with the preceding five-year period. On the other hand, the **Construction, Retail Trade, Transportation & Storage, Accommodation, Professional Services and Administrative & Support Services industries registered a negative CAGR** from 2018 to 2023, reversing the positive growth recorded in the preceding five-year period.

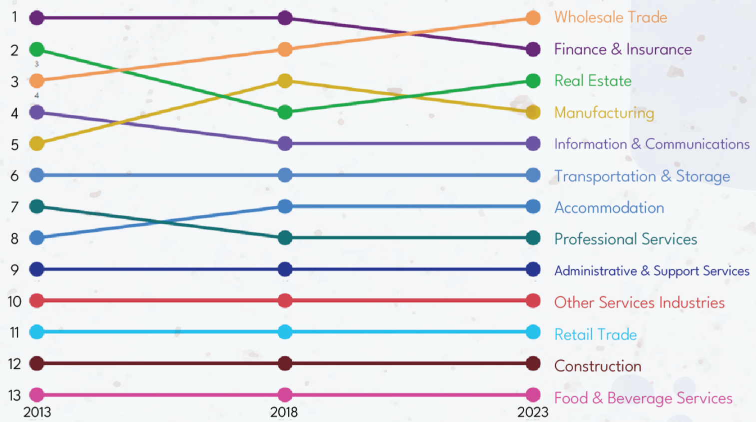
[1] Measured by real value added per worker, computed based on gross value added at basic prices in chained (2015) dollars.

Ranking of Nominal VA per worker[2] by Industry

Finance & Insurance was the most productive industry in 2013 and 2018 but was overtaken by the Wholesale Trade industry in 2023. Food & Beverage Services, Construction and Retail Trade were the least productive industries during these periods.

The Real Estate industry improved in its productivity ranking to be among the top three most productive industries in 2023, while the Manufacturing industry slipped in its ranking.

[2] Nominal value added per worker computed based on gross value added at current basic prices.

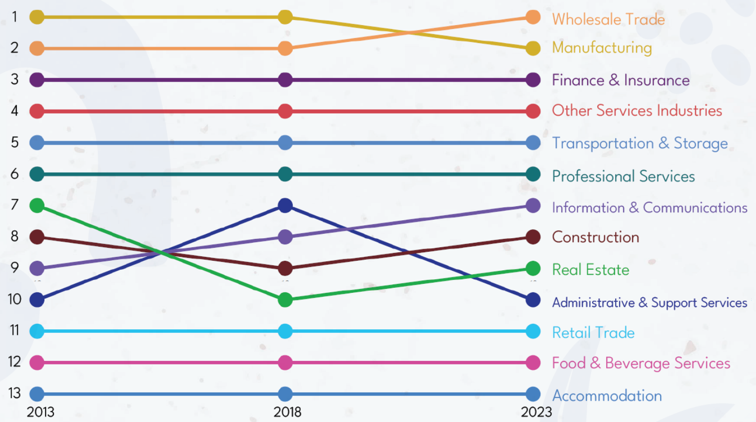


Ranking of GDP Share[3] by Industry

In 2013, 2018 and 2023, the Wholesale Trade, Manufacturing and Finance & Insurance sectors had the highest nominal GDP shares. Conversely, the Accommodation, Food & Beverage Services and Retail Trade industries had the smallest GDP shares.

In 2023, Wholesale Trade overtook Manufacturing as the industry with the largest GDP shares.

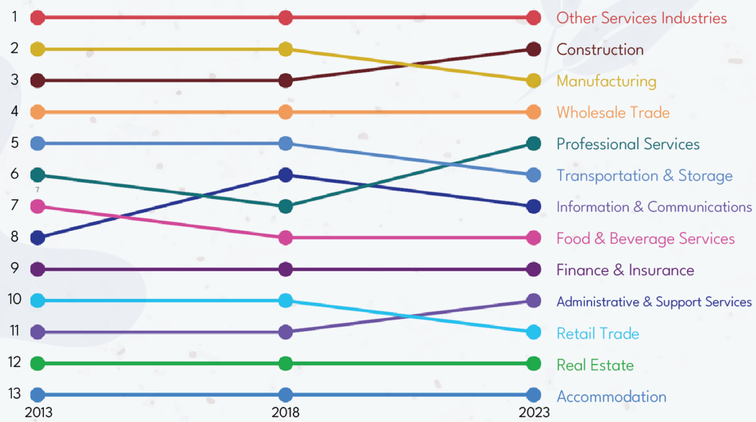
[3] Refers to the share of nominal gross value added by industry. To ensure similar breakdowns across all variables, ranking computed above excludes utilities, other goods industries, and ownership of dwellings.



