

Monthly Deflator-Based Inflation Measures Complement CPI-Based Inflation

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Introduction

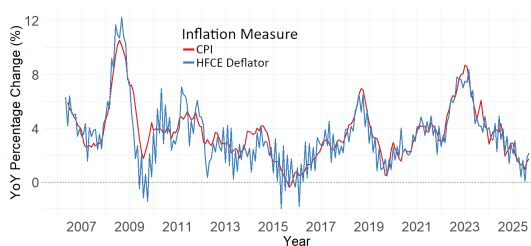
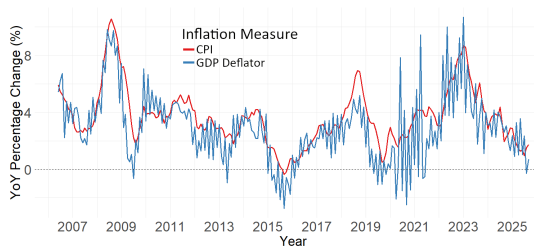
Goal : Estimate and examine alternative measures of inflation

- ▶ Quarterly National Accounts: Gross Domestic Product (GDP), Household Final Consumption Expenditure (HFCE), and Total Supply (TS)

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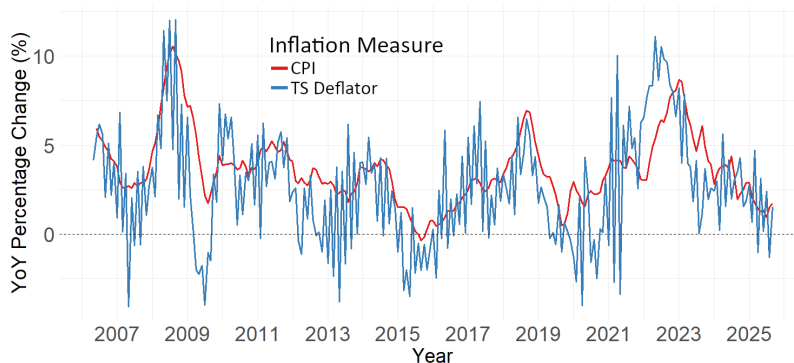
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Inflation Measures

Consumer Price Index (CPI)

- ▶ the most widely used basis for calculating inflation.

Alternative Price Indices (Implicit Deflators):

- ▶ GDP Deflator
- ▶ HFCE Deflator
- ▶ TS Deflator
 - ▷ Introduced by Hahn and Renault (2024)
 - ▷ Captures both domestic production prices and imported input prices

Motivation for Total Supply: Imports Ratio

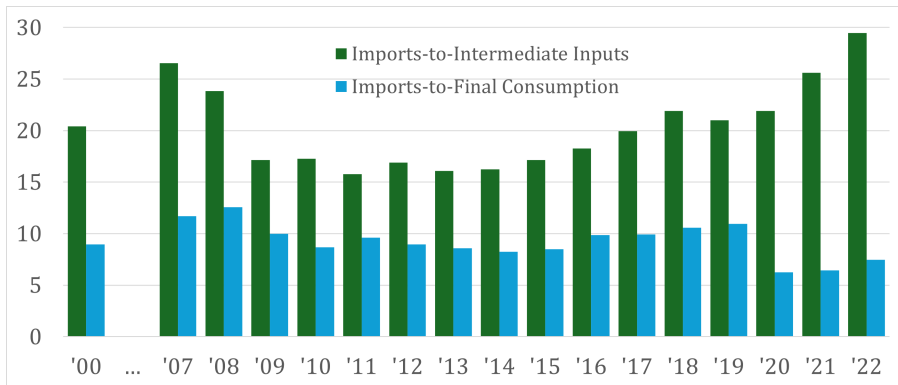


Figure 1

Source: Author's Calculations from ADB I-O Table

Comparison of Inflation Measures

	CPI	DEFLATOR		
		GDP	HFCE	TS
Core Concept	Consumer price index based on a fixed basket; out-of-pocket spending	Price of domestically produced output (all final goods and services)	Household final consumption expenditure (demand-side measure)	Price pressures from domestic and external sources, including imports
Key Bias/Feature	Subject to substitution bias	Captures changes in the composition of production	Reflects shifts in the spending patterns of households	Sensitive to external price shocks (e.g., import costs)
Frequency	Monthly (High Freq)	----- Quarterly (Low Freq) -----		
Timeliness	~5 days after reference month	----- 30-40 days after reference quarter -----		

Frequency Mismatch

Solution: Temporal Disaggregation

- ▶ Use high-frequency indicators to “break down” quarterly aggregates.

