Collaborative guidance paper on SPPI and output compilation during economic shocks

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Response rates and Pandemic effects in business sectors by Christian Stock, Service Producer Price Index, Statistics Austria

Output compilation during economic shocks: Revisiting imputation by Rohan Draper, Methodology and Analysis, Statistics Denmark

PPI seasonal adjustment during the COVID-19 pandemic by Jonathan Weinhagen, Producer Price Index, Bureau of Labor Statistics, U.S.

Output compilation during economic shocks: alternative data sources for advanced signals in service industries by Marie-Christine Bernard, Retail and Service Industries Division, Statistics Canada

Table of contents

1 Response rates

An unprecedented economic shock complicates the work of National Statistical Offices (NSOs) to produce high quality price and output statistics. Surveys of business units and administrative data were getting more difficult during the COVID-19 pandemic compared to an economically stable environment. This economic shock has affected response rates on collected data in many ways. Different strategies from NSOs all over the world were implemented to keep response rates at a high level since the outbreak of the pandemic in late 2019.

The COVID-19 pandemic is not necessarily directly comparable to other global economic crisis (e.g. financial crisis started in 2007) but provides insights into possible effects on response rates in surveys from NSOs. There were additionally restrictions from governments on social life worldwide which had large effects on selected industries. The accommodation and food service activities sector, for example, were one of the most affected industries by the pandemic.

1.1 Survey characteristics

As mentioned in the Voorburg paper from the U.S. (2021), response rates measure the percentage of data received by a survey. The basic formula from the U.S. paper is stated below and can be calculated as follows:

- (Number of prices received for a period of time)/(number of prices requested for a period of time)*100

Different periodicities (e.g. monthly, quarterly or yearly) in output and price surveys have to be considered when looking at data collection and response rates for industries. Basically, there is more flexibility with regard to time when data collection is yearly. In many surveys NSOs allow for late prices and corrections following the first index publication. This data enters the final index publication.

Mandatory surveys are useful in practice. There are strategies (e.g. monetary incentives) to increase response rates for voluntary surveys but normally they are not the same as for mandatory surveys.

In Austria, the quarterly Service Producer Price Indices (SPPI) survey for accommodation and food service activities started because of a Eurostat grant on a voluntary base from 2022 to 2023 with base year 2021. Reporting units were informed about the respective Austrian law which regulates the obligation to respond to the survey from 2023 onwards. Only 10 - 20 percent of the OENACE 5-digit level samples answered to the survey during the voluntary periods of time. It is expected, as for other service industries, that response rates will increase up to nearly 100 percent after a few quarters.[1]

[1] Austria legislation regulates the obligation for reporting units to the SPPI survey since the start of the survey with first base year 2006

1.2 Different phases in surveys

Response rates are not equal during various phases of surveys. They may be completely different in the initialisation phase of a survey compared to ongoing data collection. In addition, there are regular revisions of indices which can result in changes of response rates because of adjusted samples.

Possible phases in SPPI surveys:

- Development of new SPPIs
- Revision of existing SPPIs
- Ongoing price collection of SPPIs

The focus in this chapter is on ongoing price collection of SPPIs with regard to response rates. Experiences from output compilation are also mentioned hereafter.

The Eurostat-OECD Methodological Guide for Developing Producer Price Indices for Services (Eurostat-OECD SPPI Guide) recommends index formula as follows:

In general, it is recommended that the European Union member states should use a Laspeyres-type index formula that is in line with the EU short-term statistics regulation, which specifies all relevant aspects of the collection of service producer prices in the EU.[2] The index reference period refers to the period for which the index is set equal to 100. Eurostat set index reference periods normally every five years. With the exception of 2021, the upcoming base year will be 2025. It is a challenge for NSOs and reporting units if a base year falls into a pandemic or economic crisis. This can result in index computation issues due to incomplete survey data or unusual index movements.

1.3 Timely price collection

A timely price collection is important for the initialisation questionnaire in SPPI surveys as well as for ongoing price and output data collection. There are several possibilities to ensure that respondents return a correctly and fully completed questionnaire in a timely manner. One possible option could be a reminder system with administrative penalty proceedings if a reporting unit refuses to respond to a survey.

In times of a pandemic or an economic crisis, it makes sense to allow certain exemptions instead of financial penalties. During the COVID-19 pandemic Sweden[3] and Austria made use of cancelling financial penalties for surveys. Despite a difficult environment like the pandemic, alternatives in economic crisis are intensifying contacts to respondents via online-meeting tools, emails or telephone or grant extensions for submitting questionnaires.

Delays in administrative data deliveries are more likely in economic crisis. For example, during the COVID-19 pandemic in Austria the submission of financial statements issued by

[2] OECD/Eurostat (2014), Eurostat-OECD Methodological Guide for Developing Producer Price Indices for Services: Second Edition, OECD Publishing. http://dx.doi.org/10.1787/9789264220676-en, page 83
[3] Voorburg paper from Sweden (2022), Dealing with economic shocks – Corona pandemic in Sweden, page 2

enterprises was extended by financial authorities. The publications of output statistics were in time, only the data delivery was shortly delayed.

1.4 Initialisation process

For new sample units, the Eurostat-OECD SPPI Guide recommends in the initialisation phase of SPPI surveys the following:

Ideally, initialisation of new sample units should involve a personal visit. Where this is not possible, the initialisation may require pre-contact research, telephone calls and a dedicated (initialisation) questionnaire.[4]

Personal visits are not always possible even in times of a stable economic environment. Due to cost saving reasons, NSOs have chosen other communication channels to get in touch with respondents. Responding units were traditionally provided with an introduction to the SPPI survey and questionnaires by mail. Other possibilities of initial contact could be telephone calls or emails in combination with an initial notification via mail or electronically. Online-meetings have proved to be also very useful not just in recent COVID-19 pandemic. It is possible to present information materials and / or to support respondents in direct manner for the first use of an online survey.

Instead of initialisation of new responding units via personal visits, online-meeting tools could replace personal visits. They are cost-efficient and offer useful tools for the initialisation team and respondents. Such tools may help to increase response rates for surveys during economic crisis as well as in times of a stable economic environment.

1.5 Ongoing price and output collection

After the initialisation process in SPPI surveys, respondents are informed about the reporting of detailed service products and prices. Ideally, respondents report data in an online application form. Nevertheless, ongoing price collection could be disrupted by an unprecedented economic shock to the economy. Services may change or become unavailable. Some service sectors (e.g. accommodation and food service activities) were affected more by the COVID-19 pandemic than others.

NSOs also thought about their sample sizes during the COVID-19 pandemic. In comparison to stable economic conditions sample sizes can vary due to different strategies of NSOs in a crisis. Statistics Canada collected a smaller portion of the sample for the annual Service Industries Program in 2020.[5] Statistics Sweden increased their sample sizes for some surveys, mainly short-term statistics such as Turnover in the service sector and Index of Service Production.[6] It is difficult to recommend a certain sample change with regard to response rates at that time. Normally, response rates are expected to decrease in an economic crisis. The extent of the

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[4] OECD/Eurostat (2014), Eurostat-OECD Methodological Guide for Developing Producer Price Indices for Services, page 76

[5] Vooburg paper from Canada (2022), Dealing with economic shocks: How Statistics Canada pivoted during the pandemic, pages 2-3

[6] Vooburg paper from Sweden (2022), Dealing with economic shocks – Corona pandemic in Sweden, page 2

decrease is dependent on the crisis itself, particular survey characteristics as well as on the observed industries individually.

According to the Eurostat-OECD SPPI guide, price observations should undergo both input and output editing. The availability of respondents during the pandemic was not described as a huge problem for NSOs in the Vooburg Group papers. Availability was given if electronical devices were used by NSOs and enterprises.

As mentioned in the Canadian Voorburg paper 2022, business closures can be temporary or permanent in economic crisis. For example, Austrian enterprises in the accommodation and food service activities sector had to close their businesses for a certain time in the COVID-19 pandemic. Some of them had not opened directly after the lockdown periods ended.

The revenue-weighted response rates for selected annual surveys of service industries in the Service Industries Program in Canada were lower for 2020 compared to 2018. These response rates were lower for RY 2019 compared with those of the recent past. For some service sectors (e.g. Architectural services) minor changes could be observed when looking at 2020 in comparison to 2018. Few of them (e.g. Travel arrangement services) showed greater deviances in the COVID-19 pandemic.[7] For structural business statistics (SBS, ouput statistics on a yearly basis) in Sweden and SPPI statistics in Austria the unit response decreased only slightly in 2020 compared to previous years.[8] Similar results were provided by the U.S. for PPI response rates by sector. For nearly all industry sectors from March 2020 through March 2021, compared to pre-pandemic levels, the response rates were similar to before the pandemic. A large decline was observable for the sector entertainment, accommodation, and food services.[9]

Surprisingly, the unit non-response seems to be only slightly lower than in pre-pandemic times. Response rates from strongly affected industries by the COVID-19 pandemic and lockdowns are mentiond in the Voorburg papers. These industries (see Table 1) showed in some surveys decreased response rates. In general, a slight effect was identified on the response rate with regard to enterprises which were not that affected by the pandemic and local countries COVID-19 measurements.

Table 1: ISIC[10] Rev. 4 industries strongly affected by the pandemic

ISIC Rev. 4	Industries strongly affected by the pandemic (or lockdowns during the pandemic)
H 51	Air transport
I 55 and I 56	Accommodation and food service activities

[7] Vooburg paper from Canada (2022), pages 4-5
[8] Vooburg paper from Sweden (2022), page 3
[9] Vooburg paper from U.S. (2021), Lessons Learned from the COVID-19 Pandemic , page 4
[10] ISIC (International Standard Industrial Classification of All Economic Activities). Description: ISIC is the standard industrial classification of economic activities for worldwide use. It was developed by the United Nations. As it should also be applicable for developing countries, the level of detail is not as extensive as in national classifications of economic activities. The current version is the ISIC Rev. 4, which replaced ISIC Rev.3.1.

N 79	Travel agency, tour operator, reservation service and related activities
R R 90 R 91 R 92 R 93	Arts, entertainment and recreation Creative, arts and entertainment activities Libraries, archives, museums and other cultural activities Gambling and betting activities Sports activities and amusement and recreation activities

2 Output compilation during economic shocks: Revisiting imputation

2.1 Introduction

Economic shocks have the capacity to introduce extraordinary scenarios that test the limits of contemporary methodologies and statistical process and production capabilities. Often such occurrences instigate a need to revisit historically held assumptions with an opportunity presenting itself to test the robustness of our price statistics fundamentals. The COVID-19 pandemic[11] was no exception and can arguably be classified as previously unheard of in terms of how invasive and pervasive economic activity was impacted across the globe. Indeed, in some economies entire branches of activity, for all intents and purposes, ceased to operate with production and inherent consumption grinding to an immediate and unprecedented halt.

