Online Appendix
"The Role of Cyclical Inflation: Evidence from Japan" by Takuya Sakaguchi and Masahiko Shibamoto

A.1 Phillips-curve style regressions

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:

$$\Delta_{12}\pi_t^r = b_1^r + b_{CAI}^r CAI_t + \eta_t^r, \tag{1}$$

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

Table A1: Estimating the short-run Phillips curve with the cyclical activity index

	CSI	HCPI	CPIxfF	CPIxfFE
b_1^r	-0.01	0.00	-0.01	-0.04
	(0.06)	(0.09)	(0.09)	(0.06)
b_{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 b_{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 A1 presents the estimated coefficients from equation (1) and statistics related to estimation accuracy. Each column reports the regression results where each inflation measure is the dependent variable. In the upper panel, b_1^r is the constant term, and b_{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 b^r_{CAI} at an unknown break point in time, along with its corresponding p-value.

Table A1 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 $\hat{b}^{CSI}_{CAI}$, indicating that the relationship remains stable over time. This finding suggests that the CSI maintains a steady association with cyclical economic activity.

A.2 Local-projection results based on reduced-form domestic output innovations and a Hamilton-type oil price shock measure

We analyze the dynamic effects of domestic output innovations and oil price shocks on inflation indicators. For the log real GDP and 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:

$$z^i_{tq+hq} = \kappa^{i,hq} y_{tq} + \gamma^{i,hq} o^{\#}_{tq} + \delta^{i,hq\prime} W^i_{tq} + v^i_{tq+hq}, \tag{2}$$

where y_{tq} is the real output, measured by the real gross domestic product in logarithms and multiplied by 100 (RGDP), z^i_{tq+hq} is either y_{tq+hq} (real GDP) or π^r_{tq+hq} (inflation measure r), $o^{\#}_{tq}$ is the net oil price increase proposed by Hamilton (2003),[1] W^i_{tq} is a vector of control variables that includes the one- to four-quarter lags of y_{tq}, π^r_{tq}, and $o^{\#}_{tq}$, as well as a constant. v^r_{tq+hq} is an hq-quarter-ahead forecast error with a mean of zero. We can interpret $\kappa^{i,hq}$ and $\gamma^{i,hq}$ for $hq = 0, \cdots, HQ$ as the hq-quarter-ahead dynamic responses of z^i to an output innovation and an oil price shock, respectively.

Figure A1 presents the estimated dynamic responses to a output innovation and an oil price shock for each inflation measure. The upper panels show the hq-quarter ahead response to a one percent RGDP increase ($\kappa^{i,hq}$), and the lower panels show the hq-quarter ahead response to a 10 percent net oil price increase ($\gamma^{i,hq}$). Each line in right pannels 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 (2). The shaded areas indicate their

[1] 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.

