

Inflation Unpacked: Breaking Down the Key Components Using a Neural Phillips Curve

Joan Christine S. Allon-Pineda

BSP Research Academy, Bangko Sentral ng Pilipinas, Manila 1004, Philippines

Corresponding author. E-mail address: AllonJS@bsp.gov.ph

ORCID iD: 0009-0001-6359-6476

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Abstract

Background and Objectives: Effective monetary policymaking requires a clear understanding of the underlying drivers of inflation. For central banks such as the Bangko Sentral ng Pilipinas (BSP), this task is challenging because inflation reflects the interaction of demand-side pressures, supply-side shocks, and expectations. Key components of inflation dynamics, including the output gap and inflation expectations, are unobserved and are often difficult to measure accurately. Traditional Phillips curve models typically rely on strong assumptions, filtering methods, or survey-based proxies, which may be sensitive to misspecification, measurement error, and nonlinearities. This study applies a deep learning approach to examine inflation dynamics in the Philippines and disentangle the contributions of real activity, inflation expectations, and commodity prices within a New Keynesian Phillips Curve framework.

Methodology: The study employs a Hemisphere Neural Network (HNN), a deep neural network architecture designed to improve interpretability by grouping input variables into separate “hemispheres.” Each hemisphere corresponds to a key component of inflation: real activity, inflation expectations, and commodity prices. This structure allows the model to extract latent indicators that can be interpreted as macroeconomic states and to decompose realized inflation into component-specific contributions. Unlike standard neural networks, which often operate as black boxes, the HNN imposes an economically meaningful structure on the final layer, making the estimated components more transparent. The model is estimated using Philippine quarterly macroeconomic data and is assessed based on its ability to generate meaningful inflation forecasts, align with historical macroeconomic events, and produce interpretable indicators of the output gap and inflation expectations.

Key Findings: The results show that Philippine inflation can be decomposed into distinct contributions from real activity, inflation expectations, and commodity prices. Long-run inflation expectations remained relatively stable at around 3.5–4.5 percent over the sample period, broadly consistent with the BSP’s inflation target range of 2–4 percent. This stability suggests that expectations have remained relatively well anchored. Commodity prices account for much of the short-term volatility in inflation, particularly during episodes such as the 2014–2015 oil supply glut and the 2021–2022 global supply chain disruptions. By contrast, real activity appears to play a more important role in medium-term inflation movements, especially during the pandemic and post-pandemic recovery periods. The results also indicate that the relationship between inflation and economic activity in the Philippines remains relevant, contrary

to claims in some strands of the literature that the Phillips curve has weakened or disappeared. The HNN-derived real activity gap broadly reflects domestic economic conditions and can be interpreted as an additional measure of inflationary pressure. Similarly, the model-based measure of inflation expectations aligns with short- to medium-term expectations from businesses and professional forecasters, suggesting that it can serve as a useful supplementary indicator when survey-based measures are limited.

Policy Implications: The findings highlight the usefulness of interpretable deep learning methods for monetary policy analysis. By distinguishing between inflation driven by demand-side pressures and inflation arising from temporary supply shocks, the HNN can help policymakers assess whether inflation movements warrant monetary tightening, easing, or a more cautious policy response. Inflation driven by real activity or expectations may call for a stronger monetary policy response, while inflation caused mainly by temporary commodity price shocks may justify a more measured approach. The model's estimates of the output gap and inflation expectations can also complement existing indicators used by the BSP to assess domestic demand conditions, expectation formation, and the credibility of the inflation target. Overall, the study demonstrates that theory-guided machine learning can strengthen macroeconomic monitoring and support more targeted, evidence-based monetary policy decisions.

Keywords: Neural Network; New Keynesian Phillips Curve; Output Gap; Inflation Expectations; Monetary Policy

JEL Classification Codes: C45; E31; E32; E52

1. Introduction

Inflation dynamics has become a central concern in economic research and monetary policy, particularly following recent global disruptions. Research in this area is complex, as inflation is inherently multifaceted, reflecting both supply-side factors, such as rising production costs and supply chain disruptions, and demand-side forces, such as excess demand and inflation expectations. Cost-push inflation arising from production and supply constraints may coexist with demand-pull inflation driven by stronger spending and expectations (Blanchard & Galí, 2007; Coibion & Gorodnichenko, 2015; Santacreu & LaBelle, 2022). In conventional monetary policy frameworks, central banks are generally expected to look through temporary inflation fluctuations caused by supply-side disturbances and respond more strongly to persistent demand-side pressures. However, distinguishing between supply- and demand-driven inflation remains challenging because these forces often overlap and reinforce one another (Bandera et al., 2023). Phillips curve models provide one important framework for identifying and interpreting these inflation drivers.

The New Keynesian Phillips Curve (NKPC) has long been used to model inflation dynamics, emphasizing the complexities introduced by unobserved components such as economic slack and inflation expectations. Standard empirical approaches to the NKPC include Dynamic Stochastic General Equilibrium (DSGE) models estimated through structural vector autoregressions and Generalized Method of Moments (Christiano et al., 2005; Clarida et al., 1999; Galí & Gertler, 1999; Sbordone, 2002). However, these approaches often rely on strong identifying assumptions about the measurement of economic slack, the stability of inflation sensitivities, and the observability of expectations. In practice, such components are commonly inferred using filtering techniques, time-varying parameter models, or survey-based proxies, all

of which may be vulnerable to misspecification, endogeneity, nonlinearity, and measurement error (Blanchard et al., 2015; Coibion et al., 2018; Del Negro et al., 2020; Galí & Gambetti, 2019; Hasenzagl et al., 2022; Stock & Watson, 2019). Data-rich factor models offer another alternative, but their latent factors may function mainly as summary statistics and may not be directly relevant to inflation (Barigozzi & Luciani, 2018; Stock & Watson, 1999).

To address these challenges, this study implements a Hemisphere Neural Network (HNN) which is a deep learning approach designed to summarize large datasets while retaining interpretability. The HNN architecture groups predictors into separate “hemispheres” corresponding to key components of the NKPC, allowing the final model output to be interpreted as the sum of latent inflation drivers. This structure enables the model to extract relevant economic indicators, accommodate high-dimensional data, capture nonlinear relationships, and improve interpretability relative to conventional black-box neural networks.