One of a number of established tools in the price statistician's toolkit is imputation where the practitioner seeks to address the estimation issue through a targeted approach at the item level of the aggregation structure. In regular economic times, such a tried and tested approach provides a reasonable estimation of temporarily missing item level price development. During economic shocks, such as the pandemic, the assumptions that an item level imputation are built upon don't necessarily hold true with the breadth and depth of the imputation impacting much more aggressively the upper calculation levels of aggregation structures.

This thought exercise is seeking to promote discourse towards a more in-depth paper proposing that a concept of preservation is beneficial to be considered in parallel to the imputation and that one may consider what type of preservation is being implicitly realised just as much as what type of imputation is being explicitly applied. By preservation the price statistician considers more explicitly as part of the estimation process the purpose and users of the indicator thus expanding the decision process beyond an estimation at the item level to include resultant impact and outcome.

As stated in the CPI Manual, the principle behind imputation is that it makes use of the best available information to provide an unbiased estimate of price and price movement[12]. In discussing what implicitly or explicitly is being preserved by a certain choice of imputation method this thought exercise hopes to provoke discussion that leads to a more informed basis

[11] According to the World Health Organization (WHO) the COVID-19 pandemic was designated as a public health emergency of international concern (PHEIC) from 30th January 2020 – 5th May 2023.

[12] IMF (2020), *Consumer price index manual: concepts and methods*, Page 237

from which price statisticians can select imputation (preservation) methods that best suit their unique needs and situation.

Furthermore, breaking down imputation decisions in a structured way facilitates the collection and storage of valuable metadata connected to imputation decisions and beyond (for example, quality adjustments). Such repositories of training data enables emerging opportunities for more sophisticated price statistics production solutions unlocking more contemporary data-driven validation options.

2.2 Objectives, scope (and price statistics fundamentals)

In a consideration of *how* to impute and *what* to preserve our objectives and scope (should) play a key role. The aspects that we preserve are directly connected to how the index is being utilised. For a consumer price index (CPI) it is likely that the total aggregate and the annual movement (inflation) are the qualities being targeted for preservation. For a producer price index (PPI) the industry level and annual movement are more likely the targets for preservation. Of course instances can exists where periodic lower level aggregates are also of relevance based on user needs and index type.

During stable periods of economic activity imputation and preservation generally work hand in glove. That is, there are enough observations with similar price determining characteristics that facilitate a representative and unbiased estimate of missing item level observations. In this instance, the more classical application of a class mean imputation or targeted mean imputation would thus fulfil both imputation and preservation.

During economic shocks, however, traditional imputation practises can risk losing this alignment. This was especially apparent during the pandemic due to the extent to which missing data shifted from being localised occurrences to more comprehensive manifestations the level of which shifted on a period-by-period basis. For example, an imputation strategy built using targeted periodic movements may have needed to be reconstructed to utilise overall annual movements to better preserve factors impacting fitness-for-purpose at more aggregate levels. If the retention of the index fitness-for-purpose is more deliberately considered as part of such a decision making process it is perceived that there is a greater likelihood that the most relevant objectives are implicitly preserved and that quality guidance can be provided to users.

To this end, the PPI Manual states, “the accuracy of the method relies on the veracity of the assumptions, not the quality of the explicit estimate”[13] and in the spirit of this statement this thought exercise raises the following as important aspects for consideration:

i. Calculate (index formula) – What assumptions and/or mitigating factors exist within the index formula being utilised for calculation?

ii. Disseminate (level) – Is the key use of the index at the upper most aggregated level (e.g. CPI_{Total}) or at finer levels of detail (e.g. $PPI_{Industry}$; PPI_{Class})?

[13] IMF (2004), *Producer Price Index Manual: Theory and Practice*, Page 155

iii. Disseminate (price development) – Is the key purpose of the price index annual, quarterly or monthly price development?

iv. Disseminate (type) – Is the index published in original terms (unadjusted) or as a seasonally adjusted analytical series?

v. Review and Validate (transaction occurrence) – Why was price information unable to be collected? Has a transaction occurred but a price was unable to be collected or has there been no economic activity for the item during the comparison period?

vi. Review and Validate (substitution) – Has substitution occurred within a category; between categories or has production and/or consumption ceased entirely?

vii. Review and Validate (seasonality) – Is the missing item a highly seasonal product? Does the potential imputation source share the seasonal factor or lack of seasonality of the missing item?

viii. Review and Validate (macro-economic factors) – Are relevant economic factors (for example: employment, wages, interest rates, inventories, exchange rates, supply and demand, competition, regulatory environment) relatively similar or vastly different than previous collection periods?

ix. Review and Validate (imputation source) – Is data available to draw an imputation locally in the aggregation structure (for example, substitution and seasonal factors are localised) or is the missing data more widespread? That is, to what extent are transactions available that have similar price determining characteristics and/or price development?

Contextualising the imputation through using a set of parameters provides guidance and consequently the ability to record decisions in production systems permitting the recording of important metadata that can be applied in future decision-making. This could be enabling reflection on decisions made from one phenomenon to another or even across the life-cycle of the same phenomenon to ensure decisions made entering a new phenomenon are considered in due course at the turning point and when exiting that same phenomenon. After all, in the case of the pandemic, this was not just a singular reporting period for a singular item but rather a collective bundle of imputations forming a sustained strategy over an extended period of time. For users this also has the potential to provide valuable metadata, for example, useful when assessing coherency within statistical domains and across statistical domains.

2.3 Calculating the index

2.3.1 Imputation and preservation

As discussed, a decision on imputation (and preservation) should never be done in isolation but should embrace the objectives and scope of the index in harmonisation with other methods being utilised. Documented metadata describing all of the index fundamentals is an important precursor to making decisions about what to isolate; include; and exclude.

When an imputation is being actioned a decision is being made to impact a particular level of aggregation and also a particular movement (periodic or annual). In other words, more than just imputing a missing observation the aim should be to preserve certain qualities of our indices.

2.3.2 Seasonality

Discussed extensively in PPI, XPI and CPI manuals alike, seasonality deserves a special mention due to its somewhat hidden nature. The essence is that price statisticians should consider each period (month or quarter) as a discrete type of quality. The objective is to appropriately consider that implicit in price index development is a myriad of seasonal factors that need to be handled appropriately. In the way that statistical publications present results referring to a period (t) in comparison to a period (t-12) the seasonal variation is reasonably mitigated. This by necessity should also be considered when imputing missing observations. For example, an imputation using periodic movements from a subset of data that closely aligns to the missing item is a viable option. However, imputation using data higher up in the aggregation structure is likely required to be conducted using an annual movement or risk a price movement based on a quality change due to differences in seasonal behaviours.

2.3.3 How can we harness learnings from the pandemic?

Each option for imputation is out of necessity required to estimate certain qualities whilst holding other aspects constant (or preserved). The objectives and scope of the price index in combination with market conditions contemporary to the production period both play an important role as to which imputation best serves the item level estimate as well as the aggregate level indicator. Explicit item level actions have flow on impacts that implicitly ripple through the aggregation structure either subtly in times of abundant economic activity or more aggressively in times of economic shock.

Pandemic conditions and constraints.

- Widespread social upheaval with unprecedented constraint on movement
- Widespread shift in ability to consume leading to shifting demand side pressures (or lack thereof) and supply side constraints
- Global broad-based phenomenon impacting all sectors impacting both domestic and international supply chains
- Globalised ”just-in-time” economies faced considerable challenges
- Similar to the financial crisis the impact was broad-based in nature

Pandemic challenges for price statistics.

- Widespread missing observations deep in aggregation structures
- Missing observations could be due to inability to collect data; inability for providers to report data; or lack of economic activity
- Substitution occurred outside usual localised bounds
- Pandemic period economic factors unlike historical periods in the near past

- Shrinking levels of total consumption with potential impact on relative transaction shares

The following table provides a non-exhaustive summary of: imputation methods; what is being preserved; the resultant impact; and suitability. The final column “suitability” assigns scenarios that the imputation arguably has the capacity to provide a suitable estimate. Suitability scenarios are:

(1) Transaction has occurred but data could not be collected;

(2) Transaction has not occurred but has shifted to an alternative product/activity;

(3) Transaction has not occurred and there has been no substitution;

(4) Missing data broad-based rather than localised and no neighbouring economic activity is available

The author sees this as a precursor for discussion and eventual ratification rather than prescriptive and community feedback is welcome. A visualisation of the imputation methods are provided in Appendix A: Graphs for visual assessment of imputation methods.

Imputation, preservation and impact.

Imputation	**Preservation**	**Impact**	**Suitability ***
Carry Forward	Previous period price	Prices are left unchanged or "carried forward". This method does not take into account seasonality and will likely show irregular results when reviewing annual movements. When analysing monthly movements the carry forward pushes the aggregate towards no change for the month. In respect to deflation, assumes all value change is volume based.	(1) if prices are fixed or regulated
Historical Imputation (simple)	Historical periodic price development (e.g. monthly) and previous period annual movement.	Essentially a carry forward of the previous period annual movement thus the index is pushed towards the previous period’s annual movement. Seasonality is thus also fixed. Assumes that transactions are occurring as ‘normal’ but data was not able to be obtained. Partially accounts for substitution with products that exhibit similar seasonal behaviour. Does not account for substitution to products with different production factors and/or products that have ceased to be traded.	(1) (2) if similar price determining characteristics
Historical Imputation (average)	Historical periodic price development (based on an average of a select number of periods).	Has the same objective as the Historical Impute (simple) but aims to mitigate one-off irregularities from the previous year by factoring in multiple years.	(1) (2) if similar price determining characteristics

Targeted Mean Imputation (periodic) or (annual)	Price determining characteristics of a very specific subset of economic activity observed to be aligned with the missing observation.	Explicitly at the item level a movement is being chosen (targeted) that has price development qualities considered representative of the missing item. Implicitly the weight of the missing item is being represented by an alternative price development for the given measurement period.	(1) (2) (3) (4)
Class Mean Imputation (periodic) [imputing from the level above in the aggregation structure]	Class level periodic movement is preserved. Actual transactions are exclusively used (may include quality adjustment) therefore preserving known transaction data based on the periodic movement.	Representativeness of the target item has been effectively shifted to other items that still are being transacted and contributing to the next level up in the aggregation structure. The periodic movement for this aggregate is preserved. The imputation can also be seen to effectively presume that activities have been substituted to still actively transacted products. In this case the periodic price change has been utilised.	(1) (2) (3)
Class Mean Imputation (annual) [imputing from the level above in the aggregation structure]	Class level annual movement is preserved. Actual transactions are exclusively used (may include quality adjustment) therefore preserving known transaction data based on the annual movement.	Representativeness of the target item has been effectively shifted to other items that still are being transacted and contributing to the next level up in the aggregation structure. The annual movement for this aggregate is preserved. The imputation can also be seen to effectively presume that activities have been substituted to still actively transacted products. In this case the annual price change has been utilised.	(1) (2) (3)
Overall Mean Imputation (periodic) [imputing from a total level movement, for example Total CPI or an Industry Total PPI]	Overall level periodic movement is preserved. Actual transactions are exclusively used (may include quality adjustment) therefore preserving known transaction data based on the periodic movement.	Representativeness of the target item has been effectively shifted to other items that still are being transacted and contributing to a total level (likely published level) in the aggregation structure. The periodic movement for this total aggregate is preserved. The imputation can also be seen to effectively presume that activities have been substituted to still actively transacted products. In this case the periodic price change has been utilised.	(4)
Overall Mean Imputation (annual) [imputing from a total level	Overall level annual movement is preserved. Actual transactions are exclusively used	Representativeness of the target item has been effectively shifted to other items that still are being transacted and contributing to a total level (likely published level) in the aggregation structure. The annual movement for this total aggregate is preserved. The imputation can also be seen to effectively presume	(4)

movement, for example Total CPI or an Industry Total PPI]	(may include quality adjustment) therefore preserving known transaction data based on the annual movement.	that activities have been substituted to still actively transacted products. In this case the annual price change has been utilised.	