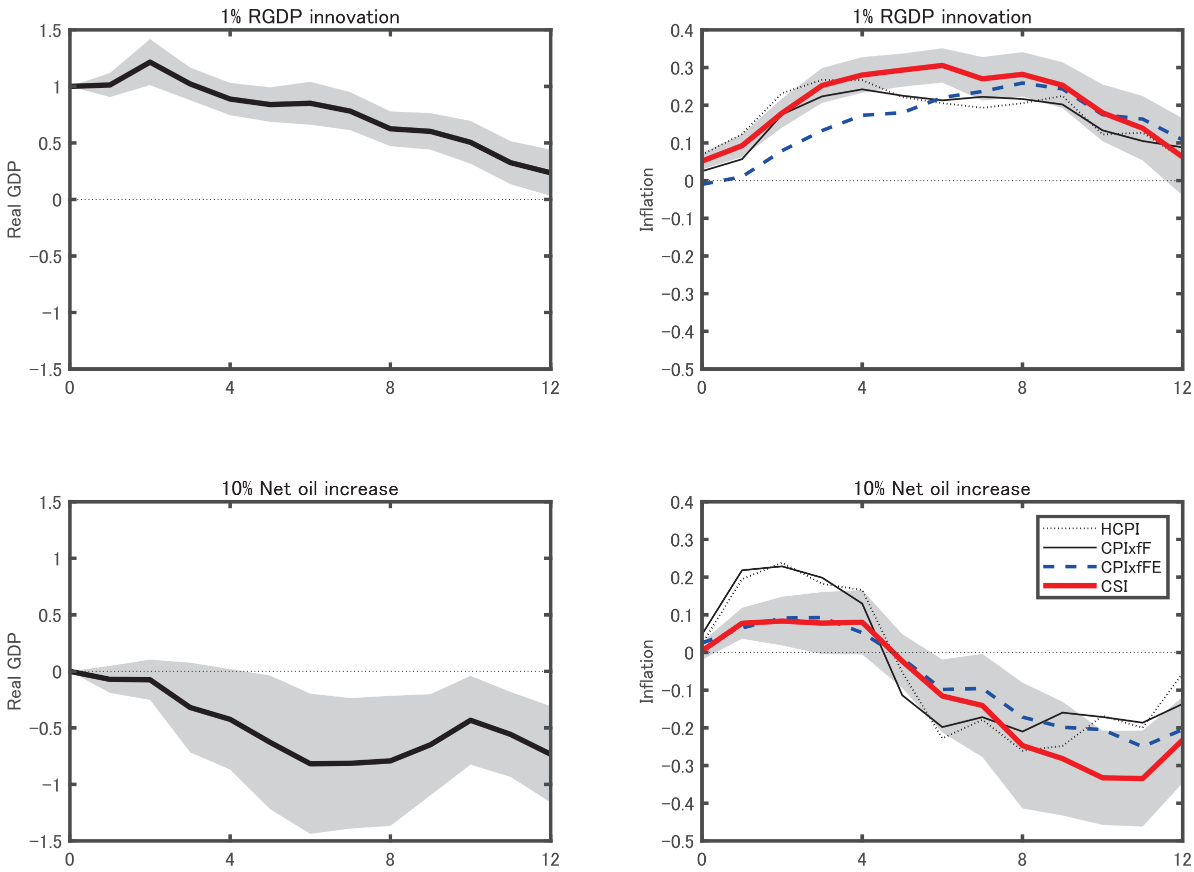

Figure A1: Dynamic effect of output innovation and oil price shock on inflation

Notes: The sample period is from the second quarter of 1983 to the fourth quarter of 2019. The solid line in panels represent the point estimates of $\kappa^{i,hq}$ and $\gamma^{i,hq}$, respectively, using the regression model (2) for log real GDP and each inflation measure of CSI, HCPI, CPIxfF, and CPIxfFE. The shaded areas denote one Newey and West (1987) heteroskedasticity and autocorrelation robust standard error confidence bands with $hq+1$-quarter lag truncation. CSI: Cyclically Sensitive Inflation, HCPI: Headline CPI, CPIxfF: CPI excluding Fresh Food, CPIxfFE: CPI excluding Fresh Food and Energy.

one HAR standard error confidence bands with $hq + 1$-lag truncation.

The CSI responds more effectively to output innovations 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 output innovations 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 persistent 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.

A.3 Measuring oil-market shocks

This subsection describes how we measure oil-market shocks following Kilian (2009), and documents the resulting shock series and impulse responses using an extended sample through December 2022. The goal is to provide transparency on the construction of the external shocks used in the main text and to verify that the identifying patterns emphasized by Kilian (2009) remain visible when the sample is extended.

We use the same data sources and variable definitions as in Kilian (2009). World crude oil production is measured by global crude oil output, the global real economic activity index is Kilian's dry-cargo-freight-rate-based activity measure, and the (nominal) oil price is the U.S. refiner acquisition cost (RAC) of imported crude oil. The real price of oil is constructed by deflating the nominal RAC series with the U.S. CPI.

We measure oil-market shocks from a monthly VAR with 24 lags estimated over January 1975 through December 2022 in the ordered vector $[\Delta \log(\text{OilProd}_t),\ \text{REA}_t,\ \log(\text{RPO}_t)]'$, where $\Delta \log(\text{OilProd}_t)$ is the log difference of world crude oil production, REA_t is Kilian's global real economic activity index, and $\log(\text{RPO}_t)$ is the log real price of oil. Structural shocks are identified using the recursive (Cholesky) structure implied by this ordering, as in Kilian (2009). This delivers three shocks: a crude oil supply shock, a global activity shock, and an oil-specific demand shock.

