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Abstract

Monitoring inflation is an important aspect of policymaking, but understanding the factors that drive inflation remains challenging. In this paper, we construct a cyclically sensitive inflation (CSI) index for Japan and examine its usefulness from several perspectives. Specifically, we investigate (1) the dynamic relationship from financial markets and the real economy to cyclical inflation, (2) how well cyclical inflation can predict future inflation trends, and (3) the effectiveness of the CSI as a real-time indicator of economic slack. Our empirical results show that the CSI can complement headline and core inflation measures and, when used together, help distinguish whether price changes are due to temporary factors or persistent pressures associated with the business cycle.

JEL Classification: C32; E31; E32; E52; E58.

Keywords: cyclical inflation; business cycle; financial market; inflation forecast; Japanese economy.

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1 Introduction

Inflation is considered as a mirror of the economic condition, because it reflects changes in demand and supply that affect the economy. For example, inflation can rise owing to demand shocks, such as rapid credit expansion, which increase aggregate demand for goods and services. Inflation can also rise owing to supply shocks, such as surges in energy prices and price revisions of goods and services that are not sensitive to the business cycle, but are closely related to people's daily lives. These factors increase input costs and reduce the availability of goods and services. Central banks need to identify the sources of inflation, whether they are demand-pull or cost-push, because they are responsible for managing monetary policy to achieve inflation stability.

In practice, central banks often rely on core inflation indicators to capture underlying changes in prices. Core inflation measures inflation by excluding volatile items, such as food and energy, which are subject to frequent and large fluctuations because of supply shocks (Gordon, 1975). Core inflation indicators are commonly used to reflect changes in the underlying trend of inflation and economic slack in communication with the public regarding monetary policy (Wynne, 2008). Although core inflation measures are simple and transparent, they have limitations. One concern is that inflation in items other than food and energy could reflect factors unrelated to economic slack or temporary shocks. Another concern is that excluding food and energy could omit valuable information about business cycles.

A straightforward way to capture the factors related to economic slack is to monitor cyclical inflation. Cyclical inflation measures how inflation changes with the business cycle. As explained in standard economics textbooks, such as Mankiw (2022), inflation accelerates when aggregate demand increases and decelerates when it decreases, in line with the trade-off between nominal inflation and real economic activity, known as the Phillips curve, in practice. Stock and Watson (2020) suggest a methodology for constructing a cyclical inflation measure from the short-run Phillips curve relation, using sectoral inflations and cyclical activity measures.[1]

This study quantitatively investigates the role of cyclical inflation in Japan. Specifically, we measure the cyclically sensitive inflation (CSI) index, which we construct by weighting

[1]The current standard approach for understanding inflation in economic literature has been using the *short-run* Phillips curve based on a triangle model of inflation, under which inflation is determined by long-term expected inflation, demand-pull pressures, and cost-push shocks. For details on the triangle model of inflation, see Gordon (1997) and the references therein.

sectoral inflations according to their joint covariation with cyclical activity. We then compare the quantitative relationship of CSI to the financial market and the real economy with headline and core inflation indicators, and we evaluate the forecasting performance of cyclical inflation for future inflation.

Japan provides a valuable example for studying the role of cyclical inflation. Since the late 1990s, when Japan's economy experienced prolonged periods of low inflation and sluggish growth, researchers have expressed concerns about instability among financial markets, the real economy, and inflation. Some studies argue that the Phillips curve does not explain well the relationship between inflation and economic activity under secular stagnation in Japan (Hoshi and Kashyap, 2021, and references therein). Other studies report empirical results that suggest instability in the relationship between financial markets and the real economy, along with a decline in the effectiveness of monetary policy (Miyao, 2000, 2005; Ugai, 2007). Developing inflation indicators that respond to cyclical factors–beyond headline and core measures–could help address these critical issues in Japan's economy.

This study makes two main contributions. First, it demonstrates how to apply the method described in Stock and Watson (2020) to Japanese data to measure CSI, and then clarifies the features of the obtained CSI, including comparisons with headline CPI and core inflations. This approach could improve inflation measurement and provide more timely information about economic conditions in Japan. Second, it empirically highlights the role of cyclical inflation. Specifically, it offers evidence supporting the usefulness of measuring cyclical inflation through the following: (1) the dynamic connection from financial markets and the real economy to cyclical inflation, (2) predicting future inflation and trend changes using cyclical inflation, and (3) using the CSI as a real-time indicator of economic slack.

The rest of this paper is organized as follows. Section 2 reviews the literature relevant to this study. Section 3 describes the methodology for constructing the CSI in Japan. Section 4 discusses the features of CSI in Japan. Section 5 provides empirical assessments of the role of cyclical inflation. Section 6 evaluates the sensitivity and robustness of the CSI measure using alternative specifications. Section 7 concludes the paper by summarizing the main findings and discussing the usefulness of CSI as a complementary indicator for inflation. The Appendix provides the methodology used to measure the cyclical activity index and detailed definitions of the variables, with data sources.

2 Literature review

Core inflation indicators are now standard tools for central banks to understand underlying inflation trends. Bryan and Cecchetti (1994) point out that because multiple factors affect inflation measures, the purpose of measuring core indicators is to remove specific components of overall price changes. This would help provide a clearer picture of *monetary* inflation movements by extracting the common trends across various goods categories. Typically, calculating core indicators involves selecting items with large price swings and excluding them from the index. For example, the U.S. measures its core index by excluding food and energy. Other methods include trimming a fixed percentage of extreme prices at both ends of the distribution for each item, which leads to techniques such as trimmed means and weighted medians (Bryan and Cecchetti, 1994). For more details on the concepts and measurement issues related to core inflation, see Wynne (2008).

Wynne (2008) highlights that the literature focuses on two primary roles of core indicators in evaluating their behavior. First, it examines whether these indicators are closely linked to shifts in money stocks and financial market conditions that affect money stocks, which are related to monetary policy. For example, Bryan and Cecchetti (1994) statistically investigate whether core inflation is influenced by past changes in the money stock or the monetary base.

Second, it evaluates whether core indicators consistently reflect inflation trends and have predictive power for future headline inflation. For example, Bryan and Cecchetti (1994) quantitatively examines the medium- and long-term forecasting ability of core inflation measures for inflation several years ahead. By evaluating this long-term predictive capacity, the study can determine whether it is possible to capture changes in the underlying inflation trend.

Core inflation is also expected to serve as a real-time indicator of economic slack. This idea is rooted in the Phillips curve framework, which suggests a link between inflation and economic activity (Fisher, 1926; Phillips, 1958). In the empirical literature of the Phillips curve, for example, Gordon (1975), Ball and Mankiw (1995), and Roberts (1995) use deviations of headline inflation from the core as a measure of cost-push shocks in the Phillips curve. Wynne (2008) discusses that, despite variations in how core inflation is measured and its importance across different countries, many central banks in advanced economies use core inflation as a communication tool to convey their economic outlook to the public.

Some studies suggest using the Phillips curve framework to develop aggregate inflation measures. For example, Quah and Vahey (1995) propose an alternative method using the structural vector autoregressive (VAR) model to construct core inflation measures, defined as the inflation component that explains the cyclical part of real output.[2] A recent paper by Stock and Watson (2020) explores a different aggregation approach to produce inflation measures that are more sensitive to business cycles, termed "cyclically sensitive inflation." They propose a method to build CSI by weighting sectoral inflations according to their correlation with cyclical activity indicators. As Stock and Watson (2020) point out, although the CSI is not suitable as a target for central banks because it does not approximate the total cost of living, it provides a real-time gauge of cyclical inflation movements and aids in assessing economic slack.

In Japan, the Bank of Japan frequently uses measures such as the CPI excluding fresh food and the CPI excluding fresh food and energy to assess economic slack and underlying inflation trends. Hogen et al. (2015) and Shiratsuka (2015) compare and discuss the roles of various core inflation indicators in Japan, including the CPI excluding fresh food, CPI excluding fresh food and energy, CPI excluding food and energy, trimmed mean, weighted median, and mode. Hogen et al. (2015) examine how these indicators relate to business cycles, finding that the CPI excluding fresh foods and the CPI excluding fresh foods and energy have stronger links with the output gap, while the mode and weighted median show weaker connections. Shiratsuka (2015) evaluates the predictive power of these indicators for future underlying inflation, finding that the CPI excluding fresh food, CPI excluding fresh food and energy, and the trimmed mean perform relatively better. However, he also observes that the predictive accuracy of the CPI excluding fresh food has been declining since the late 2000s.

Empirical studies on Japan highlight the unique challenges caused by its long period of low inflation and weak growth since the late 1990s. Researchers question the stability of the Phillips curve and the relationship between financial markets and inflation in Japan.[3] For example, in an early study, Nishizaki and Watanabe (2000) estimate the nonlinear short-run Phillips curve

[2] Quah and Vahey (1995) obtain the estimate of core inflation by using a bivariate VAR model consisting of real output and inflation with long-run restrictions, where the shock to core inflation does not affect real output in the long run, similar to those employed by Blanchard and Quah (1989) and King et al. (1991).