This study contributes to the literature by applying the HNN framework to Philippine inflation dynamics. The model estimates are shown to align with key macroeconomic concepts, including real activity, inflation expectations, and commodity price movements. The extracted output gap and inflation expectations measures are also consistent with existing indicators and provide additional information on domestic economic conditions. Moreover, the decomposition of realized inflation into component-specific contributions offers policymakers a useful framework for assessing inflationary pressures and calibrating appropriate policy responses.

The remainder of the paper is organized as follows. Section 2 describes the methodology for implementing the factorized HNN model. Section 3 presents the data and transformations. Section 4 discusses the empirical results, including the model’s inflation decomposition, estimated output gap, and inflation expectations. Section 5 concludes the study and briefly discusses its limitations and directions for future research. Section 6 presents the policy implications.

2. Methodology

This study follows the methodology of Goulet Coulombe (2024) and begins with an expectations-augmented Phillips Curve, specifically a New Keynesian Phillips Curve (NKPC) derived from a linearized New Keynesian DSGE model (Galí, 2015). The NKPC framework suggests that inflation can be explained by two key unobserved components: an abstract measure of the output gap, or a nonlinear combination of variables describing real economic conditions, and a set of price indicators and inflation expectations that directly affect inflation (Blanchard et al., 2015). This study extends the framework by incorporating commodity prices, recognizing their significant role in short-run inflation fluctuations, particularly in an emerging and import-dependent economy such as the Philippines (Hazell et al., 2022). Thus, inflation, π_t , is determined by:

$$\pi_t = \mathcal{H}_g + \mathcal{H}_\varepsilon + \mathcal{H}_c + v_t, \quad (1)$$

where the components represent real activity, price expectations, and commodity prices, respectively.

Equation (1) is estimated using a Hemisphere Neural Network (HNN), a deep neural network designed to improve interpretability by imposing structure on the model. A neural network consists of successive layers of interconnected nodes that progressively refine and transform input data as it moves through the network. While

standard neural networks often operate as black boxes, the HNN restricts the model architecture such that the final prediction is a sum of components derived from groups of predictors, which are separated at the input layer into distinct blocks or “hemispheres” (Kübler, 2021). Each hemisphere corresponds to a specific macroeconomic concept, which for this study refer to real activity, inflation expectations, and commodity prices.

Figure 1 illustrates the HNN framework’s block-additive structure. Each hemisphere processes a separate group of predictors and produces an intermediate output. The final inflation prediction is obtained by summing the intermediate outputs from all hemispheres, consistent with the additive structure of the NKPC. This block-additive architecture allows each intermediate output to be interpreted as a latent macroeconomic state or summary statistic for its respective group of variables, while ensuring relevance for inflation prediction. As a result, the HNN improves transparency and interpretability relative to a standard neural network.

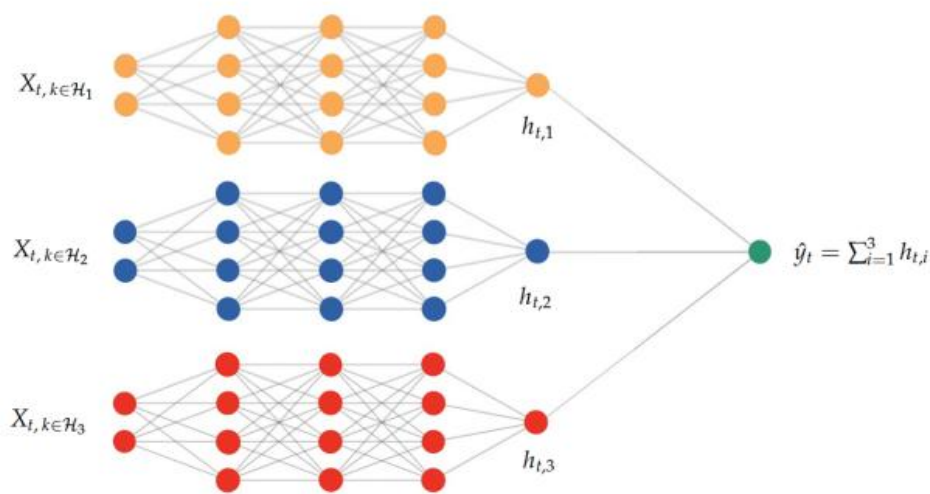


Figure 1. Simple Hemisphere Neural Network Architecture

Source: Goulet Coulombe (2024).

Note: The figure illustrates a simple HNN architecture with three hemispheres. Each hemisphere processes a separate group of input variables and produces an intermediate output, while the final prediction is obtained by summing the hemisphere-specific outputs.

The model described earlier produces one output per hemisphere, representing the contribution of each macroeconomic concept to realized inflation. For a more detailed monetary policy analysis, each hemisphere is further decomposed into two factors: a gap, or a latent indicator derived from variables related to a specific macroeconomic concept, and a time-varying coefficient that captures the evolving relationship between that concept and inflation. Equation (1) can therefore be decomposed as follows:

$$\pi_t = \theta_t \varepsilon_t + \gamma_t g_t + \delta_t c_t + v_t, \quad (2)$$

where the coefficients are time-varying and the gap terms represent latent measures of real activity, inflation expectations, and commodity price pressures. In the empirical neural network, this decomposition requires additional hemispheres containing only a trend variable. The relevant hemisphere outputs are then multiplied in the final layer, rather than simply added, to generate factorized components. For consistency, this factorization is applied to each component.