2.4 Conclusion

This thought exercise raises what it considers to be important areas for consideration when imputations are being considered as well as a summary of imputations and what they inherently preserve. This seems especially important in times of economic shocks where fundamental explicit and implicit impacts need to be kept in check and well-communicated. In terms of continued areas for investigation the following are recommended for consideration and discussion:

Preservation an integral part of imputation. Imputation seeks to solve missing data issues at the item level under certain assumptions that this will retain representativeness at the item level and resulting in accurate aggregate level indicators. It is suggested that imputation discussed in terms of preservation could enhance understanding and consistent application of imputation in statistical programmes. During an economic crisis type scenario this seems of particular importance.

Explicit and implicit impacts on the index. All too often the explicit impacts are considered without due consideration being given to implicit (or hidden) impacts. These implicit impacts and/or qualities are in equal measure important to consider in terms of communication of results and advice to users whilst also holding opportunities to exploit in production system design.

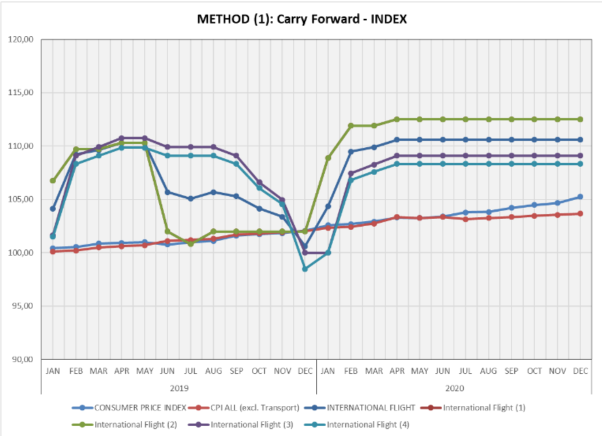
Structured approach to determining and recording imputation (and quality adjustment). This thought exercise further proposes that the development of a common language for structuring and recording metadata for imputation and quality adjustment based decisions is a productive and natural progression to take advantage of contemporary technologies. This would support the generation of training datasets useful beyond the bounds of individual statistics offices.

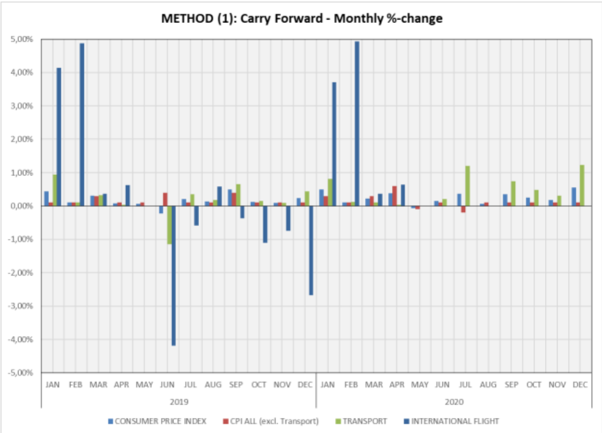
2.5 Appendices

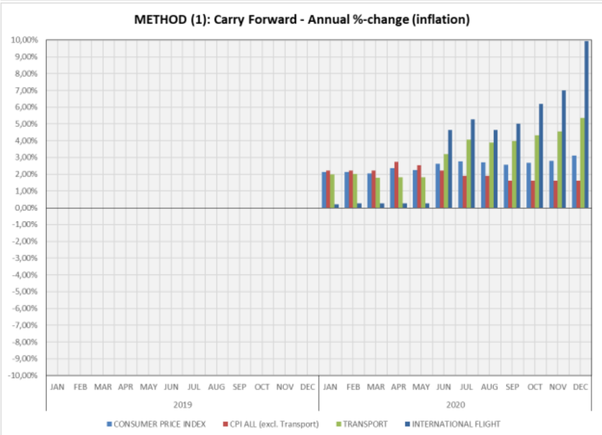
Appendix A: Graphs for visual assessment of imputation methods.

The graphs are based on a dummy dataset used for an initial assessment of the imputation methods. This dataset and calculations are held in an excel based learning model which is available upon request. 'Passenger transport by air' from May 2020 to December 2020 is the target data which is being imputed. Initial observations are provided in section 3. Calculating the index.

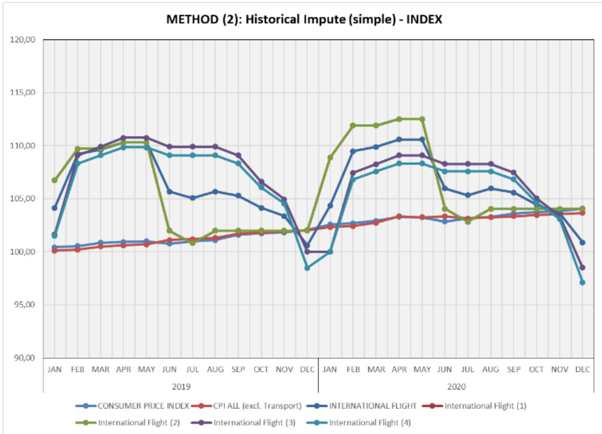
Carryforward.

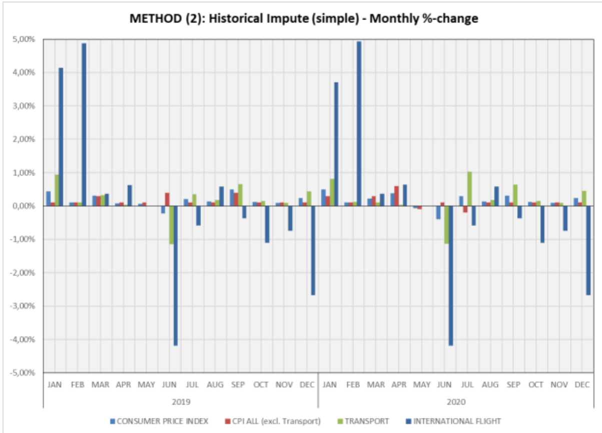


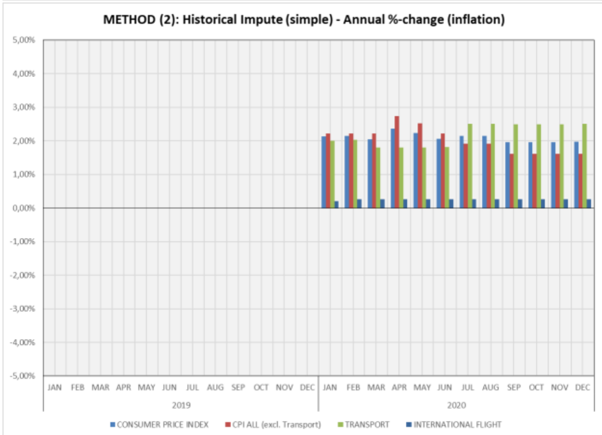




Historical Imputation.

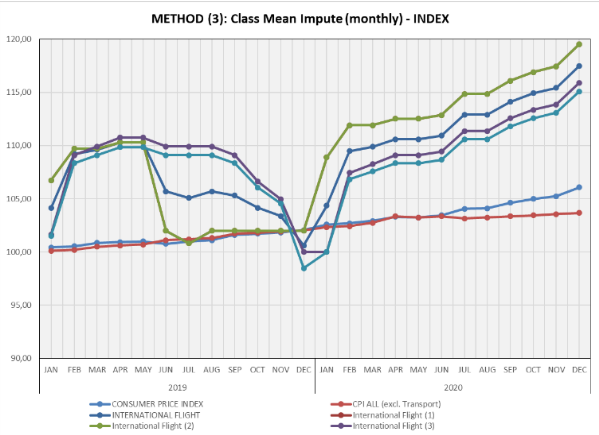


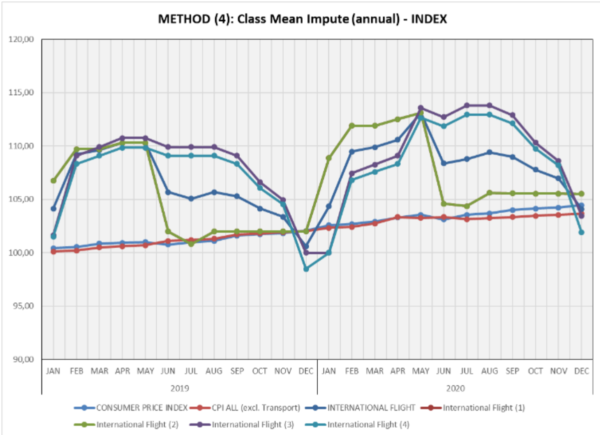


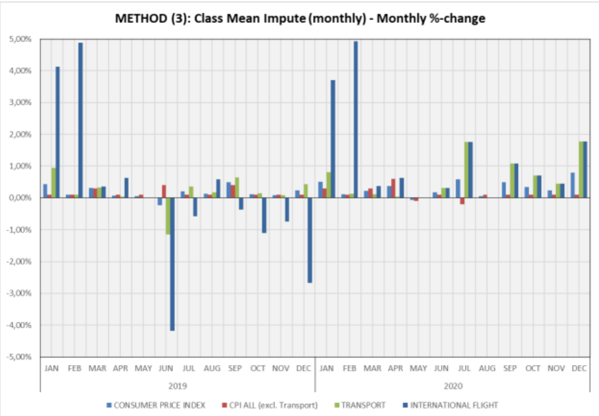


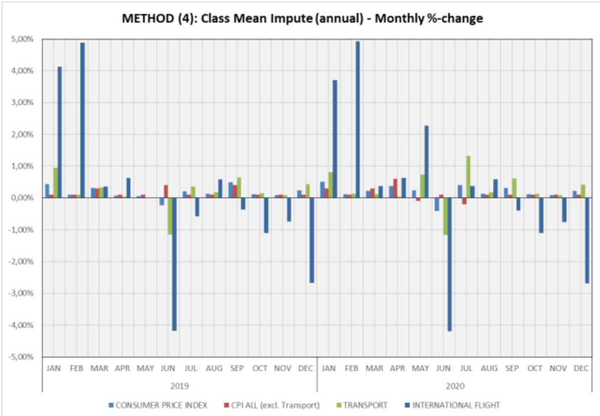
Class Mean Imputation (monthly).