[3] The significance of the Phillips curve is often debated, not only in Japan, because of uncertainties about its empirical validity and utility for policy decisions. Some research indicates that the slope of the Phillips curve has been limited since before the Great Moderation and the global financial crisis. For example, Atkeson and Ohanian. (2001) argue that Phillips curve models alone cannot reliably forecast inflation. During the prolonged stagnation following the financial crisis, many critics question whether the Phillips curve slope remains stable–specifically, how inflation responds to demand-pull pressures. For example, in the face of stable inflation despite fluctuations in unemployment, Simon et al. (2013), Blanchard et al. (2015), Hooper et al. (2020), and Del Negro et al. (2020) argue that the Phillips curve may be becoming less relevant or has flattened in recent years in the U.S. and other advanced economies.

using Japanese data and conclude that the short-run Phillips curve becomes flatter as inflation approaches zero. De Veirman (2009), Fuhrer et al. (2012), Okimoto (2019), and Hoshi and Kashyap (2021) also argue that the output-inflation trade-off has been limited in Japan since the late 1990s.[4] Miyao (2005) highlights the unstable relationship between the money stock, the real economy, and inflation since the late 1990s. Miyao (2000) and Ugai (2007) argue that the effectiveness of Japan's monetary policy on the real economy and inflation has been limited since the late 1990s.

This study builds on these insights by adapting the Stock and Watson (2020) methodology to the Japanese context. By constructing a CSI index, we aim to provide empirical evidence supporting the usefulness of measuring cyclical inflation.

3 Methodology for constructing CSI in Japan

We measure the CSI in Japan by adapting the methodology proposed by Stock and Watson (2020) to Japanese data. They consider the CSI index as a weighted average of sectoral inflations. Suppose $\pi_{it} = 100 \times \log(P_{it}/P_{it-12})$ is the year-over-year rate of inflation for sector i (in percent), where P_{it} is the price level of sector i at time t. Following Stock and Watson (2020), we estimate the weights by using a restricted nonlinear least squares estimation of the regression,

$$CAI_t = \beta_0 + \beta_1 \sum_{i=1}^{K} w_i \Delta_{12} \pi_{it} + u_t, \tag{1}$$

s.t.

$$0 \leq w_i \leq 1, \tag{2}$$

$$\sum_{i=1}^{K} w_i = 1, \tag{3}$$

where CAI_t is a cyclical activity measure and $\Delta_{12}\pi_{it} = \pi_{it} - \pi_{it-12}$ is 12-month change in inflation for sector i. The year-over-year rate of CSI is defined as $\pi_t^{CSI} = \sum_{i=1}^{K} \hat{w}_i \pi_{it}$. Our Japanese data set covers the period from February 1983 to December 2022. The sample begins with the trough of the ninth business cycle, as defined by the Cabinet Office.

We measure CAI_t as an index of cyclical activities for Japan, similar to Stock and Watson

[4]See Hoshi and Kashyap (2021) for a literature review on the price and wage Phillips curve during secular stagnation in Japan.

(2020) for the United States. Specifically, we construct CAI_t as a composite index that represents a weighted average of nine cyclical measures in the labor market and real economy. These measures are extracted as the year-over-year change in the 12-month moving average: unemployment rate, employment-population ratio, vacancy ratio, job opening ratio, unemployment insurance beneficiaries, overtime worked hour index, three-month lag of the industrial production index, three-month lag of the capital utilization index, and the tertiary industry activity index. We scale and sign the index so that a one-unit increase in CAI_t corresponds to a one percent increase in unemployment. See the Appendix for more details on the construction.

Our measured CAI is shown in Figure 1. As demonstrated, the index spikes sharply during recessions and declines gradually during expansions throughout the sample period. This result highlights our aim for the CAI to accurately represent the degree of cyclical stagnation and overheating in both the labor market and the real economy.

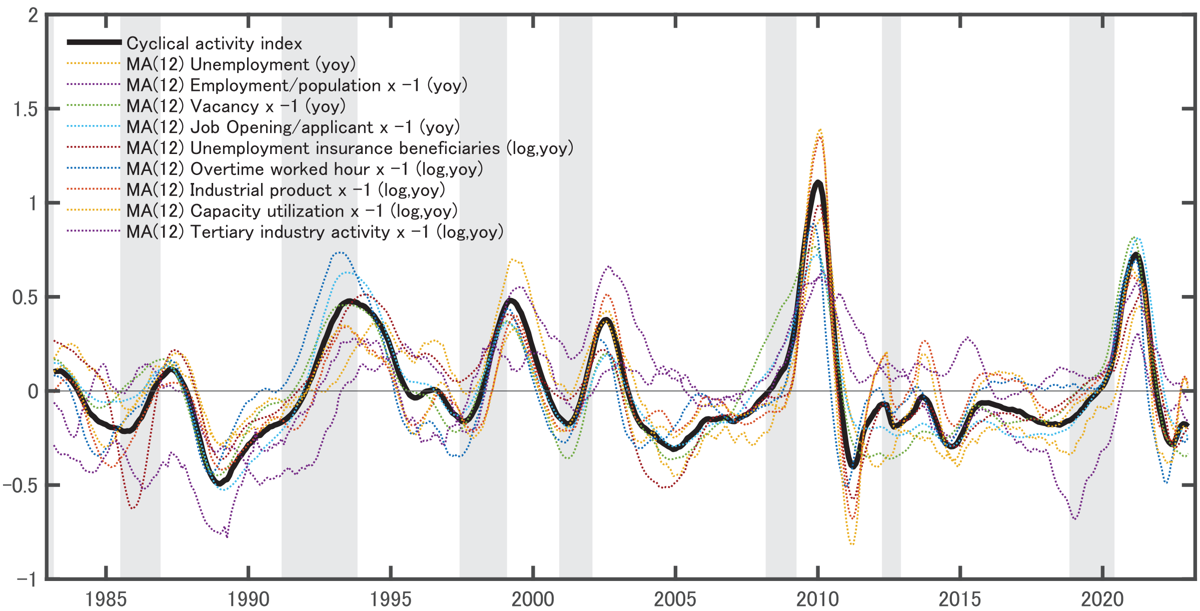

Figure 1: The cyclical activity index and cyclical activity measures in the labor market and real economy

Notes: The sample period is February 1983 to December 2022. The shaded areas indicate periods of recession in Japan, as defined by the Cabinet Office. The legend lists the cyclical activity measures. We extract cyclical activity measures as the year-over-year change in the 12-month moving average of activity measures. The cyclical activity measures in the figure are standardized to have zero mean and unit variance. The employment/population, vacancy, job opening, overtime worked hours, industrial product (lagged 3 months), capacity utilization (lagged 3 months), and tertiary industry activity measures are multiplied by -1, so they covary positively with unemployment.

We select a set of sectoral inflations that cover the main categories of consumer prices.

The Statistics Bureau of Japan produces the CPI, which includes 10 major groups of items: Food, Housing, Fuel, Light & Water Charges, Furniture & Household Utensils, Clothes & Footwear, Medical Care, Transportation and Communication, Education, Culture & Recreation, and Miscellaneous. We further divide the Food group into fresh Food and Food less fresh Food, the Transportation and Communication group into Public Transportation, Automobiles & Bicycles, Automotive Maintenance, and Communication, and the Culture & Recreation group into Recreational Durable Goods, Recreational Goods, and Recreational Services. Therefore, we use a total of $K = 16$ sectors based on the consumer price.

4 Measuring CSI in Japan

This section discusses the features of CSI in Japan. Section 4.1 presents the results of estimating a model for CSI using the methodology described in Section 3. Section 4.2 provides summary statistics of the CSI, and compares them with headline and core inflation indicators.

4.1 CSI weights on sectoral inflations

We present the results of obtaining weights on sectoral inflations within the model (1) with restrictions (2) and (3) to measure the CSI in Japan. Table 1 summarizes sectoral inflation characteristics. These include the variance of 12-month changes (Column [1]), the correlation with cyclical activity indicators (Column [2]), the obtained weights in the CSI (Column [3]), and the expenditure shares based on the 2020 CPI (Column [4]) for comparison with Column [3].

The CSI emphasizes sectors that demonstrate significant cyclical sensitivity. The main components include Clothes & Footwear, Recreational Goods, and Food less Fresh Food, all of which show a strong correlation with cyclical economic activity and relatively low variance. In contrast, sectors with low correlation to business cycles receive minimal weights. Therefore, this structure suggests that the CSI predominantly includes sectors that reflect fluctuations in the business cycle.