A stand-alone trend hemisphere is also included to separate the expectations hemisphere into short-run and long-run expectations. The resulting products, together with the stand-alone trend hemisphere, are then added in the final layer, preserving the linear NKPC structure. Thus, the final layer of the neural network is a four-factor model, such that:

$$\hat{\pi}_{t+s} = h_{\varepsilon,LR}(t) + h_{\theta}(t)h_{\varepsilon,SR}(\mathcal{H}_{\varepsilon,SR}\backslash t) + h_{\gamma}(t)h_g(\mathcal{H}_g\backslash t) + h_{\delta}(t)h_c(\mathcal{H}_c\backslash t) + v_{t+s}. \quad (3)$$

To identify the relevant coefficients, the time-varying coefficient outputs are restricted to be non-negative by passing them through an absolute value layer before they enter the final layer.

The factorized HNN model is estimated using Python's PyTorch library. Each hemisphere, whether representing a gap or a time-varying coefficient, is specified as a standard feed-forward, fully connected network. To capture the complex functions underlying the NKPC, the model uses three hidden layers with 400 neurons each for the gap hemispheres and three hidden layers with 100 neurons each for the coefficient hemispheres. Rectified Linear Unit (ReLU) activation functions are applied in the hidden layers, while the output layer uses a linear activation to preserve the additive structure of the model. The optimizer is Adam, with a learning rate of 0.05. The maximum number of epochs is set to 100, and the full sample is used as the batch size.

For model validation, 85 percent of the training sample is used to estimate the parameters, while the remaining 15 percent is used to determine the optimal stopping point based on mean squared error. Random data shuffling is conducted in four-quarter blocks to account for serial dependence. Early stopping provides ridge-type regularization on network weights (Raskutti et al., 2014), while dropout is applied at a rate of 0.2 to reduce overfitting. The main estimation uses 300 block bootstraps, while the forecasting exercise uses 50 random 85–15 data allocations to quantify uncertainty. Robustness checks using alternative model specifications, network architectures, and hyperparameters produce broadly consistent results.

3. Data

This study uses quarterly Philippine macroeconomic data from Q1 1998 to Q2 2024, yielding 106 observations. The variables were selected based on historical availability, timing of data releases, relevance to inflation dynamics, and ease of updating. The dataset is grouped into three hemispheres that correspond to the main components of the HNN model: expectations, real activity, and commodity prices. Table 1 summarizes the general composition of these hemispheres.

Table 1. General Data Categories

Expectations	Real Activity	Commodity Prices
Inflation expectations	Labor market	Oil and gas prices
Lags of inflation	Industrial production	Rice prices
Other price indices	National accounts	Supply chain index

Source: Author's compilation.

Note: The variables are grouped according to the three hemispheres used in the HNN model. The full list of variables and data sources is provided in the Appendix.

All data series are transformed into deseasonalized logged quarter-on-quarter differences, which is standard in regression-based neural network applications. Because this transformation can assign greater prior weight to hemispheres with more variables,

each transformed variable is also divided by the square root of the number of variables in its respective hemisphere. This normalization gives the hemispheres comparable prior importance before model training.

Each series is then transformed into lags of one to four quarters and moving averages of two, four, and eight quarters, following Goulet Coulombe et al. (2021). With 37 raw variables, this produces 260 lagged and moving-average series that enter the model directly. Given the relatively large number of inputs and parameters, the model applies regularization techniques, including dropout, early stopping, block shuffling, and model averaging, to reduce the risk of overfitting.

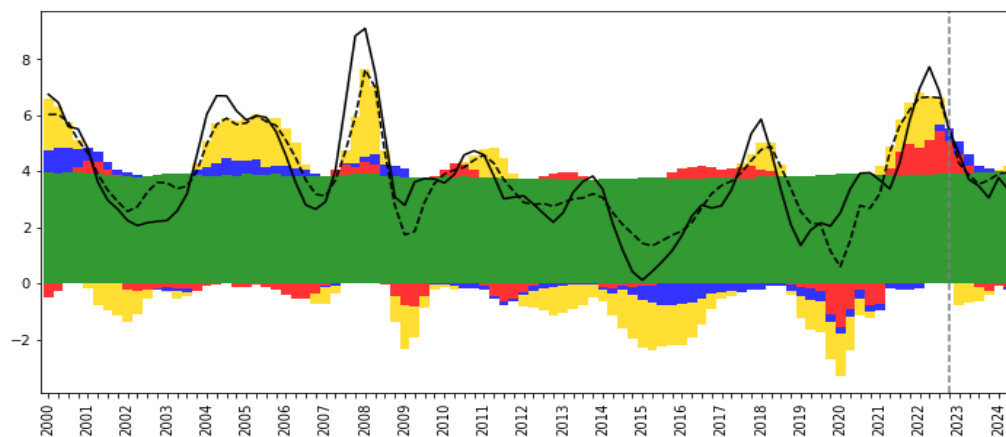
4. Results and Discussion

This section presents the main outputs of the HNN model, including inflation forecasts, hemisphere-specific contributions, latent gaps, and time-varying coefficients. The results are assessed based on their alignment with historical macroeconomic events and their validity as measures of key macroeconomic concepts, particularly the output gap and inflation expectations. Robustness checks using alternative model specifications, network architectures, and hyperparameter settings produce broadly consistent results.

4.1 Inflation Forecast and Decomposition

Figure 2 presents actual inflation, predicted inflation, and the decomposition of predicted inflation into the main HNN hemispheres. The training sample ends in Q4 2022, leaving six out-of-sample periods beginning in Q1 2023.

(a) Actual Contribution to Predicted Inflation



(b) Share of Predicted Inflation

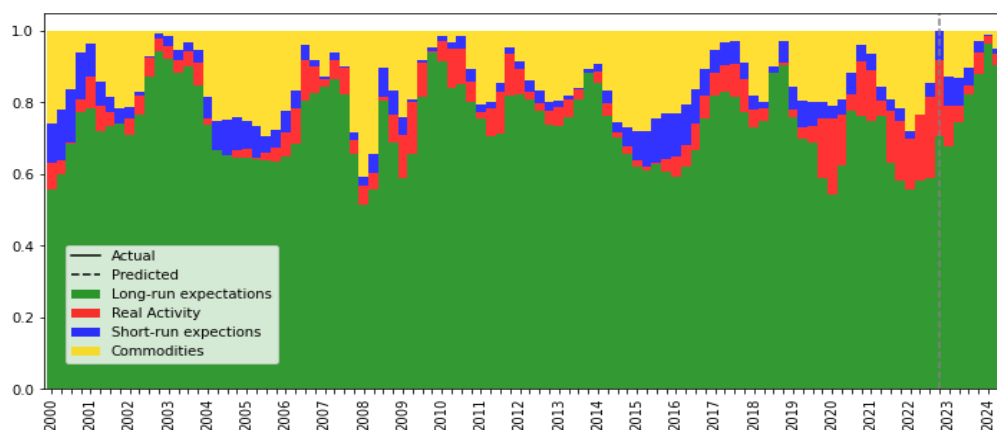


Figure 2. Inflation Forecast Based on Summed Hemisphere Contributions

Source: Author's calculations.

