PENANG INSTITUTE MONOGRAPHS

#34

5 MAY 2026

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A Framework for GDP Nowcasting and Feature-level Reading under SME Data Constraints

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EXECUTIVE SUMMARY

- Quarterly GDP is released with a lag, but indicators of SME-relevant activity are available earlier. This paper translates those signals into a disciplined nowcast of Malaysia's real GDP growth (quarter-on-quarter, non-seasonally adjusted), providing a timely monitoring input for SME policy discussions. For 2025 Q4, three multivariate nowcasting models (Elastic Net, Principal Component Regression, and Multilayer Perceptron) estimate growth between +1.33% and +3.72%, bracketing the actual reading of +3.27%. The AR(1) benchmark predicts +0.17% for the same quarter, missing the actual by over 3 percentage points.

- Forecast accuracy gains are substantial. In the primary reporting window (Excluding-COVID), the Elastic Net and Principal Component Regression reduce the root mean squared forecast error by 50% and 54% relative to the AR(1); the Multilayer Perceptron achieves a 25% reduction. The gains for the Elastic Net and Principal Component Regression are statistically significant at the 1% level; the Multilayer Perceptron also improves on the AR(1), but with weaker statistical support. In the Overall window, all three models continue to outperform the AR(1) in RMSFE terms, although statistical significance no longer reaches conventional levels.

- The two SME-relevant sectoral indicators (construction output and the Industrial Production Index for food, beverages, and tobacco) rank among the top four predictors in all three models in the primary window. The two structural employment proxies (employers and own-account workers) are present but secondary, typically in the lower half of the top 10.

- The consistent presence of SME-relevant sectoral proxies among the top predictors provides a reasonable basis for treating SME conditions as policy-relevant signals for near-term growth. Direct quarterly data on SME support measures, including subsidies disbursed where available, as well as credit to SMEs and SME labour income are not yet available in a consistent long sample suitable for this framework. Building these series is the main data priority of this paper: it would allow future updates to track the SME signal more directly and provide more targeted evidence for the SME Masterplan cycle.

- The rankings summarise where predictive relevance is concentrated in the near-term growth outlook. They do not identify directional effects or the effects of specific policy instruments on GDP. The paper is intended for monitoring and near-term assessment rather than for causal evaluation.

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Introduction

Small and medium enterprises account for 38.9% of Malaysia's GDP and 48.4% of total employment (Department of Statistics Malaysia, 2020; Vaghefi and Yap, 2021). Yet near-term economic monitoring for policy purposes faces a basic timing problem: GDP is quarterly and released with a lag, while the signals linked to SME-related activity arrive earlier but are fragmented, indirect, and often interpreted in isolation. The central empirical problem is to combine those early signals into a coherent and disciplined reading of near-term GDP growth.

The analysis pursues three objectives. First, it produces a point nowcast of Malaysia's real GDP growth, quarter-on-quarter and non-seasonally adjusted (QoQ, NSA). Second, it benchmarks that nowcast against standard baselines to assess whether the multivariate framework adds predictive value. Third, it reports feature-level rankings to identify where the predictive signal is concentrated, using SME conditions, observed through available proxy indicators as the main interpretive lens. The paper is designed for monitoring and near-term assessment, and not for estimating causal effects of SME policies or policy interventions.

Because consistent quarterly series on SME output, SME support measures, credit to SMEs, and SME labour income are not yet available over a sufficiently long sample, the framework relies on clearly labelled SME-related proxies. Employers and own-account workers capture SME-related labour-market composition, while construction output and IPI Food, Beverages & Tobacco capture SME-relevant sectoral activity. The framework therefore provides both a disciplined reading of near-term growth and a transparent statement of the measurement gap that still separates proxy-based monitoring from direct SME monitoring.

Where growth stands: the latest nowcast

Malaysia's real GDP grew by 3.27% Quarter-on-Quarter (QoQ), non-seasonally adjusted, in 2025 Q4, decelerating from +5.67% in Q3 but recording the strongest Q4 reading since 2022. In this QoQ NSA sample, the first quarter is consistently negative, in line with recurring seasonal factors including Chinese New Year timing and year-end effects: every Q1 in the sample records a contraction. After a Q1 decline of −3.52% and a subdued Q2 at +0.98%, growth strengthens to +5.67% in Q3 before easing to +3.27% in Q4, a trajectory consistent with the usual seasonal pattern and slightly above recent 2022–2024 Q4 readings.

