Monthly Prefecture-Level GDP in Japan*

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Abstract

We propose a new measure of monthly prefecture-level GDP in Japan. Our measure is derived in two steps. In the first step, we compute the production-side GDP and expenditure-side GDP using a variety of official statistics. In the second step, we compute the simple average of the two levels and make an adjustment to it to ensure consistency with the official national quarterly GDP. For more recent periods when official statistics are not available, we estimate monthly GDP using alternative data. Our monthly prefecture-level GDP measures can be used to analyze various economic questions at regional levels

Keywords: prefecture-level GDP, monthly GDP, time series forecasting, alternative data, regional economy

JEL classification: E01, E17, E37, C53, R11

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1 Introduction

For some policy analyses—including the analysis of pandemic and natural disasters—it is crucial to have access to high-frequency economic data at the regional level. In Japan, one of the fundamental statistics concerning regional economies is the Prefectural Economic Accounts. However, they are only published annually with an approximate lag of about two years until their release.[1] Some regional statistics—such as the Indices of Industrial Production (IIP) and Monthly Labor Survey (MLS) —are published on a monthly basis with a shorter lag. Yet, these datasets can only capture certain aspects of regional economies, such as production and employment. To capture the current economic conditions in a region, it is often necessary to synthesize these limited indicators along with micro-level qualitative information.[2]

This paper aims to contribute to the literature on regional economic statistics by proposing a novel measure of monthly prefecture-level GDP (Gross Domestic Product) in Japan. We also present a method for estimating—"backcasting"—recent values of monthly prefecture-level GDP.

Here is the overview of what we do in this paper. First, we construct monthly economic activity indicators for both the production and expenditure sides for each prefecture. Second, we take the simple average of these two indicators for each prefecture and make adjustments to it to ensure that the aggregated monthly prefecture-level GDP matches the national quarterly GDP. This is our monthly prefecture-level GDP. Third, for the most recent months where actual values cannot be calculated yet, we estimate GDP values using a statistical model based on the relationship with available data (alternative data) that have a relatively

[1]Several prefectures, including Hyogo, Fukuoka, and Ibaraki, estimate and publish quarterly GDP. Additionally, other prefectures such as Shimane published their quarterly GDP in the past. For those interested in the methodology of creating these quarterly preliminary Prefectural Accounts, references can be found in the work of Ashiya (2009) and Shimaneken (2020), where they explain the procedures involved in generating these estimates.

[2]There are indicators for regional economic sentiment based on surveys, such as the Bank of Japan's Tankan survey, the Cabinet Office's Economy Watchers Survey, and the Teikoku Databank (TDB) Economic Trends Survey.

shorter lag until data release. This process is referred to as "backcasting" in this paper.

The distinctive feature of our monthly prefecture-level GDP—compared to several previous studies (e.g., Yamasawa (2014, 2022) and Yamada (2014))—is that it is constructed using a wide range of information from both the production and expenditure sides. We will discuss these previous studies in detail shortly.

The monthly prefecture-level GDP constructed in this manner can be used for various regional economic analyses. As an example, this paper explores time-series correlations between GDP and factors such as population movement, the number of new COVID-19 cases, and the inflation rate in each prefecture. We find that while there are significant correlations between GDP and population movement or new COVID-19 cases in many prefectures, the coefficients of correlation vary widely among prefectures. Additionally, a positive correlation resembling the Phillips curve between monthly GDP and inflation rates is observed in many prefectures.

1.1 Literature review

This paper is related to two strands of literature: construction of high-frequency economic indicators at the state level and nowcasting economic activity.

1.1.1 High-frequency economic indicators at the state level

In recent years, there has been a surge of high-frequency economic indicators. Most studies focus on the national , several studies analyze high-frequency economic indicators at the state level. Crone and Clayton-Matthews (2005) estimate monthly coincident indexes for the 50 U.S. states using the methodology developed by Stock and Watson (1989). Baumeister et al. (2022) develop a dataset of weekly economic indicators for the 50 U.S. states based on mixed-frequency dynamic factor models. Chinn and LeCloux (2018) review the data sources and series that are useful for developing high-frequency economic indicators at the state level.

Our paper is closely related to Yamasawa (2014), Yamada (2014), and Yamasawa (2022) which construct monthly prefecture-level GDP in Japan. Below, we discuss their work and our difference from their work in some details.

Yamasawa (2014) constructs expenditure-side monthly GDP for three disaster-affected prefectures (Iwate, Miyagi, and Fukushima). He does so by combining the Regional Domestic Expenditure Index (RDEI)—which covers consumption, private residential investment, private non-residential investment, and public investment—and estimates of public consumption, net exports to other countries and net exports to other prefectures. He estimates public consumption, net exports to other countries and prefectures via panel data analysis exploiting the historical relationship between these variables and their key predictors.

Yamada (2014) constructs expenditure-side monthly GDP for all 47 prefectures in a similar manner to Yamasawa (2014), but with a different approach to estimating net exports to other countries and prefectures. He utilizes data from the Trade Statistics published by the Ministry of Finance and estimates prefecture-level net exports to other countries using information on industrial compositions. He also estimates prefecture-level net exports to other prefectures using inter-prefectural freight transportation data and imposing a constraint condition that the total net exports nationwide must be zero. Government expenditure is not estimated in the Yamada's study, unlike in Yamasawa (2014).[3]

Yamasawa (2022) constructs production-side monthly GDP for all 47 prefectures in a similar manner to Yamasawa (2014), but with supply-side variables. Yamasawa (2022) first regresses annual output of various industries from prefectural economic accounts on the annual values of the IIP, Indices of Tertiary Industry Activity (ITA), and construction output data from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). With the estimated equations, he predicts monthly prefecture-level output of each industry using the monthly data of the covariates. Finally, he constructs monthly prefecture-level GDP by summing the predicted monthly output across industries.

[3]Regarding government expenditure, although it constitutes a significant share of each prefecture's GDP, its impact on GDP fluctuations is relatively limited.

Our monthly prefecture-level GDP is different from these measures because we combine expenditure-side GDP with production-side GDP. We also take a different approach to constructing the production-side GDP compared to Yamasawa (2022). Moreover, we propose a backcasting methodology to estimate recent values of GDP using alternative data, while they do not.

1.1.2 Nowcasting GDP

This paper is also related to the literature of nowcasting GDP. Since Giannone et al. (2008) and Evans (2005), many researchers have proposed various methodologies to nowcast GDP in different countries. Banbula et al. (2011; 2013) and Carriero et al. (2015)construct nowcasts for GDP in the U.S., while Giannone et al. (2009) and Mitchell (2009) constructs nowcasts for GDP in the Euro Area and the U.K., respectively. See Bańbura et al. (2013) and Bok et al. (2018) for surveys on nowcasting in macroeconomics.

Several papers have constructed the nowcast of Japan's GDP (Hara and Yamane (2013), Urasawa (2014), Bragoli (2017), Hayashi and Tachi (2023), Nakazawa (2022) and Chikamatsu et al. (2021)).[4] These papers typically focus on nowcasting quarterly GDP, with Hara and Yamane (2013) being an exception—they nowcast monthly GDP. Most papers use variants of the dynamic factor model by extracting a number of primary components of large-scale data, while Chikamatsu et al. (2021) adapts an equation-by-equation approach. We propose a backcasting methodology based on the latter approach and adopt it to monthly prefecture-level GDP in Japan.

This paper is organized as follows. Section 2 details the methodology for constructing monthly prefecture-level GDP. Section 3 explains the methodology for backcasting GDP. Section 4 presents several examples of analyses using the monthly prefecture-level GDP, and Section 5 concludes.

[4] Recently, the Bank of Japan (BOJ) has been leading an initiative to utilize alternative data to nowcast economic activities in Japan (see Furukawa et al. (2022); Furukawa and Hisano (2022); Matsumura et al. (2021); Nakazawa (2022); Okubo et al. (2022)).

2 Construction of monthly prefecture-level GDP

In this section, we discuss the methodology for constructing monthly prefecture-level GDP in Japan.

The following is an overview of our procedure: First, for each prefecture, we construct production-side and expenditure-side GDP measures at monthly frequency. The production-side GDP ($GDP\,(P)$) is calculated as a weighted average using industry-specific weights for manufacturing, construction, and service activities on a monthly basis. The expenditure-side GDP ($GDP\,(E)$) is computed as a weighted average of four series: consumption, private investment, residential investment, and public investment.

Second, we aggregate these two GDP measures. According to the national income accounting identity, these two measures should be equal theoretically. However, due to measurement errors and the lack of information on certain components (for example, agricultural and forestry activities for production-side GDP, and public consumption and net exports for expenditure-side GDP), the production-side GDP and expenditure-side GDP typically do not coincide. To aggregate $GDP\,(P)$ and $GDP\,(E)$, we take their simple average ("unadjusted GDP") and scale it so that, when prefecture-level GDP values are aggregated to form the national GDP, that value aligns with the national quarterly GDP.

2.1 Production-side GDP

We calculate the production-side GDP for each prefecture by taking a weighted average of the following three indices: IIP (manufacturing sector), "Construction Comprehensive Statistics" (construction sector), and ITA (service sector).[5] These three indices are weighted based on the value-added share of each sector from the Economic Census - Activity Survey published by the Ministry of Internal Affairs and Communications (MIC). Below, we will provide a detailed explanation of the procedure for computing the production-side GDP for

[5] IIP and ITA are published by METI while CCS is published by MLIT.

each prefecture.

For the manufacturing sector, we use the monthly IIP data for the seasonally-adjusted composite index. The IIP (Indices of Industrial Production) is published by METI and provides monthly prefecture-level indices of manufacturing activity.

For the construction sector, we use the prefecture-level monthly data on regional construction output (nominal values) from "Quick Estimate of Construction Investment" provided by MLIT.[6] We employ the MLIT's "Construction Project Cost Deflator" (Construction Comprehensive, Nationwide) to convert these nominal values into real values. We seasonally adjust these real-valued data using the X12-ARIMA method for each prefecture.[7]

For the service sector, we use the ITA (Indices of Tertiary Industry Activity) data. The ITA is published by METI and provides monthly indices of industrial activity within service sector at the national level. Prefecture-level ITA is not available in almost all prefectures, with Tokyo being an exception. However, industry-specific weights for each prefecture are available.

We compute prefecture-level ITA by taking a weighted average using these industry-specific weights. Specifically, we calculate the index of tertiary activity in prefecture k at time t, denoted by ITA_t^k, as follows

$$ITA_t^k = \sum_i w_i^k ITA_{it}^N$$

where ITA_{it}^N represents the level of economic activity for industry i at the national level (N), and w_i^k represents the weight for industry i in prefecture k.[8] For the weights w_i^k, we use industrial value-added shares from prefectural input-output (IO) tables or the Economic

[6]Since the most recent publicly available data starts from April 2017, we extend and connect the dataset from April 2011 to March 2017, which was published in January 2021.

[7]Yamasawa (2022) has created prefecture-specific monthly production indices for the construction industry using a comparable approach.

[8]In Appendix D, we attempt to modify the ITA index based on the monthly data of six business types (department stores, supermarkets, convenience stores, electronics retailers, drugstores, and home improvement stores) from the METI's "Commercial Activity Statistics," collected by each prefecture.

Census. Most of the prefectures construct their own IO tables. Since industry classifications in those prefectural IO tables and ITA are similar, we use the industrial share information from the IO tables. For prefectures whose prefectural IO tables are not available, we use industrial value added shares from the Economic Census. Though the industrial shares from the Census are available in all prefectures, we prefer the IO weights to the Census weights because ITA industrial classifications are more similar to the IO classifications than to the Census classifications. See Appendix A and B for more detailed description of the IO and Economic Census weights respectively.

After computing the monthly prefecture-level indices for the manufacturing, construction, and service sectors, we construct the monthly prefecture-level production-side GDP by taking the weighted average of those three indices. The sectoral weights are computed based on the value added from the Economic Census for each prefecture[9]; these weights are constant over time during the sample period. If we denote IIP_t^k, $Const_t^k$, and ITA_t^k as the monthly data (with a base year average of 100 for the year 2015) for each sector in prefecture k, and s_m^k, s_s^k, and s_c^k as the respective sectoral weights for prefecture k (adjusted to ensure that their sum equals 1), then the production-side GDP for prefecture k at time t, denoted by $GDP\left(P\right)_t^k$, is given by

$$\begin{aligned} GDP\left(P\right)_t^k &= s_m^k IIP_t^k + s_c^k Const_t^k + s_s^k ITA_s^k \\ &= s_m^k IIP_t^k + s_c^k Const_t^k + s_s^k \left(\sum_i w_i^k ITA_{it}^N \right) \end{aligned}$$

Figure 1 represents the sectoral weights for each prefecture. According to the figure, they cover nearly the entire economy, encompassing both the secondary sector—including the construction industry—and the tertiary sector.

Figure 2 displays $\left\{ GDP\left(P\right)_t^k, IIP_t^k, Const_t^k, ITA_t^k \right\}$ for Tokyo and Aichi. In Tokyo, the

[9]It is important to note that the production-side GDP created here does not include the production activities of the agriculture, forestry, and fisheries sector. These sectors' contribution to the overall GDP is relatively small, and furthermore, there is no monthly data available for their production activities.