Foundation:

- ▶ Chow-Lin (1971) - Classic regression-based framework
- ▶ Fernandez (1981) - Quadratic loss function approach; Random walk residual
- ▶ Litterman (1983) - Generalization of Fernandez (1981)
- ▶ Santos Silva and Cardoso (2001) - Dynamic model assuming white noise residuals
- ▶ Proietti (2006) - Dynamic model using Kalman filter and State-space models
- ▶ Poissonnier (2017)

Using Implicit Deflators to Calculate Inflation

Implicit Deflator

$$\text{Implicit Deflator} = \frac{\text{Nominal National Account}}{\text{Real National Account}} \times 100 \quad (1)$$

Year-on-Year Growth

$$\text{Inflation Rate}_{\text{deflator}} = \left(\frac{\text{Deflator}_{\text{curr}} - \text{Deflator}_{\text{prev}}}{\text{Deflator}_{\text{prev}}} \right) \times 100 \quad (2)$$

Data

	Y_n^{lf}	$\hat{Y}_t$
2005M1		
2005M2		
2005M3/Q1	27.09	
2005M4		
2005M5		
2005M6/Q2	29.19	
...	...	...
2025M4		
2025M5		
2025M6/Q2	80.32	
2025M7		
2025M8		
2025M9/Q3	77.37	

Data

	Y_n^{lf}	$\hat{Y}_t$
2005M1		
2005M2		
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2005M5		
2005M6/Q2	29.19	
...	...	...
2025M4		
2025M5		
2025M6/Q2	80.32	
2025M7		
2025M8		
2025M9/Q3	77.37	

Table 1: Monthly Indicators

Series from PSA

Net Sales Value Index (VANSI)

Net Sales Volume Index (VONSI)

Value of Imports (FOB in USD) (VAIMP)

Volume of Imports (Gross Kg) (VOIMP)

Series from Bureau of the Treasury

Tax Revenue (in Php) (TAXREV)

Data

	Y_n^{lf}	$\hat{Y}_t$
2005M1		8.77
2005M2		9.43
2005M3/Q1	27.09	8.89
2005M4		10.13
2005M5		8.98
2005M6/Q2	29.19	10.08
...	...	...
2025M4		28.61
2025M5		23.89
2025M6/Q2	80.32	27.83
2025M7		25.02
2025M8		27.89
2025M9/Q3	77.37	24.46

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Temporal Disaggregation

We follow the framework presented by Poissonnier (2017)

- ▶ let $n = 1$ to N index the low-frequency period
- ▶ N is the total number of periods of the low-frequency
- ▶ Y_n^{lf} is the observable low-frequency we aim to disaggregate
- ▶ let f be the periodicity of the flows,
- ▶ let $t = 1$ to fN serve as the time index for high-frequency period
- ▶ X_t is the observable high-frequency indicator

Temporal Disaggregation: Model

Dynamic Model with p lags:

$$Y_t = \sum_{i=1}^p (\mu_i Y_{t-i}) + X_t \beta + \varepsilon_t \quad (3)$$

- specified at a high-frequency

Temporal Disaggregation: Aggregation Constraint

$$Y_n^{lf} = \sum_{t=(n-1)f+1}^{fn} Y_t \quad (4)$$

- ▶ can be expressed in matrix form denoted as $M(1)$.
- ▶ i.e. for $f = 3$

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- ▶ i.e. for $f = 3$

$$M(1) = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 1 & 1 & 1 \end{bmatrix}$$