Note: Panel (a) shows actual contributions to predicted inflation, with the y-axis measured in percent. Panel (b) shows each component's share of predicted inflation. The dashed line marks the beginning of the out-of-sample period.

Overall, the model performs reasonably well and does not appear to overfit the data. The HNN model produces an in-sample root mean square error (RMSE) of 0.815 and an out-of-sample RMSE of 0.276. It generally outperforms both the random walk model and the autoregressive model with one lag. The corresponding in-sample RMSEs are 1.86 and 0.80, while the out-of-sample RMSEs are 0.59 and 0.56, respectively. However, the HNN forecasts remain less accurate than those produced by the BSP's operational forecasting models (Abenoja et al., 2022; Allon, 2015; Allon et al., 2022). Although forecasting accuracy is not the primary focus of this study, it remains important because credible posterior estimates are needed before the extracted structural components can be interpreted as meaningful representations of inflation dynamics within the NKPC framework.

The decomposition also provides useful insights into Philippine inflation dynamics. First, long-run expectations, by design, account for the largest share of predicted inflation. The model is structured so that the long-run expectations hemisphere is determined by the stand-alone trend hemisphere and the means of the other components, while the remaining three components are normalized to have a mean of zero over the full sample. Second, the commodities hemisphere accounts for much of the volatility in inflation, which is consistent with the Philippines' exposure to international and domestic supply shocks as an emerging and import-dependent economy (ASEAN+3 Macroeconomic Research Office, 2024). Third, inflation during the pandemic and post-pandemic periods appears to have been driven largely by real activity, consistent with the findings of Di Giovanni et al. (2023) for the United States. During these periods, the real activity hemisphere becomes more prominent and reaches magnitudes comparable to the commodity hemisphere, as opposed to its typically more subdued nature. Fourth, the 2021–2022 increase in inflation is driven mainly by the commodities hemisphere, likely reflecting global supply chain disruptions and commodity price shocks. Finally, the latest estimates suggest easing demand and supply pressures, with inflation returning toward levels consistent with long-run expectations.

4.2 Hemisphere Output

Figure 3 presents the individual hemisphere contributions, together with confidence intervals generated from bootstrapping. The estimated long-run expectations component remains relatively stable, ranging from approximately 3.5 to 4.5 percent over the study period. This stability may reflect the absence of major shifts in Philippine inflation since the 2000s. Although long-run expectations declined at the beginning of the sample, they remained close to the upper end of the BSP's current inflation target range of 2.0–4.0 percent. The recent sequence of supply shocks also appears to have pushed long-run expectations back toward the upper bound of the target range.

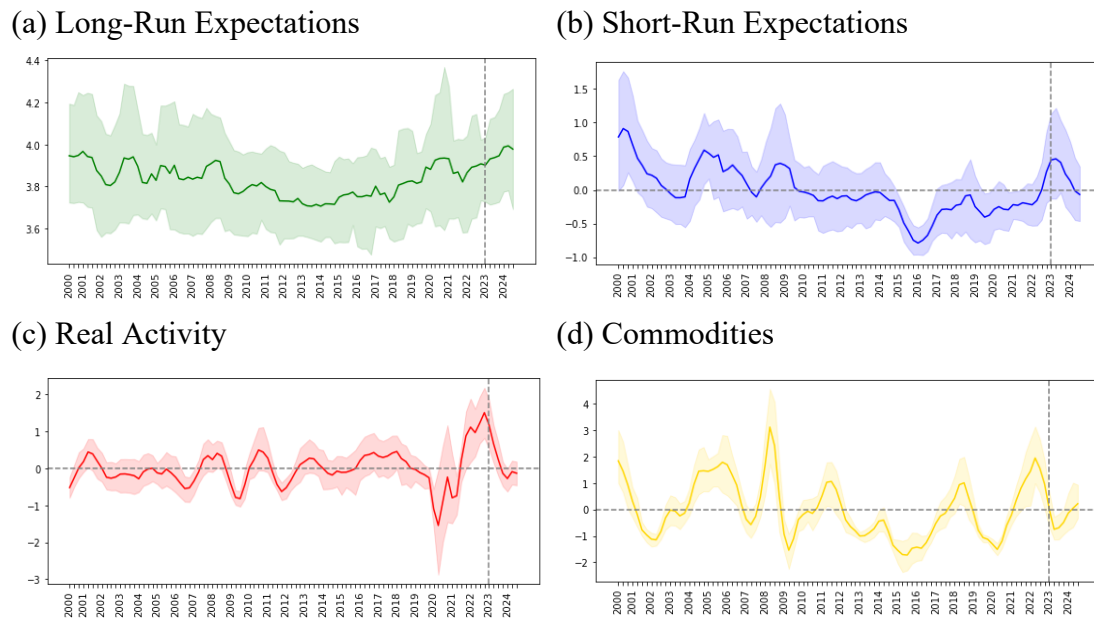


Figure 3. Contributions from the Hemisphere Neural Network Model

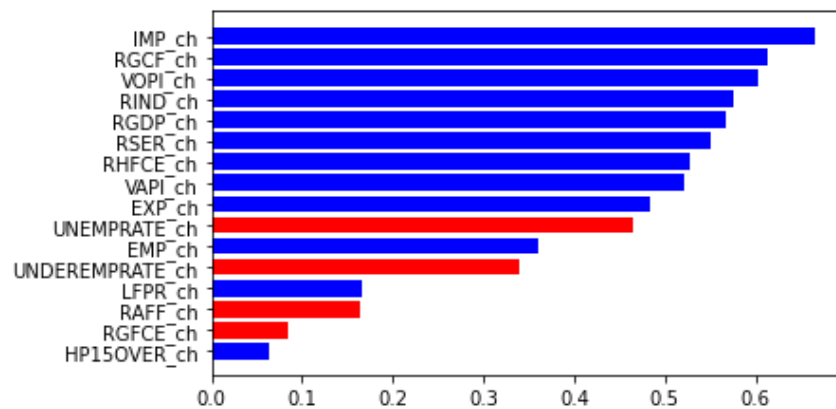
Source: Author's calculations.