Three multivariate nowcasting models, estimated on an expanding window and evaluated out of sample (OOS) from 2020 Q1, provide a disciplined cross-check on this latest reading. Two linear models are included in the comparison: an Elastic Net (EN), which selects and shrinks predictors simultaneously, and a Principal Component Regression (PCR), which compresses correlated predictors into summary components. They produce point nowcasts of +2.48% and +3.72% for 2025 Q4. A Multilayer Perceptron (MLP), included as a nonlinear challenger, returns +1.33%; its variable-level contributions are recovered ex post through Integrated Gradients. All three point to growth, with a cross-model spread of 2.4 percentage points. The AR(1) benchmark, which forecasts growth using only its own lagged value, predicts +0.17% for the same quarter: positive in sign but off by more than 3 percentage points. Across the full OOS record, the three models track both the direction and the amplitude of quarterly movements, whereas the AR(1) compresses predictions into a narrow band around the sample mean (approximately +1.1% outside COVID quarters), over-predicting when growth contracts and under-predicting when growth accelerates (Figure 1).

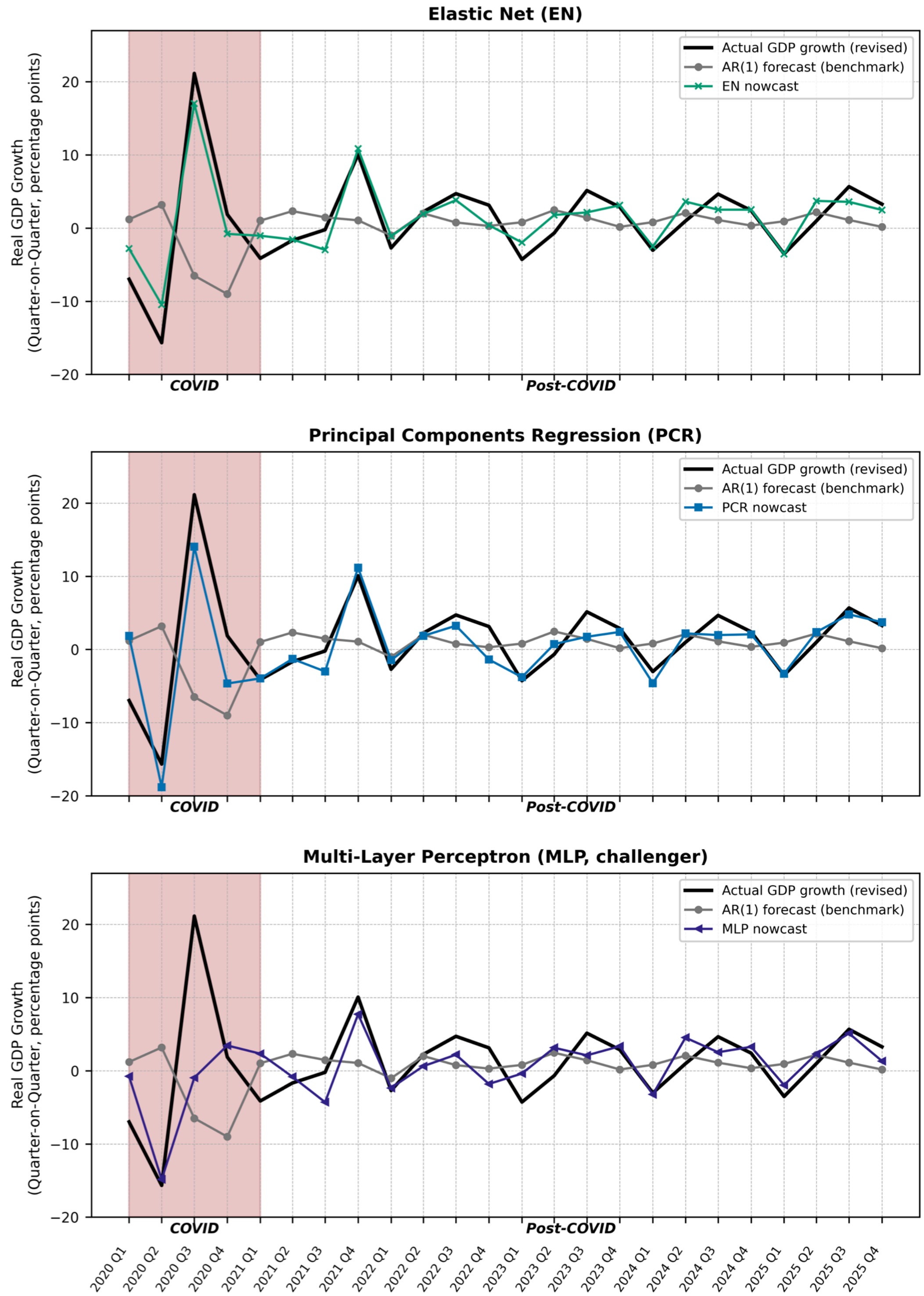

Figure 1. Actual GDP growth versus model nowcasts: Elastic Net, Principal Component Regression, Multilayer Perceptron, and the AR(1) benchmark, 2020 Q1–2025 Q4.
Each panel plots actual quarterly real GDP growth (QoQ, NSA) against the nowcast from one model and the AR(1) benchmark forecast. Shading denotes the COVID period (2020 Q1–2020 Q4).
Source: DOSM/OpenDOSM (actual GDP); Author's calculations (nowcasts and benchmark).

The root mean squared forecast error (RMSFE), which measures the typical size of the nowcast miss in percentage points, quantifies the accuracy gain. In the primary reporting window, Excluding-COVID (20 quarters, removing the COVID episode, 2020 Q1–Q4), PCR achieves 1.76 pp, EN 1.92 pp, and MLP 2.86 pp, compared with 3.83 pp for the AR(1): reductions of 54%, 50%, and 25%, respectively. In the robustness window, Overall (24 quarters, including the COVID episode), EN records 2.43 pp, PCR 3.18 pp, and MLP 5.37 pp, against 8.16 pp for the AR(1) (Table 1). When COVID quarters are included, the EN's error increases least among the three models (with a factor of 1.27, versus 1.81 for PCR and 1.88 for MLP), confirming its stability across regimes.

