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Measuring Trend Inflation Based on Financial Market Conditions: The Case of Japan

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Abstract

This paper proposes a market-based indicator of trend inflation by exploiting a cointegrating relationship between inflation and financial conditions. We model inflation jointly with long-term interest rates, the money stock, and the nominal exchange rate, and estimate the cointegrating relationship using dynamic ordinary least squares (DOLS). The implied common-trend can be expressed as a simple weighted average of observable financial series, making the indicator transparent, easy to replicate, and straightforward to update in real time via recursive estimation. Using monthly data from 1983 to 2022, we show that the indicator contains statistically significant information about future inflation and improves forecasts of two-year-ahead average inflation relative to widely used core measures. The forecasting gains reflect two mechanisms: the common-trend extraction filters out transitory movements in observed inflation and provides a cleaner real-time estimate of the contemporaneous trend toward which headline inflation tends to revert. Overall, the results suggest that financial-market information provides a useful complement to traditional core indicators for monitoring persistent inflationary pressures and for policy analysis of medium- to long-run inflation dynamics in Japan.

JEL Classification: C32; E31.
Keywords: inflation, stochastic trend, cointegration, financial market, forecasting.

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1 Introduction

Central banks rely on timely measures of underlying inflation, typically monitoring core inflation that excludes items with large transitory price changes like food and energy (Gordon, 1975; Wynne, 2008). Japan, for example, uses Consumer Price Index (CPI) inflation excluding fresh food or both fresh food and energy (Shiratsuka, 2015; Hogen *et al.*, 2015).[1] These indicators are simple but do not isolate low-frequency inflation, as transitory shocks can influence other items, and the best reflection of underlying inflation varies over time. Therefore, core measures may differ from medium- and long-term inflation crucial for policy.

This paper focuses on trend inflation, understood as the low-frequency level of inflation after abstracting from cyclical fluctuations and temporary cost-push shocks. Existing approaches often estimate trend inflation using flexible time-series models such as unobserved-components or regime-switching frameworks (e.g., Stock & Watson, 2007; Kaihatsu & Nakajima, 2018; Okimoto, 2019). Although informative, these approaches are complex and less transparent for real-time monitoring and communication.

Our economic motivation is that inflation and financial conditions are jointly driven by slow-moving nominal forces. Long-term interest rates reflect inflation expectations and real rates; the money stock reflects persistent changes in spending and liquidity; the nominal exchange rate captures external price pressures by shifting import prices and their pass-through, with implications for firms' price setting and inflation expectations. If these forces share a stochastic trend, inflation and financial variables should have a stable long-run relationship.

The contribution of this paper is to provide a simple, operational way to extract a low-frequency inflation signal from publicly observable financial data by using cointegration to identify the shared stochastic trend between inflation and financial conditions. Rather than ad hoc predictions using financial regressors, we estimate the cointegrating vector with dynamic ordinary least squares (DOLS) and map it into a weighted-average formula. This provides a transparent, easy-to-compute real-time indicator, enhancing its usefulness for practitioners and policymakers.[2]

Using Japanese monthly data from the early 1980s to 2022, we show that the resulting trend indicator removes transitory movements more effectively than standard core measures and contains statistically meaningful information about future inflation. In out-of-sample forecasts, it outperforms several widely used core inflation indicators, particularly during periods when inflation exhibits low-frequency shifts.

The remainder of the paper is organized as follows. Section 2 outlines the methodology and the construction of the real-time financial-trend indicator. Section 3 presents the empirical results, including out-of-sample forecasting comparisons.

2 Methodology

We construct a market-based indicator of trend inflation from CPI inflation and a small set of financial variables that are available over a long sample. Let P_t be the price level of the CPI aggregate in period t. CPI inflation (year-over-year, %) is then calculated as $\pi_t = 100 \times (\log(P_t) - \log(P_{t-12}))$. The long-term interest rate (%) r_t, money stock (log) m_t, and exchange rate (log) e_t, are specifically considered as series representing financial conditions. We focus on these three series to preserve simplicity and long-run data availability.

[1] Shiratsuka (2015) and Hogen *et al.* (2015) compare core measures and argue that exclusion-based core measures forecast better and comove more strongly with the output gap.

[2] Adding further market indicators (e.g., credit spreads, equity prices, inflation swaps, or survey expectations) are a natural extension, but beyond this short letter's scope due to data coverage and design choices over the long sample.

Under the maintained hypothesis that inflation and financial conditions share a common stochastic trend, we model their interdependence through the cointegrating relationship:

$$\pi_t = \phi_1 + \phi_r r_t + \phi_m m_t + \phi_e e_t + \epsilon_t, \tag{1}$$

where ϵ_t is stationary when cointegration holds. Standard unit-root and cointegration tests support the approach; tests in the Online Appendix confirm treating the series as nonstationary with one cointegrating relationship.