Figure A2 plots the measured structural shocks. The series show pronounced movements around major oil-market episodes, including the early-1980s disturbances, the global financial crisis, and the COVID-19 period.

Figure A3 reports the corresponding impulse responses of oil production, global real activity, and the real price of oil. The extended-sample responses display the qualitative patterns emphasized by Kilian (2009): (i) an adverse oil supply shock lowers oil production and raises the real price of oil on impact, with limited immediate movement in global real activity; (ii) a global real activity shock raises real activity and the real price of oil; and (iii) an oil-specific demand shock generates a sharp increase in the real price of oil, with distinct responses in production and activity. Overall, the extended-sample measurement supports the use of these

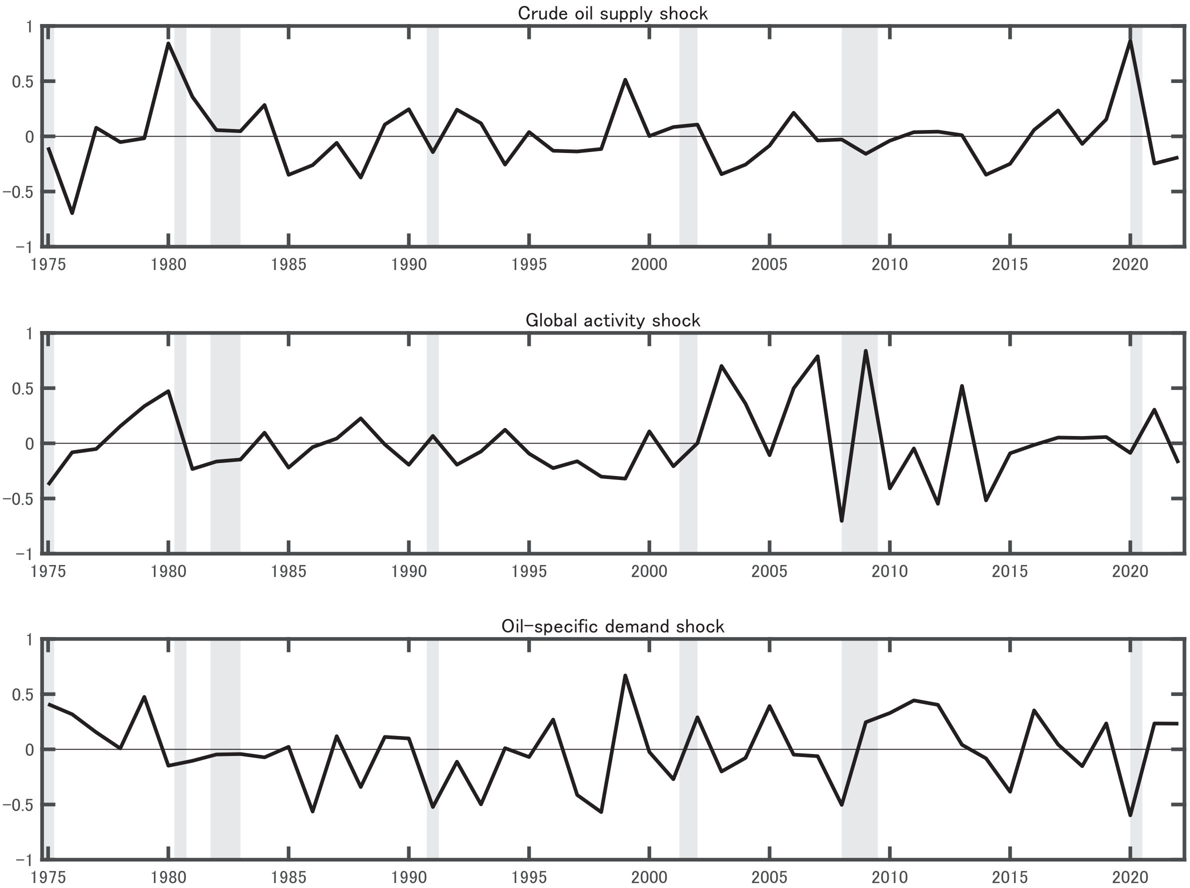

Figure A2: Kilian (2009) oil-market structural shocks, extended through December 2022

Notes: Monthly structural shocks identified from the VAR in [$\Delta \log(\text{OilProd})$, REA, $\log(\text{RPO})$] with 24 lags over January 1975 through December 2022 using the recursive ordering in Kilian (2009). Shaded areas indicate U.S. NBER recessions.

shocks as externally identified oil-market disturbances in the main analysis.