Temporal Disaggregation: Matrix Form

We can express the model in Equation 3 as,

$$\underbrace{\begin{bmatrix} Y_1 \\ \vdots \\ Y_{fN} \end{bmatrix}}_Y = \underbrace{\begin{bmatrix} 0 & 0 & 0 & \cdots & \cdots & 0 & 0 & 0 \\ \mu_1 & 0 & 0 & \cdots & \cdots & 0 & 0 & 0 \\ \mu_2 & \mu_1 & 0 & \cdots & \cdots & 0 & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots & \vdots \\ \mu_p & \mu_{p-1} & \cdots & \cdots & \cdots & 0 & 0 & 0 \\ 0 & \mu_p & \mu_{p-1} & \cdots & \cdots & 0 & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & \mu_p & \cdots & \mu_2 & \mu_1 & 0 \end{bmatrix}}_{M_1(\mu_1, \dots, \mu_p)} \underbrace{\begin{bmatrix} Y_1 \\ \vdots \\ Y_{fN} \end{bmatrix}}_Y + X\beta + \underbrace{\begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_{fN} \end{bmatrix}}_E + \underbrace{\begin{bmatrix} \mu_p & \cdots & \mu_1 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mu_p \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix}}_{M_2(\mu_1, \dots, \mu_p)} \underbrace{\begin{bmatrix} Y_{1-p} \\ \vdots \\ Y_0 \end{bmatrix}}_{Y^{init}}$$

(5)

Temporal Disaggregation: Example

$$\underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}} = \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{M}_1()} + \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}} + \underbrace{\begin{bmatrix} 1 & 49.9 & 8.78 \\ 1 & 48.4 & 6.84 \\ 1 & 52.1 & 7.89 \\ 1 & 54.0 & 12.42 \\ 1 & 52.7 & 10.04 \\ 1 & 54.1 & 8.41 \end{bmatrix}}_X \underbrace{\begin{bmatrix} \\ \\ \end{bmatrix}}_{\hat{\beta}} + \underbrace{\begin{bmatrix} \\ \\ \end{bmatrix}}_{\hat{E}} + \underbrace{\begin{bmatrix} \\ \\ \end{bmatrix}}_{\hat{M}_2()} \underbrace{\begin{bmatrix} \end{bmatrix}}_{\hat{Y}^{init}}$$

$$\underbrace{\begin{bmatrix} 27.08 \\ 29.19 \end{bmatrix}}_{Y^{lf}} = \underbrace{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}}_{M(1)} \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}}$$

Temporal Disaggregation: Example

$$\underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}} = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ -0.2 & 0 & 0 & 0 & 0 & 0 \\ 0.82 & -0.2 & 0 & 0 & 0 & 0 \\ 0 & 0.82 & -0.2 & 0 & 0 & 0 \\ 0 & 0 & 0.82 & -0.2 & 0 & 0 \\ 0 & 0 & 0 & 0.82 & -0.2 & 0 \end{bmatrix}}_{\hat{M}_1(-0.2, 0.82)} \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}} + \underbrace{\begin{bmatrix} 1 & 49.9 & 8.78 \\ 1 & 48.4 & 6.84 \\ 1 & 52.1 & 7.89 \\ 1 & 54.0 & 12.42 \\ 1 & 52.7 & 10.04 \\ 1 & 54.1 & 8.41 \end{bmatrix}}_X \underbrace{\begin{bmatrix} -.43 \\ .06 \\ .12 \end{bmatrix}}_{\hat{\beta}} + \underbrace{\begin{bmatrix} -0.13 \\ -0.20 \\ -0.29 \\ -0.38 \\ -0.47 \\ -0.49 \end{bmatrix}}_{\hat{E}} + \underbrace{\begin{bmatrix} 0.82 & -0.2 \\ 0 & 0.82 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{\hat{M}_2(-0.2, 0.82)} \underbrace{\begin{bmatrix} 8.51 \\ 9.60 \end{bmatrix}}_{\hat{Y}^{init}}$$

$$\underbrace{\begin{bmatrix} 27.08 \\ 29.19 \end{bmatrix}}_{Y^{lf}} = \underbrace{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}}_{M(1)} \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \end{bmatrix}}_{\hat{Y}}$$