Ranking of Employment Share[4] by Industry

The Ministry of Manpower's data on employment levels by industry in December showed that the Other Services Industries (which includes activities such as Public Administration & Defence, Education, Health & Social Services, Arts, Entertainment & Recreation), along with the Construction and Manufacturing industries, employed the most workers in 2013, 2018 and 2023[P], while the Real Estate and Accommodation industries employed the least. **In 2023[P], more workers were employed in the Construction industry than in Manufacturing.** The Retail Trade industry was among the industries with the lowest employment shares in 2023[P].

[4] Source: Administrative Records and Labour Force Survey, Manpower Research & Statistics Department, MOM. Data are primarily from administrative records, with the self-employed component estimated from the Labour Force Survey.
[P] : Preliminary



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SINGAPORE 2023

ECONOMY

Real Gross Domestic Product Growth was
1.1%
SINGAPORE'S GROSS DOMESTIC PRODUCT
Singapore's Gross Domestic Product Dashboard

Gross National Savings reached
S$274.6 bil

Per Capita Gross National Income was
S$95,455

Labour Force Participation Rate was
68.6%

Overall Unemployment Rate was
1.9%

International Visitor Arrivals was
13.6 mil

Nominal Value Added for the Manufacturing Sector was
S$115.6 bil

Investment Commitments in Manufacturing and Services (Fixed Assets Investments) amounted to
S$12.7 bil

Inflation Rate was
4.8%
Why does the reported inflation differ from my personal experience?
Why does the reported inflation differ from my personal experience? Infographic

Air Cargo Tonnage was
1.7 mil tonnes

Sea Cargo Handled reached
591.7 mil tonnes

Total Merchandise Trade was
S$1,205.7 bil

SOCIO-DEMOGRAPHY

Total Population was
5.9 mil as at end-Jun 2023
Population Trends Dashboard

Mean Years of Schooling was
Male: **12.0 years**
Female: **11.4 years**
for residents aged 25 years and older

Proportion of Owner-Occupied Resident Households* was
89.7%

Total Marriages was
28,303^P

Resident Total Fertility rate was
0.97 per female

Mobile Population Penetration Rate reached
163.8%

Residential Wired Broadband Household Penetration Rate was
92.1%

Median Monthly Household Income from Work Per Household Member was**
S$3,500
Why does the reported median household Income differ from my personal experience? Infographic

Physical Crimes rate was **337**
Scams & Cybercrimes rate was **851**
per 100,000 population

P: Preliminary
* Refers to the proportion of households where the household reference person and / or any other member(s) in the household owns the dwelling unit.
** Includes Employer CPF Contributions.