In the main text, we aggregate the monthly shocks to quarterly frequency and use them as externally identified shocks in local projections for Japan's real GDP and inflation measures.

A.4 Forecasting HCPI: CSI versus 10% trimmed mean inflation

This section examines whether CSI improves the accuracy of headline CPI (HCPI) forecasts relative to the 10% trimmed-mean inflation measure, which is often used as a robust core indicator. We evaluate forecast performance using the mean squared forecast error (MSE) and Diebold and Mariano (1995) statistics computed relative to the CSI-based direct-forecast benchmark.

We consider a simple direct-forecast regression in which future average HCPI inflation is regressed on an inflation indicator, and a corresponding random-walk benchmark in which the indicator itself is used as the forecast.

$$\pi_{t+12}^{HCPI} = \theta_1^r + \theta_\pi^r \pi_t^r + \upsilon_{t+12}^{r,DF}, \tag{3}$$

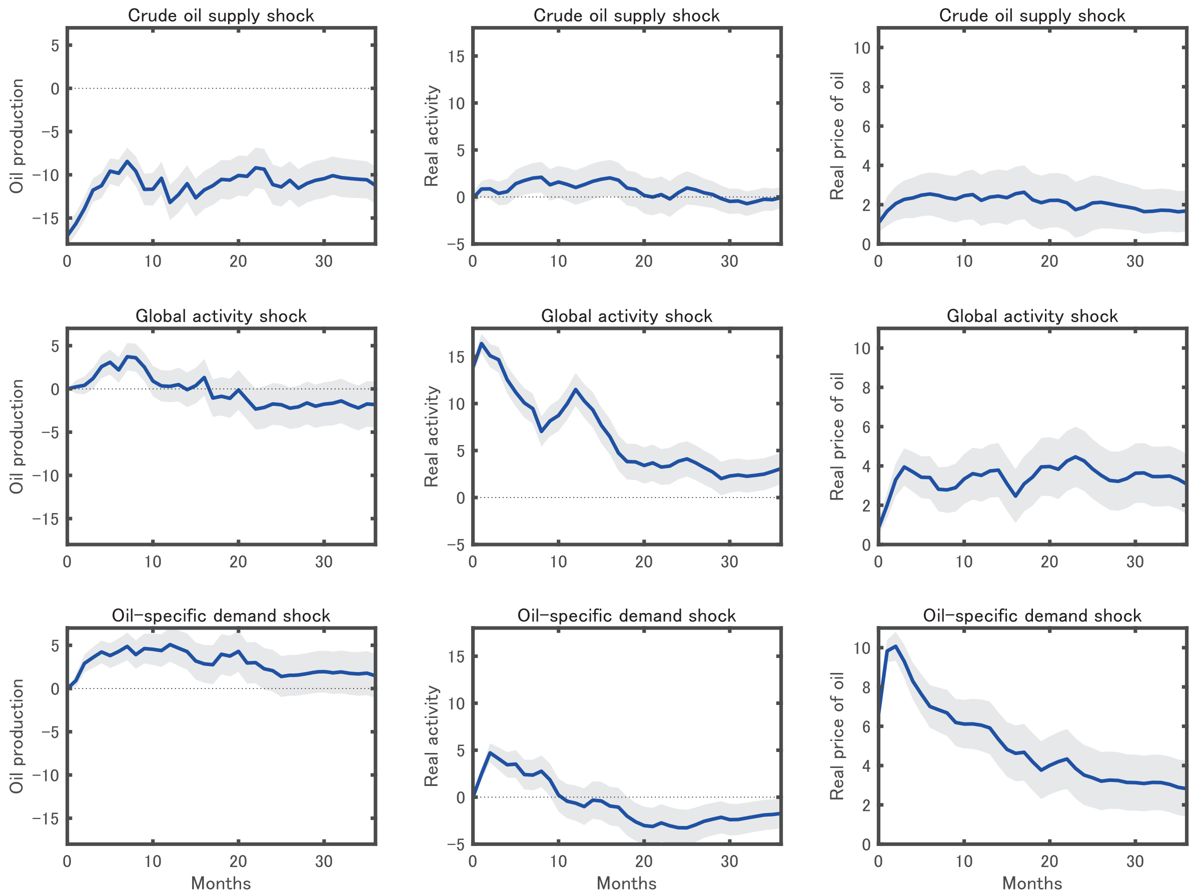

Figure A3: Impulse responses of oil-market variables to Kilian (2009) structural shocks, extended through December 2022

Notes: Solid lines denote point estimates. The shaded areas denote one-standard-error bands, calculated using 1000 bootstrap samples. We set the lag length to 24 months in the reduced-form vector autoregressive (VAR) estimation. Estimation samples span from January 1975 to December 2022.

$$\pi_{t+12}^{HCPI} = \pi_t^r + v_{t+12}^{r,RW} . \tag{4}$$

Table A2 shows that the CSI-based direct forecast delivers a slightly smaller MSE than the direct forecast based on the 10% trimmed mean, although the difference is not statistically decisive. More importantly, when compared with the random-walk benchmark based on the 10% trimmed mean, the CSI-based direct forecast yields a clearly smaller MSE, and the Diebold–Mariano statistic indicates that the improvement is statistically meaningful. Taken together, these results suggest that CSI is at least as informative as the trimmed-mean measure for forecasting headline inflation at the one-year horizon, and that CSI provides additional forecasting content beyond a simple random-walk benchmark based on a robust core measure. This finding is consistent with the main forecasting results reported in Section 5.3.