We estimate the cointegrating parameters using the DOLS (Stock & Watson, 1993):

$$\pi_t = \phi_1 + \phi_r r_t + \phi_m m_t + \phi_e e_t + \sum_{i=-k}^{k} \psi_{r,i} \Delta r_{t-i} + \sum_{i=-k}^{k} \psi_{m,i} \Delta m_{t-i} + \sum_{i=-k}^{k} \psi_{e,i} \Delta e_{t-i} + \epsilon_t, \tag{2}$$

where k denotes the lead and lag orders of the first-difference of financial series as control variables to address potential endogeneity in cointegrated systems. We select k in a data-driven manner by minimizing the Akaike Information Criterion over $k = 0, 1, \cdots, 15$.

The trend inflation at time t is constructed as the fitted long-run component using information available up to t. Specifically, we re-estimate (2) recursively (expanding-window) using data up to t to obtain $\phi_{1|t}, \phi_{r|t}, \phi_{m|t}$, and $\phi_{e|t}$, and define $\pi_{t|t}^{rme} \equiv \phi_{1|t} + \phi_{r|t} r_t + \phi_{m|t} m_t + \phi_{e|t} e_t$. Recursive estimates are statistically efficient when the long-run relationship is stable. Tests show no instability in the cointegrating regression parameters (see the Online Appendix). To assess uncertainty, especially in early parts of the recursive sample, we compute pointwise confidence bands for trend inflation estimates, which remain tight, validating the indicator's reliability (see the Online Appendix).

3 Empirical results

3.1 Data and implementation

We use headline CPI inflation, the 10-year Japanese government bond yield, M2, and the nominal effective exchange rate over February 1983-December 2022. Five core inflation indicators are examined as alternative measures of underlying inflation: total excluding fresh food (CPIxfF), total excluding fresh food and energy (CPIxfFE), and three distribution-based measures (Trimmed mean, Weighted median, and Mode). Details are in the Online Appendix.[3]

Figure 1 shows the headline inflation, the measured common-trend $\pi_{t|t}^{rme}$, and the core inflation indicators. The trend series is smoother than exclusion-based core measures (CPIxfF and CPIxfFE), indicating that transitory fluctuations are largely removed. Relative to the distribution-based measures, the proposed series more clearly tracks low-frequency movements, consistent with its construction as a long-run component.

Figure 1 also illustrates the indicator's behavior during major episodes. Headline inflation reacts sharply to transitory shocks but typically reverts toward the estimated trend, which moves more gradually and acts as a slow-moving anchor. This is evident around the financial crisis, the 2013-2016 swing, and the COVID-19 crisis, where headline inflation fluctuates widely while the trend rises or falls smoothly. Overall, the indicator filters short-lived movements while tracking gradual shifts in underlying inflation pressures.[4]

[3]This paper does not cover real-time vintage-data exercises due to the unavailability of historical real-time CPI vintages over the long sample.

[4]The low-frequency pattern of our trend estimate–near zero after the late 1990s and rising after the 2013 regime change but staying below 2%–is consistent with model-based trend inflation measures for Japan (Kaihatsu & Nakajima, 2018; Okimoto, 2019).

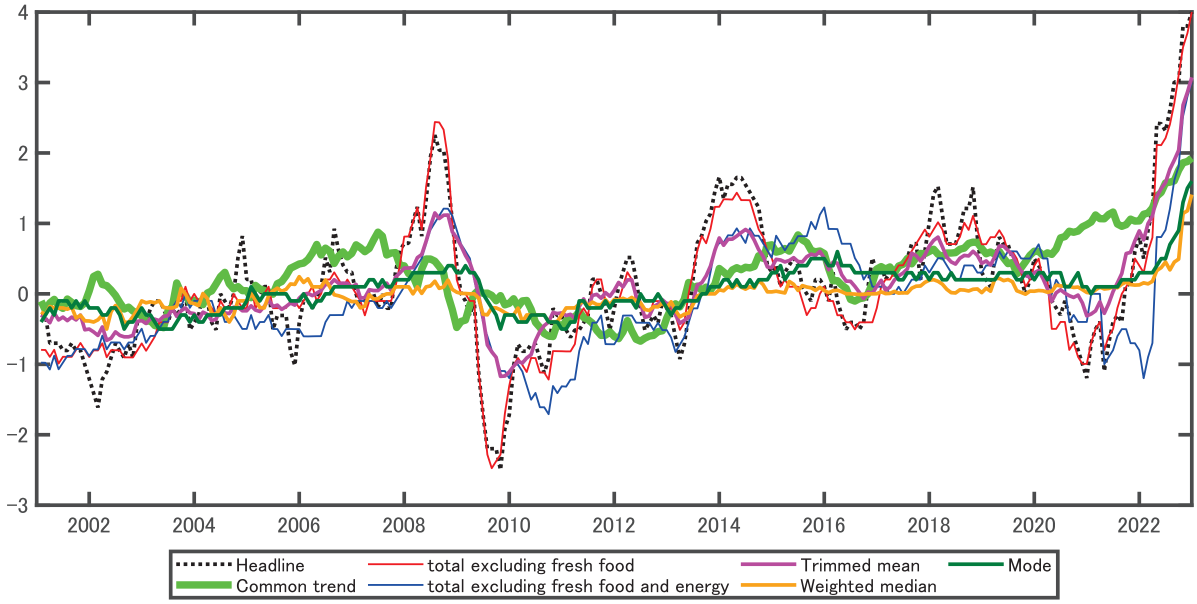

Figure 1: CPI inflation, common-trend, and core inflation indicators

Notes: The sample period runs from January 2001 to December 2022.