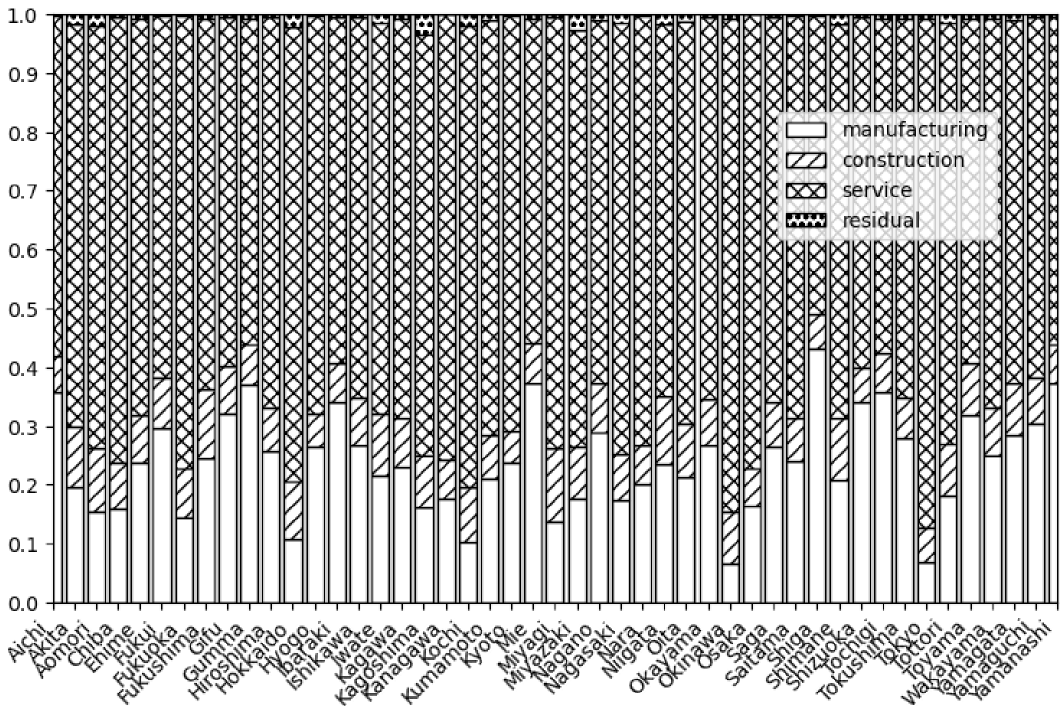

Figure 1: Sectoral weights by prefecture

service sector accounts for over 80% of the total weight. As a result, the fluctuation of its production-side GDP is largely explained by the dynamics of ITA. Both the manufacturing and service sectors experienced a significant decline in production around the time of the declaration of the state of emergency (SOE) in April 2020. Conversely, the construction sector did not experience a substantial decline during the same period, although it does exhibit a downward trend throughout the COVID-19 crisis.[10]

In Aichi, the service sector carries around 60% weight while the manufacturing sector accounts for around 40%. As a result, the production-side GDP fluctuates approximately midway between ITA and IIP. According to the figure, IIP experienced a more pronounced decline during the SOEs than ITA in Aichi.

[10] Furthermore, it should be noted that monthly data of ITA (with a base year of 2015) for Tokyo are available. These data closely mirror the movements of ITA's monthly data created using national monthly industry-level data and industry-specific weights for Tokyo.

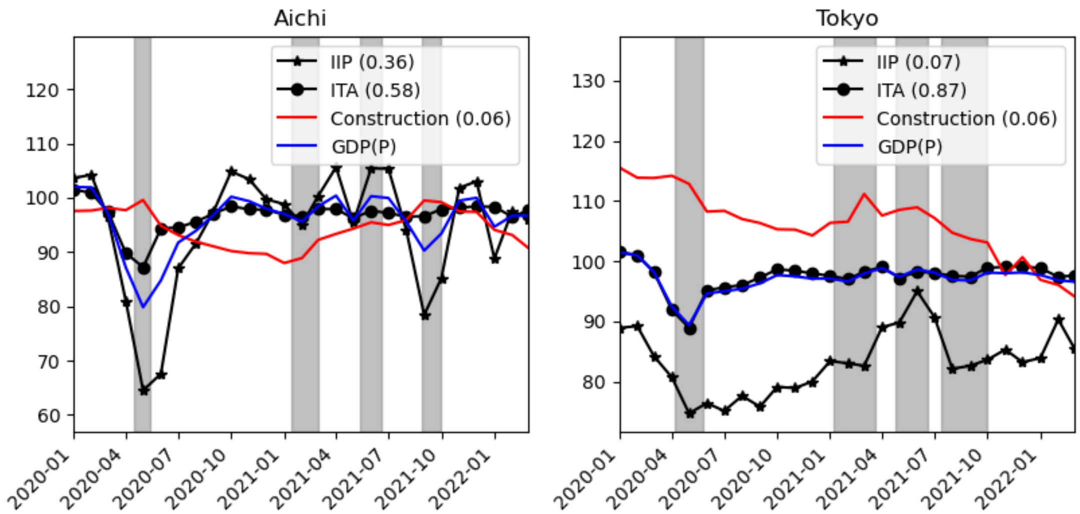

Figure 2: Production-side GDP: Aichi and Tokyo

2.2 Expenditure-side GDP

We calculate the expenditure-side GDP for each prefecture using the "Regional Domestic Expenditure Index" (RDEI) provided by the Cabinet Office.[11] The RDEI comprises four indices: the regional consumption index, the regional private residential index, the regional private corporate investment index, and the regional public investment index. For each of these indices, monthly data (real, seasonally adjusted) are publicly available for each prefecture, starting from January 2005 for the regional consumption index and January 2012 for other indices. We seasonally adjust each of these indices using X-12-ARIMA. We compute the expenditure-side GDP by taking a weighted average of those data (normalized to be 100 in 2015), where weights are the real expenditure values of the corresponding items in the Prefectural Economic Accounts (PEA).[12] We denote the expenditure-side GDP for prefecture k at time t by $GDP\,(E)_t^k$.

Figure 3 presents the growth rate of the expenditure-side GDP and its decomposition into the four components of RDEI for Tokyo and Aichi since 2020.

[11] For detailed documentation of RDEI, see Tanabe et al. (2012) and Mitani et al. (2019).

[12] In the original data, the base year for the consumption series is 2012, while that for other three series is 2005.

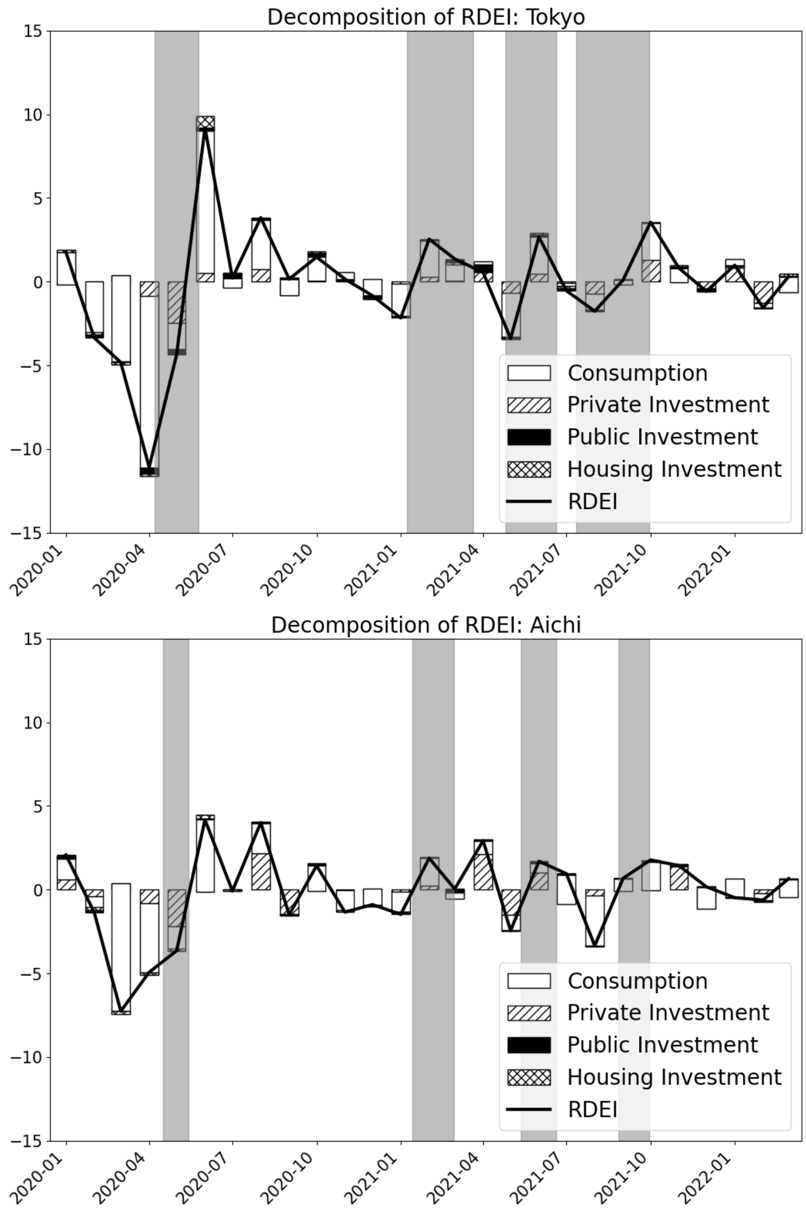

Figure 3: Expenditure-side GDP (contribution decomposition): Tokyo and Aichi

According to the figure, private consumption is the primary driver of fluctuations in both prefectures. However, private investment is also a significant component explaining the fluctuation of RDEI in Aichi, whereas it is not in Tokyo. This difference is consistent with the difference observed in the production-side GDP between Tokyo and Aichi prefectures, as discussed at the end of Section 2.1.

2.3 Aggregation to prefecture-level GDP

Thus far, we have explained how to construct monthly production-side and expenditure-side GDP at a prefecture level. We now explain how to aggregate them to obtain the monthly prefecture-level GDP.

We start by taking a simple average of production-side and expenditure-side GDP.

$$\widetilde{GDP}_t^k = 0.5 \times GDP\left(E\right)_t^k + 0.5 \times GDP\left(P\right)_t^k$$

This simple average—"unadjusted GDP"— for each prefecture can be aggregated across prefectures to obtain the national GDP. However, this national GDP may not necessarily align with the quarterly estimates (QE) of the national GDP published by the Cabinet Office. To make our aggregated national GDP consistent with the QE for each quarter, we make the following adjustments to the unadjusted GDP of each prefecture.

First, we aggregate GDP across prefectures using the value-added weights from the Economic Census for each prefecture, denoted by ω^k. This aggregation generates the monthly data for the national GDP

$$\widetilde{GDP}_t^n = \sum_k \omega^k \widetilde{GDP}_t^k$$

Let's call $\widetilde{GDP}_t^n$ "the unadjusted national GDP." Next, we time-aggregate the monthly values for each quarter to calculate the quarterly data for national GDP. Let's normalize the official national GDP from the Cabinet Office so that its average value in 2015 is 100 and call it $QE_{\tau(t)}^n$. Then, we multiply each prefecture's unadjusted GDP by the ratio of official national GDP to the unadjusted national GDP.

$$GDP_t^k = \left(\frac{QE_{\tau(t)}^n}{\sum_{s \in S(\tau(t))} \widetilde{GDP}_s^n} \right) \widetilde{GDP}_t^k = \kappa_{\tau(t)} \widetilde{GDP}_t^k$$

This is our monthly prefecture-level GDP. In this equation, we use a set of quarter-specific coefficients $\kappa_{\tau(t)}$ for an adjustment. Here, $\tau\left(t\right)$ represents the quarter that includes a specific month t and $S(\tau(t))$ denotes the set of all months contained within that quarter $\tau(t)$. For example, when t is January 2020, $\tau(t)$ is the first quarter of 2020 and $S(\tau(t))$ consists of {January 2020, February 2020, March 2020}. By construction, if we aggregate our monthly prefecture-level GDP, both across prefectures and across months, the resulting national GDP coincides with the official national GDP.[13]

Figure 4 displays the production-side GDP, expenditure-side GDP, their simple average, and monthly GDP for Aichi and Tokyo (2015 = 100).

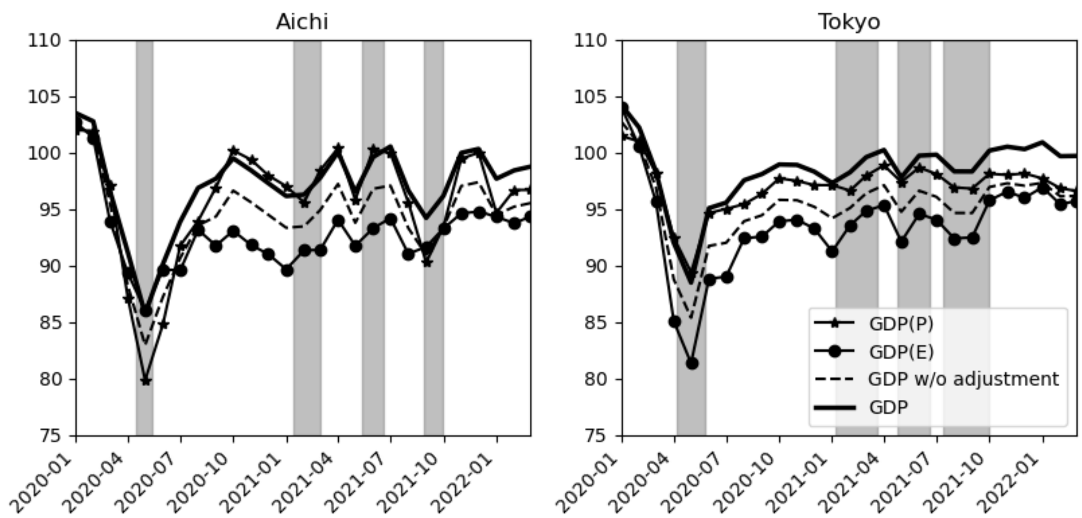

Figure 4: Monthly GDP: Aichi and Tokyo

Figure 5 compares our monthly national GDP with the official national quarterly GDP and the national monthly GDP constructed by the Japan Center for Economic Research (JCER). For comparison, all three GDP measures are standardized to have an average of 100 for the first quarter of 2020. According to the figure, our monthly national GDP aligns with the official quarterly national GDP. Our monthly national GDP also moves closely with JCER's monthly national GDP.