Find out more: Singapore Economy Infographic

Find out more: Singapore Population Infographic

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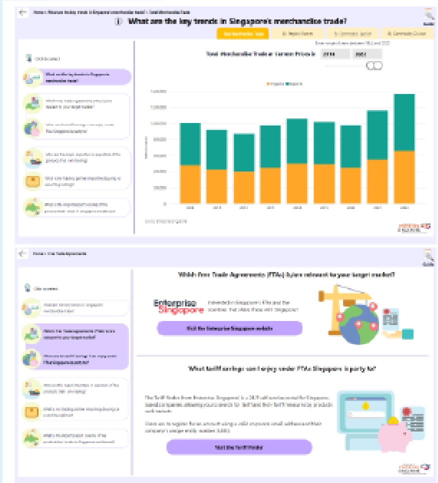
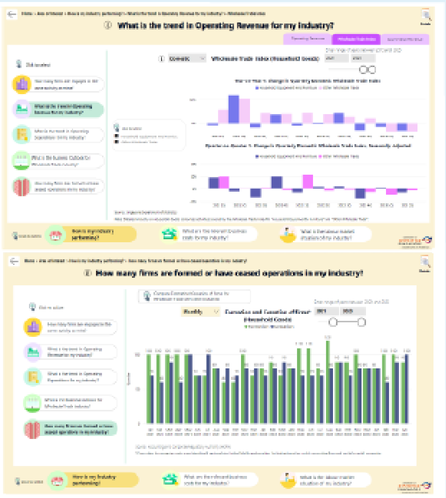
DATA TOOLS FOR WHOLESALE TRADE INDUSTRY NOW AVAILABLE ON THE SINGSTAT WEBSITE

Provides Customer Insights

Use the ‘**Know My Trading Partners**’ data tool to gain insights on trends in Singapore’s international trade, free trade agreements and key trade statistics.





Provides Industry Insights

Use the ‘**Know My Industry**’ data tool to understand industry trends, business outlook, business/ rental costs and labour market situation.

Facilitates Benchmarking of Performance

Use the ‘**Benchmark My Performance**’ data tool to compare financial ratios, efficiency ratio, profit margin, profit per worker and revenue per worker.

Access the data tools at [Data for Businesses](#).

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OVERSEAS VISITORS

During October 2023 to March 2024, the Singapore Department of Statistics (DOS) hosted virtual sharing sessions with Japan and New Zealand, and jointly conducted virtual sharing sessions with ASEAN Secretariat's ASEAN Statistics Division.

Digital Agency, Government of Japan

Research Team led by Mr Hiroyuki Orita, Director, Council for Digital Administrative and Fiscal Reforms

Statistics New Zealand

- Team led by Mr Mark Sowden, Government Statistician, Government Chief Data Steward and Chief Executive of Stats NZ
- Team led by Mr Pedro Souza, Senior Advisor, Customer Insights

Sharing Sessions under ASEAN-Help-ASEAN Framework

National Statistical Offices of ASEAN Member States

EXPERTISE SHARING AT INTERNATIONAL FORA

During October 2023 to March 2024, DOS also shared our expertise at the following international fora:

Asia-Pacific Stats Café Series: Data Governance across Asia and the Pacific, with a Focus on the East and North East Asia Subregion

Featured DOS's Chief Statistician as speaker

Joint Meeting of the Steering Groups of the UN Economic and Social Commission for Asia and the Pacific Committee on Statistics

Presented on Data Governance and Management in DOS

28th Meeting of the Wiesbaden Group on Business Registers

Presented on Experimental Use of New Data Sources for Prompt Identification of Changes in Firms' Status

4th Meeting of the Workgroup on Measuring E-commerce and the Digital Economy and Task Group Meeting on Measuring E-commerce Value

Presented on Measuring E-commerce in Singapore

Asia-Pacific Stats Café Series: Measuring E-commerce and Consumer Price Index (CPI) Online Price Collection

Presented on Online Price Collection for the CPI and Experiences on the 2021 International Comparison Programme

13th Session of the ASEAN Community Statistical System Committee (ACSS)

Presented on the End-Term Review of the ACSS Strategic Plan and DOS's Public Communications Capabilities as well as the Pilot Programme on the Use of APIs for Data Submission

22nd Technical Evaluation and Review Workshop on 2021 International Comparison Program (ICP) for Asia and the Pacific

Presented on Web Scraping for the Compilation of Consumer Price Index (CPI), Integration of ICP with CPI in ICP 2021 and Proposed Survey Framework for ICP 2024

18th Management Seminar for the Heads of National Statistical Offices in Asia and the Pacific

Presented on Singapore's Experience in Applying Fundamental Principle of Official Statistics - Misuse of Statistics

38th Meeting of the Voorburg Group on Service Statistics

Presented on Singapore's Producer Price Indices E-Survey System

GovInsider: Festival of Innovation 2024

Represented in the panel as speaker on Open Data: Enabling Transparency and Accountability in Government