Table 1. Nowcast accuracy for all models (Elastic Net, Principal Component Regression, Multilayer Perceptron) by reporting window (Excluding-COVID, Overall).

	Excluding-COVID (20 quarters)		**Overall (24 quarters)**	
Model	**RMSFE**	**RMSFE gain over AR(1)**	**RMSFE**	**RMSFE gain over AR(1)**
AR(1) benchmark	3.834	—	8.161	—
EN	1.917	0.500	2.433	0.702
PCR	1.757	0.542	3.179	0.610
MLP	2.858	0.255	5.374	0.342

RMSFE is the root mean squared forecast error; lower values indicate more accurate nowcasts. The RMSFE gain measures the proportional reduction in forecast error relative to the AR(1) benchmark: gain = 1 - (model RMSFE / AR(1) RMSFE). A value of 0.500 means the model reduces forecast error by 50%. Excluding-COVID evaluates 20 out-of-sample quarters after removing the four COVID quarters (2020 Q1–Q4); Overall evaluates all 24 out-of-sample quarters. Full statistical test results in Appendix, Table A2.

Source: Author's calculations based on DOSM/OpenDOSM and BNM data.

A Diebold-Mariano test (DM) with small-sample correction shows that EN and PCR outperform the AR(1) benchmark in the Excluding-COVID window at the 1% level. The MLP also improves on the AR(1), but the statistical evidence is weaker: one-sided p = 0.039 and two-sided p = 0.078. In this compact sample, the result suggests that near-term GDP fluctuations are captured more consistently by penalised linear dynamics than by more complex non-linear interactions. In the Overall window, all three models continue to outperform the AR(1) in RMSFE terms, but statistical significance no longer reaches conventional levels. Full test statistics are reported in Appendix, Table A2. Against a Stock-Watson diffusion-index benchmark (SW-DI), the three models also reduce forecast error, though statistical significance does not reach conventional levels in this compact sample[2] (Appendix, Figures A1 and A3).