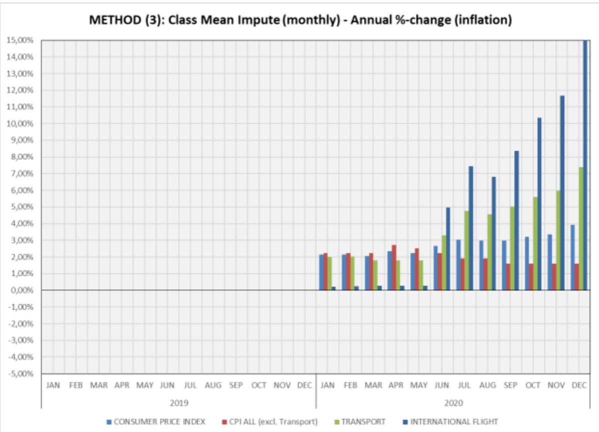
Class Mean Imputation (annual)

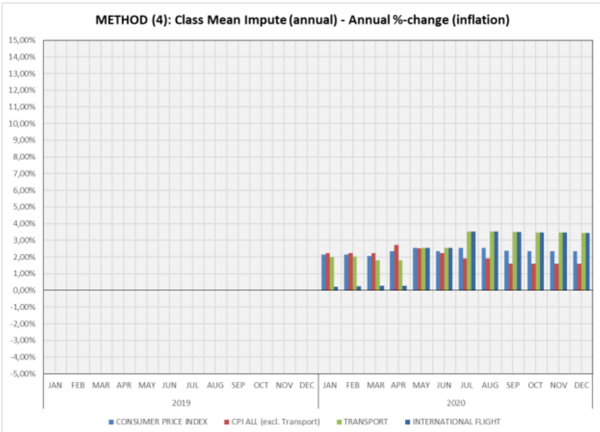




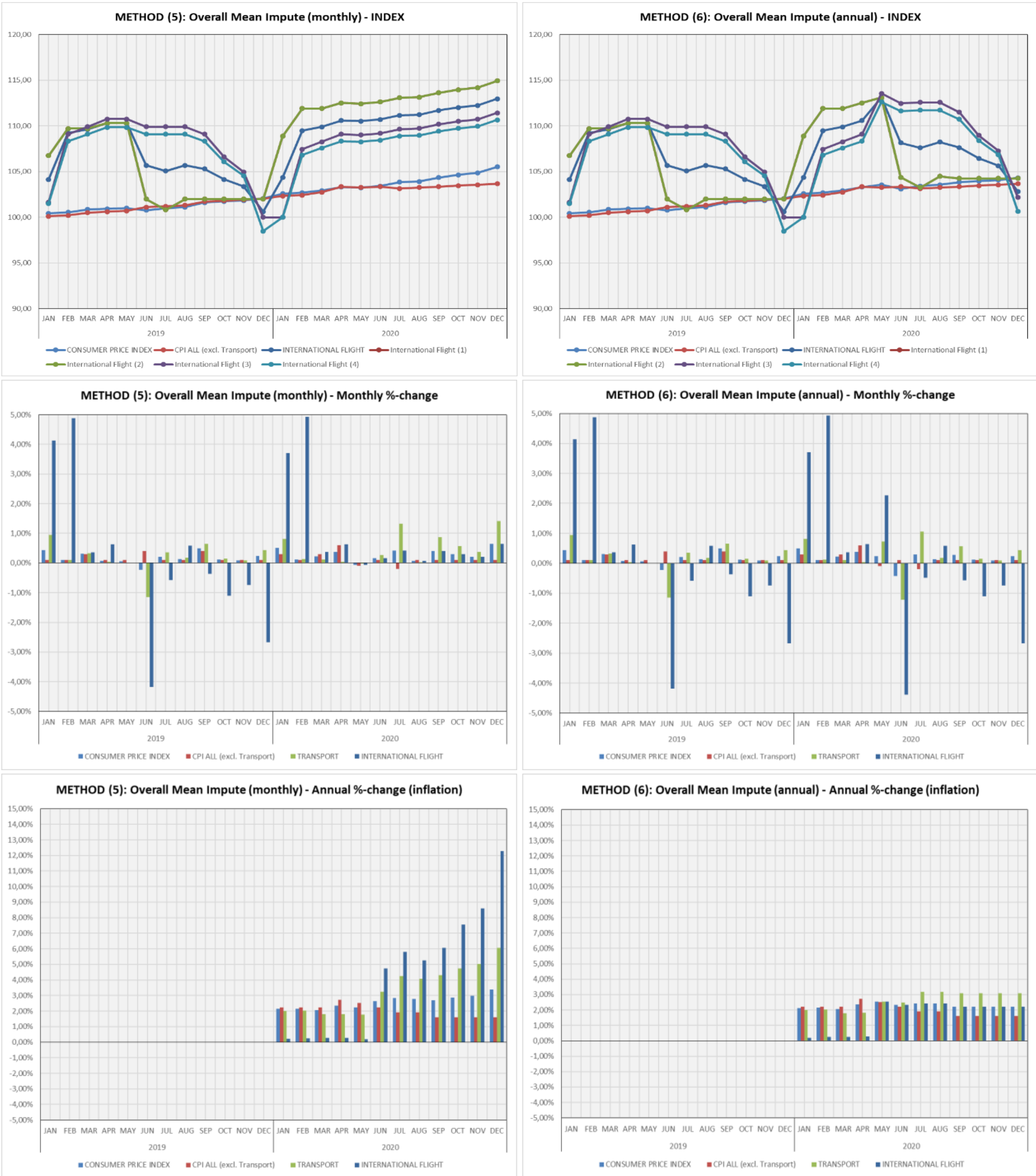








Overall Mean Imputation (monthly). Overall Mean Imputation (annual)



3 PPI seasonal adjustment during the COVID-19 pandemic

The U.S. Bureau of Labor Statistics (BLS) publishes seasonally adjusted Producer Price Index (PPI) time-series data monthly. Seasonal adjustment removes within-year seasonal patterns from data, which have demonstrated regularly occurring within-year patterns over many years. In the case of price indexes, these within-year patterns may result from changing of seasons, production cycles, model changeovers, holidays, and sales. Seasonally adjusted data are usually preferred for short-term price analysis because they allow data users to focus on changes that are not typical for the time of year. To seasonally adjust data, the U.S. PPI uses the U.S. Census Bureau's X-13ARIMA-SEATS software to implement a filter-based approach that employs moving averages of historical data to estimate the seasonal pattern of a time series. After staff estimate the seasonal pattern, the data are seasonally adjusted by removing the within-year seasonal movements from the time series.[14] [15]

From 2020 to 2023, multiple U.S. PPI series measured extreme price movements because of the coronavirus disease 2019 (COVID-19) pandemic and subsequent supply chain issues. Because historical data is used to estimate seasonal patterns, these extreme price movements may have adversely affected seasonal adjustment. This chapter explains how the U.S. PPI program mitigated the effects of the COVID-19 pandemic on seasonally adjusted price indexes. In particular, an explanation of how the U.S. PPI greatly increased the scope of intervention modeling to alleviate the effects of the COVID-19 pandemic on seasonal adjustment is provided.

3.1 Seasonal methodology

The U.S. PPI program uses direct and indirect seasonal adjustment methods. To implement direct seasonal adjustments, seasonal factors are applied to unadjusted data to remove within-year seasonal patterns. Indirect adjustment is a method of seasonal adjustment used for aggregate series. In this method, two or more directly adjusted component indexes are combined into higher-level time series. Seasonal factors are not estimated for or applied to indirectly adjusted series. In the U.S. PPI, commodity-based indexes and Final Demand–Intermediate Demand (FD–ID) aggregation system indexes are eligible for seasonal adjustment. Most of the U.S. PPI commodity data which receive seasonal adjustment are directly adjusted. By contrast, all FD–ID indexes are seasonally adjusted using an indirect method.

3.1.1 Direct adjustment

The U.S. PPI tests all series that are eligible for direct adjustment for seasonality, and if seasonality is found, the series are seasonally adjusted. Seasonal adjustment and seasonality testing are both accomplished using X-13ARIMA-SEATS, a software program published by the U.S. Census Bureau Methodologically, adjustments are based on the X-11 variant of the Census II.[16] X-11 is a filter-based approach, that employs moving averages to estimate trend and seasonal components in turn. Components are refined through several iterations of

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[14] This article is draws largely from and updates the previous May 2022 *Monthly Labor Review Article* "PPI and CPI seasonal adjustment during the COVID-19 Pandemic" by Blake Hoarty, Steven Muri, Daniel Pollatta, Maria Rodgers, Jonathan Weinhagen, and Jeffery Wilson.

[15] Although the US PPI uses X-13 ARIMA, a filter-based method, for seasonal adjustment the issues and potential solutions presented in the paper are also applicable for a model-based approach to seasonal adjustment such as Tramo-Seats.

[16] Julius Shiskin, Allan H. Young, and John C. Musgrave, "The X-11 variant of the Census method II seasonal adjustment program," Technical Paper 15 (U.S Bureau of the Census, February 1967), The X-11 Variant of the Census Method II Seasonal Adjustment Program (Technical Paper 15).

weighted moving averages. PPI uses a multiplicative time-series decomposition model by default, calculated as

$$Y_t = T_t * S_t * I_t.$$

In this model, Y_t, is the value of the observed series at time t, T_t represents the trend-cycle component at time t, $S_t$is the seasonal component at time t, and I_t is the irregular component at time t. To enable the use of symmetric moving-average filters on a series, X-13 ARIMA-SEATS uses an ARIMA (Auto-Regressive Integrated Moving Average) modeling facility to forecast and backcast observations at the endpoints of the data.

The PPI uses three primary measures, known as quality control (QC) statistics, to determine whether a particular index should be seasonally adjusted: *F*(*s*), *M7*, and *Q*. *F*(*s*) is a measure of stable seasonality, M7 determines the amount of moving seasonality relative to the amount of stable seasonality, and *Q* is a weighted average of several diagnostic statistics. In general, for a series to be deemed seasonal it must meet the following QC thresholds: *F*(*s*) ≥ 7, M7 < 3, *Q* < 1.

Lower-level commodity PPIs that are found to exhibit a level of seasonality warranting adjustment (on the basis of meeting the QC thresholds) are directly adjusted by applying a seasonal factor to the unadjusted index according to

$$I_t^s = {I_t^u}/_{\mathrm{SF}_t} * 100,$$

where I_t^s is the seasonal index value at time t, I_t^u is the unadjusted index value at time t, and SF_t is the seasonal factor at time t. (The estimate of seasonal component from the previous equation.) Seasonal factors indicate the seasonal pattern of a time series and are derived from historical unadjusted data. Seasonal factors are relatively stable over time. PPI typically uses 8 years of unadjusted monthly data to develop factors and test seasonality for both sets of indexes.