[13] We have

$$QE^n_{\tau(t)} = \sum_{s \in S(\tau(t))} \sum_k \omega^k GDP^k_s$$

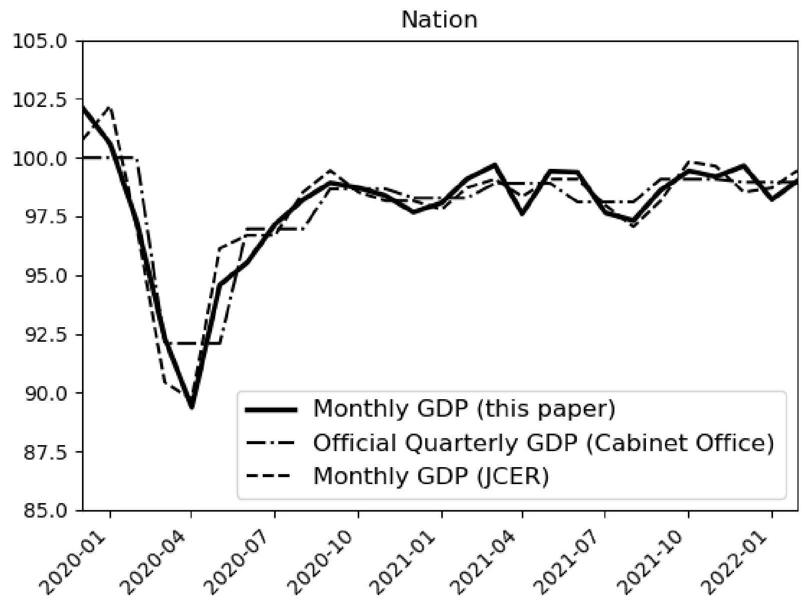

Figure 5: Monthly GDP: Nation

2.4 The timing of the construction of monthly prefecture-level GDP

The timing of constructing production-side GDP, expenditure-side GDP, and overall GDP depends on the release schedule of the underlying data.

For the production-side GDP, we use three datasets: (i) national ITA, (ii) prefecture-level IIP, and (iii) prefecture-level construction statistics. Preliminary and final values of the national ITA are released with a two-month and five-month lag respectively. Preliminary and final values of the prefecture-level IIP are released with a two-month and three-month lag respectively. Final values of the prefecture-level construction statistics are released with a two-month lag.[14] Hence, we can compute the production-side GDP with a two-month lag.

For the expenditure-side GDP, we use prefecture-level RDEI, which is the only input. Prefecture-level RDEI is released quarterly in March, June, September, and December. At each release timing, monthly data for the previous quarter are published at a time, which means that there is a lag of three to five months in updating the expenditure-side GDP.

[14]Note that retrospective revisions to deflators can occur at any time.

To construct the monthly prefecture-level GDP, we also need the Cabinet Office's Quarterly Estimates (QE). The Cabinet Office releases the preliminary estimate of the previous quarter in February, May, August, and November. For example, the first preliminary estimate for the July to September period is published in November.[15] Consequently, there is a lag of three to five months in updating our monthly GDP.

3 Backcasting the prefecture-level GDP

As explained in the preceding section, we can only compute monthly prefecture-level GDP with a lag of 3 to 5 months.[16] In this section, we describe the methodology of backcasting—estimating GDP for the most recent months when the actual GDP is not yet computable. The estimation takes the advantage of the statistical relationship between historical values of GDP and alternative data—a collection of private sector data and public statistics that are not part of the GDP calculation.

Table 1 summarizes the alternative data used in our backcasting procedure. For example, the private sector data include human mobility and web search results and public statistics include National Family and Income Survey by Ministry of Internal Affairs and Communications (MIC) and Commercial Statistics by Ministry of Economy, Trade and Industry (METI).

[15] The second interim report update will occur thereafter (in March, June, September, and December).

[16] For any particular month, it requires a lag of two months for production-side GDP and three to five months for expenditure-side GDP to construct actual GDP from official statistics such as IIP or ITA. It requires a lag of two to four months for the QE adjustments implying that we can compute our monthly GDP as soon as official data for expenditure-side GDP are released.

Name	Description	Source	Lag
Mobility	Mean of the monthly medians of the four data: retail stores, amusement facilities, public transportation, and offices	Google "COVID-19: community mobility report "	0
Restaurants	N of views of restaurant information, compared to 2019	Retty "Food Data Platform" *	0
DI All	Business diffusion index, all types (YoY)	TDB, "Business Trends Survey"	1
DI Manufacturing	Business diffusion index, manufacturing (YoY)	TDB, "Business Trends Survey"	1
Job vacancy	N of job offers, vs. same period in 2019	HRog "HRog list for academia" *	2
Event tickets	N of event ticket sales, vs. same month in 2019	Ticket PIA*	2
Household Expenditure	Amount of expenditure of households of two or more people (YoY)	MIC "National Family and Income Survey"	2
Grocery	Amount of sales in department stores / supermarkets (YoY)	METI"Commercial Statistics"	2
Convenience	Amount of sales in convenience stores (YoY)	METI"Commercial Statistics"	2
Electronics	Amount of sales in electronics stores (YoY)	METI "Commercial Statistics"	2
Drugs	Amount of sales in pharmacies (YoY)	METI "Commercial Statistics"	2
Construction	Amount of expected construction cost (YoY)	MLIT "Report on Statistical Survey on Construction Start"	2
Tracks	N of sales of new light four-wheel vehicles by prefecture (freight cars; YoY)	Japan Mini Vehicles Association	3
Cars	N of sales of new light four-wheel vehicles by prefecture (passenger cars; YoY)	Japan Mini Vehicles Association	4

Table 1: Description of the alternative data: * Data are retrieved from V-RESAS. TDB = Teikoku Databank, MIC = Ministry of Internal Affairs and Communications, METI = Ministry of Economy, Trade and Industry, MLIT = Ministry of Land, Infrastructure, Transport and Tourism.

Some of these variables are available at a frequency higher than monthly (e.g., Mobility, Restaurants, Job vacancy, Event tickets). In our backcasting procedure, we aggregate all data to a monthly frequency. We make seasonal adjustments to these variables by computing year-on-year changes. Figure 6 illustrates the evolution of the alternative data for Tokyo.

The data used for backcasting GDP can be categorized into five groups based on when they become available: (i) data that become available in the month when the actual GDP becomes computable (Mobility, Restaurants), (ii) data that become available with a one-month lag (Job vacancy, DI All, DI Manufacturing), (iii) data that become available with a two-

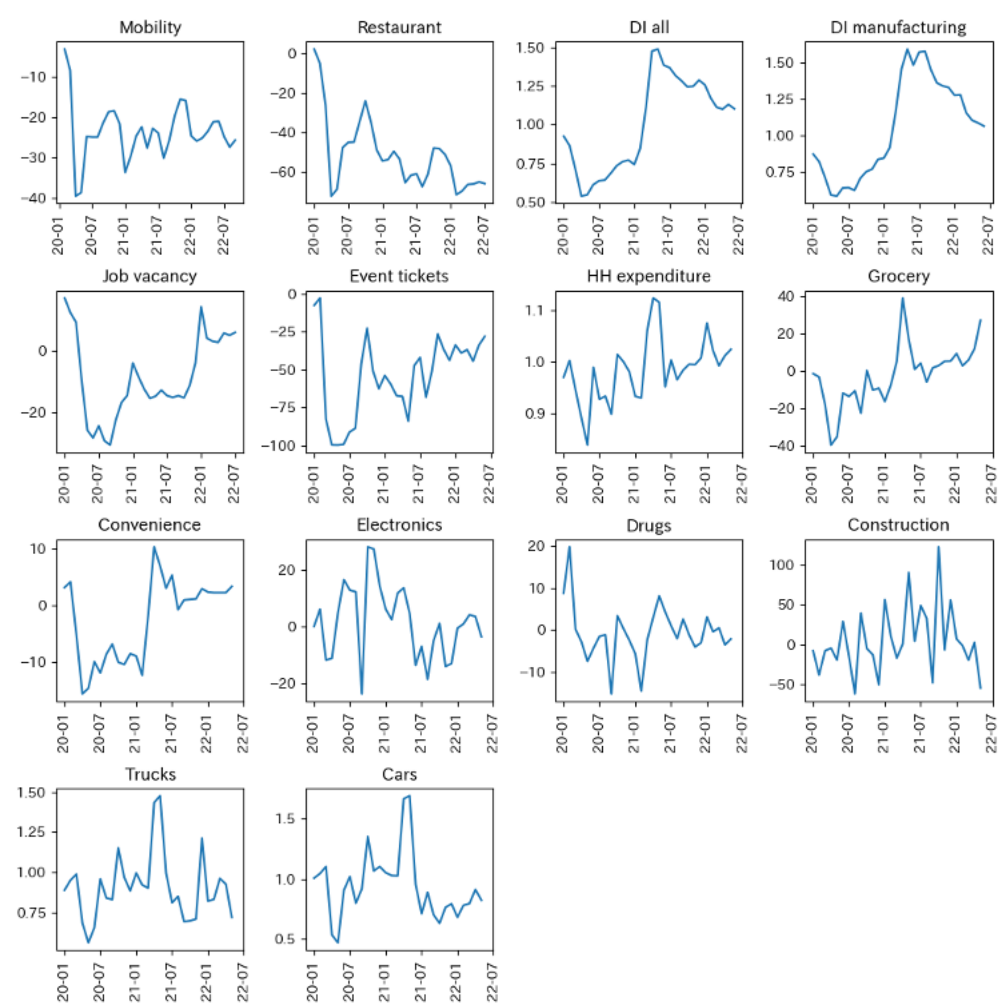

Figure 6: Alternative data: Tokyo

month lag (Event tickets, Household expenditure, Grocery, Convenience, Electronics, Drugs, Construction, production-side GDP), (iv) data that become available with a three-month lag (Tracks), and (v) data available with a four-month lag (Cars). We use our production-side GDP described in Section 2.1 as one of the data sources because production-side data become available before we compute GDP and it can help us better backcast GDP.

Note that some variables might be useful in backcasting actual GDP in some times but not in other times. For example, there is a strong correlation between Mobility and GDP during COVID-19 crisis due to repeated declarations of a state of emergency. However, such correlation has became weaker over time.[17] Also some of the data may be discontinued at

[17]In Section 4, an analysis is conducted regarding the correlation between monthly GDP at the prefectural

some point in time.[18]

3.1 Backcasting methodology

Let T_{now} be the current period and T_{GDP} be the most recent month at which we can compute our monthly GDP. Let $s = T_{now} - T_{GDP}$, representing the length of the backcasting period. The objective of backcasting is to estimate GDP for the period when we cannot yet compute GDP, specifically for $t = T_{GDP} + 1, T_{GDP+2}, ..., T_{GDP} + s = T_{now}$.

Backcasting involves two stages.[19] In the first stage, we estimate an Autoregressive Distributed Lag (ADL) model for each alternative data source. In the second stage, we combine the projected values obtained from each alternative data source using weighted averaging, with the weights determined by the variances of the error terms of each estimated model. Below, we elaborate each stage.

In the first stage, we estimate the following ADL model for each alternative data x listed in Table 1 in each prefecture k:

$$GDP_t^k = \mu_x^k + \gamma_x^k GDP_{t-1}^k + \beta_{x,0}^k x_t^k + \beta_{x,1}^k x_{t-1}^k + \epsilon_{x,t}^k \text{ for } t = T_{START,x}^k + 1, ..., T_{GDP} \tag{1}$$

where $T_{START,x}^k$ is the first date where data x is available in prefecture k, $\epsilon_{x,t}^k$ is an i.i.d error term with mean zero and standard error σ^k. GDP_t^k represents the our monthly GDP (in logarithmic form). We assume GDP_t^k follows an $I(0)$ process.[20]We use the least squares method to obtain estimates for the parameters $\left(\mu_x^k, \gamma_x^k, \beta_{0,x}^k, \beta_{1,x}^k, \sigma_x^k\right)$.

With the estimated parameters, we can project GDP for $t = T_{GDP} + 1, ..., T_{now}$ recursively.

level and variables such as human mobility and the number of new infections.

[18]Note that the Google Community Mobility Reports ceased to be published in October 2022.

[19]We follow the approach of Stock and Watson (2003).

[20]Assuming $I(0)$ process for the level of GDP is a bit unusual, but makes sense in Japan for our sample period. Also, our backcasting accuracy analysis shows that the backcasting is more accurate under the $I(0)$ than under the $I(1)$ assumption. See Appendix E for more information.

Namely,

$$
\begin{aligned}
\widehat{GDP}^k_{T_{GDP}+1,x} &= \hat{\mu}^k + \hat{\gamma}^k GDP^k_{T_{GDP}} + \hat{\beta}^k_0 x^k_{T_{GDP}} + \hat{\beta}^k_1 x^k_{T_{GDP}-1}, \\
\widehat{GDP}^k_{T_{GDP}+j,x} &= \hat{\mu}^k + \hat{\gamma}^k \widehat{GDP}^k_{T_{GDP}+j-1,x} + \hat{\beta}^k_0 x^k_{T_{GDP}+j-1} + \hat{\beta}^k_1 x^k_{T_{GDP}+j-2},
\end{aligned}
$$

for $j = 2, 3, ..., s$. In the projection of $\widehat{GDP}^k_{T_{GDP}+j,x}$ for $j = 2, ..., s$, the right-hand side of the estimation equation involves the recursive substitution of GDP values, with $\widehat{GDP}^k_{T_{GDP}+j-1,x}$ being used iteratively. This projection is possible because alternative data are available for the period $t = T_{GDP} + 1, ..., T_{now}$.

In the second stage, we average the estimated GDP values obtained from each alternative data source in the first stage for each prefecture k. In computing the average, we put more weight for an alternative data source that has a higher explanatory power. Note that the set of available alternative data depends on the projection horizon j because, as discussed earlier, the timing of the release varies across alternative data. Specifically, the weight for an alternative data source x with projection horizon j for prefecture k is denoted by $\hat{w}^k_{j,x}$ and is given by the following:

$$
\hat{w}^k_{j,x} = \frac{\left(s^k_x\right)^{-1}}{\sum_{x' \in X_{T_{GDP}+j}} \left(s^k_{x'}\right)^{-1}}, \tag{2}
$$

where

$$
s^k_x = \sqrt{\frac{\sum_{t=T^k_{START,x}+1}^{T_{GDP}} \hat{\epsilon}^k_{x,t}}{T_{GDP} - T^k_{START,x} - 4}}. \tag{3}
$$

X_t represents a time-varying set of alternative data available at time t and $x \in X_t$ is a specific alternative data in that set. s^k_x is the standard error, the numerator of the right-hand side of (3) is the sum of squared residuals for the estimation equation (1) using a particular alternative data source x.