The 2025 Q4 nowcasts point to moderate positive growth consistent with the broader macro trajectory through the year. The feature rankings locate the signal within that trajectory and identify the variables

[2] The Stock-Watson diffusion-index benchmark is reported as a traditional secondary reference. Its information set is more lagged than that of the main model suite and should therefore not be interpreted as a fully symmetric comparator.

carrying the most policy-relevant information, with SME-related conditions providing the main interpretive lens.

What drives the signal: features and SME conditions

Across the Excluding-COVID window (20 quarters), feature rankings are constructed from model-specific importance measures: mean absolute coefficients for the EN and PCR, and mean absolute integrated gradients for the MLP. The resulting ranking identifies the variables with the largest average contribution to the nowcast in magnitude terms. It does not recover the average sign of that contribution and should therefore be read as a summary of relative predictive importance rather than as evidence on directional or causal effects on GDP.

The discussion distinguishes two SME blocks, structural employment proxies and sectoral activity proxies, from a broader set of macro-context families[3]. These groupings are descriptive only and are not numerically aggregated.

The main finding is convergence across models. In the Excluding-COVID window, three methodologically distinct models (a sparse linear model, a factor-compression model, and a nonlinear neural network) agree on the same core of top four predictors: currency in circulation, exports, construction output (value of work done), and IPI Food, Beverages & Tobacco. The order varies: construction output ranks first in the EN and second in the PCR, while currency in circulation ranks first in the PCR and the MLP. All four features remain in the top four positions across all three models, and the same core remains in place in the Overall window, confirming that the result is not an artefact of a particular sub-period. Two of these four features belong to the SME sectoral activity block (construction output and IPI Food, Beverages & Tobacco): the SME-related predictive signal is strong, broad-based across model classes, and stable across reporting windows. The coincident indicator occupies the fifth position in all three models and both windows without exception (Figure 2).

[3] The complete variable grouping is reported in the Methodological Appendix.