3.1.2 Intervention analysis

Nonseasonal events, such as natural disasters, pandemics, or wars, can distort the underlying seasonal pattern of an index. Intervention analysis entails estimating and removing the one-off effects of these events from indexes before they are tested for seasonality and before seasonal factors are developed. The goals of intervention analysis are to determine whether a seasonal pattern exists and to correctly estimate seasonal factors despite any distortion that might arise in the pattern. PPI applies intervention analysis to selected directly adjusted indexes. To conduct intervention analysis, the PPI uses X-13ARIMA-SEATS. Using that method (X-13), PPI estimates ARIMA models that include prespecified intervention variables for a time series. These variables are used to identify the statistical significance and relative effects of nonseasonal events on time series. In cases where a nonseasonal event (such as the COVID-19 pandemic) is found to significantly affect a time series, the effects of the event can be removed from the original time series by using the estimated coefficients from the ARIMA model. Three types of intervention variables are employed: outliers, level shifts, and ramps. (Ramps allow for a linear increase or decrease in the level of a series over a specified time interval.) After nonseasonal effects are removed from the original time series, standard direct seasonal adjustment methods as described earlier are applied to the indexes to test for seasonality and to develop seasonal factors.

More than 1,000 producer price indexes are currently eligible for direct seasonal adjustment. Conducting intervention modeling on this entire set of indexes is not feasible because of resource constraints. Consequently, PPI performs intervention modeling on only a relatively small set of indexes. For a PPI to be an intervention candidate, the relative importance (share) of the index must be at least 1 percent of a major FD–ID index. The major FDs–IDs include goods for final demand, services for final demand, processed goods for intermediate demand, unprocessed goods for intermediate demand, or services for intermediate demand. Each year, PPI examines all intervention candidates to determine whether intervention modeling will improve seasonal adjustment of the series and performs intervention modeling if it leads to more accurate seasonal adjustment. Since 2020, PPI relaxed the relative importance criteria to address widespread extreme price movements resulting from the COVID-19 pandemic. (See section on mitigating the effects of the COVID-19 pandemic.)

3.1.3 Indirect adjustment

High-level indexes, such as the PPI for final demand, are indirectly seasonally adjusted by aggregating lower-level series that are components of higher-level indexes. Seasonally adjusted components are used when available (that is, when the lower-level index received a seasonal adjustment); otherwise, unadjusted indexes are used. PPI indirectly adjusts all its FD–ID indexes, as well as any indexes that are aggregates of intervention indexes. In this manner, interventions estimated for lower-level indexes are indirectly included in aggregate indexes.

3.1.4 Yearly revisions and projected factors

Each year, with the release of January data, seasonal factors are recalculated to reflect price movements that occurred during the just-completed calendar year. Seasonal factors are recalculated 5 years back, and all seasonally adjusted data are updated on the basis of these new factors. For example, in January 2021, factors were recalculated from 2013 to 2020 data and seasonal data from 2016 to 2020 were updated according to the new set of factors. After the yearly revision, indexes for the next year are calculated with the previous year's set of seasonal factors. For instance, the 2020 factors, from the January 2021 revision, are used to calculate indexes throughout 2021.

3.2 Potential negative effects of COVID-19 on seasonal adjustment

In many cases the extreme price movements that occurred since 2020 created substantial challenges for seasonal adjustment, making detection of seasonality more difficult and estimation of the seasonal patterns less accurate. For example, COVID-19 related shocks caused prices in numerous indexes to move in different directions or to occur in different months than would have been historically expected, thereby reducing measured seasonality.

As a measure of the potential reduction in detectable seasonality, Table 2 presents QC statistics from seasonality tests conducted on the unadjusted PPI for final demand. Tests were conducted with the use of 8 years of data, ending with the year listed in the table. For example, 2019 tests were conducted with data from 2012 to 2019. If COVID-19-related price movements made detection of seasonality more difficult in PPI data, a decline in the seasonality test statistics would be expected when data past 2019 are included. For final demand $F(s)$ falls from 21.95 with data through 2019 to 8.83 with data through 2020, indicating a clear decrease in detectable seasonality. Tests with data through 2021 and 2022 show a partial recovery in detectable seasonality but not to pre-pandemic levels. (Recall, values of $F(s) \geq 7$, M7 < 3 and $Q < 1$ indicate seasonality.)

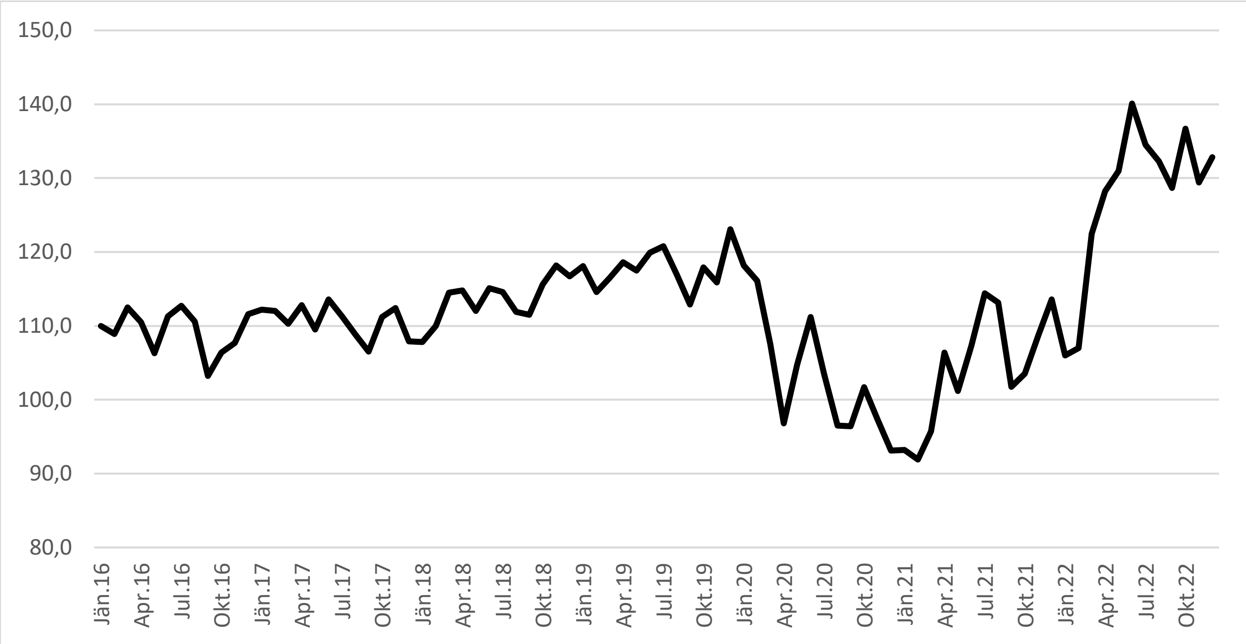
Table 2: PPI for final demand, QC statistics

End year	F(s)	M7	Q
2022	13.34	0.84	0.44
2021	13.77	0.67	0.43
2020	8.83	0.76	0.63
2019	21.95	0.49	0.37

High-level testing indicates a decrease in observable seasonality after 2020 in PPI data. For one to understand the underlying causes of this general decline, a detailed example of airline services prices is presented. The example shows how extreme price movements reduced the amount of detectable seasonality in the PPI for airline services and distorted the normally observed seasonal patterns. The airline example is indicative of what occurred for many price indexes since 2020.

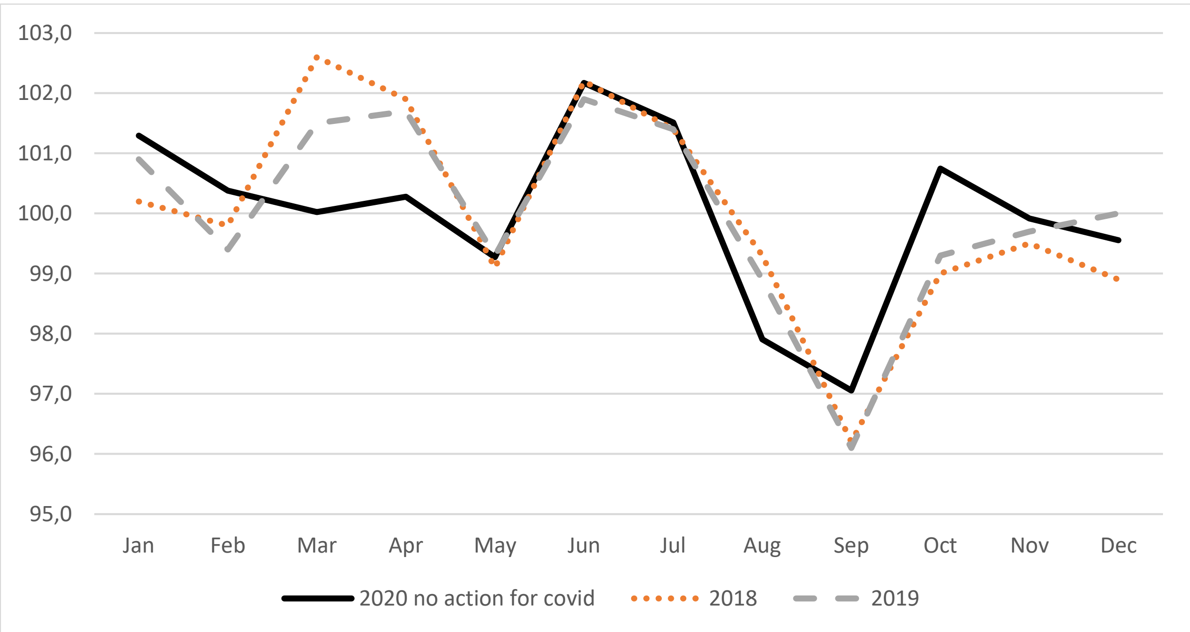
Chart 1 presents the PPI for airline passenger services from January 2016 through December 2022. Prior to the pandemic, prices were increasing gradually and, in general, there were summer, spring, and winter seasonal peaks. The behavior of the index changed dramatically in 2020. From December 2019 through April 2020, the PPI for airline passenger services fell approximately 21 percent. The PPI then jumped almost 15 percent from April to June and then decreased for most of the remaining the year. Throughout 2021 and 2022, the airline passenger index generally rose at a high rate, and there were notable summer and winter peaks in both years.

Chart 1: PPI for airline passenger services, index levels



To show how these extreme price movements affected seasonality, Chart 2 compares seasonal factors for airline passenger services estimated with data from two pre-COVID-19 periods (2011–18 and 2012–19) to those estimated with data from the COVID-19 period (2013–20). The factors presented are from the final year of the estimation period. As can be seen, the seasonal patterns estimated with pre-COVID-19 data differ from those estimated with data during the COVID-19 period. For PPI, the pre-COVID-19 factors project prices to rise approximately 2.3 percent from February to April, while the factors estimated during the COVID-19 period anticipate prices will fall 1.1 percent over this same period. The large declines in airline prices in the early part of 2020 clearly affected seasonal factors.