Temporal Disaggregation: Example

$$\underbrace{\begin{bmatrix} 8.77 \\ 9.43 \\ 8.89 \\ 10.13 \\ 8.98 \\ 10.08 \end{bmatrix}}_{\hat{Y}} = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ -0.2 & 0 & 0 & 0 & 0 & 0 \\ 0.82 & -0.2 & 0 & 0 & 0 & 0 \\ 0 & 0.82 & -0.2 & 0 & 0 & 0 \\ 0 & 0 & 0.82 & -0.2 & 0 & 0 \\ 0 & 0 & 0 & 0.82 & -0.2 & 0 \end{bmatrix}}_{\hat{M}_1(-0.2, 0.82)} \underbrace{\begin{bmatrix} 8.77 \\ 9.43 \\ 8.89 \\ 10.13 \\ 8.98 \\ 10.08 \end{bmatrix}}_{\hat{Y}} + \underbrace{\begin{bmatrix} 1 & 49.9 & 8.78 \\ 1 & 48.4 & 6.84 \\ 1 & 52.1 & 7.89 \\ 1 & 54.0 & 12.42 \\ 1 & 52.7 & 10.04 \\ 1 & 54.1 & 8.41 \end{bmatrix}}_X \underbrace{\begin{bmatrix} -.43 \\ .06 \\ .12 \end{bmatrix}}_{\hat{\beta}} + \underbrace{\begin{bmatrix} -0.13 \\ -0.20 \\ -0.29 \\ -0.38 \\ -0.47 \\ -0.49 \end{bmatrix}}_{\hat{E}} + \underbrace{\begin{bmatrix} 0.82 & -0.2 \\ 0 & 0.82 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{\hat{M}_2(-0.2, 0.82)} \underbrace{\begin{bmatrix} 8.51 \\ 9.60 \end{bmatrix}}_{\hat{Y}^{init}}$$

$$\underbrace{\begin{bmatrix} 27.08 \\ 29.19 \end{bmatrix}}_{Y^{lf}} = \underbrace{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}}_{M(1)} \underbrace{\begin{bmatrix} 8.77 \\ 9.43 \\ 8.89 \\ 10.13 \\ 8.98 \\ 10.08 \end{bmatrix}}_{\hat{Y}}$$

Linking High-Frequency Estimates to Low-Frequency Data

Solving for Y , we have

$$Y = (I - M_1(\mu_1, \dots, \mu_p))^{-1}(X\beta + E + M_2(\mu_1, \dots, \mu_p)Y^{\text{init}}) \quad (6)$$

To enable comparison with the observed LF and disaggregated HF:

$$Y^{lf} = M(1)Y = M(1)(I - M_1(\mu_1, \dots, \mu_p))^{-1}(X\beta + E + M_2(\mu_1, \dots, \mu_p)Y^{\text{init}}) \quad (7)$$

$$\underbrace{Y^{lf} - M(1)(I - M_1(\mu_1, \dots, \mu_p))^{-1}(X\beta + M_2(\mu_1, \dots, \mu_p)Y^{\text{init}})}_{\Theta} = \underbrace{M(1)(I - M_1(\mu_1, \dots, \mu_p))^{-1}}_{M_3} E \quad (8)$$

Model Specification

The dynamic model in Equation 3 can be specified with p lags for the dependent variable.

Assume a first-order autoregressive structure, $AR(1)$, for the error term, such that:

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t, \quad |\rho| < 1 \quad (9)$$

where u_t is a white noise process which is assumed to be normal with mean 0 and variance σ^2 .

Maximum Likelihood Estimation

The maximization of the likelihood of the model is:

$$\begin{aligned} \max_{E, \mu, \beta, \Omega} \quad & \frac{1}{\sqrt{(2\pi)^N |\Omega|}} \exp\left(-\frac{1}{2} E' (\Omega^{-1}) E\right) \\ \text{s.t.} \quad & M_3 E = \Theta \end{aligned} \tag{10}$$

Error vector, E , follows a multivariate normal distribution with mean zero and covariance matrix Ω

Concentrated Likelihood Function

$$\hat{E} = \Omega M_3' (M_3 \Omega M_3')^{-1} \Theta, \quad (11)$$

as a result we can substitute Equation 11 into Equation 10 to maximize a concentrated likelihood function:

$$\max_{\mu, \beta, \Omega} \frac{1}{\sqrt{(2\pi)^N |\Omega|}} \exp\left(-\frac{1}{2} \Theta' (\Omega^\theta)^{-1} \Theta\right) \quad (12)$$

with $\Omega^\theta = M_3 \Omega M_3'$ the variance-covariance matrix of Θ .