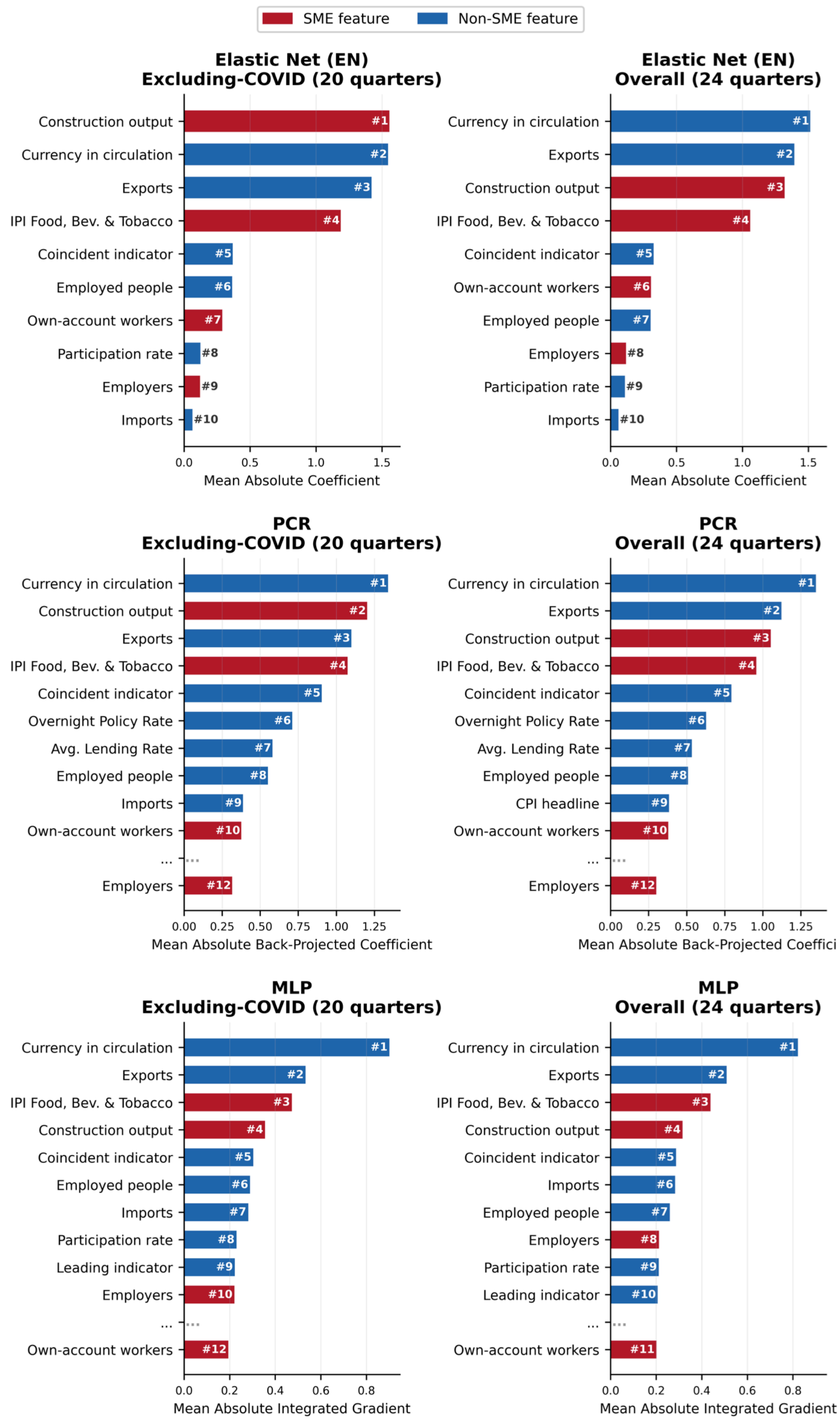

Figure 2. Feature ranking by model, Excluding-COVID (left) and Overall (right) windows. Each panel ranks predictors by their average contribution to the nowcast (model-specific measures; see Methodological Appendix). The top 10 features are shown, together with any SME-block feature ranked below the top 10; an ellipsis marks gaps in ordinal ranks. Red bars denote SME features. The left column covers 20 out-of-sample quarters excluding 2020 Q1–Q4; the right column covers all 24 out-of-sample quarters.
Source: Author's calculations based on DOSM/OpenDOSM and BNM data.

The two SME-relevant sectoral indicators are consistently among the top-ranked predictors in the Excluding-COVID window. Construction output is especially prominent there, ranking first in the EN, second in the PCR, and fourth in the MLP; in the COVID-only window, its ranking drops markedly, suggesting that much of its predictive content comes from normal quarters rather than pandemic extremes. IPI Food, Beverages & Tobacco remains stable among the top four predictors across models and windows. By contrast, the two SME structural employment proxies (employers and own-account workers) carry a weaker but still non-negligible signal. In the EN, both remain inside the top 10; in the PCR and MLP, one remains inside the top 10 while the other sits just outside it. The overall pattern indicates that SME-related predictive content is strongest in sectoral activity indicators and weaker in structural employment composition.

Among the broader macro-context variables, currency in circulation ranks first or second in every model and window, making it the most consistently highly ranked predictor in the system. Exports also remain among the leading predictors across models and windows, in line with Malaysia's trade openness and the sensitivity of quarterly GDP to external demand. Policy rates show a more model-dependent pattern: in the Excluding-COVID window, the PCR places the Overnight Policy Rate and the Average Lending Rate in the upper middle of the ranking, whereas the EN largely suppresses them and the MLP places them in the lower half. A conservative interpretation is that interest rates contain some predictive information, but in this compact sample, their signal is weaker than that of activity, liquidity, and external-sector variables. The stability of the core predictor set gives the monitoring framework a clear anchor. Future updates should therefore track not only the nowcast itself, but also any material reordering of this core set, especially any slippage by SME sectoral proxies or any further weakening of the structural employment proxies.

Implications for policy monitoring

Five areas warrant close attention in the coming quarters, based on their predictive weight and stability across models.