The numerator of (3) is the sum of squared residuals for the estimation equation (1) using a particular alternative data source x, and s^k_x is the standard error. In other words, when s^k_x

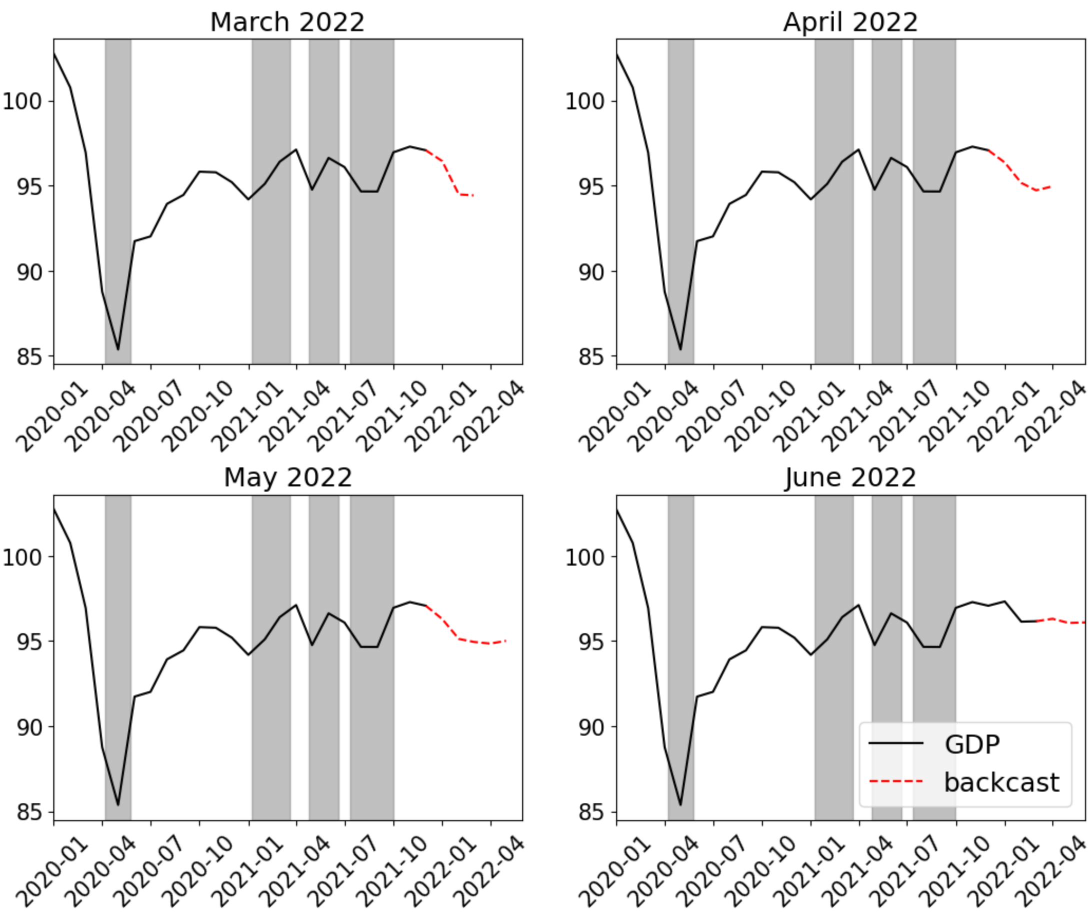

Figure 7: Backcasting: Tokyo

is larger, the weight assigned to the projected GDP value associated with x becomes smaller.

Using these weights, the average GDP in a prefecture k can be calculated as follows:

$$\widehat{GDP}^k_{T_{GDP}+j} = \sum_{x' \in X_{T_{GDP}+j}} \hat{w}^k_{j,x} \widehat{GDP}^k_{T_{GDP}+j,x} \tag{4}$$

for $j = 1, ..., s$. We take this value as our GDP backcast.

Figure 7 depicts GDP backcasts obtained in this manner for specific periods in time. In particular, it shows backcasts for four different values of T_{now}: March, April, May, and June 2022. When T_{now} is March 2022, T_{GDP}—the most recent period in which actual GDP is available— is December 2021. In this case, $s = T_{now} - T_{GDP} = 3$ and we backcast GDP for January, February, and March 2022, as shown by the red dashed line. When T_{now} is April

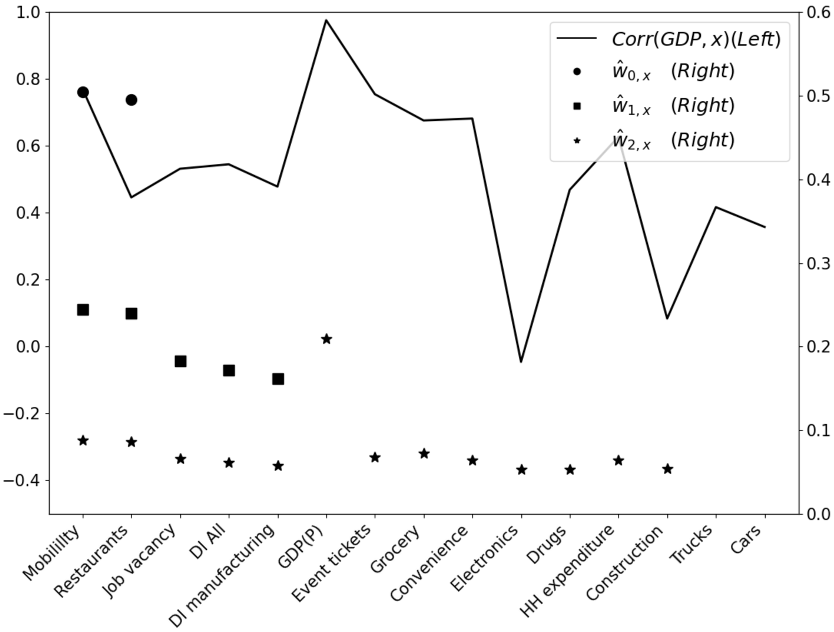

Figure 8: Weights in backcasting (dot, square, star) and correlation between GDP and alternative data (black solid line): Tokyo

2022, T_{GDP} is still December 2021. In this case, $s = 4$ and we backcast GDP for January, February, March, and April 2022. Similarly, when T_{now} is May 2022, T_{GDP} is still December 2021. In this case, $s = 5$ and we backcast GDP for January, February, March, April, and May 2022.

When T_{now} is June 2022, T_{GDP} becomes March 2022. Thus, $s = 3$ and we backcast GDP for April, May, and June 2022.

Note that there are three different backcasts for March 2022 GDP, corresponding to T_{now} being March, April, and May 2022. The set of available alternative data is different across these three cases, and thus, the weight assigned to each alternative data within each set is different across three cases. You can see the time-varying nature of available alternative datasets and associated weights in Figure 8, which displays the weights $\hat{w}_{j,x}^k$ for $j = 0$ (dot), $j = 1$ (square), and $j = 2$ (star) used for calculating the GDP backcast for March 2022. These lags correspond to T_{now} being March 2022, April 2022, and May 2022 respectively.

As shown in the figure, the set of available alternative data expands over time. In March ($j = 0$), there are only two alternative data sources (dot). In April, there are five (square). In May, there are 13 available alternative data sources (star). Reflecting the changing set, the weight changes over time. For example, the weight for human mobility is 0.50 in March, but it becomes 0.24 in April and 0.09 in May.

When a certain alternative data source exhibits a higher correlation with GDP, the source tends to receive a higher weight. The solid black line in Figure 8 shows the correlation coefficients between the actual GDP and each alternative data source x over the sample periods. The production-side GDP exhibits a stronger correlation with GDP and receives a higher weight. Electronics and Construction exhibit weaker correlations with GDP and receive lower weights.

To better understand the structure of our backcasting procedure, it is useful to point out that any given point in time t can be counted from either T_{GDP} or T_{now}. For instance, if we let $i = s - j$ for $j = 1, 2, ..., s$ noting that $T_{GDP} + j = T_{now} - s + j$, we have $T_{now} - i = T_{GDP} + j$, or

$$\widehat{GDP}^k_{T_{now}-i,x} = \widehat{GDP}^k_{T_{GDP}+j,x}$$

for $i = 0, 1, ..., s - 1$. In essence, calculating projected GDP values $\widehat{GDP}^k_{T_{GDP}+j,x}$ for future periods $j = 1, 2, \ldots, s$, with T_{GDP} representing the most recent point at which past actual values are known, is equivalent to calculating projected GDP values $\widehat{GDP}^k_{T_{now}-i,x}$ for past periods $i = 0, 1, \ldots, s - 1$, taking T_{now} as the current time point.

Table 2 illustrates the relationship between the month $T_{now} - i$ when GDP is backcasted and the values of T_{GDP}, T_{now}, and i. Let's focus on the case where T_{GDP} is December 2021 and T_{now} is March 2022 (the fourth row in the table). When $i = 0$, we backcast GDP for March 2022; when $i = 1$, we backcast for February 2022; and when $i = 2$, we backcast for January 2022, looking backward from T_{now}. This is equivalent to backcasting GDP when $j = 3, 2, 1$ looking forward from T_{GDP}. Note that more alternative data are available when i is larger or when j is smaller.

		i	0	1	2	3	4
s	T_{GDP}	T_{now}					
3	9	12	12	11	10		
4	9	1	1	12	11	10	
5	9	2	2	1	12	11	10
3	12	3	3	2	1		
4	12	4	4	3	2	1	
5	12	5	5	4	3	2	
3	3	6	6	5	4		1

Table 2: Structure of backcasting

Note: Except for the row of i and column of s, numbers indicate months such as 9 = September.

3.2 Backcasting accuracy

In this subsection, we examine the backcasting accuracy through out-of-sample validation using past data. To deepen our understanding of backcasting accuracy, we present several figures and develop arguments step by step.

We begin by investigating the differences between the actual GDP and the backcasted GDP for January to March 2022 when T_{now} is May 2022. If T_{now} = May 2022, T_{GDP} = Dec 2021, as can be seen in Table 2. Figure 9 illustrates this difference. In the figure, our backcasted values (red dotted line) lie below the actual GDP (blue solid line), which can be computed only in June 2022. We correctly predict the downward trend of GDP from January to March 2022, though the magnitude of the decline does not exactly match the actual decline. For T_{GDP} = Dec 2021, we can draw two additional backcasting lines each corresponding to T_{now} = April 2022 and T_{now} = March 2022. For any T_{GDP}, we can draw

Since the actual GDP can be computed every three months as discussed in 2.4, it is possible to draw a backcasting line from various points in time such as March, June, September, and December. For instance, when drawing the backcasting line from December, actual GDP is known up to December, but values from January onwards are not yet known. This situation arises when calculating GDP backcast values for January and beyond in the months of March, April, and May (as actual GDP up to March is revealed in June). Similarly, we can

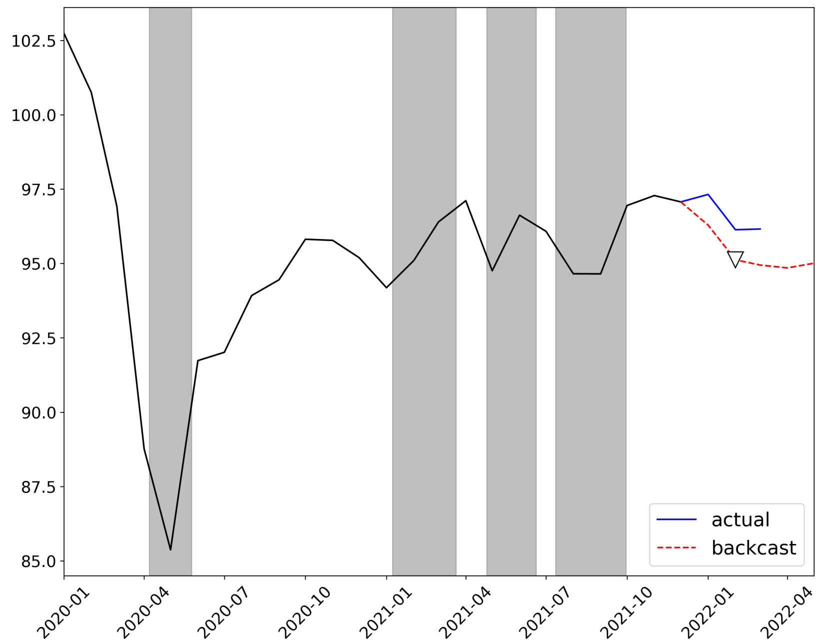

Figure 9: Actual and backcast values (T_{now} = May 2022): Tokyo

draw a backcasting line from September onwards in December, January, and February. In this way, for each quarter (March, June, September, and December), we can draw three distinct lines corresponding to different backcast points, as depicted in Figure 10. In the figure, a solid black line represents the actual GDP and red dashed lines are backcasted GDP values from different points in time. We have three distinct backcasting lines for March, June, September, and December of 2021. Our backcasting lines for March overestimate the actual GDP whereas backcasting lines for September underestimate it. The backcasting lines for June predict the actual GDP quite well.

Now, let's focus on the backcasting from December 2021 onwards. The three backcasting lines correspond to the prediction of GDP as of March, April, and May 2022. For a particular point in time (e.g. March 2022), we have three vertically aligned backcast values denoted by circle (March, $i = 0$), square (April, $i = 1$) and triangle (May, $i = 2$), as shown in Figure 10. It is evident that the triangle ($i = 2$) is the closest while the circle ($i = 0$) is the furthest from the actual value. Figure 11 presents these backcasting errors for the GDP of March 2022. Initially (as of March), the GDP value was backcasted to be about 1.75% lower than the actual value.

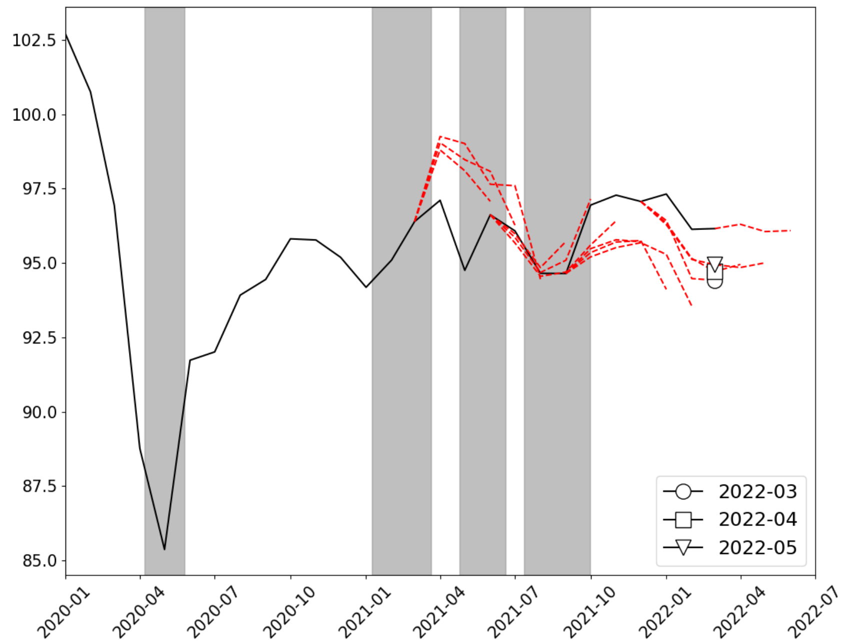

Figure 10: Actual and backcast GDP: Tokyo

However, as more alternative data became available, the backcasts are revised with a higher accuracy.