Estimated Error and Disaggregated HF Series

$$\hat{E}_{MLE} = \hat{\Omega} \hat{M}_3' (\hat{M}_3 \hat{\Omega} \hat{M}_3')^{-1} \hat{\Theta}, \quad (13)$$

$$\hat{Y}_t = \sum_{i=1}^p \left(\hat{\mu}_i \hat{Y}_{t-i} \right) + X_t \hat{\beta} + \hat{\varepsilon}_t. \quad (14)$$

Monthly Indicators

Table 2: Selected Monthly Indicators

	In Real Terms (2018 = 100)			In Nominal Terms		
Y_t	GDP	HFCE	TS	GDP	HFCE	TS
X_t	VONSI	VOIMP	VONSI	VANSI	VAIMP	VAIMP
	TAXREV*	TAXREV*	TAXREV*	TAXREV	TAXREV	TAXREV

Note: TAXREV* is expressed in real terms, deflated using CPI

Inflation Measure: GDP Deflator vs. CPI

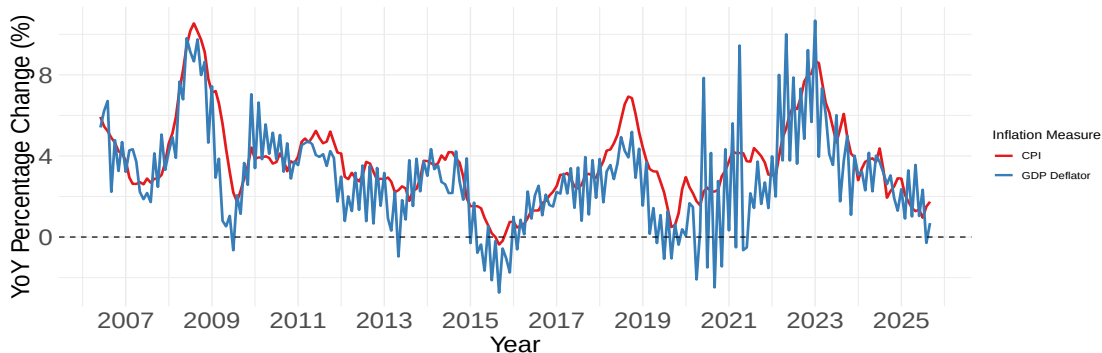


Figure 2

Inflation Measure: HFCE Deflator vs. CPI

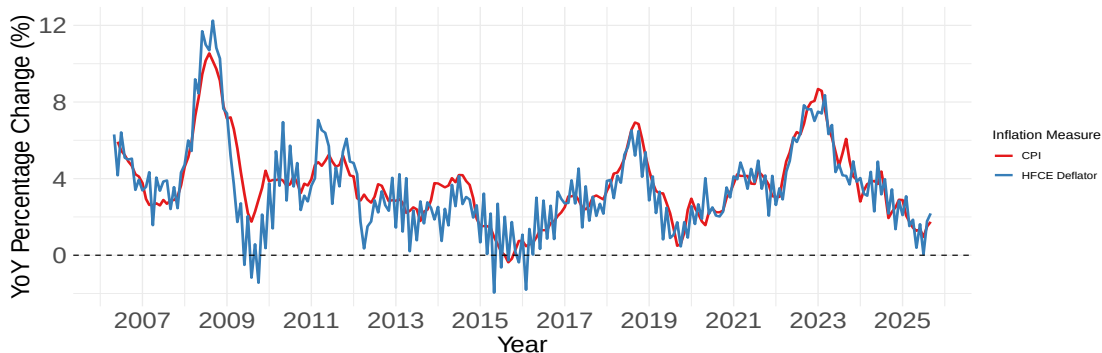


Figure 3

Inflation Measure: TS Deflator vs. CPI

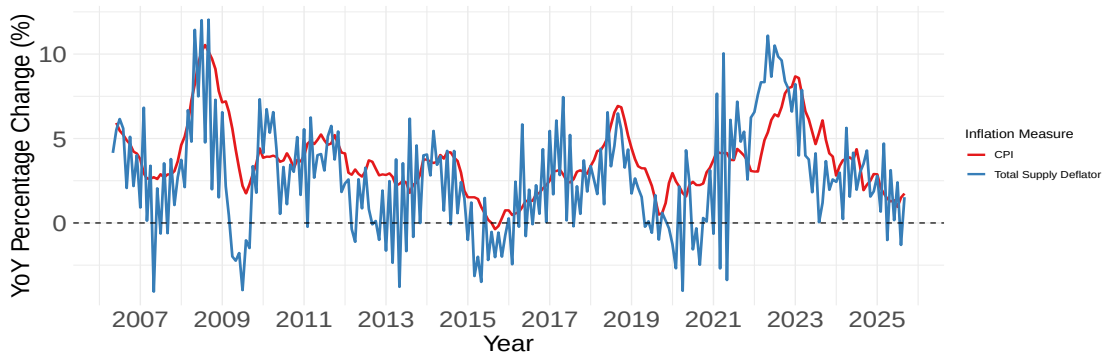
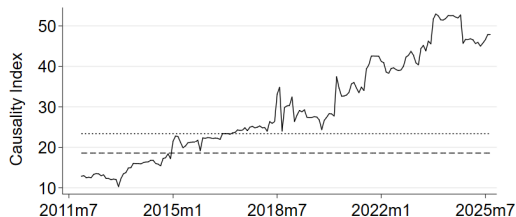
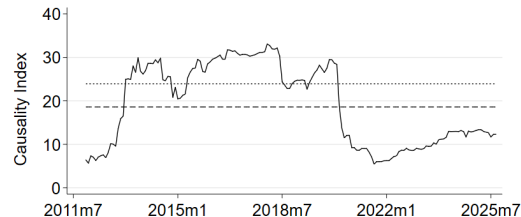


Figure 4

Time-Varying Granger Causality: GDP Deflator and CPI



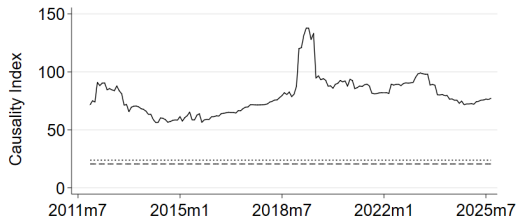
(a) CPI $\xrightarrow{\text{G-Cause}}$ GDP Deflator