Chart 2: PPI for airline passenger services, seasonal factors



To further examine the effects of the pandemic on the seasonality of PPI for airline passenger services, Table 3 compares QC statistics estimated with data from 2012 to 2019 with those estimated with data from 2013 to 2020. The pre-COVID-19 QC statistics indicate that airline passenger services are seasonal ($F(s) \geq 7$, M7 < 3 and $Q < 1$). The inclusion of 2020 data substantially changes the seasonality test results for airline passenger services. $F(s)$ declines approximately 10 percentage points and no longer indicates seasonality.

Table 3: PPI for airline passneger services, QC statsitics

QC stats for airline services	F(s)	M(7)	Q
2020	3.91	1.30	0.99
2019	13.25	0.62	0.75

This section illustrates, using both high-level and a detailed commodity-level example, how the extreme price movements affected the detection and estimation of seasonal patterns in price index data.

3.3 Mitigating the effects of the COVID-19 pandemic on seasonal adjustment

In response to the COVID-19 pandemic, the U.S. PPI expanded the scope of intervention analysis. In general, for a PPI to be an intervention candidate, the relative importance (share) must be at least 1 percent of a major FD–ID index. Beginning in 2020, the PPI program relaxed its relative importance rules for intervention candidates and expanded the number of series for which intervention analysis was conducted. The goal of this increased scope for intervention work was to mitigate the effects the COVID-19 pandemic had on seasonal adjustment.

For the 2020 annual seasonal revision, economists evaluated each series that was directly seasonally adjusted in 2019 by visually examining it for extreme price movements in 2020. They generated QC statistics with data from 2013 to 2020 and compared them with those generated with data from 2012 to 2019. Next, they generated seasonal factors with data from 2013 to 2020 and compared them to those generated with data from 2012 to 2019. They ran automatic outlier detection and manually searched for outliers during the COVID-19 period. Finally, they consulted expert industry and commodity analysts.

Generally, the COVID-19 pandemic was deemed to adversely affect seasonal adjustment of a series relative to prior revisions when some combination of the following occurred:

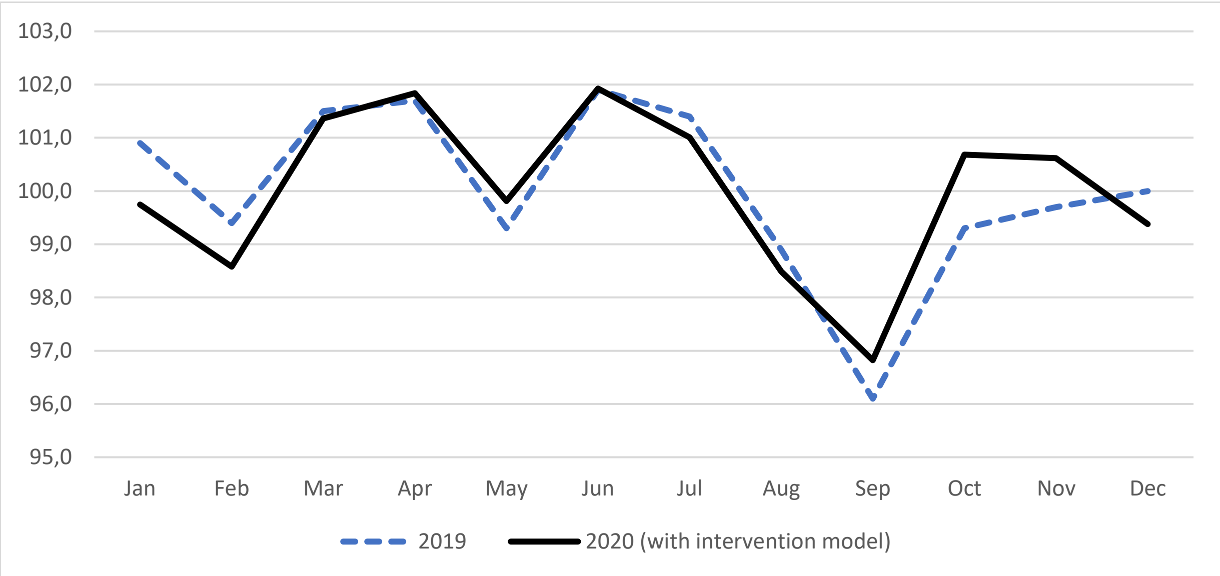
- Extreme price movements occurred in 2020.
- QC statistics changed substantially when COVID-19 period data were included in their estimation.
- Seasonal factors changed substantially when COVID-period data were included in their estimation.
- Auto -outlier and manual searches detected outlier points in 2020.

- Expert industry analysts indicated that COVID-19 was interfering with the typical seasonal pattern observed in the data.

In cases where this testing indicated that COVID-19-related price movements would adversely affect seasonal adjustment of a series, the series was included as an intervention series for 2020. For series that were added because of the impact of COVID, only interventions from 2020 were included in their models during the 2020 seasonal process. Because extreme price movements continued throughout 2021 and 2022, the same process used in 2020 was followed for the 2021 and 2022 seasonal revisions, but the set of potential intervention points was expanded to include 2020-2022.

Returning to the airline passenger services example, in 2020 analysts determined that extreme price movements resulting from the COVID-19 pandemic adversely affected the seasonality of the index, as there were substantial changes in both seasonal factors and QC statistics after 2020 data were included (see Chart 2 and Table 3). For this reason, intervention modeling was used to offset the effects of the COVID-19 pandemic on seasonal adjustment. The intervention model included ramps in 2020 from February to April, April to June, and June to August, as well as a level shift in November 2020. Chart 3 compares seasonal factors for airline passenger services estimated with 2012–19 data with those estimated with data from 2013 to 2020, employing the intervention model.

Chart 3: PPI for airline passenger services, seasonal factors



Employing the intervention model in 2020 resulted in factors substantially more similar to those estimated in 2019. In addition, after employing the intervention model the F(s) and M7 statistics indicate seasonality. The Q statistic, however, does not indicate seasonality as it is somewhat above the 1.0 threshold. (See table 4.) While the seasonality tests in 2020 conducted after intervention modeling did not quite indicate seasonality in airline passenger services, implementation of intervention substantially improved the seasonality test statistics and brought the seasonal factor more in line with those from previous years. Importantly, the U.S. PPI employs a rule that once a series is deemed seasonal, that series must fail seasonality tests for three consecutive years before it is not seasonally adjusted. For this reason, even though the Q statistic did not meet the seasonality threshold, the index was still seasonally adjusted and therefore accurate seasonal factors were needed.

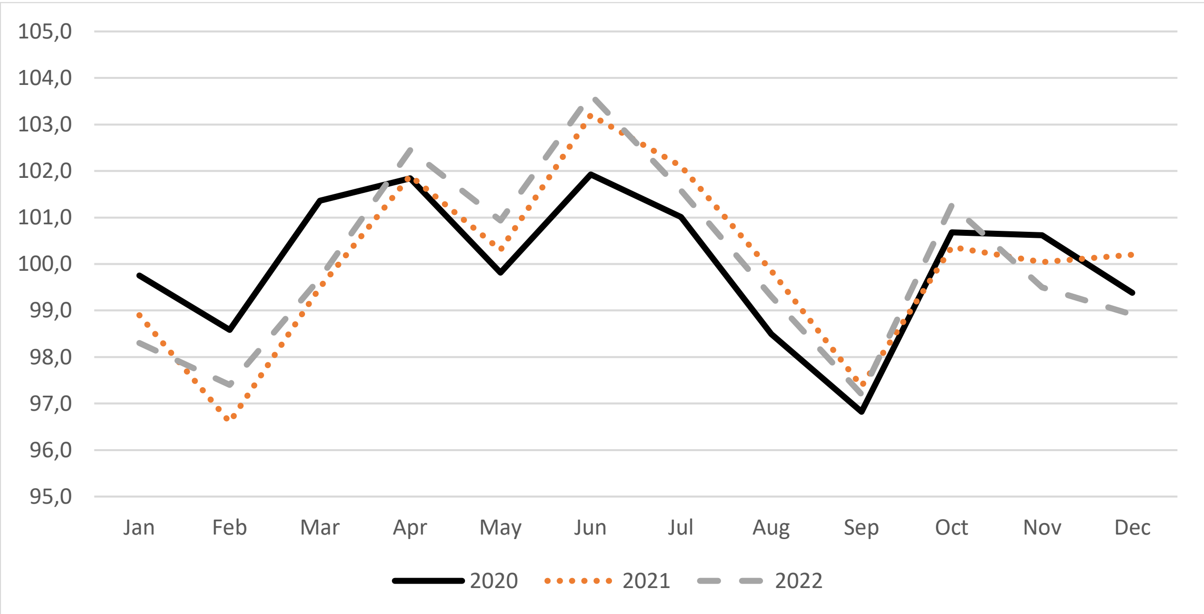
Table 4: QC Statistics for PPI for airline passenger services (with intervention models)

Year	F(S)	M7	Q
2020	8.412	0.708	1.19
2021	7.131	0.901	1.03
2022	7.656	0.903	0.95

As noted earlier, because extreme price movements resulting from the COVID-19 pandemic continued in 2021 and 2022, PPI allowed new interventions for 2021 and 2022 to be included for intervention series. For airline passenger services, the general model developed in 2020 was retained and level shifts were added for July 2021, September 2021, and March 2022.

Chart 4 compares seasonal factors for airline passenger services generated with intervention models from 2021 through 2023. Overall, the seasonal factors maintain similar patterns as those from 2019. In addition, for 2021 and 2022 the F(s) and M7 tests indicate seasonality. The Q statistic is very close to indicating seasonality in 2021 and does indicate seasonality in 2022. The intervention work conducted on this series enabled PPI to continue its seasonal adjustment and retain reasonable seasonal factors despite the extreme price movements resulting from the COVID 19 pandemic.

Chart 4: PPI for airline passenger services, Seasonal factors with intervention models



After considerable analysis, PPI expanded the scope of intervention work in 2020 to offset the effects of the COVID-19 pandemic on the seasonal factors used for seasonal adjustment in 2021. Economists applied intervention analysis on 76 PPI series in 2020, as compared with 41 in 2019. Of the 76 series, 36 series were added strictly to mitigate COVID-19 effects on seasonal adjustment and, thereby, only contained interventions in 2020. The total number of interventions for PPI increased 64 percent from 2019 to 2020. This increased scope of intervention work continued in 2021 and 2022.

3.4 Conclusion

The COVID-19 pandemic caused extreme movements in many producer price indexes since 2020. Because PPI uses historical data to estimate seasonal factors, the extreme price movements resulting from the COVID-19 pandemic created difficulties in estimating seasonal data. To overcome these difficulties, PPI expanded the scope of intervention modeling. The number of series PPI conducted intervention analysis on rose by more than 85 percent from 2019 to 2020. Likewise, the total number of actual interventions in the PPI increased by approximately 64 percent from 2019 to 2020. As a result of this additional intervention modeling, the seasonal revisions to historical data seen from 2020-2022 for PPI data were in line with previous revisions, indicating successful mitigation of the effects of the COVID-19 pandemic on seasonally adjusted data.