HEAR FROM OUR OFFICERS ON THEIR INTERNATIONAL STATISTICAL INVOLVEMENT

Suzanne Wong
Deputy Director,
Business Statistics Division,
Member of the United Nations Advisory Committee on Post Adjustment Questions (ACPAQ)

The ACPAQ is an expert subsidiary body of the International Civil Service Commission (ICSC). The Advisory Committee provides technical advice on the methodology of the UN Post Adjustment System (PAS), which is designed to equalise the purchasing power of the remuneration of UN officials serving in different locations around the world. As a member of the Advisory Committee, I advise the ICSC Secretariat on various aspects of the methodology underpinning the PAS, including cost-of-living measurements and calculations of related indices, and the development of general statistical methodology. I also review the methodological research and development undertaken by the Secretariat and make recommendations to the Commission.

My work in the Advisory Committee aligns with DOS's commitment to international collaboration and engagement, and the sharing of expertise and best practices to address common challenges and priorities. I am honoured to contribute my statistical knowledge and experience in the Advisory Committee, and to work alongside esteemed colleagues in the field of price statistics, survey methodology and international comparison of cost-of-living.

The work performed by ACPAQ is done in full independence and with impartiality. So, while I serve in the Advisory Committee in my personal capacity, my appointment is a reflection of the international community's trust and confidence in the integrity and professionalism of DOS and the Singapore Public Service.

Image source: https://icsc.un.org/Home/ACPAQSubsidiary

Ng Li Hiang
Senior Manager,
Input-Output Tables Division,
Seconded to the Organisation for Economic Co-operation and Development (OECD) in Paris, France

I had the opportunity to be seconded to the OECD for 11 months where I joined the National Accounts Division of the Statistics and Data Directorate. I was part of the Environmental-Economic Accounts team and contributed to the work on air emissions, energy flows, and mineral and energy resources. I also participated in the digital economy statistical work on the digital supply and use tables, as well as 'data as an asset' which is one of the main changes to be introduced in the revised international macroeconomic statistics guidelines.

During the secondment, I had the opportunity to collaborate with the colleagues in the OECD, other international organisations such as the United Nations and National Statistical Offices. The secondment has been a valuable experience and I look forward to applying what I have learnt to my work in DOS and fostering collaboration opportunities with international organisations and National Statistical Offices.

Release of SSOC 2024

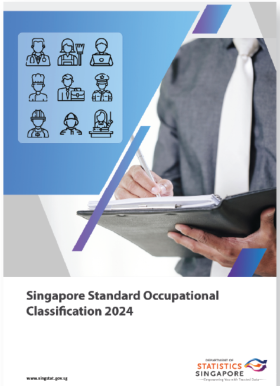
The Singapore Standard Occupational Classification (SSOC), the national statistical standard for classifying occupations, has been updated and released!

KEY CHANGES FOR SSOC 2024

- Replacement of 'Skill Specialisation' and 'Skill Level' terminologies by 'Broad Job Specialisation' and 'Broad Job Level' respectively
- Creation of new codes to reflect the emerging occupations, especially in the Infocomm Technology sector
- New minor group created for Social Services, Counselling and Related Professionals
- Reclassification of occupations to more appropriate SSOC codes
- Improvements to occupation titles, alphabetical index and detailed definitions

SSOC 2024 AT A GLANCE

- 14th edition of the SSOC.
- Reviewed by a multi-agency working group led by DOS.
- Covered more than 1,000 occupations (5-Digit SSOC).
- About 20 obsolete occupations removed and over 20 new occupations created.



Access the latest SSOC 2024 documents at **go.gov.sg/ssoc**

Use the SSOC Search for a quick and easy search of occupations and codes at **go.gov.sg/ssoc-search-engine**

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Statistics Singapore Newsletter Issue 1, 2024

The Statistics Singapore Newsletter is issued twice a year by the Singapore Department of Statistics.

It aims to inform readers on recent statistical findings as well as latest information on statistical methodologies, processes, products and services.

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