(Inflation Measure)



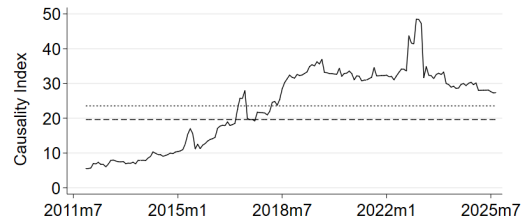
(b) GDP Deflator $\xrightarrow{\text{G-Cause}}$ CPI
(Inflation Measure)

Figure 5

Time-Varying Granger Causality: HFCE Deflator and CPI



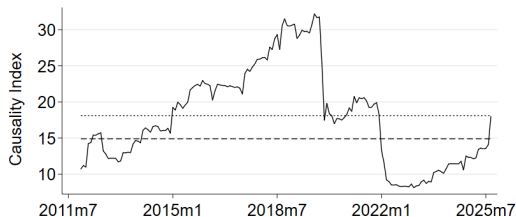
(a) CPI $\xrightarrow{\text{G-Cause}}$ HFCE Deflator
(Inflation Measure)



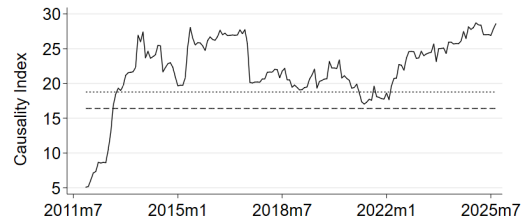
(b) HFCE Deflator $\xrightarrow{\text{G-Cause}}$ CPI
(Inflation Measure)

Figure 6

Time-Varying Granger Causality: TS Deflator and CPI



(a) CPI $\xrightarrow{\text{G-Cause}}$ TS Deflator
(Inflation Measure)



(b) TS Deflator $\xrightarrow{\text{G-Cause}}$ CPI
(Inflation Measure)

Figure 7

Conclusion

- ▶ CPI based inflation → inflation based on deflator: strong and persistent.
- ▶ Causality from these deflators to CPI is weak and not stable over time
- ▶ TS deflator demonstrates meaningful and time-varying predictive content for CPI, particularly in the later sample. This suggests that it may capture additional information not fully embedded in CPI, potentially related to external price pressures.