Note: The y-axes are measured in percentage points. The solid lines represent the median estimates, while the shaded areas show the 85% confidence intervals generated from 300 bootstraps. The dashed line marks the beginning of the out-of-sample period.

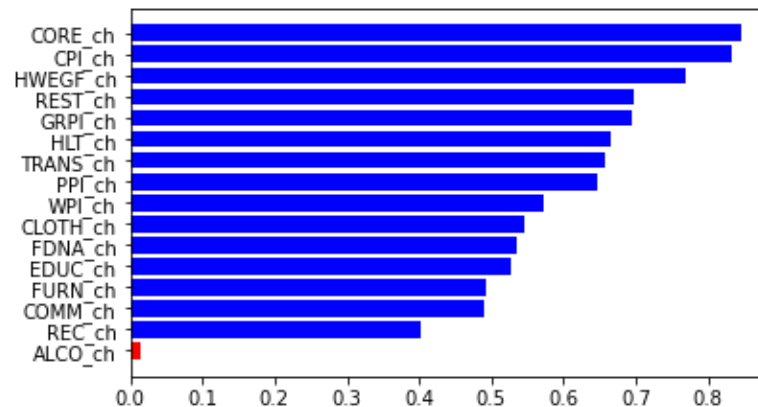
The short-run expectations component contributes the least among the hemispheres and has been negative since the early 2010s. It reached its lowest point during the 2014–2015 oil supply glut, when domestic inflation fell to its lowest level in three decades. However, recent inflationary episodes have raised short-run expectations, similar to the pattern observed for long-run expectations. The commodities component is more volatile around zero, consistent with the transitory nature of commodity price shocks. It rises during known shock episodes, such as the Global Financial Crisis and the pandemic, when commodity prices and supply chain disruptions intensified. It declines during episodes of downward price pressure, including the 2014–2015 oil supply glut and the 2019 rice tariffication period.

Figure 4 reports the correlations between the estimated gap measures and their corresponding input variables. These correlations help assess whether the model-extracted gaps reasonably represent their intended macroeconomic concepts. The chart shows the average correlation for each input variable because the model includes both lags and moving averages.

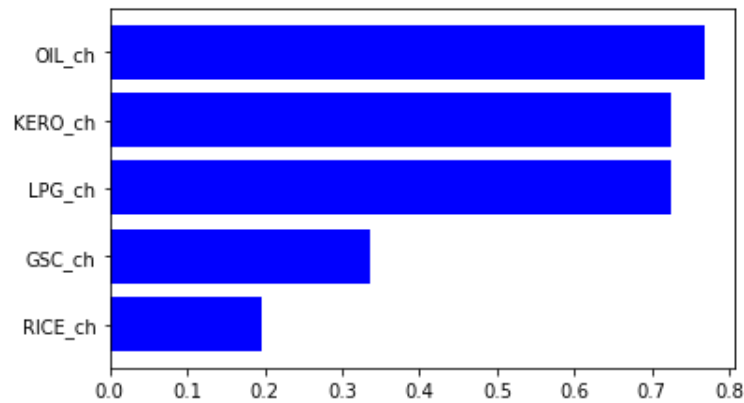
(a) Real Activity



(b) Short-run Expectations



(c) Commodities

**Figure 4.** Correlation between Gaps and Input Variables

Source: Author's calculations.

Note: The y-axis labels are presented as variable codes for readability. The full list of variable names and codes is provided in Appendix.

Figure 4(a) shows that the real activity gap is most strongly correlated with imports and gross capital formation. This pattern supports the interpretation of the real activity gap as a measure of the output gap, as both imports and capital formation can reflect productivity, investment activity, and broader demand conditions (Griliches, 1992; Kim et al., 2007). Figure 4(b) shows that the short-run expectations gap is primarily associated with core inflation, which is commonly used as an indicator of underlying inflation trends and short-run expectation formation (Johnson, 1999). Figure 4(c) indicates that the commodities gap is most closely related to Dubai crude oil prices,

which is expected given the Philippines' exposure to global oil price shocks as an import-dependent economy.

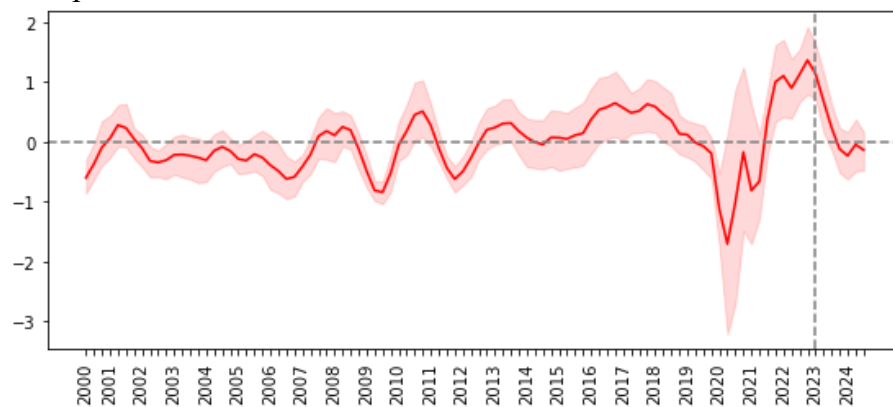
Overall, the hemisphere outputs are broadly consistent with their intended macroeconomic interpretations. Long-run expectations capture the stable component of inflation, short-run expectations reflect movements in underlying price pressures, the real activity gap aligns with domestic demand conditions, and the commodities component captures short-lived supply-side shocks.