Let $\widehat{GDP}^k_{t-i}$ be the backcasted GDP for prefecture k, at a past time point t with an i-period lag, and GDP^k_{t-i} be its actual value. The backcasting accuracy for each prefecture k can be evaluated by using the following two metrics:

$$MAE^k_i = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\widehat{GDP}^k_{t-i} - GDP^k_{t-i}}{GDP^k_{t-i}}\right|$$

$$RMSE^k_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{\widehat{GDP}^k_{t-i} - GDP^k_{t-i}}{GDP^k_{t-i}}\right)^2},$$

where MAE^k_i represents the Mean Absolute Error, while $RMSE^k_i$ represents the Root Mean Squared Error.

Figure 12 displays the values of MAE^k_i and $RMSE^k_i$ for Tokyo and the average values for

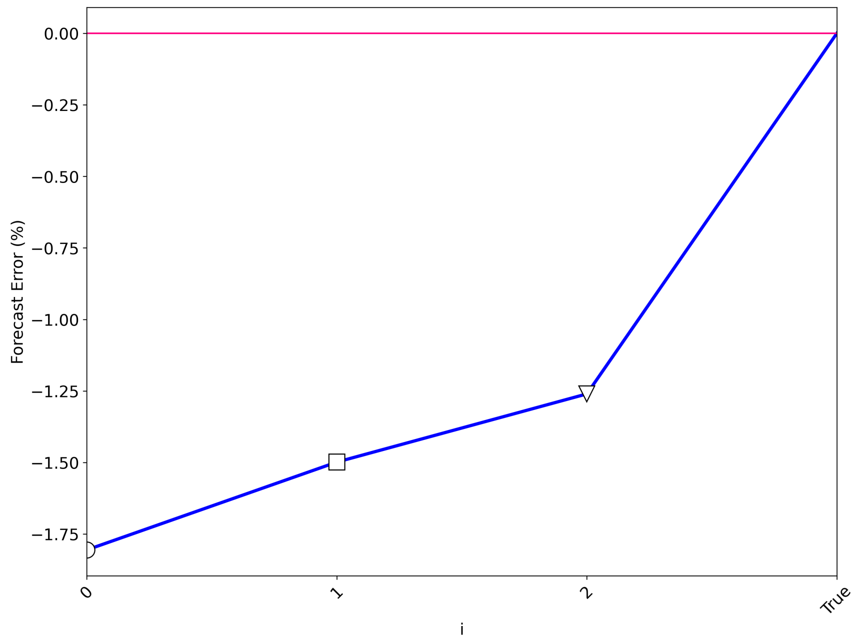

Figure 11: Backcasting error ($T_{now} - i =$ March, 2022): Tokyo

Note: $i = 0$ indicates the backcast error as of March 2022, $i = 1$ indicates that of April 2022, and $i = 2$ indicates that of May 2022, respectively. The actual value is computed in June 2022.

all prefectures ($k = 1, ..., 47$) across different values of i. Notably, backcast accuracy improves significantly at $i = 2$. This improvement occurs because the production-side GDP, which is used in the calculation of actual GDP, becomes available at $i = 2$.

4 Analyses using the monthly prefecture-level GDP

4.1 Comparison of the monthly prefecture-level GDP

Figure 13 shows the monthly GDP (normalized to 2020 Q1 = 100) for all 47 prefectures—thin grey lines—and the national monthly GDP—thick blue line—from January 2020 onwards. According to the figure, there is a considerable heterogeneity across prefectures regarding the evolution of the monthly GDP. For instance, the size of the decline in GDP in May 2020—which is associated with the declaration of the state of emergency—varies significantly among prefectures. The subsequent recovery also exhibits heterogeneity across

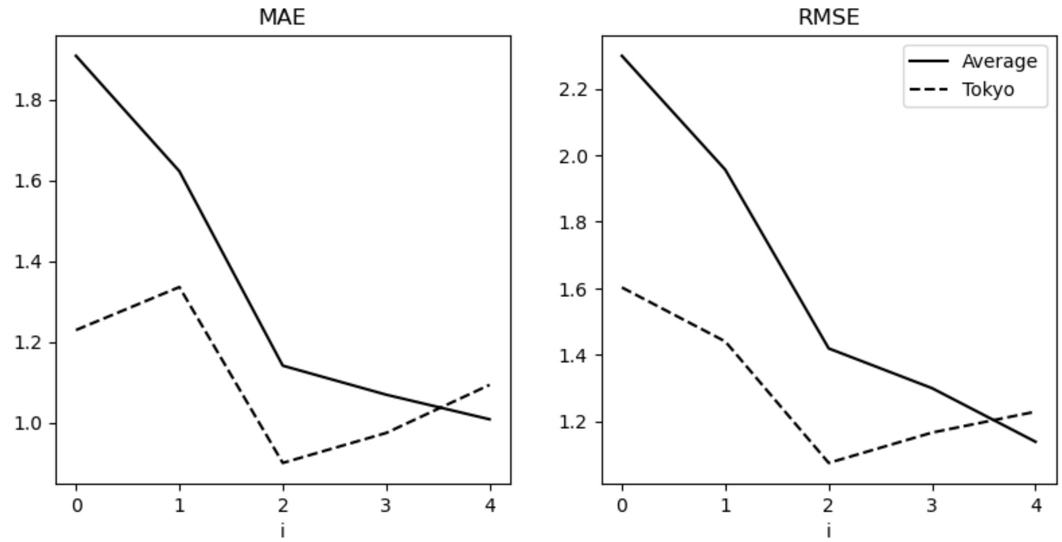

Figure 12: Backcasting accuracy

prefectures.

Figure 14 presents the monthly GDP for Tokyo, Aichi, Gunma, and Tokushima. Gunma experienced the most significant downturn in May 2020, while Tokushima experienced the least severe downturn during the same period. Tokushima's GDP exceeded the pre-Covid level after the summer of 2020. While GDP for Tokyo, Aichi, and Gunma generally follow a similar trajectory, the decline in GDP in May 2020 was larger in Aichi and Gunma than in Tokyo, likely reflecting the fact that Aichi and Gunma have a higher share of manufacturing industries.

4.2 Analyses using the monthly prefecture-level GDP

The prefecture-level GDP can also prove its utility when combined with other datasets for regional economic analysis.[21] In this subsection, we examine three empirical relationships using our monthly GDP: (i) the relationship between GDP and population mobility,[22] (ii) the

[21]Serizawa et al. (2022) utilized annual GDP for each prefecture in prefectural economic accounts and paired it with flood data for each prefecture to estimate the impact of floods on annual GDP.

[22]For instance, Fujii and Nakata (2021) estimated the relationship between our monthly GDP and the population mobility data since 2020 and incorporated this relationship into an epidemiological macroeconomic model to analyze the trade-off between economic activity and infection control measures.

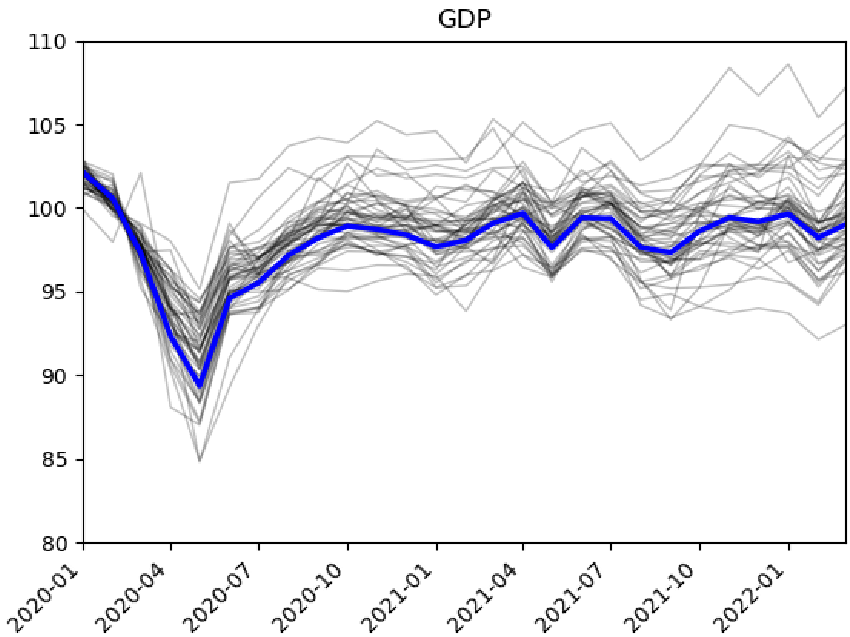

Figure 13: Monthly GDP by prefecture

relationship between GDP and COVID-19 infection, and (iii) the relationship between GDP and inflation.

Figure 15 presents the scatterplots of monthly GDP and population mobility for Tokyo, Hokkaido, Gunma, and Hyogo from January 2020 to March 2022. Tokyo—shown by the top-left panel—exhibits the correlation coefficient between monthly GDP and population mobility of 0.69, which is the highest among the 47 prefectures. Hyogo—shown by the bottom-right panel—exhibits a similarly high correlation coefficient of 0.68, while Hokkaido—shown by the top-right panel—exhibits the lowest correlation at 0.02. Gunma—shown by the bottom-left panel—exhibits the correlation coefficient of 0.43, which is the median value across all 47 prefectures. During the COVID-19 pandemic, there is a positive correlation between monthly GDP and population mobility in all prefectures.

The correlation coefficient is larger in the early phase of the COVID-19 crisis (from January 2020 to March 2021) during which the first and second declarations of a state of emergency led sharp declines in both population mobility and GDP. In Figure 15, we report corre-

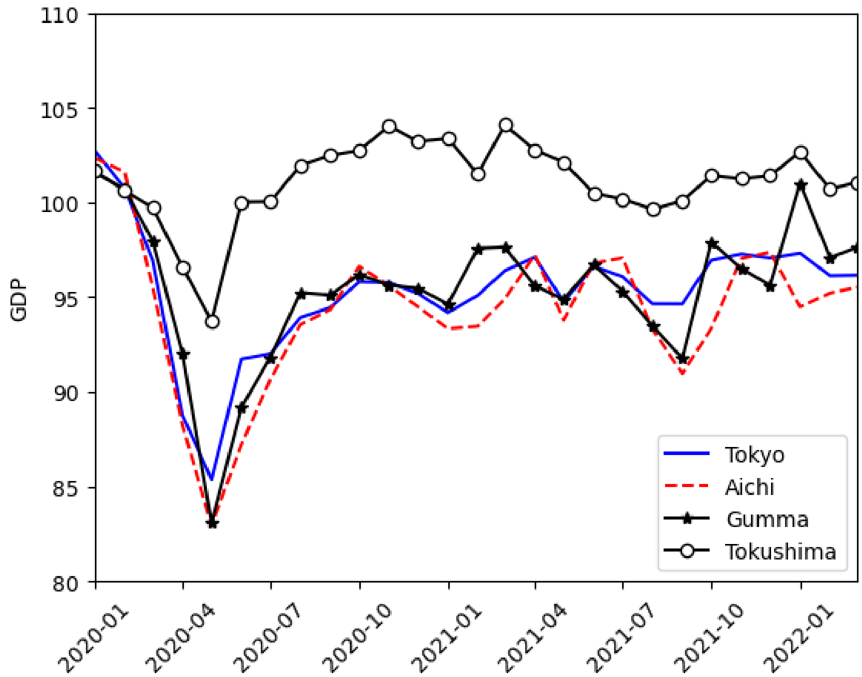

Figure 14: Monthly GDP: Tokyo, Aichi, Gunma, and Tokushima

lation coefficients for the early phase of COVID-19 crisis as well as the entire sample period. For example, it is 0.78 in Tokyo in the early phase of the COVID-19 crisis, versus 0.69 in the entire sample period.

Figure 16 displays the scatterplots of weekly GDP and the week-on-week change in new COVID-19 cases for Tokyo, Kagoshima, Fukuoka, and Tokushima from January 2020 to March 2022. In this exercise, weekly GDP was derived through linear interpolation of the monthly GDP. Tokushima—shown by the bottom-right panel—exhibits the highest correlation coefficient at 0.243, while Kagoshima—shown by the top-right panel—exhibits the lowest at -0.094. Fukuoka—shown by the bottom-left panel—exhibits the correlation coefficient of 0.024, which is close to the median value across prefectures. Tokyo—shown by the top-left panel—exhibits the correlation coefficient of -0.006, ranking 34th among the 47 prefectures. There is a positive correlation between weekly GDP and the growth rate of new cases in 29 prefectures, alluding to the presence of a trade-off between economic activity and infection control.