Note that the CSI is not primarily intended to measure the cost of living. Unlike the CPI, the CSI assigns lower weights to sectors closely linked to daily consumer needs, such as Food less Fresh Food and Housing. In contrast, the CPI allocates a significant weight to these sectors,

Table 1: Variance, correlation with cyclical activity, and CSI weights for the sectoral inflations

	[1]	[2]	[3]	[4]
Sectoral Inflation				
Fresh Food	132.63	-0.08	0.0005	0.0396
Food, less Fresh Food	2.24	-0.47	0.1010	0.2230
Housing	0.21	-0.22	0.0639	0.2149
Fuel, Light & Water Charges	27.75	-0.39	0.0584	0.0693
Furniture & Household Utensils	2.78	-0.32	0.0347	0.0387
Clothes & Footwear	1.44	-0.51	0.3600	0.0353
Medical Care	10.02	-0.18	0.0530	0.0477
Public Transportation	3.65	-0.15	0.0001	0.0167
Automobiles & Bicycles	0.67	-0.26	0.0748	0.0235
Automotive Maintenance	37.85	-0.04	0.0000	0.0650
Communication	48.18	-0.03	0.0118	0.0441
Education	8.65	-0.17	0.0349	0.0304
Recreational Durable Goods	41.14	-0.09	0.0000	0.0077
Recreational Goods	2.48	-0.33	0.1319	0.0316
Recreational Service	5.28	-0.21	0.0718	0.0518
Miscellaneous	3.51	-0.05	0.0032	0.0607

[1] Variances of 12-month change in year-over-year sectoral inflation.
[2] Correlations of 12-month change in year-over-year sectoral inflation with the composite index of cyclical activity measures.
[3] CSI weights.
[4] CPI (2020) weights.

Notes: The sample period is February 1983 to December 2022. CSI represents cyclically sensitive inflation. CSI weights are obtained by nonlinear least squares estimation of the regression in eq. (1), with restrictions given in eq. (2) and eq. (3). CPI (2020) weights reflect the share of each sector in consumption expenditure during 2020, which serves as the weight reference period.

which allows it to better reflect overall price changes. These differences show that the CSI is not designed to monitor broad movements in the cost of living, because it emphasizes different components compared to the CPI.

In summary, the CSI aims to reflect the state of business cycles and is fundamentally distinct from the CPI. By focusing on sectors that have a high correlation with cyclical conditions, the CSI seeks to capture fluctuations in economic conditions. In contrast, sectors related to daily living can receive lower weights in the CSI, which reinforces its role as a distinct measure from the CPI for analyzing economic phenomena.

Table 2: Summary statistics of aggregate inflation measures

	CSI		HCPI		CPIxfF		CPIxfFE	
Subsample	[1]	[2]	[1]	[2]	[1]	[2]	[1]	[2]
Average of π_t^r	1.56	0.10	1.26	0.09	1.26	0.06	1.52	-0.06
Variance of π_t^r	1.24	0.81	1.14	0.85	0.87	0.76	0.77	0.51
12-month autocorrelation of π_t^r	0.71	0.40	0.50	0.02	0.64	0.04	0.69	0.27

[1] Feb. 1983 - Apr. 1997
[2] May 1997 - Dec. 2022

Notes: CSI: Cyclically Sensitive Inflation, HCPI: Headline CPI, CPIxfF: CPI excluding Fresh Food, CPIxfFE: CPI excluding Fresh Food and Energy.

4.2 Time-series properties of the CSI

We analyze the time-series properties of the CSI in Japan and compare them with other aggregate inflation measures. We consider headline CPI (HCPI) inflation, π_t^{HCPI}, and core indicators, CPI excluding fresh food (CPIxfF), π_t^{CPIxfF}, and CPI excluding fresh food and energy (CPIxfFE) inflation, π_t^{CPIxfFE}, as alternative measures of inflation.[5] Table 2 compares summary statistics for the CSI and headline and core inflation measures–HCPI, CPIxfF, and CPIxfFE–across two subsample periods: 1983–1997 and 1997–2022. We report the mean, variance, and 12-month lag autocorrelation coefficient for each index.

The mean and variance of the CSI are similar to those of CPI inflations. The CSI does not significantly deviate from headline and core inflation indicators in any period, indicating that it can be assessed similarly to the CPI regarding average inflation. The mean values of the CSI are comparable to those of CPIxfFE in the early period and HCPI in the later period, while its variance aligns with HCPI in both subsample periods.

The CSI shows more persistent movements in price. Its autocorrelation coefficient exceeds that of HCPI and matches those of CPIxfF and CPIxfFE. This suggests that the CSI effectively mitigates the effect of volatile components, such as fresh food and energy.

Overall, these findings affirm the CSI's comparability to headline and core inflation measures and its effectiveness in capturing persistent inflations. The CSI's mean and variance align with CPI inflation, but it shows higher autocorrelation. Therefore, while both indices are comparable,

[5] In many developed countries, inflation excluding food and energy is usually measured as a core inflation measure. However, as Shiratsuka (2015) and Hogen et al. (2015) point out, it is less a good predictor of future inflation and less relevant to the business cycle. Therefore, in this study, we consider inflation excluding fresh food and inflation excluding fresh food and energy as candidates for core inflation indicators for Japan.

they differ in sensitivity to transient influences, which helps distinguish persistent inflation trends from temporary price changes caused by transitory factors.

5 Role of cyclical inflation: Empirical assessments

Similar to previous studies on core inflation, measuring cyclical inflation indicators is expected to have three implications. First, they are significantly affected by both financial markets and the real economy. Second, they provide valuable information for predicting future inflation and identifying shifts in the inflation trend. Third, they help assess the level of economic slack in real time by monitoring the cyclical fluctuations that underlie inflation.

This section presents empirical analyses of three roles of cyclical inflation: first, the influence of financial markets and the real economy on the CSI (subsection 4.1); second, how the CSI can predict future medium-term and long-term inflation (subsection 4.2); and third, the use of the CSI as a real-time indicator of economic slack for timely insights (subsection 4.3).

5.1 Linkage from financial market and real economy to cyclical inflation

We empirically analyze how financial markets and the real economy influence the CSI. The CSI is expected to relate to the money stock and financial markets because it is designed to respond effectively to cyclical activity. Although, as discussed in Section 2, many previous studies indicated that the relationship between financial markets, the real economy, and inflation in Japan became unstable after the late 1990s, factors unrelated to the business cycle that affect inflation could be so significant that they obscure the true links among these variables. In addition to demand-driven shocks, we also consider the effect of rising oil prices on cyclical inflation. If oil price increases are only temporary cost-push factors, their effect on cyclical inflation could be limited. However, rising oil prices could slow economic activity, potentially putting downward pressure on cyclical inflation in the future. In this subsection, we quantitatively assess these two issues.

5.1.1 Information content of money stock and financial conditions for CSI

We present empirical evidence on the information content of money stock and financial variables for aggregate inflation indicators. Specifically, we examine inflation predictability using the following predictive regression model:

$$\pi_t^r = \sum_{i=1}^{I}\sum_{j=1}^{J}\phi_{i,j} f_{i,t-j} + \sum_{j=1}^{J}\psi_j \pi_{t-j}^r + \mu^r + \xi_t^r, \tag{4}$$

where π_t^r is the inflation for one of the four indices in month t: CSI, HCPI, CPIxfF, and CPIxfFE, f_{it} for $i = 1, \cdots, I$ are candidate financial variables, and ξ_t^r is a zero-mean forecast error for inflation π_t^r. We estimate the regression (4) by ordinary least squares (OLS). We consider five candidate financial variables: M2 money stock ($m2$), short-term interest rate (sr), term spread (ls), stock price (sp), and exchange rate (er). To statistically examine the significant information content of candidate financial variables for inflation dynamics, we compute heteroskedasticity-robust F statistics, following White (1980), for the test under the null hypothesis that the coefficients of the one-to-J-month lags of $f_{i,t}$ for each $i = m2, sr, ls, sp$, and er are all equal to zero ($\phi_{i,1} = \cdots = \phi_{i,J} = 0$). The lag length J in the estimation is set to 12 months.

Table 3 summarizes the results of the estimation from the predictive regressions discussed earlier. It presents the F-statistics for each financial predictor across four inflation measures: CSI, HCPI, CPIxfF, and CPIxfFE, in three sample periods: the full sample, the pre-1997 subsample, and the post-1997 subsample. Each cell displays the F-statistics for the joint significance of the associated lagged financial variable.

Table 3 presents strong evidence that financial markets have predictive power for the CSI. When the dependent variable is the CSI, most F-statistics–except for the lags of ls, which are independent variables–show that the null hypothesis of zero coefficients is strongly rejected in the full sample, as well as in the subsamples before and after 1997. This result indicates that money stock and financial market variables tend to lead future changes in the CSI.