The experience of the U.S. PPI with seasonal adjustment during the COVID-19 pandemic indicates that during periods of widespread economic shocks, it is necessary for price programs to devote significant resources to seasonal intervention modeling. Furthermore, because the shocks will remain in the data used to estimate seasonal factors for at least eight years, the expansion of resources dedicated to intervention modeling will need to continue for a number of years after the shocks subside.

4 Output compilation during economic shocks: alternative data sources for advanced signals in service industries

4.1 Introduction

The pandemic has caused significant fluctuations in economic activity across various industries in Canada. To better understand the impact of the pandemic on the economy, alternative estimates to annual survey data have been developed. This chapter discusses how analyzing alternative data sources can help improve the understanding of economic trends ahead of estimates based on annual industry survey data. Annual business survey estimates at Statistics Canada are available with lags of 10 to 15 months after the reference year for most service industries. However, relying on alternative data can provide more timely estimates (generally with lags of just a few months). This is important as many service industries in Canada experienced unusual volatility during the pandemic and post-pandemic periods. Producing timelier estimates of these industries' performance would allow businesses and policy makers to respond more effectively to rapid changes in industry conditions.

The pandemic has brought about changes to the operating environment of service industries in Canada. While some industries have been able to adapt to the lockdowns, public health restrictions, and other changes to the business environment, others have struggled to do so. This has created new opportunities for growth through the digital economy, while also hurting industries that could not adequately adapt. To provide a first look at economic trends months earlier than annual business survey estimates, administrative data and other alternative data sources can be used. These sources offer an advanced point of reference compared to annual business survey estimates.

4.2 Leveraging alternative data sources

To produce more timely estimates of industry performance in the service sector, Statistics Canada has made greater use of administrative tax data in its business annual statistics program. The use of tax data has been particularly important to the Service Industries Program, which produces detailed estimates of operating revenue, expenses, and salary and wage statistics at the industry level for a variety of service sector industry groupings[17]. While estimates for most service industries are produced on an annual basis, biennial estimates are produced for arts and culture industries[18].

4.2.1 Canada Revenue Agency —goods and services tax revenues and payroll deduction as proxy indicators for growth performance

The pandemic and changing macroeconomic conditions have necessitated a more timely approach to data collection than traditional annual business surveys. The processing of information collected in traditional business surveys is a multi-step process that includes integrating, transforming, validating, aggregating, and linking data from different data sources into the correct formats, structures, and levels required for processing.

Statistics Canada has made use of administrative tax data in place of survey data for many years. Specifically, tax data has been used as direct replacement in survey imputation or estimation. T1 tax data, obtained from the Canada Revenue Agency (CRA), is used as a replacement for survey data for unincorporated businesses, while T2 tax data is used to replace survey data for incorporated businesses which are too small to survey. However, T1 and T2 tax data is only available with a large lag. Specifically, tax data for a given year only becomes available after April 30th of the following year[19], due to filing deadlines. However, at the onset of the pandemic, the Government of Canada introduced fiscal measures to help businesses such as extending the payment deadline for 2019 to September 30, 2020[20]. This created longer lags for the availability of 2019 tax data.

As the pandemic accelerated the need for service industry indicators, Statistics Canada's Service Industries Program made greater use of data from alternative administrative datasets, such as goods and services tax (GST) revenue data and payroll deduction (PD7) files,[21] to estimate operating revenue[22] and salary expenses during the pandemic and post-pandemic

[17] Statistics Canada. "Administrative Data." Accessed January 29, 2024. https://www.statcan.gc.ca/en/our-data/where/administrative-data.
[18] The arts and culture service surveys are produced biennially for Canadian Heritage, a federal Canadian department that governs arts, culture, and heritage policies. This represents 9 surveys that have financial data collected as well as many industry characteristics.
[19] Or June 15 for self-employed individuals or common-law partners
[20] Canada Revenue Agency. "Extension to the payment deadline for 2019 income tax returns." Accessed January 26, 2024. https://www.canada.ca/en/revenue-agency/news/newsroom/tax-tips/tax-tips-2020/extension-payment-deadline-2019-income-tax-returns.html.
[21] Employer payroll deduction remittances to the Canada Revenue Agency.
[22] Operating revenue is a key input in the measurement of national economic production statistics such as gross domestic product (GDP) and is indispensable for tracking economic activity performance, conducting macroeconomic analysis, and developing monetary and fiscal policy measures.

periods. GST is a value-added tax levied by the federal Canadian government and is essentially borne by the final consumer. Importantly, exports of services are GST exempt[23]. The GST revenue data and the PD7 files are not formally used as replacement for annual survey data in the Service Industries Program. However, these data sources are used in a data replacement strategy in monthly surveys for sales of most small and medium locations of food services and drinking places establishments for example, as well as a select group of large locations to avoid collection of these units. Administrative GST data is also used as an auxiliary source of data for editing and imputation when respondent data is not available in other monthly surveys[24].

The GST and PD7 files were also reviewed to ensure consistency and comparability with the Services Industries Program's annual business survey estimates. While not always consistent with survey data, the GST and PD7 data for several industries, namely professional, administrative, culture, art, entertainment and recreation services, were found to be historically comparable with survey data, and could be used to obtain advanced estimates of operating revenue for these industries. The chart below compares the advanced estimates from administrative data for operating revenue with the actual survey estimates for selected service industries in the pandemic and post-pandemic period from 2020 to 2022 (see Chart 5). In all cases, the growth rates of the advanced estimates were in the same direction and within the same magnitude as the growth rates of survey estimates.

[23] The GST is a 5% tax levied on all goods and services provided in Canada with some exceptions. There are 0% taxed industries. All businesses with annual revenues greater than $30,000 must register for a GST account and are required to file GST remittances. The frequency of remittance depends on their annual revenue with businesses with annual revenue greater than $6 million filing monthly and businesses with annual revenue between
$1,5 million and $6 million filing quarterly. Businesses with annual revenues between $30,000 and $1,5 million are required to file annually.

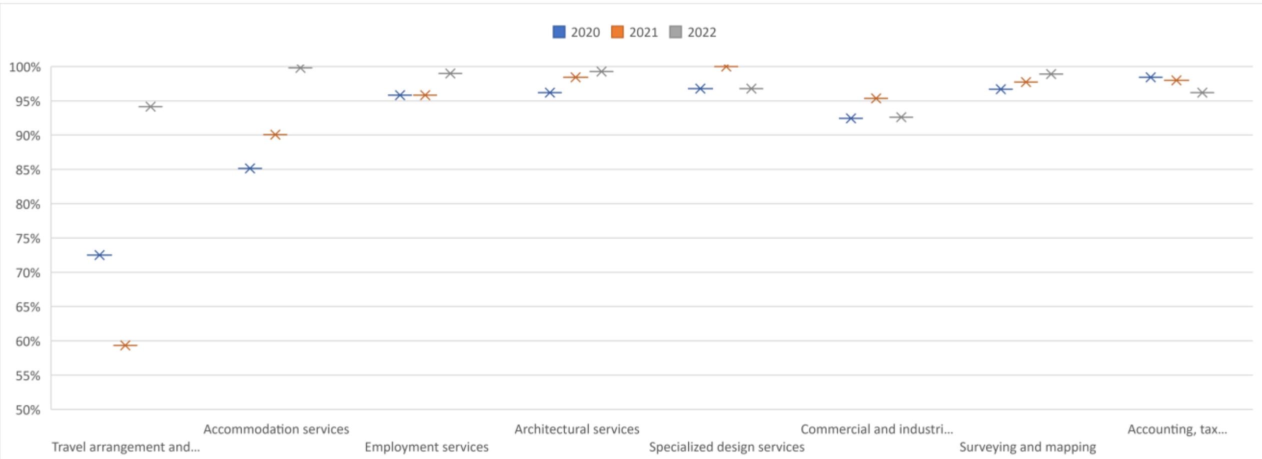
[24] Snijkers, Ger. February 2023. Integrating Alternative and Administrative Data into the Monthly Business Statistics: Some Applications from Statistics Canada. In Advances in Business Statistics, Methods and Data Collection. John Wiley & Sons, Ltd.

Chart 5: Advanced and actual revenue estimates for select service industries, percentage change, 2020-2022, Canada

Source: Annual survey of services industries program

In terms of accuracy of growth performance, the advanced estimates based on administrative data were at least 90% accurate compared with survey estimates (see Chart 6). Nevertheless, the service industries with the largest swing in growth throughout the pandemic and postpandemic period, travel arrangement and reservation services and accomodation services, had the lowest growth rate accuracy using administrative data. Accuracy is one component of data quality. In the case of using the GST data, we are conceding on accuracy but gaining on timliness[25].

Chart 6: Accuracy of advanced estimates for select service industries , per cent, reference year 2020 to 2022



Source: Annual survey of services industries program

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[25] Statistics Canada. “Policy on Informing Users of Data Quality and Methodology.” Accessed January 29, 2024. https://www.statcan.gc.ca/en/about/policy/info-user.

The advanced estimates are a reliable source for an early signal at a time of great volatility in the economy. Despite the pandemic running its course, the service industries are still facing unusual volatility and adapting to structural economic changes. The Canadian economy is dealing with inflationary price pressures, solid population growth, skilled labour shortages and ongoing supply chain disruptions.

4.3 Conclusion

The use of alternative data sources met the need for timelier estimates of industry performance, at a time of significant economic volatility. There are however limitations, and the use of these data sources is not without challenges. Administrative data is not necessarily subjected to the same data quality and consistency checks as traditional survey data, and often do not correspond exactly with the variables targeted in the survey questionnaire.

While the use of GST and PD7 data files was helpful in meeting the need for timely data, it was not a good proxy for all industries in the Service Industries Program. Furthermore, revenue estimates based on GST data may be biased by industry misclassifications in the GST remittances, resulting in lower quality estimates than those produced by industry surveys. Estimates based on administrative data may not be at the same granular level as survey estimates. It however provides a more cost efficient and quicker understanding of economic trends which can help policy makers at a time of changing economic conditions. The GST data files are also now being used to analyze both annual and monthly economic services industry trends. Monthly econometric nowcast models of the GST have been developed for most professional, administrative, culture, and arts service industries where there are no monthly surveys. These models rely on current economic indicators and real-time data. The nowcast estimates of the GST are inputs into Statistics Canada’s monthly industry real GDP advanced estimate.