3.2 Out-of-sample prediction comparison

We assess predictive performance by forecasting average CPI inflation over two years. The out-of-sample period is split into January 2001–December 2012, a low-inflation period, and January 2013–December 2021, marked by rising inflation.

Table 1 shows out-of-sample performances of the common-trend forecast, core inflation forecasts, and an average forecast over two periods. The table presents mean-squared error (MSE), Diebold & Mariano (1995) statistic (DM) for predictive superiority testing, and Model Confidence Set (MCS) p-values (Hansen *et al.*, 2011) for comparing predictive accuracy.

First, the common-trend indicator dominates the exclusion-based core measures. It yields lower MSEs and significant DM statistics relative to CPI excluding fresh food (CPIxfF) and CPI excluding fresh food and energy (CPIxfFE) in both subsamples. Consistent with this, the MCS results exclude CPIxfF and CPIxfFE from the 90% MCS in both periods, while the trend indicator remains in the set.

Second, the comparison with distribution-based indicators depends on the inflation environment. During 2001-2012, distribution-based indicators–especially the weighted median–perform well, and the common-trend forecast does not uniformly dominate them. At the 90% level, the MCS retains the trend indicator along with the weighted median and some closely performing alternatives (including the mode and the simple combination forecast), indicating that the best-performing measure is hard to pin down in this low-inflation subsample. By contrast, during 2013-2021, the trend forecast performs best with the lowest MSE, and the MCS results are more decisive: all core measures, including distribution-based indicators and the combination forecast, are excluded from the 90% MCS, leaving the trend as the only member of the set. This pattern is consistent with the view that financial-market information helps track low-frequency movements in inflation in real time.

Overall, the forecasting gains primarily reflect the indicator's ability to filter out transitory movements and to provide a cleaner real-time estimate of the contemporaneous trend toward which headline inflation tends to revert.

Table 1: Prediction comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prediction period: January 2001 - December 2012							
MSE	0.46	1.07	0.94	0.60	0.33	0.40	0.52
DM	-	-1.89	-3.23	-1.05	2.00	0.78	-0.68
MCS p-value	0.174	0.041	0.000	0.096	1.00	0.174	0.125
Prediction period: January 2013-December 2021							
MSE	0.79	2.15	2.23	1.43	1.39	1.27	1.43
DM	-	-3.05	-2.46	-2.31	-2.05	-1.76	-2.25
MCS p-value	1.00	0.003	0.013	0.051	0.051	0.051	0.013

(1) Common-trend (2) total excluding fresh food (3) total excluding fresh food and energy (4) Trimmed mean (5) Weighted median (6) Mode (7) Combination (Average (1)-(6))

Note: MSE denotes the mean-squared prediction error over two prediction periods, January 2001 to December 2012 and January 2013 to December 2021. DM denotes the Diebold & Mariano (1995) statistic for testing the significance of predictive superiority of common-trend forecast with respect to each core inflation forecast. All DM tests are implemented with Newey & West (1987) heteroskedasticity and a serial correlation robust covariance matrix with the truncation parameter $P^{1/4}$ where P is the prediction sample size. MCS p-values report the inclusion p-value p_{MCS} from the Model Confidence Set (MCS) procedure of Hansen *et al.* (2011). The loss is squared forecast error for 24-month-ahead average inflation. p-values are obtained by a block bootstrap (5000 replications; block length $P^{1/4}$).

3.3 Additional analyses

We conduct additional analyses to assess robustness and sensitivity.

The Online Appendix reports (i) alternative cointegration estimators (fully modified OLS), (ii) sensitivity to the starting date of the real-time exercise, and (iii) sensitivity to different dynamic specifications. These verify that the main conclusions from Figure 1 and Table 1 are not artifacts of a specific estimation choice.

Next, we perform 18-year rolling-window estimates for sensitivity analysis, which can be unstable due to limited data, especially for low-frequency movements like Japan's inflation from the early 2000s to early 2010s. Rolling windows lack enough variation to identify trends, causing unstable cointegration estimates (see the Online Appendix). Recursive estimation, which accumulates information over time, better captures low-frequency trends and is our main method.

We also conduct a sensitivity check using year-over-year changes in financial variables, which may obscure stochastic trends. Although estimates and forecasts differ from the benchmark, cointegration tests do not support the time-series assumptions (see the Online Appendix). This underscores the importance of incorporating the cointegration relationship when constructing the trend indicator.

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Conflict of interest

Masahiko Shibamoto states that there is no conflict of interest.

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