Alternatives to CPI-Based Inflation

Neriza Chow & Andrew Adrian Pua

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Monthly Indicator: Net Sales Index

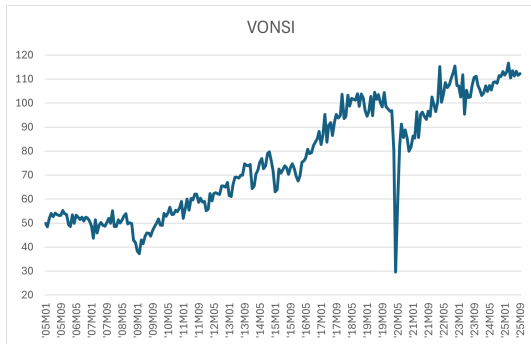


Figure 8: Volume

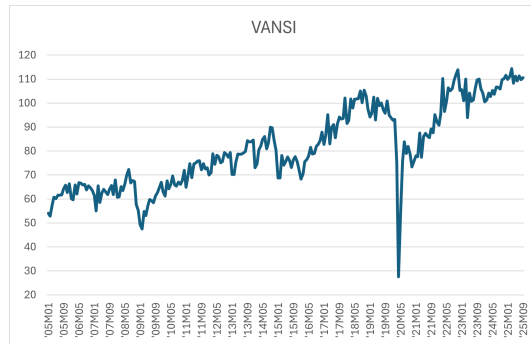


Figure 9: Value

Monthly Indicator: Imports

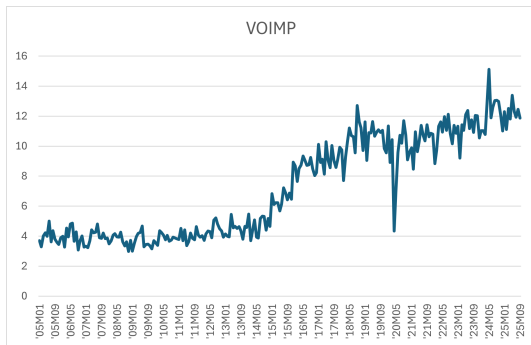


Figure 10: Volume

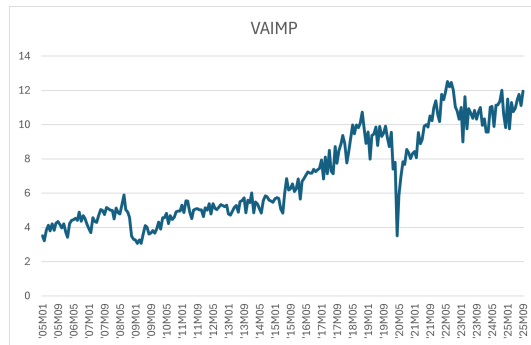


Figure 11: Value

Monthly Indicator: TAX Revenue

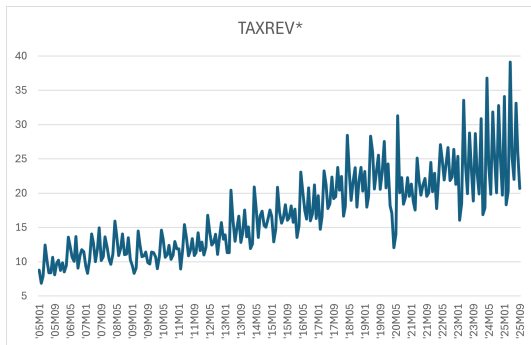