Table A2: Monthly forecast accuracy for one-year-ahead headline inflation: CSI versus 10% trimmed-mean inflation

Model		In-sample
Direct forecast: $\hat{\pi}_{t+12}^{HCPI} = \hat{\theta}_1^r + \hat{\theta}_\pi^r \pi_t^r$		
	CSI (benchmark)	0.896
	10% Trim	0.920
		(-1.124)
Random-walk forecast: $\hat{\pi}_{t+12}^{HCPI} = \pi_t^r$		
	10% Trim	1.083
		(-2.076)

Notes: The table reports MSFEs for one-year-ahead (12-month-ahead average) HCPI inflation. The "Direct forecast" uses a regression of future average HCPI inflation on the indicator shown in the row (CSI or 10% trimmed mean). The "Random-walk forecast" uses the indicator itself as the forecast. The evaluation period begins in January 2002 because the 10% trimmed-mean inflation series is available only from January 2001, and the construction of the one-year-ahead forecast evaluation requires the corresponding initial observations. Numbers in parentheses are Diebold–Mariano (1995) statistics for equal predictive accuracy computed relative to the CSI-based direct-forecast benchmark. CSI: cyclically sensitive inflation; 10% Trim: 10% trimmed-mean inflation.

A.5 Forecast performance including and excluding the COVID-19 pandemic period

This section checks whether the unusual inflation dynamics during the COVID-19 period materially affect the relative forecasting performance of CSI. We therefore compare forecast errors computed from the same one-year-ahead direct-forecast specification in (3) across (i) the full sample and (ii) a subsample that ends in December 2019 and thus excludes the COVID-19 pandemic period.

Table A3: Forecasting performance of CSI and other aggregate indicators: full sample and subsample excluding the COVID-19 pandemic period

Model		Full sample	Subsample
Direct forecast: $\hat{\pi}_{t+12}^{HCPI} = \hat{\theta}_1^r + \hat{\theta}_\pi^r \pi_t$			
	CSI (benchmark)	0.839	0.722
	HCPI	0.998	0.857
	CPIxfF	0.963	0.820
	CPIxfFE	0.981	0.794

Notes: The table reports MSEs for one-year-ahead (12-month-ahead average) HCPI inflation from the direct-forecast regression. The full-sample evaluation is February 1984 through December 2022. The subsample evaluation is February 1984 through December 2019, excluding the COVID-19 period. CSI: cyclically sensitive inflation; HCPI: headline CPI; CPIxfF: CPI excluding fresh food; CPIxfFE: CPI excluding fresh food and energy.