The variation in the predictive strength of financial market variables for certain inflation measures suggests that acyclical components within these measures may influence results. From February 1983 to April 1997, all inflation indicators show statistically significant relationships with financial variables. However, from May 1997 to December 2022, only HCPI maintains a significant link with financial variables. Comparing these periods reveals that the stability of CPIxfF and CPIxfFE has decreased over time. These findings imply that the reduced predictive power of financial variables for inflation is not due to a diminished forecasting ability, but is instead caused by the inclusion of acyclical components in headline and core inflation measures.

Table 3: Predictive content of financial variables for aggregate inflation measures

	Full sample February 1983-December 2022				Subsample February 1983-April 1997				May 1997-December 2022			
Dependent variable	CSI	HCPI	CPIxfF	CPIxfFE	CSI	HCPI	CPIxfF	CPIxfFE	CSI	HCPI	CPIxfF	CPIxfFE
Predictor												
$m2$	1.91	2.33	1.39	1.22	2.96	3.06	4.36	3.13	3.28	2.23	1.22	1.13
	[0.03]	[0.01]	[0.17]	[0.26]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.27]	[0.33]
sr	2.84	2.76	1.64	1.20	2.45	4.34	5.07	2.33	3.20	3.28	1.15	1.33
	[0.00]	[0.00]	[0.08]	[0.28]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.32]	[0.20]
ls	0.70	0.72	1.13	0.94	0.74	0.42	1.42	1.15	1.48	1.33	0.71	1.35
	[0.75]	[0.73]	[0.34]	[0.51]	[0.71]	[0.95]	[0.17]	[0.33]	[0.13]	[0.20]	[0.74]	[0.19]
sp	1.90	1.40	1.22	0.96	2.42	2.60	1.88	2.05	1.53	2.64	1.51	1.06
	[0.03]	[0.16]	[0.27]	[0.49]	[0.01]	[0.00]	[0.05]	[0.03]	[0.11]	[0.00]	[0.12]	[0.40]
er	3.90	4.93	4.62	2.77	3.47	5.11	5.44	3.32	2.22	2.30	2.83	1.14
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.00]	[0.33]

Notes: We run regression model (4) for the aggregate inflation measure described in the upper header on the financial variables. We include the one-to-12-month lags of inflation and the constant as control variables in the regression model. This table reports White (1980) heteroskedasticity-robust F-statistics that test the restriction that the coefficients on the one-to-12-month lags of the predictor described in the left header are all equal to zero. The numbers in brackets are the p-values of the test. CSI: Cyclically Sensitive Inflation, HCPI: Headline CPI, CPIxfF: CPI excluding Fresh Food, CPIxfFE: CPI excluding Fresh Food and Energy. $m2$: M2 (log), sr: Call rate (log), ls: 10-year Japanese government bond yield − call rate, sp: Stock price (log), er: Nominal effective exchange rate (log).

5.1.2 Responses of CSI to macroeconomic fluctuations

We examine the degree and stability of the short-run trade-off between each aggregate inflation measure and the cyclical activity measure. For each measure, we run the following Phillips curve relation:

$$\Delta_{12}\pi_t^r = \beta_1^r + \beta_{CAI}^r CAI_t + \eta_t^r, \tag{5}$$

where η_t^r, with a mean of zero, represents the stochastic deviation component from the short-run Phillips curve.

Table 4: Estimating the short-run Phillips curve with the cyclical activity index

	CSI	HCPI	CPIxfF	CPIxfFE
β_1^r	-0.01	0.00	-0.01	-0.04
	(0.06)	(0.09)	(0.09)	(0.06)
β_{CAI}^r	-2.17	-1.95	-1.89	-1.44
	(0.21)	(0.36)	(0.37)	(0.18)
Adjusted-R^2	0.48	0.22	0.27	0.29
MSE	0.40	1.03	0.75	0.40
sup-WaldF	3.93	2.05	2.87	8.35
	[0.38]	[0.77]	[0.58]	[0.06]

Notes: This table presents the OLS regression results for the 12-month change in each aggregate inflation measure, r =CSI, HCPI, CPIxfF, or CPIxfFE, on the constant term and the cyclical activity index. We obtain the cyclical activity index by scaling and signing the first principal component, which we calculate using the nine standardized indicators, to the 12-month change in filtered unemployment. The numbers in parentheses are Newey and West (1987) heteroskedasticity and autocorrelation robust (HAR) standard errors for least squares with a 12-month lag truncation. The estimated constant term and its standard error are not reported. MSE is the mean of the square of the difference between the actual and estimated value for each regression model. *sup*-WaldF denotes a HAR F statistic, where the null hypothesis is that the regression model is stable throughout the sample period, and the alternative hypothesis is that there is a structural break in coefficient β_{CAI}^r at an unknown point in time. The numbers in brackets are the p-values for the test statistic *sup*-WaldF, which we compute using the critical values proposed by Andrews (1993) and Hansen (1996). The sample period is from February 1983 to December 2022. CSI: Cyclically Sensitive Inflation, HCPI: Headline CPI, CPIxfF: CPI excluding fresh Food, CPIxfFE: CPI excluding fresh Food and Energy.

Table 4 presents the estimated coefficients from equation (5) and statistics related to estimation accuracy. Each column reports the regression results where each inflation measure is the dependent variable. In the upper panel, β_1^r is the constant term, and β_{CAI}^r is the estimated coefficient on the CAI. The numbers in parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation robust (HAR) standard errors for least squares with a 12-month lag truncation. The lower panel reports the adjusted R^2, the mean squared error

(MSE), and the sup-Wald F-statistic for testing a structural break in coefficient β^r_{CAI} at an unknown break point in time, along with its corresponding p-value.

Table 4 shows that the CSI responds effectively to the CAI through its construction. When we use the CSI as the dependent variable, the estimated coefficient on CAI is -2.17, which indicates that a one-unit increase in CAI–equivalent to a one percent rise in the unemployment rate–corresponds to a 2.17 percent decrease in the CSI. Additionally, the adjusted R^2 for the CSI regression is 0.48, suggesting that about half of the variation in CSI can be attributed to CAI. For HCPI and CPIxfF, the adjusted R^2 values range from 20 percent to 30 percent, and their MSEs are significantly larger than those of CSI, indicating the influence of many factors beyond cyclical activity. In the case of CPIxfFE, despite having a similar MSE as the case of CSI, its low R^2 raises concerns that cyclical factors may be excessively removed. Overall, these results imply that the CSI is an inflation measure that can be effectively explained by cyclical activity.

Furthermore, the CSI consistently responds to the CAI over time. The results of the sup-Wald test show no statistically significant structural breaks in the estimated coefficient $\hat{\beta}^{CSI}_{CAI}$, indicating that the relationship remains stable over time. This finding suggests that the CSI maintains a steady association with cyclical economic activity.

Next, we analyze the dynamic causal effects of demand-pull shocks and oil price shocks on inflation indicators. For the quarterly average of each inflation measure π^r_{tq} at quarter tq for $r =$CSI, HCPI, CPIxfF, and CPIxfFE, we run the following local projection model:

$$\pi^r_{tq+h} = \kappa^{r,h} y_{tq} + \gamma^{r,h} o^{\#}_{tq} + \delta^{r,h\prime} W_{tq} + v^r_{tq+h}, \tag{6}$$

where y_{tq} is the real output, measured by the real gross domestic product in logarithms and multiplied by 100 (RGDP), $o^{\#}_{tq}$ is the net oil price increase proposed by Hamilton (2003),[6] W_{tq} is a vector of control variables that includes the one- to four-quarter lags of π^r_{tq}, y_{tq}, and $o^{\#}_{tq}$, as well as a constant. v^r_{tq+h} is an h-quarter-ahead forecast error with a mean of zero. We can interpret $\kappa^{r,h}$ and $\gamma^{r,h}$ as the dynamic responses of inflation to a demand-pull shock and an exogenous oil price shock, respectively.

Figure 2 presents the estimated dynamic responses to a demand-pull shock and an oil price

[6] Hamilton (2003) proposes the net oil price increases as the measure of oil price shocks to take into account the fact that energy price decreases do not produce economic boom, and an oil price increase that just reverses a recent decline has little effect on the macroeconomy.