Figure 12: Volume

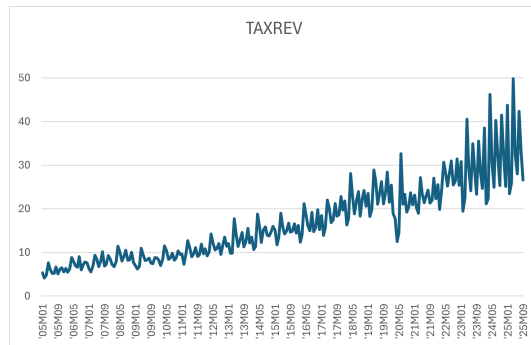
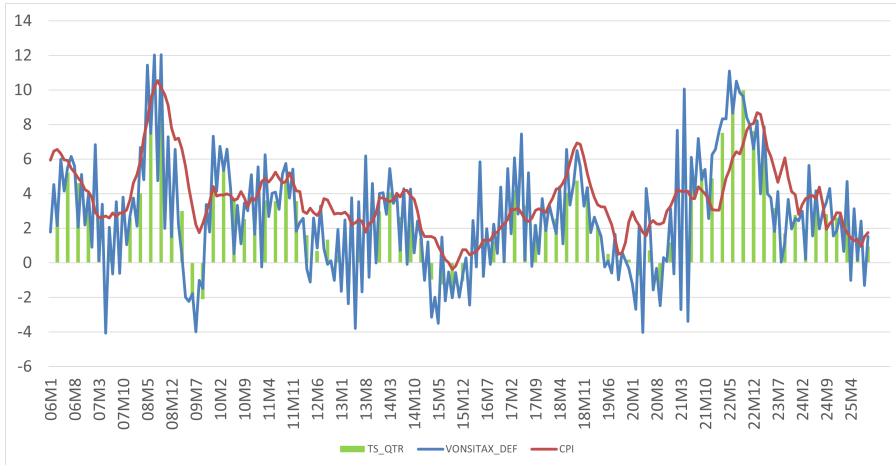
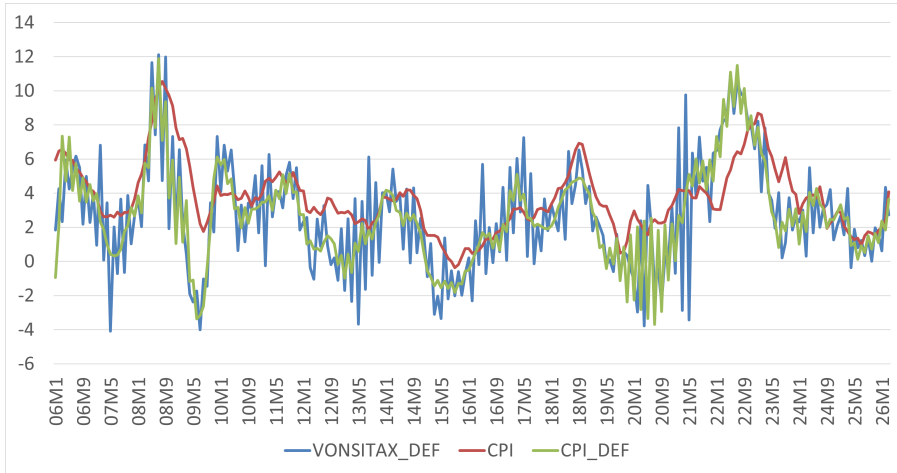


Figure 13: Value

Total Supply



Total Supply: 2026 Q1



Time-Varying Granger Causality: TS Deflator and CPI

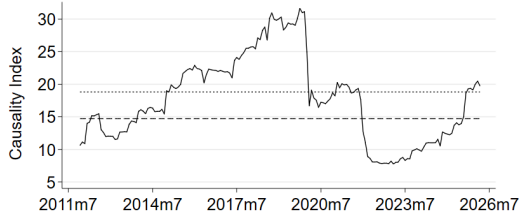


Figure 16: CPI $\xrightarrow{\text{G-Cause}}$ TS Deflator
(Inflation Measure)

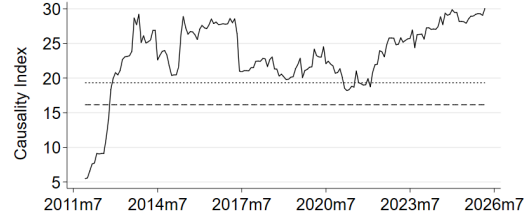


Figure 17: TS Deflator $\xrightarrow{\text{G-Cause}}$ CPI
(Inflation Measure)