4.3 Output Gap and Inflation Expectations

4.3.1 Output Gap

Figure 5 presents the real activity gap and the time-varying coefficient of the real activity hemisphere. The real activity gap can be interpreted as an HNN-based measure of the output gap because it summarizes labor market, output, and production indicators while remaining relevant for explaining inflation within the NKPC framework. The gap aligns with major macroeconomic events: turning negative during crisis periods due to subdued demand conditions (e.g., 2008–2009 Global Financial Crisis and the 2020–2022 pandemic), and positive during recovery periods with stronger demand and economic reopening. In recent quarters, the gap has narrowed, suggesting a gradual return toward normal economic conditions.

(a) Output Gap



(b) Phillips Curve Coefficient

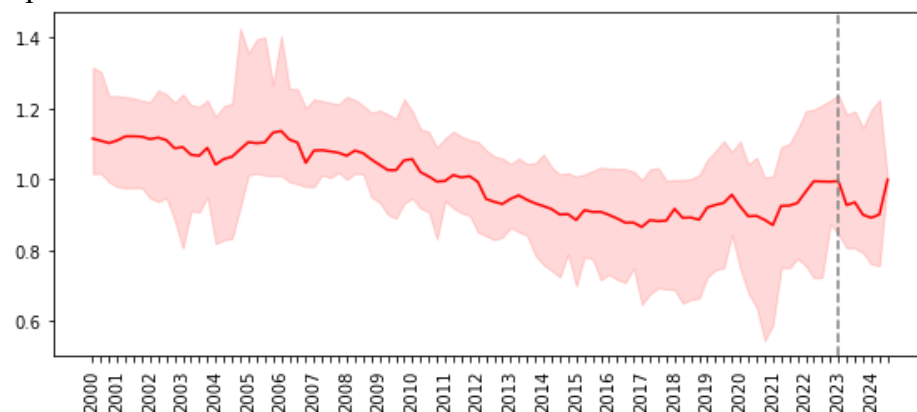


Figure 5. Components of the Real Activity Hemisphere

Source: Authors' calculations.

Note: The solid lines represent the median estimates, while the shaded areas show the 85% confidence intervals generated from 300 bootstraps. The dashed line marks the beginning of the out-of-sample period.

The time-varying coefficient of the real activity hemisphere represents the Phillips curve coefficient, or the relationship between inflation and real economic activity. The coefficient is positive by construction, consistent with NKPC theory: an economy operating above capacity tends to exert upward pressure on prices, while an economy operating below capacity tends to dampen inflation. The results suggest that the Phillips curve remains relevant for the Philippines, contrary to claims in parts of the literature that the relationship has weakened or disappeared (Del Negro et al., 2020; Hooper et al., 2020; Inoue et al., 2025). However, the coefficient has flattened slightly over time, which is consistent with the more conservative view that the loss of the Phillips curve may reflect methodological choices or data limitations, rather than actual changes in the inflation process (Kuttner & Robinson, 2010). The modest increase observed during the post-pandemic recovery is also consistent with recent evidence from industrialized economies (Ari et al., 2023; Hobijn et al., 2023).

Figure 6 compares the HNN output gap with existing output gap measures produced by the BSP. Although these measures differ in magnitude and occasionally in direction, they display broadly similar patterns during key episodes, particularly the Global Financial Crisis and the pandemic. The HNN estimate also follows these events but appears smoother than the other measures.

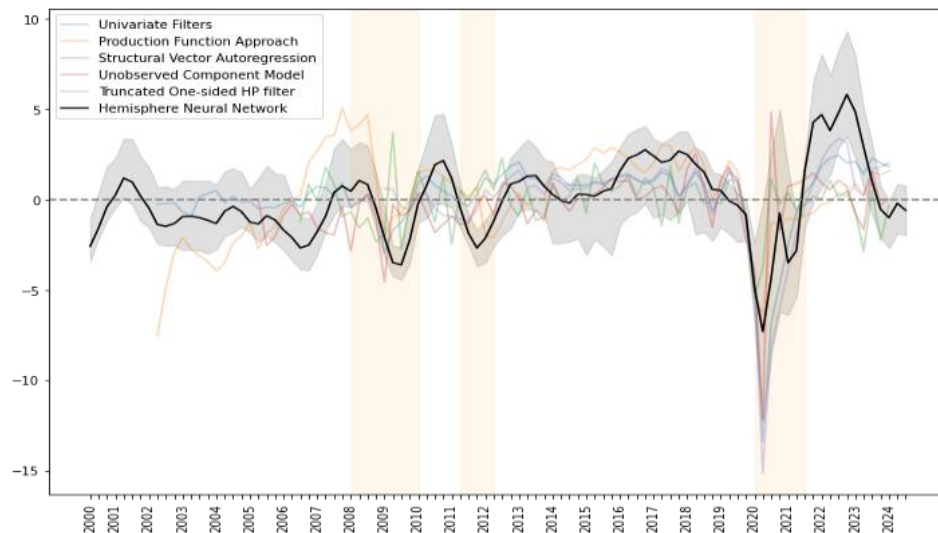


Figure 6. Output Gap Measures

Source: BSP and author's calculations.

Note: The y-axis represents output gap expressed as percent of potential output. The HNN output gap is rescaled to match the average standard deviation of the other output gap measures. The shaded areas indicate periods with significantly negative output gaps.

Table 2 reports the correlations between the HNN output gap and alternative BSP output gap measures. The HNN estimate is most closely correlated with filter-based measures, particularly the Filter Estimation Method and the truncated one-sided Hodrick-Prescott filter. Full alignment is not expected because the measures are conceptually different. Conventional output gaps are generally defined as deviations of actual output from estimated potential output. By contrast, the HNN output gap is better interpreted as an abstract gap between aggregate demand and aggregate supply conditions and is conceptually closer to marginal cost in a New Keynesian DSGE formulation (Goulet Coulombe, 2024).