Table A3 shows that CSI continues to deliver the smallest MSE among the aggregate indicators considered, both in the full sample and in the subsample excluding the COVID-19 period.

Thus, although the pandemic episode may affect the overall level of forecast errors, it does not drive the relative ranking of indicators: the favorable forecast performance of CSI is already present in the pre-pandemic sample. This suggests that CSI's relative forecast performance is not driven solely by the post-pandemic episode.

A.6 Sensitivity and robustness of CSI

This subsection reports the detailed robustness checks summarized in Section 6 of the main text. We consider three alternative constructions. First, we allow the CSI weights to vary over time by estimating them over rolling 20-year windows. Second, we construct an energy-excluded CSI to examine whether the benchmark index is driven by energy-price pass-through. Third, we construct a Tier-C-excluded CSI by assigning zero weight to the Tier C sectors identified in Table 2 of the main text. These exercises distinguish sensitivity in the sectoral composition of CSI from robustness in the resulting aggregate index.

Table A4 reports the variance of the 12-month change in sectoral inflation, its correlation with cyclical activity, and the estimated CSI weight for three 20-year subsamples. The sectoral weights vary across the windows. Clothes and Footwear and Housing receive relatively large weights in the earliest window; Automobiles and Bicycles and Furniture and Household Utensils become more important in the middle window; and Automobiles and Bicycles, Recreational Goods, Clothes and Footwear, and Public Transportation receive relatively large weights in the most recent window. Thus, the sectors providing the strongest cyclical signal change over time.

Table A5 compares the benchmark weights with the energy-excluded and Tier-C-excluded specifications. Excluding energy components changes some individual weights but leaves the main contributors broadly similar. The Tier-C-excluded specification mechanically assigns zero weight to Tier C sectors and reallocates weight mainly toward Clothes and Footwear, Housing, Food less Fresh Food, Recreational Goods, Recreational Services, and Automobiles and Bicycles.

The central robustness result concerns the aggregate index rather than the invariance of individual sectoral weights. Figure A4 compares the benchmark CSI with the rolling-weight, energy-excluded, and Tier-C-excluded series. Although the estimated sectoral weights differ across windows and specifications, all four CSI measures display very similar time-series movements. The benchmark results therefore do not depend materially on fixed full-sample weights, energy-related components, or sectors whose inflation frequently departs substantially from headline inflation.

Taken together, the exercises show sensitivity in the sectoral composition but robustness in the aggregate CSI. The sectors receiving large weights change over time, and alternative exclusions reallocate weights across categories. Nevertheless, the resulting CSI series remains stable and continues to capture a common cyclical inflation signal.

Table A4: 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 estimated by nonlinear least squares estimation of the regression in eq. (1) with restrictions eq. (2) and eq. (3) in the main text for each subsample described in the upper header.

Table A5: CSI weights under alternative constructions: benchmark, energy-excluded, and Tier-C-excluded

	Benchmark	Energy-excluded	Tier-C-excluded
Sectoral inflation			
fresh Food	0.0005	0.0024	0
Food, less fresh Food	0.1010	0.1857	0.1640
Housing	0.0639	0.1161	0.2004
Fuel, light & water charges	0.0584	0.0000	0
Furniture & household untensils	0.0347	0.0231	0.0263
Clothes & footwear	0.3600	0.3070	0.3226
Medical care	0.0530	0.0509	0
Public transportation	0.0001	0.0001	0.0174
Automobiles & Bicycles	0.0748	0.0602	0.0783
Automotive maintenance	0.0000	0.0256	0
Communication	0.0118	0.0077	0
Education	0.0349	0.0208	0
Recreational durable goods	0.0000	0.0000	0
Recreational goods	0.1319	0.1074	0.1111
Recreational service	0.0718	0.0929	0.0798
Miscellaneous	0.0032	0.0002	0.0001

Notes: The sample period is February 1983 to December 2022. "Benchmark" reports the baseline CSI weights estimated by nonlinear least squares from eq. (1), subject to the constraints in eqs. (2) and (3) in the main text. "Energy-excluded" re-estimates CSI weights using sectoral inflation series that exclude energy components. "Tier-C-excluded" imposes zero weights on all Tier C sectors (as classified in Table 2 in the main text) and re-estimates the remaining weights under the constraints in eqs. (2) and (3) in the main text, with weights renormalized to sum to one. CSI denotes cyclically sensitive inflation.