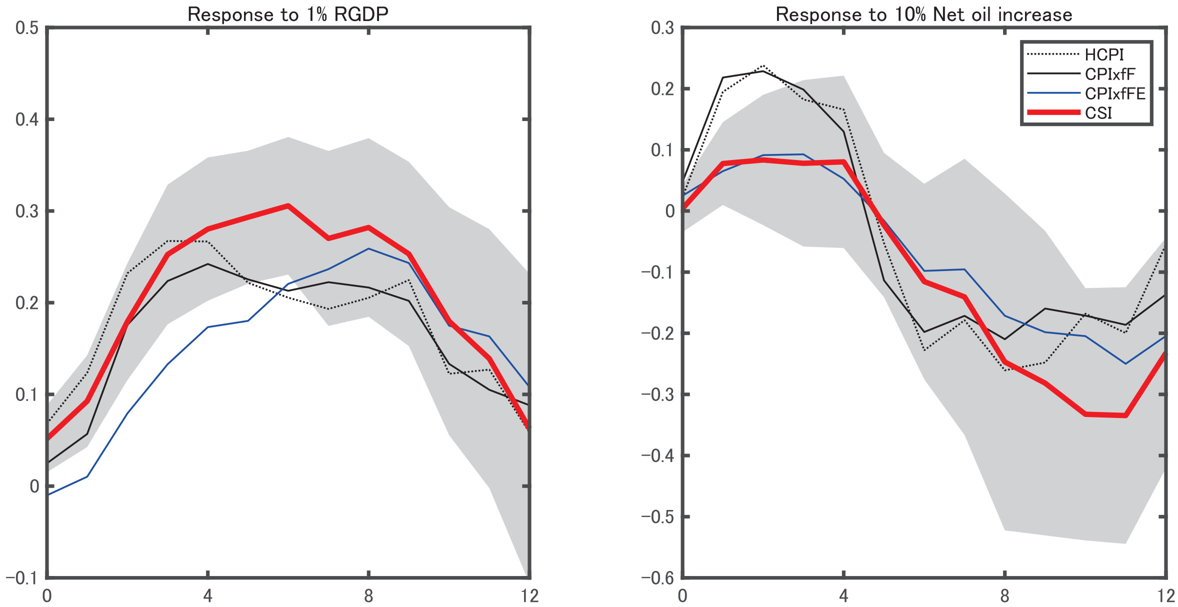

Figure 2: Dynamic causal effect of demand-pull shock and oil price shock on inflation

Notes: The sample period is from the second quarter of 1983 to the fourth quarter of 2019. The solid line in left and right panels represent the point estimates of $\kappa^{r,h}$ and $\gamma^{r,h}$, respectively, using the regression model (6) for each inflation measure of CSI, HCPI, CPIxfF, and CPIxfFE. The shaded areas denote 90% confidence bands for CSI responses calculated using Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors with h-month lag truncation. CSI: Cyclically Sensitive Inflation, HCPI: Headline CPI, CPIxfF: CPI excluding Fresh Food, CPIxfFE: CPI excluding Fresh Food and Energy.

shock for each inflation measure. The left panel shows the h-quarter ahead response to a one percent RGDP increase ($\kappa^{r,h}$), and the right panel shows the h-quarter ahead response to a 10 percent net oil price increase ($\gamma^{r,h}$). Each line corresponds to a different inflation measure: CSI, HCPI, CPIxfF, and CPIxfFE. The bold solid line represents the point estimates for CSI responses obtained from regression model (6). The shaded areas indicate their 90% confidence bands, which we construct using HAR standard errors with $h+1$-lag truncation.

The CSI responds more effectively to demand-pull pressures than headline and core inflation indicators. After a one percent increase in real GDP, it peaks between the 4th and 8th quarters, with a magnitude of about 0.3 percent. Both HCPI and CPIxF peak around the 4th quarter, with a limited response of 0.2 to 0.3 percent, which indicates weaker reactions than the CSI. CPIxfFE also increases from 0.2 to 0.3 percent; however, its response is slower and generally less robust than the CSI. These results show that the CSI reacts to demand-pull factors more effectively and persistently than other aggregate inflation indicators.

The CSI shows a more subdued immediate reaction to oil price shocks compared to headline and core inflation indicators, but it faces significant downward pressure in the long run. After a 10 percent increase in oil prices, the CSI initially rises by less than 0.1 percent, which is not statistically significant, and then decreases to around -0.3 percent over time. This pattern indicates a minimal short-term reaction but a more significant long-term effect. In contrast, both HCPI and CPIxF immediately rise by about 0.2 percent and later settle around -0.2 percent, which demonstrates a strong short-run reaction followed by a reversal. CPIxfFE initially rises by 0.1 percent and then decreases to about -0.2 percent in the long term. Although these reactions align with the CSI's stronger long-term effect, the overall response magnitude is smaller. These results imply that, while the CSI has a weaker immediate response to cost-push shocks, it is more significantly affected by demand-pull factors over time.

The CSI can serve as a valuable indicator of changes in the underlying trend of inflation. Our empirical results show that, unlike headline and core inflation indicators that are sensitive to transitory cost-push shocks, the CSI responds strongly to demand-pull pressures and better reflects medium- to long-term changes in economic slack because of supply-side shocks. Therefore, the CSI reliably indicates changes in inflation trends by reflecting adjustments in economic slack, while it is less influenced by transitory inflation fluctuations.

5.2 Forecasting future inflation and trend shifts

We examine how cyclical inflation can predict future medium- and long-term inflation. As explained in Section 3.1, the autocorrelation of the CSI is relatively high compared to headline and core CPI inflations, indicating that cyclical inflation is persistent, while acyclical inflation is not. If cyclical inflation plays a role in inflation persistence, then changes in cyclical inflation should provide useful insights for forecasting future inflation and trend shifts. In this subsection, we present empirical analysis comparing the forecasting ability of cyclical and acyclical inflation for medium- and long-term horizons.

First, we measure both cyclical and acyclical inflation. We use the CSI to decompose headline CPI inflation into these two components, as follows:

$$\pi_t^{HCPI} = \lambda \pi_t^{CSI} + \pi_t^a = \pi_t^c + \pi_t^a, \tag{7}$$

where the cyclical component is defined as the portion explained by the CSI, and the acyclical component is the difference between headline inflation and the cyclical part. Figure 3 illustrates the measurement of cyclical and acyclical inflation.

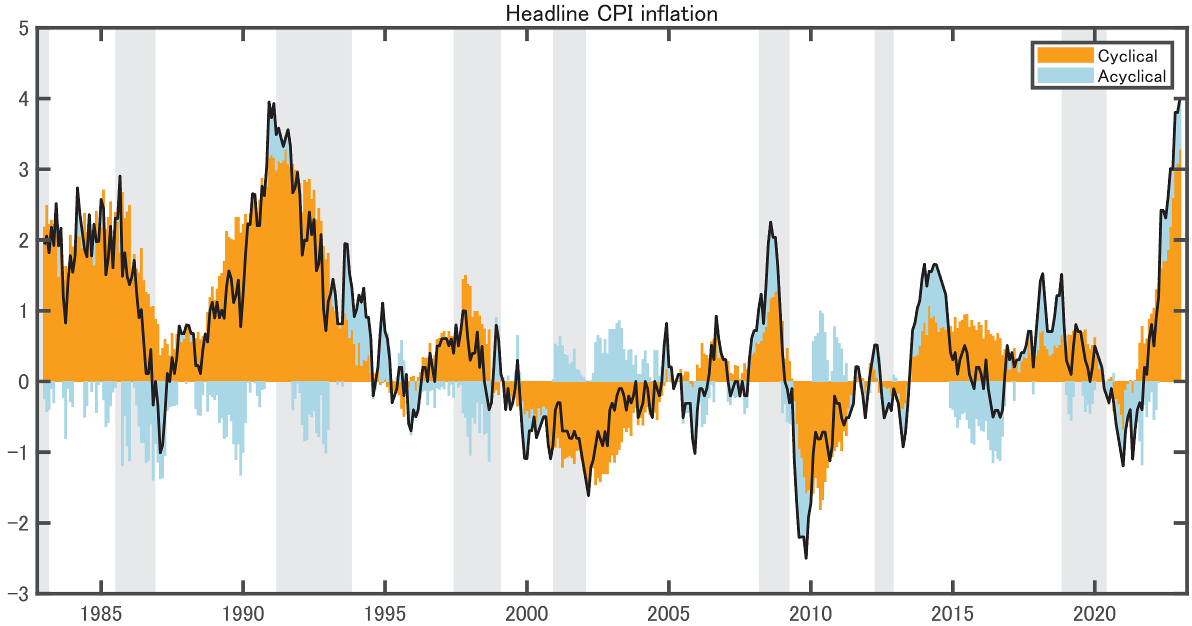

Figure 3: Cyclical and acyclical CPI inflation

Notes: The sample period is from February 1983 to December 2022. The dotted line indicates the year-over-year headline CPI inflation. The shaded areas show periods of recession in Japan, as defined by the Cabinet Office.

Referring to the inflation forecast evaluation by Bryan and Cecchetti (1994), we assess the accuracy of the cyclical and acyclical components in forecasting headline inflation over one- to four-year horizons. Let Π_t^H be the average future headline CPI inflation over a horizon of H months, defined as $\Pi_t^H = 1200/H \times \log(HCPI_{t+H}/HCPI_t)$ in percent. We then analyze a regression model where this average inflation over longer horizons is predicted by cyclical and acyclical components:

$$\Pi_t^H = \phi_1^H + \phi_c^H \pi_t^c + \phi_a^H \pi_t^a + \epsilon_t^H, \tag{8}$$

where H indicates 12, 24, 36, or 48 months, and ϵ_t^H is the forecast error with mean zero.