Table 2. Correlation of the HNN Output Gap with Alternative Measures

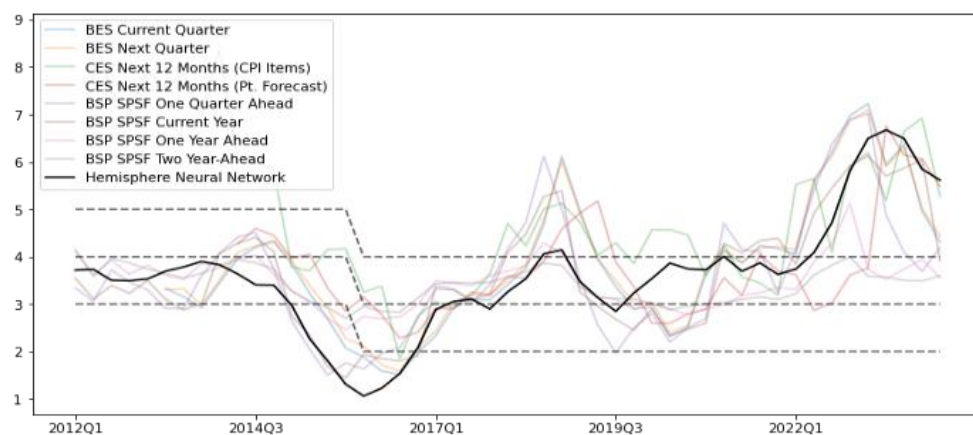
Measure	Correlation
Univariate filters	0.683
Production function approach	0.470
Structural vector autoregression	0.196
Unobserved component model	0.412
Truncated one-sided Hodrick-Prescott filter	0.685

Source: Author's calculations.

4.3.2 Inflation Expectations

Inflation expectations in the NKPC framework reflect bounded rationality and price-setting behavior, in contrast to rigid fully rational expectations. Survey-based measures can provide direct proxies for inflation expectations, but theory offers limited guidance on which horizon or group of expectations is most relevant for realized inflation (Binder, 2015; Coibion et al., 2018; Yellen, 2016). The HNN expectations hemispheres therefore provide an alternative model-based measure by extracting a summary of price-related indicators that is most relevant to inflation dynamics.

Figure 7 compares the HNN-based inflation expectations with existing BSP survey-based measures. The HNN measure combines the long-run and short-run expectations components and is rescaled to align with the average mean and standard deviation of the existing measures. The comparison includes expectations from the Business Expectations Survey, the Consumer Expectations Survey, and the BSP Survey of Private Sector Forecasts.

**Figure 7.** Inflation Expectations Measures

Source: BSP and author's calculations.

Note: The y-axis represents inflation in percent. The HNN estimate is rescaled to match the average standard deviation of the other expectation measures.

Table 3 shows that the HNN expectations measure is most strongly correlated with the Business Expectations Survey's current- and next-quarter forecasts and the BSP Survey of Private Sector Forecasts' current-year forecast. This suggests that the HNN-based measure reflects short- to medium-term expectations among businesses and professional forecasters. Because some survey-based expectation measures are available only from 2012 onward, the HNN estimate may serve as a useful proxy for empirical analysis when survey data are limited.

Table 3. Correlation of HNN Inflation Expectations with Alternative Measures

Measure	Correlation
BES Current Quarter	0.846
BES Next Quarter	0.844
CES Next 12 Months (CPI Items)	0.693
CES Next 12 Months (Pt. Forecast)	0.619
BSP SPSF One Quarter Ahead	0.730
BSP SPSF Current Year	0.857
BSP SPSF One Year Ahead	0.627
BSP SPSF Two Year-Ahead	0.575

Source: Author's calculations.

Note: BES refers to the Business Expectations Survey, CES refers to the Consumer Expectations Survey, and BSP SPSF refers to the BSP Survey of Private Sector Forecasts.

5. Conclusions

Identifying the factors that drive inflation is essential for effective monetary policymaking, but it remains challenging because key components of inflation dynamics, such as the output gap and inflation expectations, are often unobserved. This study applies a Hemisphere Neural Network (HNN) within a New Keynesian Phillips Curve framework to decompose Philippine inflation into contributions from real activity, inflation expectations, and commodity prices.

The results show that the HNN model captures economically meaningful inflation components. Long-run inflation expectations remain relatively stable at around 3.5–4.5 percent over the sample period, broadly consistent with the BSP's inflation target range. Commodity prices account for much of the short-term volatility in inflation, reflecting the Philippines' exposure to external and domestic supply shocks. Real activity contributed strongly during the pandemic and post-pandemic periods, with latest estimates suggesting a return to normal economic conditions. The estimated real activity gap also provides a useful additional measure of the output gap, while the expectations component aligns with short- to medium-term expectations from businesses and professional forecasters. The Phillips curve relationship also remains relevant for the Philippines, although the estimated coefficient has flattened slightly over time. Overall, decomposing realized inflation into its real activity, expectations, and commodity price components via an HNN model provides a useful framework for assessing the sources and persistence of inflationary pressures.

This study is subject to some limitations. The relatively small number of observations compared to the complexity of the model raises the possibility of overfitting, although regularization techniques, bootstrapping, and robustness checks help mitigate this concern. The block-additive structure of the HNN also improves interpretability but may not fully capture interactions across inflation predictors. Future research could extend the model by incorporating additional hemispheres, such as those representing monetary policy, financial conditions, or global spillovers, and by applying the framework to other macroeconomic relationships involving latent components.

6. Policy Implications

The HNN model can support monetary policy analysis by helping identify whether inflationary pressures arise mainly from demand-side factors, such as real activity and expectations, or from supply-side factors, such as commodity price shocks. The appropriate policy response depends on the source and persistence of inflation,

with demand-driven pressures requiring a more active monetary policy response and temporary supply-driven pressures calling for a more cautious approach.