4.4 Annex

4.4.1 Correspondence table

CORRESPONDENCE TABLE			
NAICS		ISIC	
	Travel arrangement and reservation services		
561510	Travel agencies	N7911	Travel agency activities
561520	Tour operators	N7912	Tour operator activities
561590	Other travel arrangement and reservation services	N7990	Other reservation service and related activities
	Accommodation services		
721111	Hotels	I5510	Short term accommodation activities
721111	Hotels	I5590	Other accommodation
721112	Motor hotels	I5510	Short term accommodation activities
721113	Resorts	I5510	Short term accommodation activities
721114	Motels	I5510	Short term accommodation activities
721120	Casino hotels	I5510	Short term accommodation activities
721120	Casino hotels	R9200	Gambling and betting activities
721191	Bed and breakfast	I5510	Short term accommodation activities
721192	Housekeeping cottages and cabins	I5510	Short term accommodation activities
721198	All other traveller accommodation	I5510	Short term accommodation activities
721211	Recreational vehicle (RV) parks and campgrounds	I5520	Camping grounds, recreational vehicle parks and trailer parks
721212	Hunting and fishing camps	I5520	Camping grounds, recreational vehicle parks and trailer parks
721213	Recreational (except hunting and fishing) and vacation camps	I5520	Camping grounds, recreational vehicle parks and trailer parks
721310	Rooming and boarding houses	I5590	Other accommodation
	Employment services		
561310	Employment placement agencies and executive search services	N7810	Activities of employment placement agencies
561320	Temporary help services	N7820	Temporary employment agency activities
561330	Professional employer organizations	N7830	Other human resources provision
	Architectural services		
541310	Architectural services	M7110	Architectural and engineering activities and related technical consultancy
541320	Landscape architectural services	M7110	Architectural and engineering activities and related technical consultancy
	Specialized design services		
541410	Interior design services	M7410	Specialized design activities
541420	Industrial design services	M7410	Specialized design activities
541430	Graphic design services	M7410	Specialized design activities
541490	Other specialized design services	M7410	Specialized design activities
	Commercial and industrial machieney and equipment rental and leasing		
532410	Construction, transportation, mining, and forestry machinery and equipment rental and leasir	N7730	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
532420	Office machinery and equipment rental and leasing	N7730	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
532490	Other commercial and industrial machinery and equipment rental and leasing	N7730	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
	Surveying and mapping		
541360	Geophysical surveying and mapping services	M7110	Architectural and engineering activities and related technical consultancy
541370	Surveying and mapping (except geophysical) services	M7110	Architectural and engineering activities and related technical consultancy
	Accounting, tax preparation, bookeeping and payroll services		
541212	Offices of accountants	M6920	Accounting, bookkeeping and auditing activities; tax consultancy
541213	Tax preparation services	M6920	Accounting, bookkeeping and auditing activities; tax consultancy
541215	Bookkeeping, payroll and related services	M6920	Accounting, bookkeeping and auditing activities; tax consultancy

5 Pandemic effects in business sectors

Table 5 shows the number of Austrian enterprises of OENACE 2008 H - N from 2019 till the current available year 2021.[26] During the COVID-19 pandemic the number of enterprises increased each year with a stronger increase in 2021. Different trends can be observed when looking at H - N individually.

Table 5: Trend of number of enterprises* in Austria (2019 - 2021)

OENACE 2008 H - N	2019	2020	2021
H Transportation and storage	15.049	14.379	15.717

[26] OENACE (Austrian Statistical Classification of Economic Activities). The OENACE is the Austrian version of the NACE. An additional hierarchical level - the national subclasses - was added to represent the Austrian economy in a more detailed and specific way. All the other levels of OENACE are identical with the levels of NACE. The current version is the OENACE 2008, which came into force on 1 January 2008

I Accommodation and food service activities	48.243	45.345	46.840
J Information and communication	22.065	22.514	29.437
K Financial and insurance activities	6.730	6.940	12.362
L Real estate activities	20.481	25.111	21.885
M Professional, scientific and technical activities	74.440	74.566	91.868
N Administrative and support service activities	20.254	18.738	25.225
Sum of OENACE 2008 H - N	207.262	207.593	243.334
* Enterprise as statistical unit Source: Statistics Austria database			

In the accommodation and food service activities industry, the number of enterprises 2021 were below the COVID-19 pre-pandemic level. The number of enterprises were rising 2021 for all the other OENACE H - N compared to 2019. Two of them, H Transportation and storage and N Administrative and support service industries, reflect a downward trend in 2020 with a recovery 2021. Stronger fluctuations can be observed for K and N.

The decrease of number of employees in the Swedish business sector in 2020 were at the same level as 2009. Even though the government supported short-time work allowance the number of employees decreased in the total business sector with 2.5% compared with 2019. For all the other years of time series 2007 - 2020 a continued growth of the variable was observable.[27]

Table 6 shows the turnover of Austrian enterprises of OENACE 2008 H – N from 2019 till the current available year 2021. During the COVID-19 pandemic turnover decreased each year. No turnaround was observable in 2021 despite of a stronger increase in number of enterprises. The decrease of turnover in 2021 for H - N were around 10% compared to 2019. Different trends can be observed when looking at H - N individually.

As mentioned in the paper from Sweden (2022), the COVID-19 pandemic did not cause a great decrease in net turnover[28]. The decrease in 2020 was only 3% compared to 2019, only half the decrease of the financial crisis in 2009. This effect was also observable for Austria when looking at certain OENACE codes. For these OENACE codes the decrease amounted ~5% in 2020 compared to 2019.[29]

[27] Number of employees (full-time equivalents) in the Swedish business sector 2007-2020, SEK billion, NACE A-S (excl. K, O). Vooburg paper from Sweden (2022), pages 6-7

[28] Figure 1. Net turnover in the Swedish business sector 2007-2020, SEK billion, NACE A-S (excl. K, O), Net turnover does not include any subsidies or grants related to the pandemic or any other forms of subsidies and grants. During the pandemic, the government issued several subsidies that the enterprises could apply for, among these were short-time work allowances, lowered employer contributions, and other subsidies related to reduced income, page 5

[29] Source: Statistics Austria database, turnover without Value Added Tax (VAT), OENACE codes B-S (excl. O-R)

Table 6: Trend of turnover* in Austria (2019 - 2021)

OENACE 2008 H – N	2019	2020	2021
H Transportation and storage	45.236.721	41.425.055	44.271.355
I Accommodation and food service activities	22.322.384	16.390.760	14.862.675
J Information and communication	26.995.654	27.366.040	27.992.803
K Financial and insurance activities	53.746.587	51.502.882	46.655.872
L Real estate activities	20.797.208	22.215.459	21.598.962
M Professional, scientific and technical activities	38.416.003	38.388.087	32.001.465
N Administrative and support service activities	27.024.335	22.789.214	22.411.967
Sum of OENACE 2008 H - N	234.538.892	220.077.497	209.795.099
* Without Value Added Tax (VAT) - in 1.000 EUR Source: Statistics Austria database			

I 55 Accommodation and I 56 Food and beverage service activities were heavily affected by the COVID-19 pandemic. Turnover decreased by ~35% between 2019 and 2020. There were more industries that showed a negative trend and could be more sensitive to economic crisis. According to the other Voorburg papers on this topic, further service sectors are H 51 Air transport, N 79 Travel agency, tour operator and other reservation service and related activities and R 91 Libraries, archives, museums and other cultural activities.

Turnover in some industries decreased somewhat stronger once but not with such a percentage change for 2020 and 2021. This was observable for M Professional, scientific and technical activities with ~17% in 2021 and N Administrative and support service activities with ~16% in 2020.

Other industries showed strong resilience during the COVID-19 pandemic and could be less sensitive to economic crisis. A positive trend in 2020 and 2021 was observable for J Information and communication. Included in this industry is J 58 Publishing activities, J 59 Motion picture, video and television programme production, sound recording and music publishing activities, J 60 Programming and broadcasting activities, J 61 Telecommunications, J 62 Computer programming, consultancy and related activities and J 63 Information service activities.

Table 7 shows newly founded Austrian enterprises of OENACE 2008 H - N from 2019 till the current available year 2021. During the COVID-19 pandemic the number of newly founded enterprises decreased each year. Different trends can be observed when looking at H - N individually.

In 2020, a decreasing trend was observable for nearly all OENACE codes except for L Real estate activities enterprises. J Information and communication showed only a slight decrease in this year with a positive trend the following year. A negative trend was visible for some Austrian industries in 2021 compared to 2019 which seem to be more affected by the COVID-19 pandemic. Decreases of newly founded enterprises were observed for H Transportation and storage with ~ 33% and I Accommodation and food service activities with ~37%.

Table 7 Newly founded enterprises in Austria (2019 - 2021)

OENACE 2008 H - N	**2019**	**2020**	**2021**
H Transportation and storage	1.580	1.180	1.055
I Accommodation and food service activities	3.295	2.655	2.074
J Information and communication	1.923	1.855	2.078
K Financial and insurance activities	609	485	527
L Real estate activities	413	510	1.426
M Professional, scientific and technical activities	4.838	4.295	5.180
N Administrative and support service activities	2.345	2.021	2.133
Sum of OENACE 2008 H - N	15.003	13.001	14.473

* Till 2020 without Group K 64.2 Activities of holding companies, from 2013 till 2020 also without Group 64.3 Trusts, funds and similar financial entities

** Differences from rounding up/down not offset

Source: Statistics Austria database

Table 8 shows Austrian business closings of OENACE 2008 H - N from 2019 till the current available year 2021. During the COVID-19 pandemic the number of business closings decreased 2020 and increased the following year. Different trends can be observed when looking at H - N individually.

In 2020, a decreasing trend was observable for nearly all OENACE codes except for L Real estate activities compared to 2019. Only I Accommodation and food service activities slightly decreased again 2021. The industries H Transportation and storage, J Information and communication, K Financial and insurance activities, L Real estate activities, M Professional, scientific and technical activities and N Administrative and support service activities showed increased business closings in 2021.

In Canada, there was a peak in business closures at the beginning of 2020. It is noted that: Closing businesses are businesses that transitioned from having at least one employee in the previous month to having no employees in the current month. These instances occur when a small firm goes out of business, when a large firm closes an establishment temporarily or permanently, and when a seasonal firm ceases business activity for the year. After that peak business closures till Sep-21 were approximately on the same level as before.[30]

Table 8 Business closing in Austria (2019 - 2021)

OENACE 2008 H - N	**2019**	**2020**	**2021**
H Transportation and storage	1.409	1.063	1.236
I Accommodation and food service activities	3.373	2.763	2.737
J Information and communication	1.402	993	1.719
K Financial and insurance activities	509	466	500
L Real estate activities	318	412	808
M Professional, scientific and technical activities	4.411	3.652	4.524
N Administrative and support service activities	1.752	1.464	1.907
Sum of OENACE 2008 H - N	13.174	10.813	13.431

* Preliminary data for 2021

** Till 2020 without Group K 64.2 Activities of holding companies, from 2013 till 2020 also without Group 64.3 Trusts, funds and similar financial entities

*** Differences from rounding up/down not offset

Source: Statistics Austria database

It seems that an economic shock like the COVID-19 pandemic did not cause a great decrease in the number of enterprises or turnover for all industries. For Austria, there was an increase of newly founded enterprises observable in 2021. Business closings (2019 - 2021) were approximately on the same level as before in Austria and Canada. It is not clear yet if there are delayed effects for 2022 onwards.

[30] Vooburg paper from Canada (2022), page 4