Table 5 presents the results of the inflation forecast evaluation from regression model (8). Each column reports the results where the future average inflation for each horizon of the next one, two, three, and four years serves as the forecasting variable.

The results show that cyclical inflation measures are effective in forecasting even over long horizons. The coefficient for cyclical inflation is statistically significant across all forecast horizons. This finding suggests that long-term inflation, four years ahead, will increase by about

Table 5: Forecasting long-horizon CPI inflation with cyclical and acyclical inflation

	Π_t^H Horizon H in Months			
	12	24	36	48
Cyclical inflation ϕ_c^H	0.80	0.63	0.51	0.42
	(0.10)	(0.13)	(0.11)	(0.09)
Acyclical inflation ϕ_a^H	-0.01	-0.10	-0.14	-0.09
	(0.17)	(0.16)	(0.17)	(0.21)
Adjusted-R^2	0.52	0.41	0.34	0.27
MSE	0.68	0.69	0.66	0.64

Notes: This table shows the results for future average headline inflation over the horizons described in the upper header, focusing on cyclical and acyclical inflation. The constant terms are included as control variables in the regression model. The numbers in parentheses are Newey and West (1987) heteroskedasticity and autocorrelation robust (HAR) standard errors for least squares with a $H+1$-month lag truncation. We do not report the estimated constant term and its standard error. MSE is the mean squared error of forecasts of inflation. These forecasts cover the period from February 1983 to the most recent available data, ending in December 2022, depending on the horizon H.

0.42 percent in response to a one percent increase in cyclical inflation. Furthermore, cyclical inflation explains approximately 30 percent of the variation in long-term inflation. In contrast, acyclical inflation does not show statistical significance at these horizons. This result implies that demand-driven fluctuations in cyclical inflation signal potential changes in the underlying inflation trend, while temporary shifts in acyclical inflation caused by transient shocks are likely to decrease quickly.

5.3 Real-time assessment of economic slack

We assess the effectiveness of the CSI as a real-time indicator of economic slack. Although headline and core CPI inflation measures aim to reflect the overall cost of living, relying solely on these indicators is not enough to fully understand changes in economic conditions, especially when they are affected by factors unrelated to the business cycle. On the other hand, we expect the CSI to help us identify early signs of rising inflation as cyclical conditions become tighter. By comparing the behaviors of the CSI with headline and core inflation measures, we can determine whether demand-pull factors or other causes drive inflation fluctuations in real time. This subsection examines how useful the CSI is as a real-time measure of economic slack by analyzing the historical behavior of the CSI alongside headline and core inflation measures during key turning points in Japan's business cycles.

Figure 4 displays the aggregate year-over-year inflations for Japan from February 1983 to December 2022. The red thick solid line represents the CSI, the black dotted line indicates the HCPI, the black solid line shows the CPIxfF, and the blue solid line corresponds to the CPIxfFE. Shaded areas denote official recession periods, as defined by the Cabinet Office of Japan.

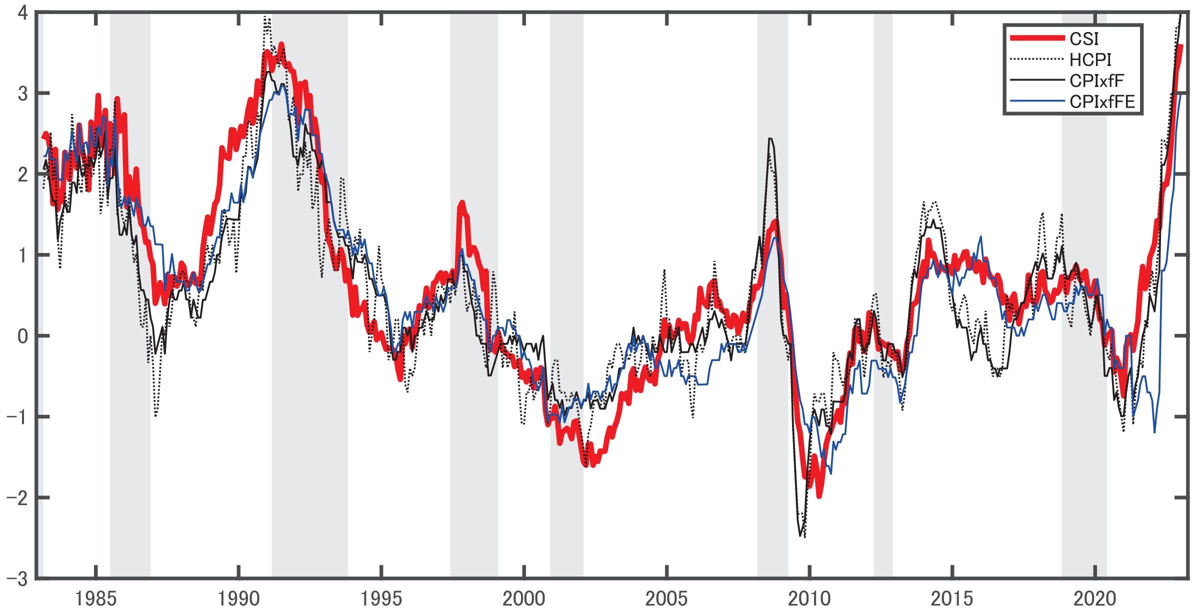

Figure 4: Aggregate year-over year inflations for Japan

Notes: The sample period is from February 1983 to December 2022. The shaded areas indicate periods of recession in Japan, as defined by the Cabinet Office. CSI refers to Cyclically Sensitive Inflation, HCPI refers to Headline CPI, CPIxfF refers to CPI excluding Fresh Food, and CPIxfFE refers to CPI excluding Fresh Food and Energy.

Figure 4 highlights clear differences in movement between CSI and other inflation indicators during specific periods. These differences are especially noticeable in four phases: the recovery from the late 1980s to the early 1990s, the downturn in the early 2000s, the recovery around 2005, and the recovery in the 2020s.

During the late 1980s economic recovery, the CSI shows a rapid expansion before headline and core inflation indicators. The CSI rises sharply, exceeding 2 percent before 1990, which indicates that the acceleration of the recovery begins early. In contrast, headline and core inflation measures do not surpass 2 percent until the 1990s, which gives the impression that the recovery is slower.

During the early 2000s economic downturn, the CSI shows a sharper slowdown than headline and core inflation measures. The CSI steadily decreases, dropping below -1.5 percent, which indicates a more serious economic decline. Meanwhile, headline and core inflation measures remain near -1 percent, suggesting the downturn is comparatively mild.

During the economic recovery around 2005, the CSI shows more noticeable growth compared to headline and core inflation indicators. From early 2002 to early 2008, the CSI steadily increases from -1.5 percent to 1 percent, which indicates a consistent economic recovery. In contrast, headline and core inflation measures remain near 0 percent, which suggests that the recovery appears limited.

During the economic recovery since 2021, the CSI shows an earlier rebound compared to headline and core inflation measures. Although the CSI temporarily falls to around -1 percent, it quickly rises back to near 0 percent, which indicates early signs of economic improvement. In contrast, headline and core inflation measures, after also dropping to -1 percent, again decrease to the same level, which shows no clear evidence of recovery.

Our analyses show that the CSI is a useful real-time indicator for assessing economic conditions. While headline and core inflation measures also tend to rise during recovery periods and fall during downturns, they generally lag behind the CSI or exhibit significant, wave-like volatility. Therefore, headline and core inflation measures are less effective for gauging current economic conditions and capturing business cycle fluctuations, although their main purpose remains to reflect changes in the cost of living. Using the CSI as a complementary indicator for headline inflation helps us identify the sources of inflation, whether they are demand-pull pressures or other cost-push shocks, in real time.

6 Sensitivity and robustness

We summarize two sets of sensitivity analyses. First, following Stock and Watson (2020), we examine how the dynamics of CSI are affected by the potential instability of weights throughout the sample period. The benchmark CSI weights are derived from the full data set spanning February 1983 to December 2022, which raises the question of whether these weights and the resulting CSI remain stable over time. Second, we evaluate the CSI excluding energy to assess its influence. By comparing the dynamics of the benchmark CSI with those of the energy-excluded CSI (CSIxE), we aim to show that the benchmark CSI exhibits persistent time-series features, not solely because it omits sectors with highly volatile inflation, such as energy–similar to core inflation–but also because cyclical factors inherently generate persistent inflation trends.

We first examine whether CSI weights have varied over time because of changes in the Japanese economic environment. Table 6 presents the variance of the 12-month change in sectoral inflations (Column [1]), their correlation with cyclical fluctuations (Column [2]), and the estimated weights in the CSI (Column [3]) across three subsample periods, each covering a 20-year window: 1984–2003, 1994–2013, and 2003–2022.