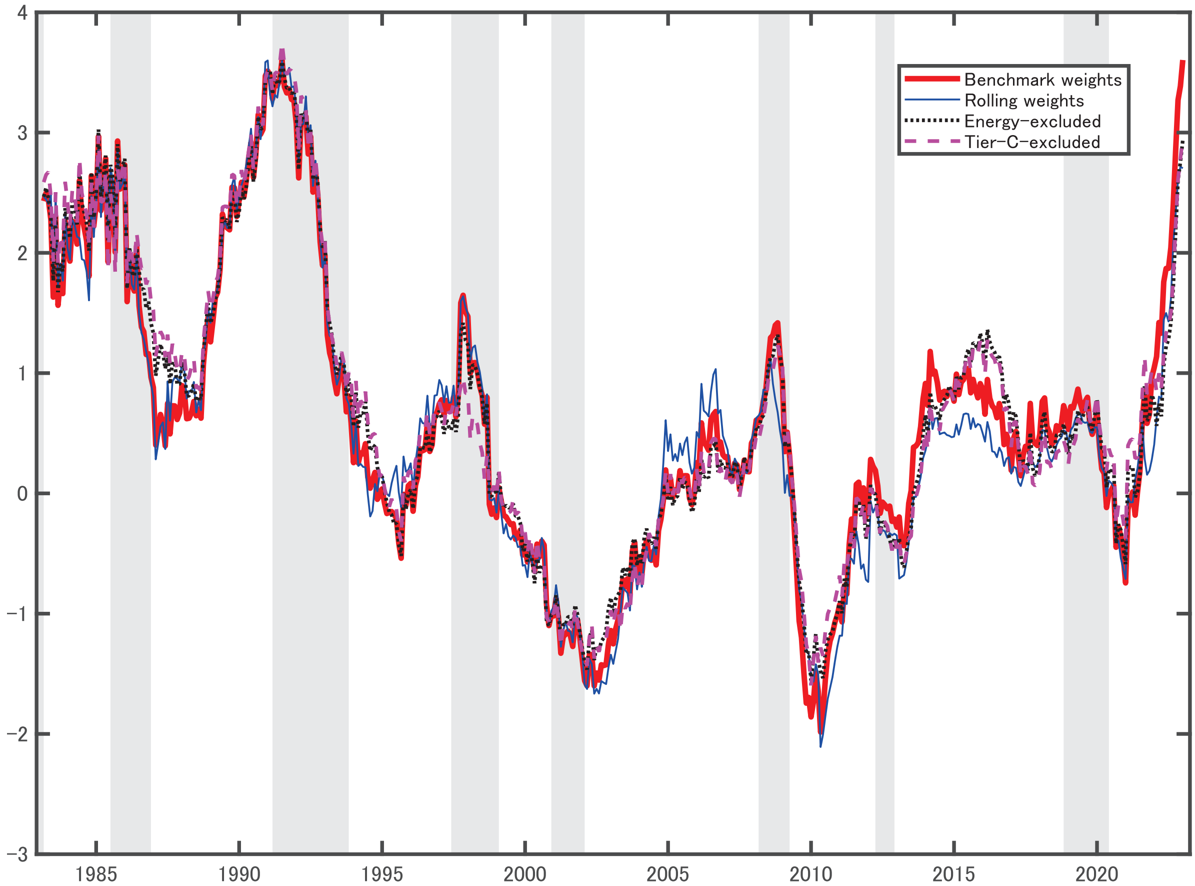

Figure A4: CSI under alternative weighting schemes: benchmark (thick solid), rolling weights (thin solid), energy-excluded (dotted), and Tier-C-excluded (dashed)

Notes: The sample period is February 1983 to December 2022. The rolling-weight CSI is computed by re-estimating eq. (1) each month using a 240-month rolling window; the first window spans February 1983 to January 2003. Shaded areas indicate recession periods in Japan as defined by the Cabinet Office.

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