Figure 8 compares the contributions of the HNN hemispheres with significant policy rate adjustments implemented by the BSP. The green-shaded areas represent policy rate hikes, which are expected to coincide with positive demand-side pressures from real activity or expectations. The red-shaded areas represent policy rate cuts, which are expected to coincide with negative demand-side pressures or weakening economic conditions.

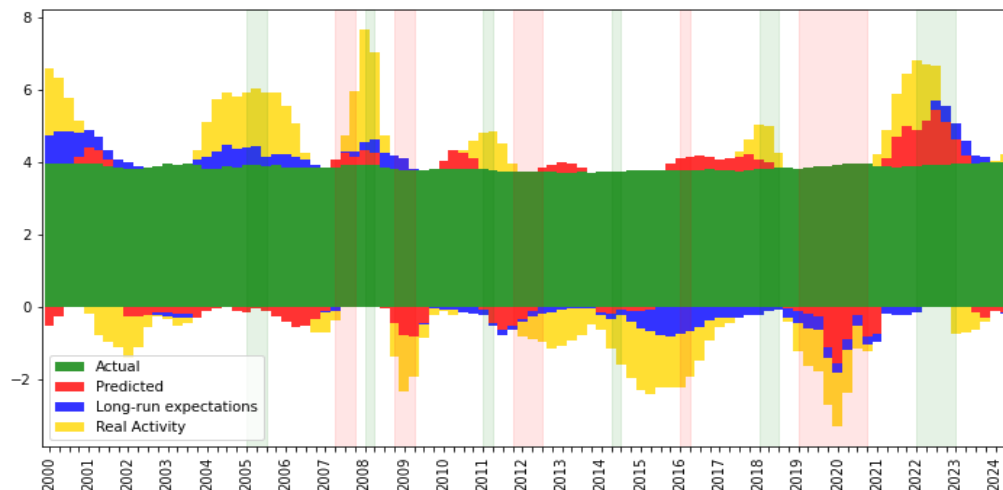


Figure 8. HNN Hemisphere Contributions and Monetary Policy Actions

Source: BSP and author's calculations.

Note: The y-axis represents inflation in percentage points. The red-shaded areas indicate policy rate cuts, while the green-shaded areas indicate policy rate hikes.

The results suggest that most major policy rate movements align with inflationary pressures from real activity or short-run expectations, particularly over the past decade. This pattern indicates that the HNN decomposition can help policymakers identify the source of inflation and support data-driven policy decisions. When inflation is driven mainly by real activity or expectations, the model may help confirm the need for monetary tightening. Conversely, when inflation is driven largely by commodity price shocks, the model may help policymakers assess whether inflationary pressures are likely to be temporary.

The HNN estimates can also complement existing BSP indicators. The real activity hemisphere provides an additional measure of the output gap, while the expectations hemisphere offers a model-based indicator of short- to medium-term inflation expectations. These indicators can help policymakers monitor domestic demand conditions and assess the anchoring of inflation expectations. Overall, the HNN framework provides a transparent and theory-guided machine learning tool that can enhance inflation monitoring and support more targeted monetary policy decisions.

7. Ethics Statement

This study used secondary data from publicly available sources and did not involve human participants, personal identifiable information, or primary data collection. Therefore, ethics committee approval was not required.

8. References

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9. Appendix

Table 4. Data Sources

Hemisphere	Variable	Code	Source
Real Activity	Gross Domestic Product, real	RGDP	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Agriculture, Forestry, and Fishery, real	RAFF	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Industry, real	RIND	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Services, real	RSER	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Exports, real	EXP	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Imports, real	IMP	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Household Final Consumption Expenditure, real	RHFCE	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Government Final Consumption Expenditure, real	RGFCE	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Gross Capital Formation, real	RGCF	Philippine Statistics Authority, Quarterly National Accounts
Real Activity	Volume of Production Index	VOPI	Philippine Statistics Authority, Monthly Integrated Survey of Selected Industries

Hemisphere	Variable	Code	Source
Real Activity	Value of Production Index	VAPI	Philippine Statistics Authority, Monthly Integrated Survey of Selected Industries
Real Activity	Unemployment Rate	UNEMPRATE	Philippine Statistics Authority, Labor Force Survey
Real Activity	Total Number of Employed Persons	EMP	Philippine Statistics Authority, Labor Force Survey
Real Activity	Underemployment Rate	UNDEREMPRATE	Philippine Statistics Authority, Labor Force Survey
Real Activity	Household Population 15 Years Old and Over	HP15OVER	Philippine Statistics Authority, Labor Force Survey
Real Activity	Labor Force Participation Rate	LFPR	Philippine Statistics Authority, Labor Force Survey
Expectations	Headline Consumer Price Index	CPI	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Core Consumer Price Index	CORE	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Food and Non-Alcoholic Beverages CPI	FDNA	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Alcoholic Beverages and Tobacco CPI	ALCO	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Clothing and Footwear CPI	CLOTH	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Housing, Water, Electricity, Gas, and Other Fuels CPI	HWEGF	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Furnishings, Household Equipment, and Routine Household Maintenance CPI	FURN	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Health CPI	HLT	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Transport CPI	TRANS	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Information and Communications CPI	COMM	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Education CPI	EDUC	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Recreation, Sports, and Culture CPI	REC	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Restaurants and Miscellaneous Goods and Services CPI	REST	Philippine Statistics Authority, Consumer Price Index and Inflation Rate
Expectations	Producer Price Index	PPI	Philippine Statistics Authority, Monthly Integrated Survey of Selected Industries

Hemisphere	Variable	Code	Source
Expectations	General Wholesale Price Index	WPI	Philippine Statistics Authority, Price Indices
Expectations	General Retail Price Index	GRPI	Philippine Statistics Authority, Price Indices
Commodity Prices	Dubai Crude Oil Price	OIL	International Monetary Fund
Commodity Prices	Domestic Kerosene Prices	KERO	Department of Energy
Commodity Prices	Domestic LPG Prices	LPG	Department of Energy
Commodity Prices	Domestic Rice Prices	RICE	Philippine Statistics Authority
Commodity Prices	Global Supply Chain Pressure Index	GSC	Federal Reserve Bank of New York

Source: Author's compilation.