Table 6 shows that the CSI weights on sectoral inflations vary considerably across subsample periods. From January 1984 to December 2003, Clothes and Footwear, and Housing are the primary components of the CSI. Between January 1994 and December 2013, Automobiles and Bicycles, and Furniture and Household Utensils also become prominent, in addition to the earlier items. In the most recent period, from January 2003 to December 2022, Automobiles and Bicycles, Recreational Goods, Clothes and Footwear, and Public Transportation emerge as the main components. This shift indicates that the sectors more strongly correlated with cyclical activities have changed over time.

Next, we report the results of calculating CSI weights using sector inflation that excludes the influence of energy. Table 7 shows that the CSIxE weights are similar to those in the benchmark CSI weights. The main components of the CSIxE, in descending order, are Clothes and Footwear, Food (less fresh food), Housing, and Recreational Goods. This is consistent with the benchmark CSI weights, which rank Clothes and Footwear, Recreational Goods, and Food (less fresh food) as the main components. This finding indicates that excluding energy components does not significantly alter the CSI's weight structure.

Here, more importantly for robustness checks in this section, we verify whether CSI, which accounts for potential weight changes over time, and CSIxE behave similarly to the benchmark CSI. Figure 5 displays the year-on-year changes in CSI using benchmark weights (solid line), CSI using rolling weights (dotted line), and CSIxE (dashed line). The rolling weights are calculated with a 240-month (20-year) window.

Figure 5 confirms the robustness of the benchmark CSI. The CSI with benchmark weights shows similar dynamics to those using rolling weights and weights that exclude energy. This result indicates robustness to the sample period and to the inclusion of energy.

These results show that the benchmark CSI has a robust structure that is resistant to

Table 6: Variance, correlation with cyclical activity, and CSI weights for sectoral inflations: Subsample

	Subsample Jan. 1984 - Dec. 2003			Jan. 1994 - Dec. 2013			Jan. 2003 - Dec. 2022		
	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
Sectoral inflation									
fresh Food	151.27	-0.09	0.0072	153.85	-0.02	0.0062	117.43	-0.05	0.0000
Food, less fresh Food	1.45	-0.25	0.0196	2.56	-0.47	0.0008	2.93	-0.59	0.0630
Housing	0.33	-0.25	0.2203	0.15	-0.42	0.3550	0.07	-0.21	0.0000
Fuel, light & water charges	12.17	-0.34	0.0722	18.66	-0.54	0.0413	42.31	-0.42	0.0281
Furniture & household untensils	0.78	-0.23	0.0560	2.36	-0.51	0.1121	4.63	-0.36	0.0030
Clothes & footwear	1.88	-0.64	0.4096	1.62	-0.61	0.1965	0.90	-0.41	0.1577
Medical care	17.44	-0.32	0.0464	17.00	-0.23	0.0235	3.92	-0.02	0.0093
Public transportation	4.34	-0.02	0.0000	2.05	-0.28	0.0254	1.09	-0.40	0.1532
Automobiles & Bicycles	0.63	-0.03	0.0001	0.55	-0.39	0.1588	0.43	-0.51	0.3021
Automotive maintenance	18.83	-0.06	0.0000	38.27	-0.02	0.0000	50.59	-0.02	0.0000
Communication	9.47	0.21	0.0000	12.28	0.13	0.0000	86.48	-0.10	0.0153
Education	0.32	-0.29	0.0633	15.78	-0.15	0.0265	16.85	-0.18	0.0292
Recreational durable goods	21.17	-0.06	0.0000	47.55	-0.01	0.0000	60.21	-0.09	0.0031
Recreational goods	3.08	-0.29	0.1046	1.67	-0.42	0.0254	1.44	-0.43	0.1669
Recreational service	1.27	-0.21	0.0001	1.90	-0.44	0.0285	9.30	-0.23	0.0692
Miscellaneous	1.78	0.07	0.0006	4.22	-0.12	0.0001	4.83	-0.12	0.0000

[1] Variances of 12-month change in year-over-year sectoral inflation.
[2] Correlations of 12-month change in year-over-year sectoral inflation with the composite index of cyclical activity measures.
[3] CSI weights.

Notes: CSI represents the cyclically sensitive inflation. CSI weights are obtained by nonlinear least squares estimation of the regression in eq. (1) with restrictions eq. (2) and eq. (3) for each subsample described in the upper header.

Table 7: Benchmark CSI and CSI excluding Energy weights for sectoral inflation

	Benchmark CSI weights	CSIxE weights
Sectoral inflation		
Fresh Food	0.0005	0.0024
Food, less fresh Food	0.1010	0.1857
Housing	0.0639	0.1161
Fuel, light & water charges	0.0584	0.0000
Furniture & household untensils	0.0347	0.0231
Clothes & footwear	0.3600	0.3070
Medical care	0.0530	0.0509
Public transportation	0.0001	0.0001
Automobiles & Bicycles	0.0748	0.0602
Automotive maintenance	0.0000	0.0256
Communication	0.0118	0.0077
Education	0.0349	0.0208
Recreational durable goods	0.0000	0.0000
Recreational goods	0.1319	0.1074
Recreational service	0.0718	0.0929
Miscellaneous	0.0032	0.0002

Notes: The sample period is February 1983 to December 2022. CSI represents cyclically sensitive inflation. In constructing CSIxE, we use sectoral inflations that exclude Energy. The benchmark CSI and CSIxE weights are obtained by nonlinear least squares estimation of the regression in eq. (1), subject to the restrictions in eq. (2) and eq. (3).

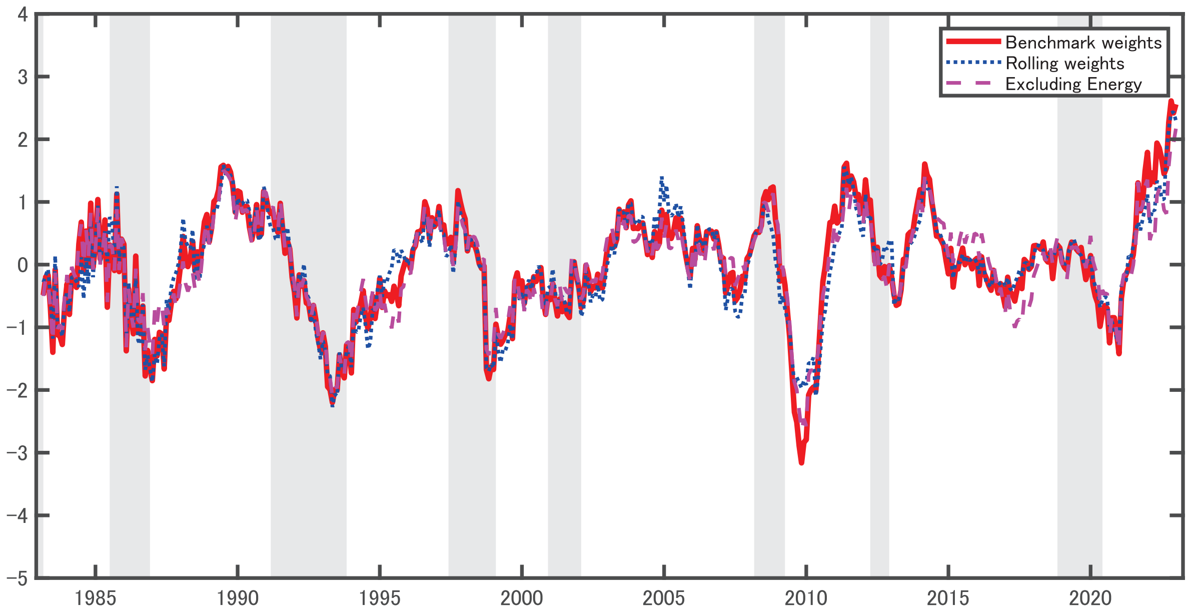

Figure 5: 12-month changes in year-over-year CSI inflation using Benchmark (solid), Rolling (dotted), and Excludes energy (dashed) weights.

Notes: The sample period is from February 1983 to December 2022. The rolling weights are estimated using rolling regressions with a 240-month window, with the first sample period from February 1983 to January 2003. The shaded areas show periods of recession in Japan, as defined by the Cabinet Office.

changes in external conditions, such as component composition and whether energy is included or excluded. Although the CSI weights are unstable, the CSI remains stable over time because it consistently assigns high weights to sectors that are sensitive to cyclical fluctuations. Furthermore, energy exclusion has minimal effect on the CSI's composition or dynamics, indicating stability without depending on specific shocks or sector categories. Overall, these features show that the CSI in Japan reliably captures business cycles.