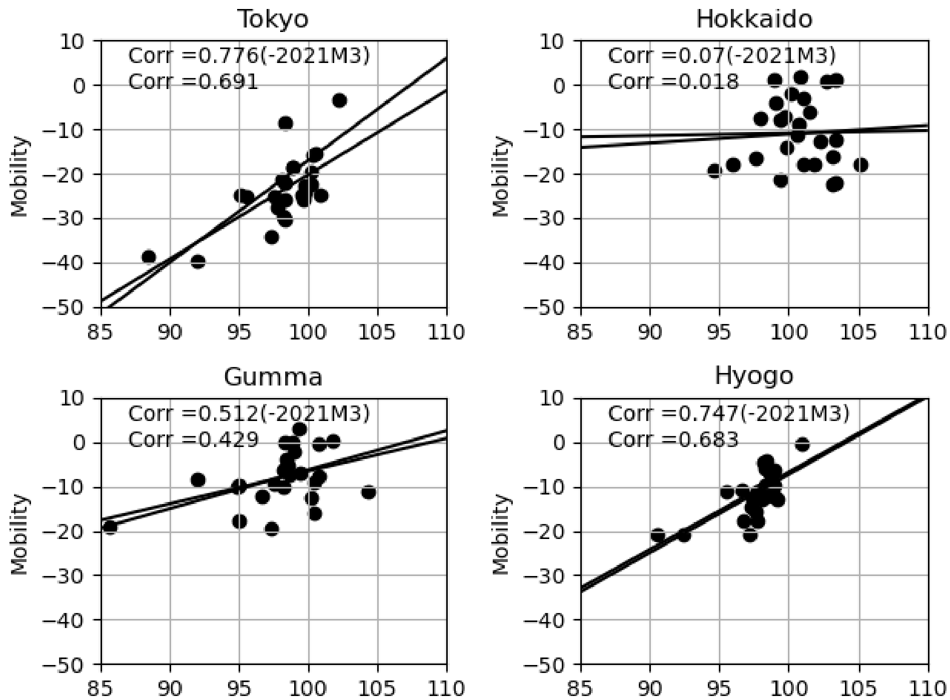

Figure 15: Monthly GDP and mobility: Tokyo, Hokkaido, Gunma, and Hyogo

The analyses presented above focus on the balance between infection control and economic activity using data from the COVID-19 pandemic period. In our last exercise, we conduct a more classical macroeconomic analysis, namely the relationship between GDP and inflation, including data outside the pandemic period. Figure 17 presents scatterplots of monthly GDP and year-on-year change in Consumer Price Index (excluding fresh food) by prefecture for Tokyo, Fukushima, Yamagata, and Yamaguchi from April 2015 to March 2022.[23] We observe a positive correlation between monthly GDP and inflation—reminiscent of the Phillips curve—in most of the prefectures (43 out of 47 prefectures). Tokyo—shown by the top-left panel—exhibits the correlation coefficient of 0.53. Yamaguchi—shown by the bottom-right panel—exhibits the highest correlation coefficient at 0.738, while Fukushima—shown by the top-right panel—exhibits the lowest at -0.184. Yamagata—shown by the bottom-left panel—exhibits the correlation coefficient of 0.346, which is close to the median

[23]We use the CPI in prefectural capital as prefecture-level data because they are the only available inflation data by prefecture. To exclude the impact of the consumption tax hike in April 2014, the sample period was set to begin from April 2015.

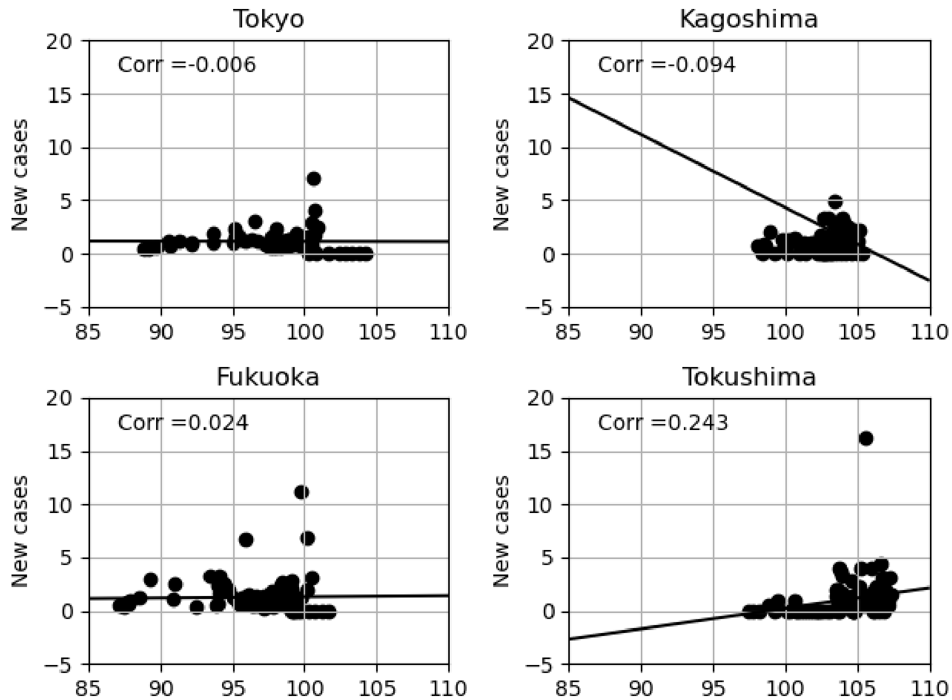

Figure 16: Weekly GDP and the growth rate of new COVID-19 cases: Tokyo, Kagoshima, Fukuoka, and Tokushima

value across prefectures.

To investigate whether the relationship between GDP and inflation changed during the COVID-19 pandemic, we employ panel estimation following the methodology outlined by Hazell et al. (2022). The estimation equation is as follows:

$$\pi_{it} = D_i + \beta_1 GDP_{it} + \beta_2 I_t GDP_{it}$$

Here, π_{it} represents the prefectural CPI (excluding fresh food) year-on-year change (%), GDP_{it} is the prefectural GDP, D_i represents prefecture dummies, and I_t is a dummy variable that takes the value 1 after February 2020 (indicating the post-COVID period). The sample period covers from April 2015 to March 2022, with a sample size of 3,948.

Table 3 shows the estimation results. The slope of the Phillips curve, β_1, is estimated to be 0.049, and it is statistically significant at the 1% level. Additionally, the post-COVID dummy

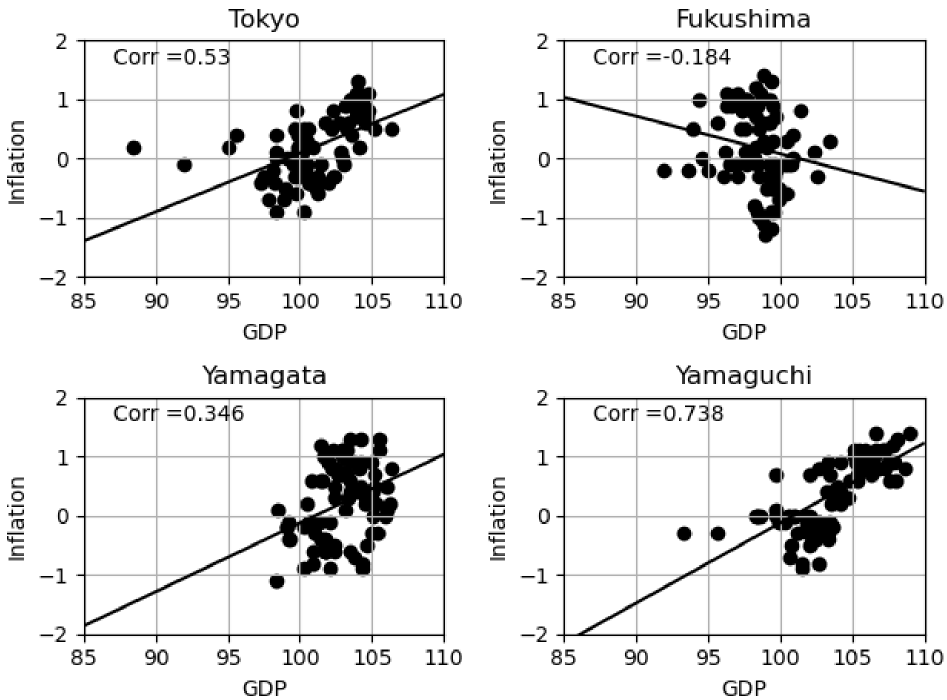

Figure 17: Monthly GDP and CPI inflation: Tokyo, Fukushima, Yamagata, and Yamaguchi

variable is found to have a negative and statistically significant coefficient, suggesting that the relationship between GDP and inflation weakened during the COVID-19 pandemic period.[24]

5 Conclusion

This paper has presented a new measure of monthly prefecture-level GDP. Our measure is based on the combination of production-side GDP and expenditure-side GDP. For periods where more recent official statistics were unavailable, we backcast our monthly GDP using alternative data sources. Readers can use our monthly prefecture-level GDP for a wide range of regional economic analyses.

[24]When controlling for time dummies to account for medium to long-term inflation expectations and other macroeconomic factors, $\beta_1$becomes negative (-0.009) and statistically significant. Additionally, when using the prefectural CPI (excluding fresh food and energy) year-on-year change as the inflation rate, β_1 remains negative (-0.050) and statistically significant.

	dep. var = π_{it}
$\hat{\beta}_1$	0.049
	(13.35)
$\hat{\beta}_2$	0.005
	(25.66)
N	3948
$\bar{R}^2$	0.256

Table 3: Estimation of the Phillips curve (t-statistics in parentheses)

Our analysis can be extended in two dimensions. First, there are ways to improve our GDP measure itself. For instance, if alternative data for a particular sub-sector by prefecture (e.g. POS cash register data for restaurants or electricity usage in commercial districts) are available, we can incorporate them in our GDP construction to reflect the actual regional economic conditions more precisely (Appendix D discusses the effect of incorporating alternative data in a retail sector). Second, there are ways to improve our backcasting methodology. The availability of higher-frequency alternative data may improve the accuracy of backcasting. Alternative methodologies such as mixed-data sampling (MIDAS), dynamic factor model (DFM) and machine learning may improve the accuracy of backcasting. We leave these extensions for future research.

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A Industry weights using Input-Output (IO) data

As discussed in the main text, we use the 2015 prefectural IO tables to compute the ITA industrial weights w_i^k for 43 prefectures. We calculate the ITA weights based on IO tables by matching industries from the ITA classifications to IO classifications based on industry names. Our classification mapping is either one-to-one or many-to-one. For instance, the ITA classification "Electricity" corresponds to the IO classification "Electricity" (one-to-one). However, the ITA classifications "Wholesale Trade," "Retail Trade," and "Real Estate and Land Sales" correspond to a single IO classification "Commerce" (many-to-one). When mapping is many-to-one, we use the national-level ITA weights for proportional allocation. Table 4 illustrates the matching between the ITA classifications and IO classifications. Some IO industry classifications do not have corresponding ITA industry classifications.

We compute ITA weights using IO tables since ITA weights are not available at the prefecture level. However, at the national level, both ITA and IO weights are available. To check the validity of our industry matching, we can compare the national-level ITA and IO weights. Figure 18 displays the IO weights and ITA weights at the national level. Our matching procedure appears reasonable for the purpose of making the weights as equal as possible.

B Industry weights using the Economic Census

In four prefectures (Niigata, Ishikawa, Nara, Okinawa), we use the 2016 Economic Census, instead of IO tables, to compute the ITA industrial weights w_i^k. We do so because for these four prefectures, prefectural IO tables are not available. Since the Census classifications and ITA classifications cannot be matched easily, we use the IO classifications as an intermediate step. For the mapping between the Census and IO classifications, we use more disaggregated industry classifications (subcategory) to merge the two datasets and aggregate up to the IO classifications. Specifically, we use the methodology outlined by Urayama (2021) to

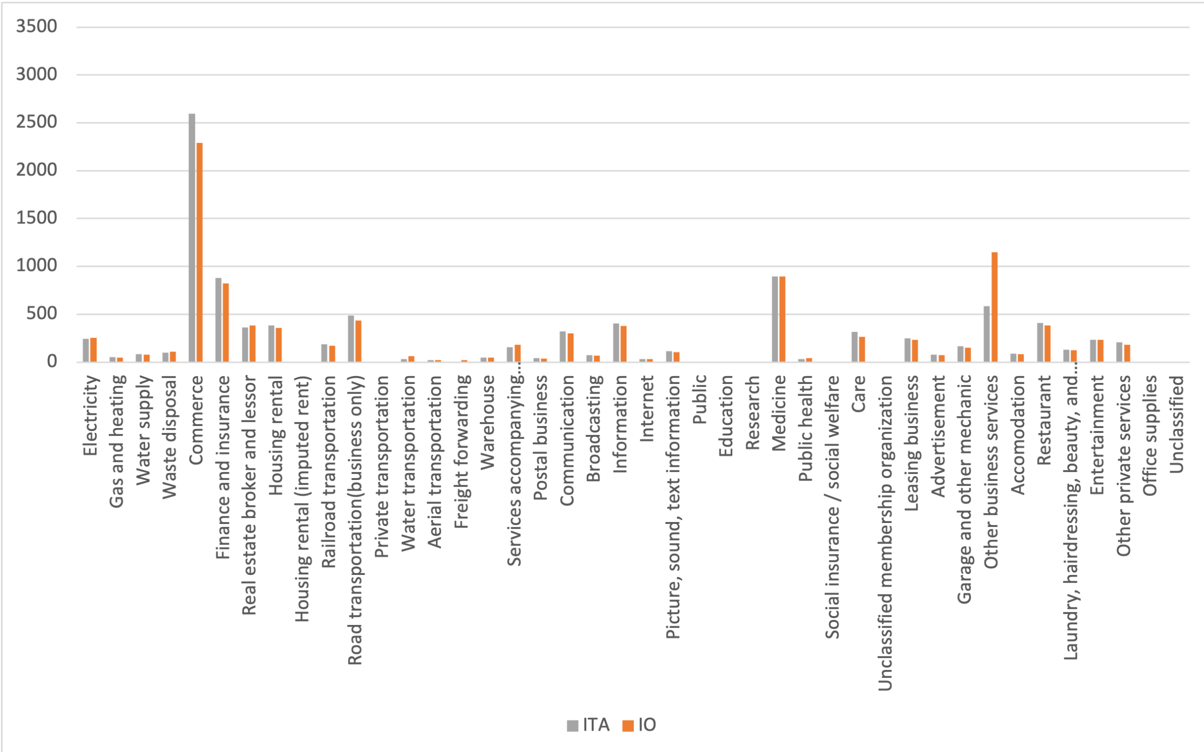

Figure 18: IO weights and ITA weights

proportionally allocate the value-added for each subcategory in the Economic Census to subcategories within the IO classification using national weights. For the mapping between the IO and ITA classifications, we follow the approach described in Appendix A.

We can check the validity of our matching procedure from the Census to IO classifications in a similar manner to Figure 18. Comparing the Census-based weights and IO-based weights at the national level as shown in Figure 19, we can confirm the similarity of these two weights.