7 Concluding remarks

This paper introduces a CSI index specifically designed for Japan. The index aims to better capture inflation patterns closely linked to the business cycle. By adapting the methodology of Stock and Watson (2020), we construct the CSI using sectoral inflations weighted by their correlation with cyclical economic activity. This approach allows the CSI to highlight sectors sensitive to business cycles, distinguishing it from headline and core inflation measures that often include acyclical components. Empirical results show that the CSI is more strongly associated with financial markets and real economic fluctuations, detects signals of upcoming inflation trend changes, and serves as a useful real-time indicator of economic slack.

The findings of this study suggest that the CSI serves as a complement to the headline and core CPI, and holds potential for policy applications. The CSI captures inflationary movements driven by cyclical economic fluctuations, while CPI inflation reflects changes in the cost of living. Therefore, combining the two indices enables policymakers to distinguish whether observed inflation is attributable to transitory factors or to persistent pressures arising from the business cycle. This complementary relationship contributes to a more accurate identification of the underlying drivers of inflation.

The CSI developed in this study offers significant potential for further applications and extensions. First, integrating the CSI time series into empirical analyses in finance and macroeconomics can allow for a more in-depth examination of the relationship between inflation, financial variables, and business cycle dynamics. While we provide a preliminary analysis of the link between the CSI, financial markets, and real economic activity, future research can enhance these findings by applying the CSI within structural VAR models and macroeconometric frameworks, which may yield deeper empirical insights with policy relevance.

Second, applying the CSI construction methodology from this study to data from other countries could provide valuable insights through cross-country comparisons. In this paper, we construct the CSI using Japanese data and analyze it alongside other inflation indicators, focusing on its statistical properties and its links with financial and real economic variables. However, the characteristics and functions of the CSI might differ significantly across countries because of differences in economic structures and policy environments. Conducting international comparisons would increase understanding of how business cycles relate to inflation in various national contexts.

Finally, this study's findings could open new avenues for understanding inflation dynamics and developing monetary policy practices. In monetary policy research, there is a theoretical basis for targeting core inflation, which excludes inflation in flexible-price sectors, to achieve the goal of price stability. This approach is based on the premise that price stickiness, which causes welfare loss, underpins inflation persistence. Therefore, stabilizing persistent inflation in sticky-price sectors is crucial for macroeconomic stability (Aoki, 2001). However, previous studies, such as Bils and Klenow (2004), have pointed out that the degree of price stickiness and inflation persistence are not necessarily correlated, which raises questions about whether core inflation is an appropriate policy target. On the other hand, the results of this paper suggest that managing policies to stabilize cyclical inflation could help stabilize both the business cycle and underlying headline inflation. Still, it remains unclear *why* cyclical pressures cause persistence in inflation dynamics. The theoretical foundation for persistent inflation caused by business cycles could enhance the practical use of cyclical inflation measures in monetary policy.

A Appendix

A.1 Constructing cyclical activity index

We construct the cyclical activity index in five steps. First, we create a data set of six labor market variables and three real economic variables: the unemployment rate, employment-population ratio, vacancy ratio, job opening ratio, unemployment insurance beneficiaries, overtime worked hour index, 3-month lag of the industrial production index, 3-month lag of the capital utilization index, and the tertiary industry activity index. Second, we calculate the filtered activity measures as the year-over-year change in the 12-month moving average of activity measures for month t. Third, we calculate the first principal component using standardized filtered activity measures with zero mean and unit variance. Fourth, we regress the following equation to scale and sign the factor to filtered unemployment, $\tilde{u}_t$:

$$\tilde{u}_t = \gamma_1 + \gamma_{pc} pc_t + v_t, \tag{9}$$

where γ_1 and γ_{pc} are the intercept and slope coefficient, respectively, and v_t is an error term. Finally, given the estimate of γ_{pc}, we compute the composite index as $CAI_t = \hat{\gamma}_{pc} pc_t$. We refer to the composite index of CAI_t as the cyclical activity index, representing a weighted average of the year-over-year change in the 12-month moving average of real activity measures.

A.2 Variable definitions

- Sectoral inflation π_i: year-over-year rate of consumer price (2020=100) by each sector: Fresh Food, Food less Fresh Food, Housing, Fuel, Light & Water Charges, Furniture & Household Utensils, Clothes & Footwear, Medical Care, Public Transportation, Automobiles & Bicycles, Automotive Maintenance, Communication, Education, Recreational Durable Goods, Recreational Goods, Recreational Services, and Miscellaneous; retrieved from the Ministry of Internal Affairs and Communications. To calculate consumption-tax-adjusted series for the period from April 1989 to March 1990, April 1997 to March 1998, April 2014 to March 2015, and October 2019 to September 2020, we remove the average of the absolute values of the year-over-year increase at the time of the tax hike and the decrease one year after, without relying on detailed structural models or assumptions about full pass-through.

- HCPI, CPIxfF, and CPIxfFE inflation: year-over-year rate of consumer price index (2020 = 100) inflation for all items, all items less fresh foods, and all items less fresh foods and energy, respectively (2020 = 100); consumption-tax-adjusted series for the period from April 1997 to March 1998 and April 2014 to March 2015; calculated backward for the period before December 1989 using the monthly change in the index with adding 1.2 in March 1989 to eliminate the influence of the consumption tax from April 1989; retrieved from the Ministry of Internal Affairs and Communications.

- Unemployment: unemployment over labor force ratio, percent, retrieved from NIKKEI

NEEDS FINANCIAL QUEST.

- Employment/population: total employed person over population ratio, percent. Total employed person, 10,000 persons, seasonally adjusted series, retrieved from NIKKEI NEEDS FINANCIAL QUEST. Population: estimated population at the beginning of the month, 10,000 persons, retrieved from NIKKEI NEEDS FINANCIAL QUEST.

- Vacancy: (Number of effective job openings minus number of job offerings) over labor force ratio, percent. Number of effective job openings, thousands persons, seasonally adjusted series, retrieved from NIKKEI NEEDS FINANCIAL QUEST. Number of job offerings, thousands persons, retrieved from NIKKEI NEEDS FINANCIAL QUEST, seasonally adjusted series obtained using the Census X-12. Labor force, 10,000 persons, seasonally adjusted series, retrieved from NIKKEI NEEDS FINANCIAL QUEST, divided by 10.

- Job opening/applicant: effective job offer ratio, multiplier, seasonally adjusted series, retrieved from NIKKEI NEEDS FINANCIAL QUEST.

- Unemployment insurance beneficiaries: actual number of employment insurance beneficiaries, thousands persons, retrieved from NIKKEI NEEDS FINANCIAL QUEST, seasonally adjusted series obtained using Census X-12, taking the logarithm.

- Overtime worked hour: index of nonscheduled hours worked, all industry (30 persons or more), seasonally adjusted series (2020 = 100), retrieved from NIKKEI NEEDS FINANCIAL QUEST, taking the logarithm.

- Industrial product: index of industrial production, mining and manufacturing, seasonally adjusted series (2015 = 100), retrieved from NIKKEI NEEDS FINANCIAL QUEST, taking the logarithm.

- Capital utilization: index of capital utilization, manufacturing, seasonally adjusted series (2015 = 100), retrieved from NIKKEI NEEDS FINANCIAL QUEST, taking the logarithm.

- Tertiary industry activity: index of tertiary industry activity, seasonally adjusted series (2015 = 100), retrieved from NIKKEI NEEDS FINANCIAL QUEST, taking the logarithm.

- $m2$: M2 money stock; seasonally adjusted series (monthly average, 100 million yen); retrieved from NIKKEI NEEDS FINANCIAL QUEST.

- sr: The Yeo-Johnson transformation of uncollateralized overnight call rate (monthly average, %); monthly series retrieved from the Bank of Japan statistics for the period from July 1985 to December 1994 and calculated backward for the period before June 1985 using the monthly change in the collateralized overnight call rate; retrieved from the Bank of Japan statistics.

- ls: Spread between long-term interest rate and short-term interest rate (%). Long-term rate measured by 10-year Japanese government bond yields (end of month, %), retrieved from NIKKEI NEEDS FINANCIAL QUEST. Short-term interest rate measured by uncollateralized overnight call rate.

- sp: Tokyo Stock Price Index (TOPIX) (end of month); retrieved from NIKKEI NEEDS FINANCIAL QUEST.

- er: Nominal effective exchange rates by the BIS, 2010 AVERAGE=100 retrieved from NIKKEI NEEDS FINANCIAL QUEST.

- RGDP: real gross domestic product; National accounts statistics compiled according to 1993 SNA and 2008 SNA (benchmark year=2011) from the 1st quarter of 1980 through the 4th quarter of 2018 (Data prior to 1994 using the 1993 SNA series), chain-linked method (1993 SNA and 2008 SNA), seasonally adjusted quarterly series retrieved from HAVER ANALYTICS (billion yen).

- $o^{\#}$: Net oil increase proposed by Hamilton (2003); oil price increases that exceed the maximum price observed over the previous 12 quarters. Oil prices measured by West Texas Intermediate (WTI) retrieved from FRED. quarterly average.

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