C Comparison between our monthly prefecture-level GDP and Prefectural Economic Accounts

The Cabinet Office publishes the Prefectural Economic Accounts (PEA), which is the only official statistics of prefecture-level GDP and is available at annual frequency. As an external

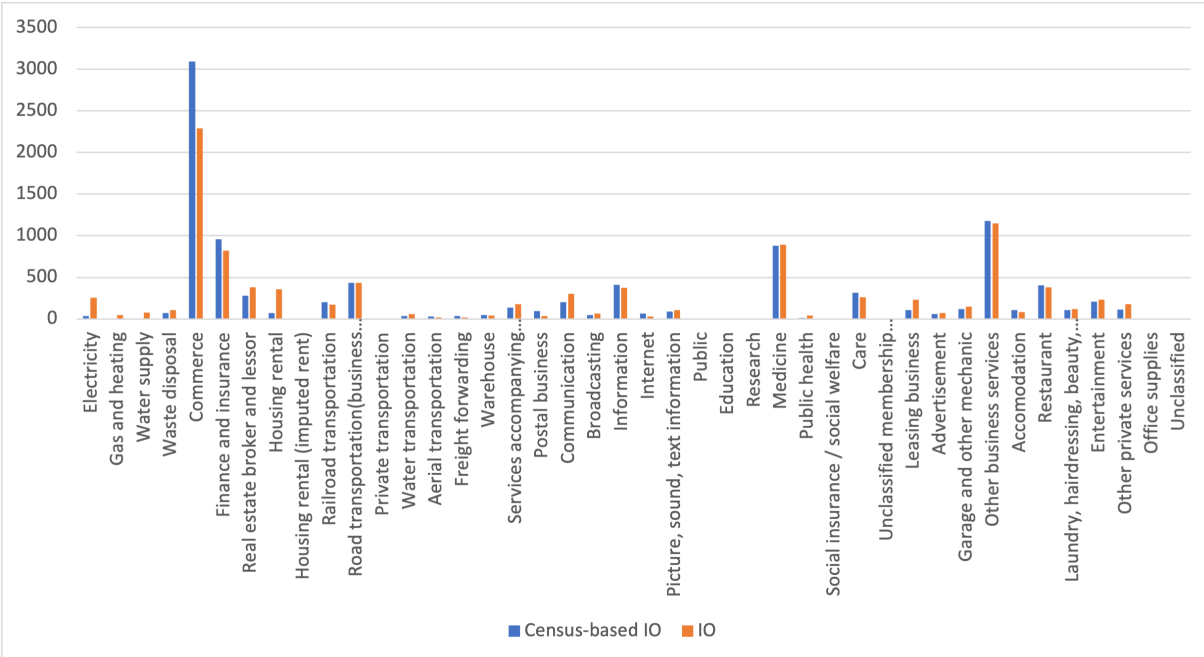

Figure 19: IO weights and Census weights

validation, we compare our GDP to the Prefectural Economic Accounts (PEA). Since the PEA is at an annual frequency, we aggregate our monthly prefecture-level GDP to an annual level. Figure 20 compares our GDP and the PEA for each prefecture for the years 2013 to 2018. Overall, our GDP aligns with the PEA though the difference can be non-trivial in some prefectures in certain years.

Figure 21 quantifies the difference between our GDP and the PEA for each prefecture using Root Mean Squared Errors (RMSE). The mean RMSE is 2.2%. There is some variability among prefectures. Shiga exhibits the largest RMSE (4%). Hyogo exhibits the smallest RMSE (0.6%).

D Modifications of ITA using the Current Survey of Commerce (CSC)

One concern about our production-side GDP is that our service sector index (ITA) may not fully capture prefecture-specific shocks. By construction, our ITA index cannot reflect month-prefecture-specific shocks since we use time-invariant industry weights by prefecture. In fact, if we compare the IIP—available monthly for each prefecture— and the ITA data as in Figure 22, the ITA trends are substantially less heterogeneous across prefectures than the IIP trends. To address issue, we can modify our ITA index by incorporating monthly prefecture-level retail sector data. For the retail sector, the METI publishes monthly data for six specific types of retail businesses (department stores, supermarkets, convenience stores, electronics retailers, drugstores, and home improvement centers) in the Current Survey of Commerce (CSC). Figure 23 displays the CSC retail index for 44 prefectures excluding Kagoshima, Okinawa, and Kumamoto.[25][26] Unlike the ITA, substantial heterogeneity is evident among prefectures in the CSC data.

Figure 24 presents the modified prefectural-level ITA data with the CSC retail index. While there is some degree of heterogeneity among prefectures, it remains limited as in the original series in the bottom panel of Figure 22. The impact of using the CSC data is limited because the retail industry share (around 10%) is limited in the overall service sector. If we have access to monthly prefecture-level alternative data of other industries in service sector, our ITA index can be improved capturing more prefecture-specific shocks.

[25] For these three prefectures, the CSC data are not available.

[26] We observe a notable upward spike in September 2019 corresponding to the consumption tax increase and a downward spike in April 2020 corresponding to the first declaration of a state of emergency due to pandemic.

E Accuracy of the backcasting

In this section, we examine the accuracy of backcasting using different specifications for the GDP estimation equation. There are eight different backcasting specifications based on the combination of three factors: 1) whether the dependent variable in the estimation equation is in logs or differences, 2) whether the estimated values for alternative data sources are weighted averages or simple averages, and 3) whether the data used for estimation comprises the entire historical sample or only the past 12 months.[27]

Figure 25 presents the backcasting accuracy of those eight specifications based on both MAE and RMSE. Each line indicates the mean MAE or RMSE across the backcasting timing i for each specification. Tables 5 and 6 show the corresponding numbers with more information. When comparing these backcasting methods, it becomes apparent using logged levels as the dependent variable in the estimation equation yields better backcasting accuracy compared to using differences.[28] Furthermore, employing a weighted average of estimated values using the residuals of the estimation equation for alternative data sources appears to enhance backcasting accuracy compared to taking a simple average. Finally, using the entire sample period, compared to the 12-month rolling window sample, may improve the backcasting accuracy overall although there are some exceptions depending on i.

[27] Since we have two options for each of the three factors, there are $2^3 = 8$ combinations.

[28] The null hypothesis, which posits the presence of a unit root, was rejected based on the results of the Augmented Dickey-Fuller test for GDP stationarity. Specifically, among the 47 prefectures, the null hypothesis was rejected at the 5% significance level for 17 prefectures and at the 10% significance level for 22 prefectures.

ITA type	*IO type*		*ITA type*	*IO type*
Electricity	Electricity		Internet	Internet
Gas	Gas and heating		Picture, sound, text information	Picture, sound, text information
Heating			Medicine	Medicine
Water supply	Water supply		Public health	Public health
Waste disposal	Waste disposal		Social welfare and care business	Care
Wholesale	Commerce		Leasing business (including rent-a-cars)	Leasing business
Retail			Advertisement	Advertisement
Real estate sales			Car mechanic (for business use)	Garage and other mechanic
Finance and insurance	Finance and insurance		Other mechanic	
Real estate broker	Real estate broker and lessor		Car mechanics (for personal use)	
Rental office lessor			Professional service	Other business services
Parking space lessor			Compound service	
Housing rental	Housing rental		Employment referral / agency	
Railroad	Railroad transportation		Security	
Road passenger transportation	Road passenger transportation (business only)		Academic / research institute	
Road freight transportation	Road freight transportation (business only)		Technical service	
Water transportation	Water transportation		Accommodation	Accommodation
Aerial transportation	Aerial transportation		Restaurant	Restaurant
Warehouse	Warehouse		Laundry, hairdressing, beauty, and bathing	Laundry, hairdressing, beauty, and bathing
Services accompanying transportation	Services accompanying transportation		Entertainment	Entertainment
Postal business	Postal business		Other living-related services	Other private services
Communication	Communication		Learning support	
Broadcasting	Broadcasting		Pet and veterinarian	
Information	Information			

Table 4: Concordance between ITA and IO classifications

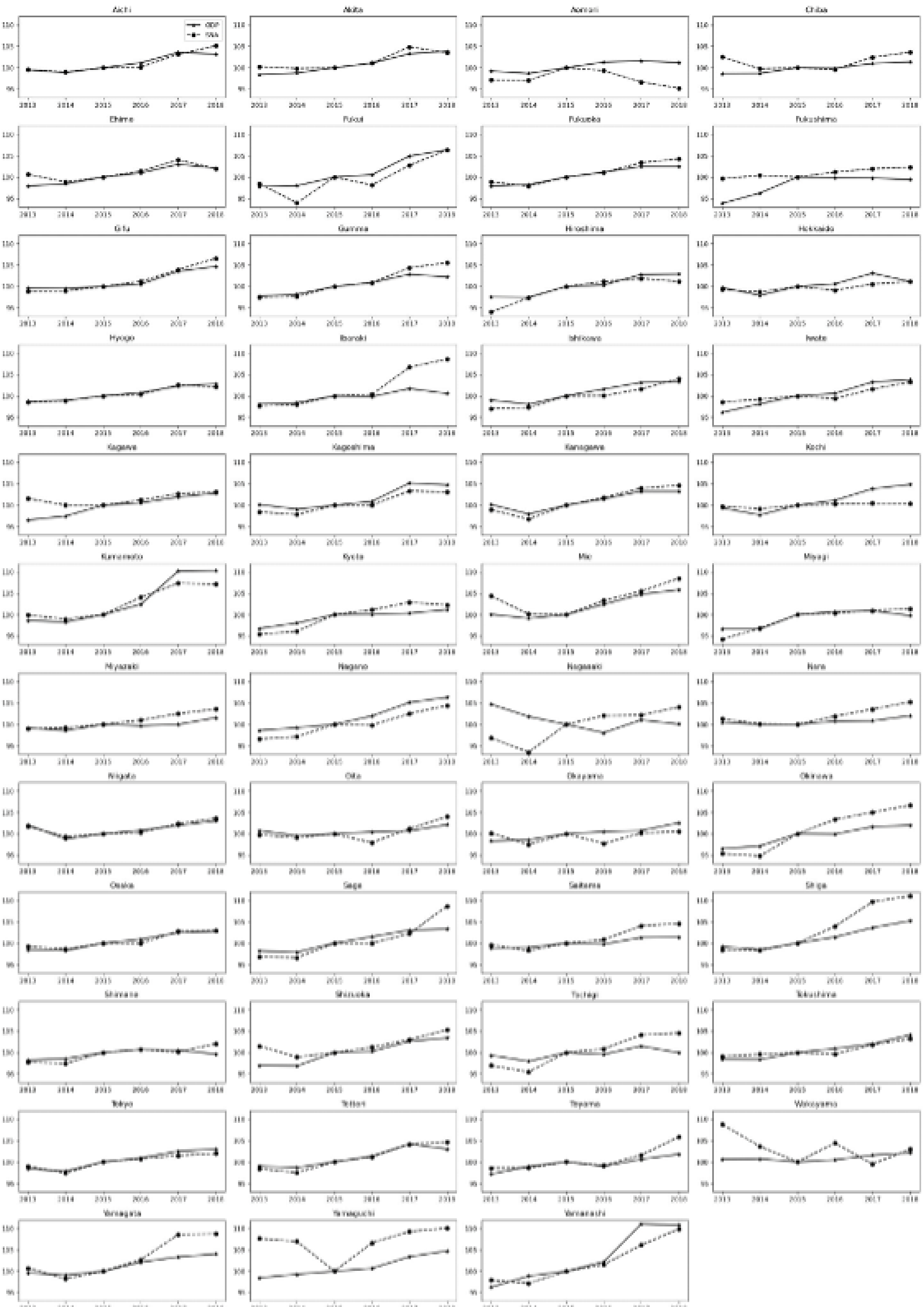

Figure 20: Comparison to the Prefectural Economic Accounts: time series

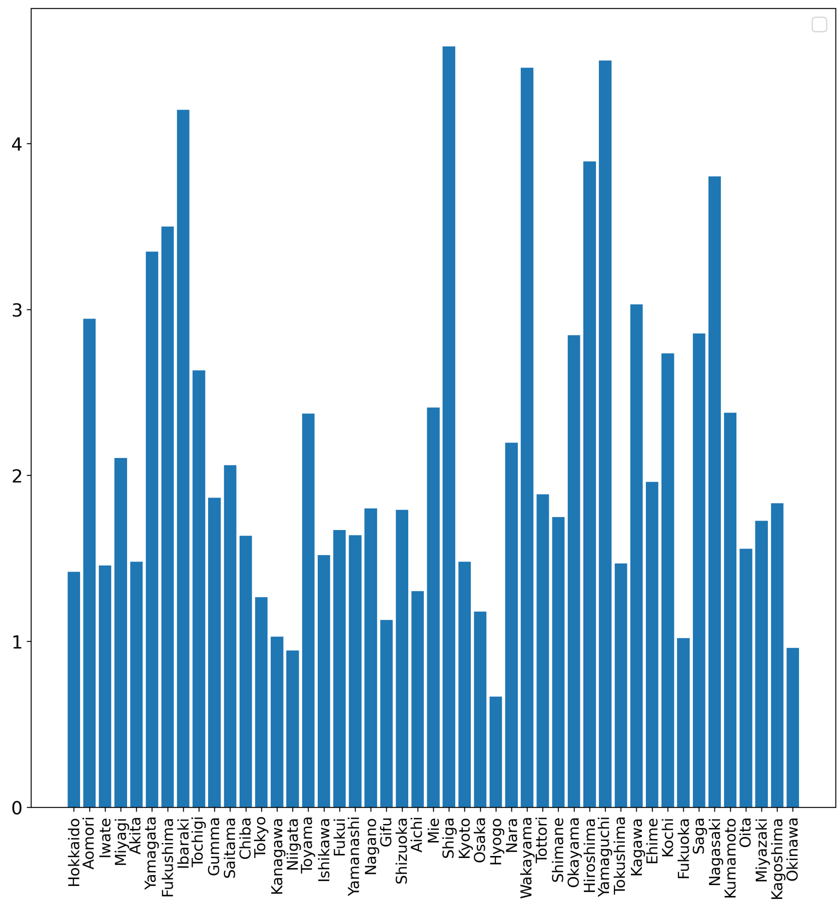

Figure 21: Comparison to the Prefectural Economic Accounts: RMSE

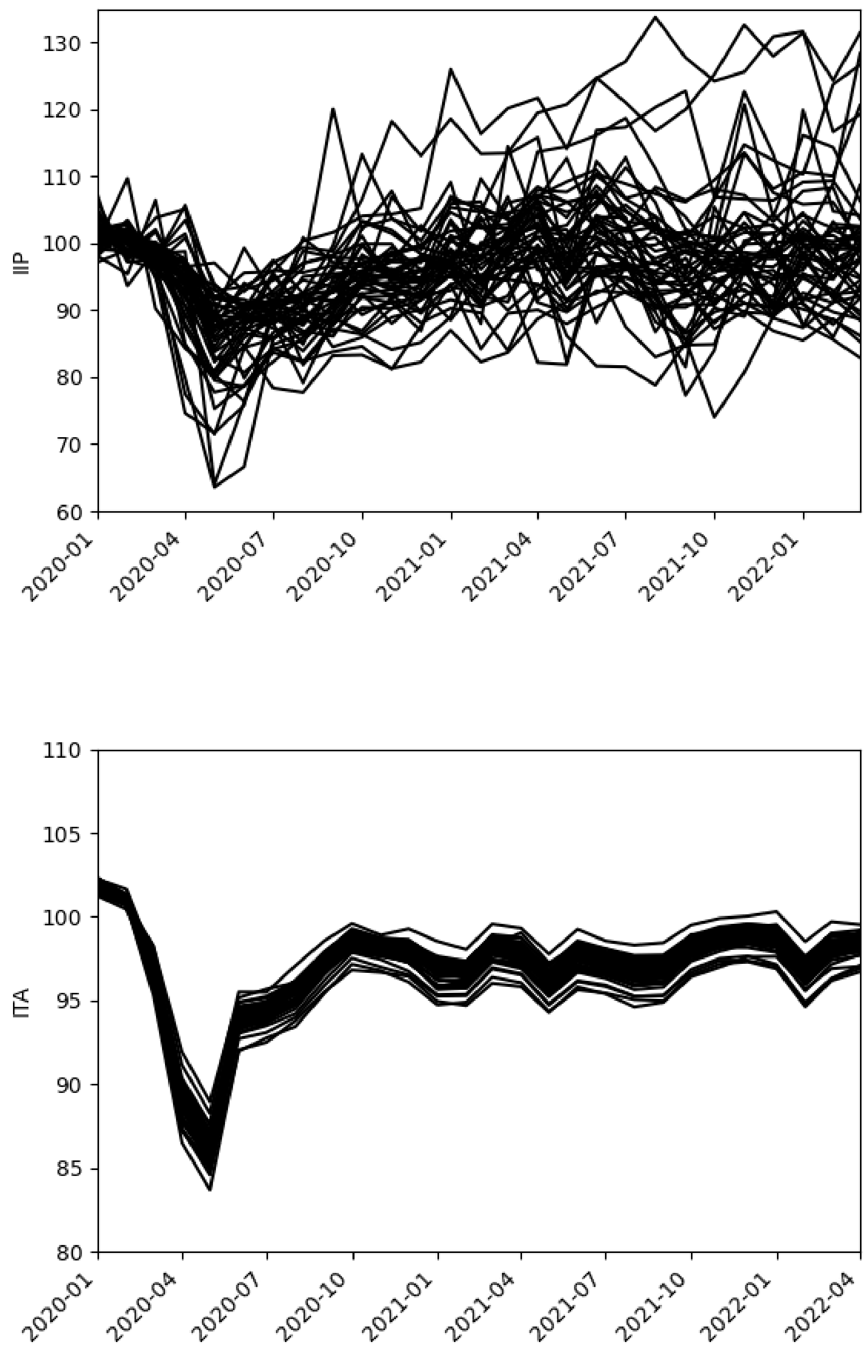

Figure 22: Monthly IIP and monthly ITA by prefecture

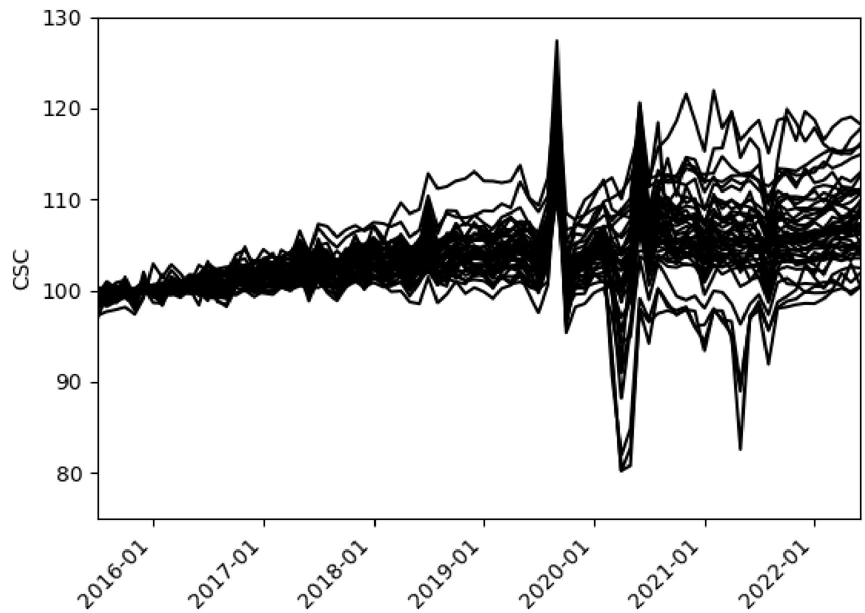

Figure 23: CSC retail index (seasonally adjusted) by prefecture

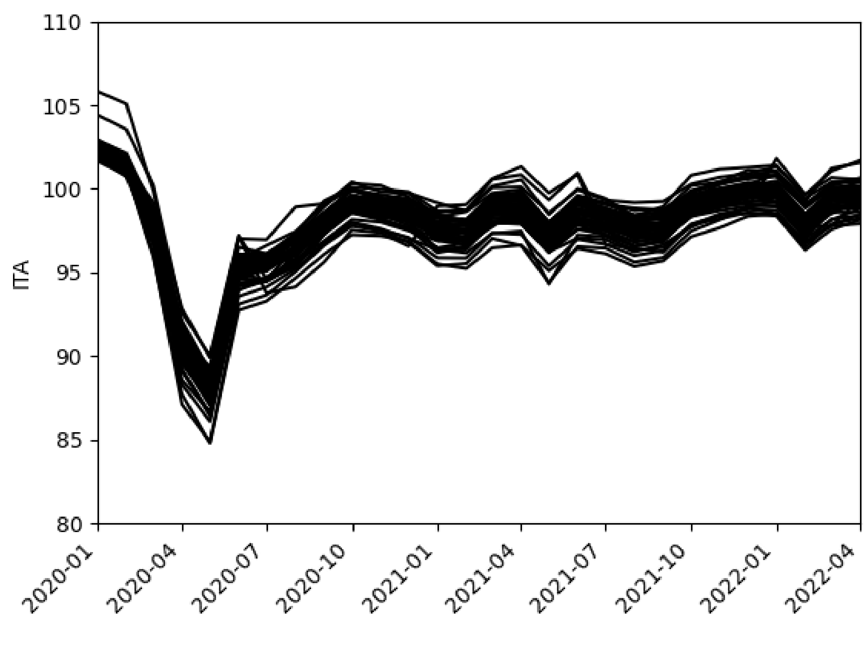

Figure 24: Monthly ITA by prefecture (with a correction by CSC)

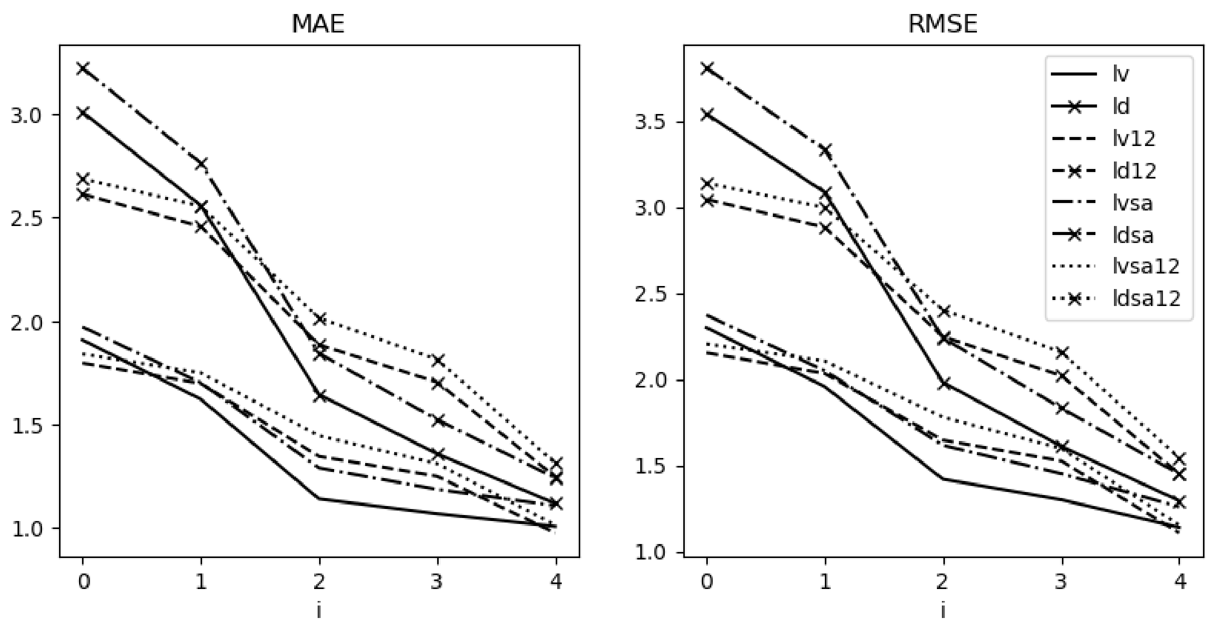

Figure 25: Backcasting accuracy

Note: In the legend, “v” denote the log values whereas “d” denote the differences. Also “12” indicates that the sample period is only the past 12 months, and “SA” indicates that the estimated value for alternative data are simple averages.

(a) Log-level

	Weighted average, full sample (baseline) i					Weighted average, rolling-window sample i				
	0	1	2	3	4	0	1	2	3	4
Mean	1.829	1.561	1.113	1.101	1.063	1.695	1.606	1.263	1.209	0.975
Median	1.714	1.411	1.045	0.962	0.960	1.576	1.474	1.161	1.085	0.833
10 percentile	2.581	2.309	1.626	1.612	1.576	2.604	2.429	1.740	1.715	1.353
90 percentile	1.074	0.878	0.678	0.620	0.443	1.002	0.975	0.841	0.793	0.451

	Simple average, full sample i					Simple average, rolling-window sample i				
	0	1	2	3	4	0	1	2	3	4
Mean	1.880	1.628	1.248	1.216	1.161	1.727	1.645	1.347	1.267	1.012
Median	1.807	1.528	1.139	1.070	1.052	1.579	1.560	1.255	1.125	0.864
10 percentile	2.706	2.427	1.852	1.758	1.698	2.671	2.509	1.927	1.773	1.428
90 percentile	1.068	0.898	0.769	0.655	0.468	1.018	0.958	0.866	0.843	0.443

(b) Log-difference

	Weighted average, full sample i					Weighted average, rolling-window sample i				
	0	1	2	3	4	0	1	2	3	4
Mean	2.916	2.490	1.595	1.344	1.147	2.522	2.393	1.835	1.684	1.271
Median	2.986	2.477	1.576	1.165	0.959	2.461	2.380	1.769	1.537	1.032
10 percentile	4.007	3.445	2.275	2.170	1.731	3.743	3.291	2.361	2.341	1.742
90 percentile	1.760	1.479	0.906	0.819	0.649	1.568	1.491	1.219	1.021	0.666

	Simple average, full sample i					Simple average, rolling-window sample i				
	0	1	2	3	4	0	1	2	3	4
Mean	3.104	2.670	1.769	1.493	1.259	2.581	2.475	1.945	1.781	1.329
Median	3.217	2.601	1.787	1.301	1.053	2.487	2.434	1.844	1.626	1.103
10 percentile	4.453	3.783	2.418	2.325	1.957	3.742	3.328	2.473	2.422	1.811
90 percentile	1.896	1.512	0.977	0.868	0.708	1.616	1.597	1.326	1.083	0.715

Table 5: Backcasting accuracy: MAE

(a) Log-level

	Weighted average, full sample (baseline)					Weighted average, rolling-window sample				
	i					i				
	0	1	2	3	4	0	1	2	3	4
Mean	2.186	1.857	1.324	1.321	1.189	2.030	1.914	1.520	1.450	1.085
Median	1.983	1.748	1.246	1.174	1.084	1.877	1.824	1.433	1.353	0.955
10 percentile	3.313	2.762	1.910	1.929	1.710	3.206	2.830	2.075	1.933	1.521
90 percentile	1.271	0.972	0.803	0.760	0.521	1.219	1.071	1.025	0.953	0.532

	Simple average, full sample					Simple average, rolling-window sample				
	i					i				
	0	1	2	3	4	0	1	2	3	4
Mean	2.239	1.927	1.489	1.467	1.306	2.062	1.965	1.622	1.518	1.129
Median	2.073	1.827	1.429	1.338	1.196	1.884	1.910	1.553	1.433	0.975
10 percentile	3.354	2.909	2.150	2.179	1.862	3.231	2.857	2.156	2.039	1.508
90 percentile	1.255	0.993	0.921	0.872	0.527	1.231	1.067	1.062	0.989	0.551

(b) Log-difference

	Weighted average, full sample					Weighted average, rolling-window sample				
	i					i				
	0	1	2	3	4	0	1	2	3	4
Mean	3.430	2.999	1.904	1.572	1.313	2.938	2.805	2.173	1.979	1.462
Median	3.579	3.026	1.915	1.503	1.172	2.934	2.858	2.046	1.849	1.325
10 percentile	4.779	4.293	2.665	2.361	1.854	4.110	3.938	2.782	2.708	1.931
90 percentile	2.132	1.702	1.120	0.937	0.723	1.770	1.754	1.486	1.270	0.757

	Simple average, full sample					Simple average, rolling-window sample				
	i					i				
	0	1	2	3	4	0	1	2	3	4
Mean	3.660	3.211	2.125	1.769	1.451	3.008	2.897	2.302	2.097	1.541
Median	3.755	3.134	2.069	1.669	1.293	2.921	2.850	2.127	1.922	1.358
10 percentile	5.148	4.855	2.964	2.660	2.021	4.080	4.059	2.844	2.808	2.101
90 percentile	2.253	1.774	1.215	1.014	0.843	1.831	1.854	1.580	1.292	0.834

Table 6: Backcasting accuracy: RMSE