- Construction output. The strongest or near-strongest SME-relevant sectoral indicator in the Excluding-COVID window and still among the top-ranked predictors across all three models. In the underlying data, construction output slowed from +7.7% QoQ in 2024 Q1 to +2.1% in 2025 Q4. Further weakening would likely soften the nowcast and signal weaker conditions in SME-intensive activity.
- Exports. One of the most important external-sector predictors across models and windows. Shifts in global demand, tariff regimes, or geopolitical conditions that affect Malaysia's trade flows would be reflected in the nowcast.
- Currency in circulation. The most consistently top-ranked predictor across models and windows, proxying domestic liquidity conditions. A sustained decline would warrant attention as a potential signal of shifting liquidity conditions in the economy.
- IPI Food, Beverages & Tobacco. The second SME-relevant sectoral indicator and consistently among the top four predictors across models and windows. A divergence between IPI Food, Beverages & Tobacco and construction output would indicate fragmentation within the SME-related predictive signal, warranting closer scrutiny of sector-specific dynamics.
- SME structural employment proxies (employers, own-account workers). These remain secondary. The EN places both within the top 10; the PCR and MLP each retain one within the top 10, with the other just outside it. If both were to move into the top five in a future update, that would signal a stronger role for SME-typical employment patterns in the predictive mix. If the

remaining top-10 proxy in each model were to drop out, the structural SME signal would weaken further.

These results are intended to inform SME policy discussions, including the SME Masterplan cycle (World Bank Group, 2020), not to serve as impact evaluations. The rankings indicate where the near-term predictive signal concentrates; they do not identify which policy levers to adjust or by how much.

An important gap for evidence-based SME policymaking is the absence of long, consistent quarterly series that are specific to SMEs and aligned with the 2015 Q2–2025 Q4 GDP sample. Priority candidates for future inclusion, when coverage and continuity allow, are SME loans outstanding (credit to SMEs), the SME wage bill (labour income proxy), and distributive-trade indicators such as wholesale and retail activity, which are typically SME-intensive. These series can enter first as a clearly labelled satellite module on a shorter sample and migrate into the core dataset once a consistent quarterly history is established.

Near-term Malaysian growth remains positive, the multivariate nowcasts materially outperform the AR(1) benchmark, and a meaningful share of the predictive signal passes through SME-relevant sectoral indicators. The stable predictive content of these indicators does not identify policy effects, but it does provide a reasonable basis for treating SME conditions as policy-relevant signals in the growth outlook and for strengthening the monitoring infrastructure around them. The immediate data priority is to build quarterly series on SME support measures, credit to SMEs, and SME labour income, so that future updates can track the SME signal more directly rather than mainly through sectoral indicators. Future updates will show whether the current signal remains anchored in construction output and IPI Food, Beverages & Tobacco or shifts toward a different mix of predictors.

Methodological Appendix

We base the empirical analysis on a single quarterly estimation panel covering 43 observations from 2015 Q2 to 2025 Q4, drawn from one archived revised-data vintage timestamped 2026-03-16 (Kuala Lumpur time). The panel includes 18 economic predictors, three seasonal dummies (Q1, Q2, Q3), and two shock dummies (positive and negative). This compact design reflects the purpose of the paper: to provide a disciplined monitoring framework for near-term GDP growth under current Malaysian data constraints, while retaining sufficient structure for benchmark comparison and feature-level interpretation. The grouping of predictors into SME and macro-context families, described below, serves narrative interpretation only and does not enter any numerical aggregation of feature importance.

Predictors are grouped into two SME blocks, structural employment proxies (employers and own-account workers) and sectoral activity indicators (construction output and IPI Food, Beverages & Tobacco), plus broader macro-context families: composite cyclical indicators (leading and coincident indexes); financial conditions (the Overnight Policy Rate, the Average Lending Rate, currency in circulation, and the MYR/USD exchange rate); labour-market conditions (participation and unemployment rates); cost pressures (producer and consumer prices); and the external sector (exports and imports). Seasonality and shock dummies enter separately as controls. These groupings are descriptive only and do not enter any numerical aggregation of feature importance.

We select the SME variables as monitoring proxies, not as direct measures of SME output, SME support, or policy effects. The framework therefore tracks SME-relevant exposure rather than direct SME outcomes or programme effects. The structural block captures labour-market statuses most closely associated with self-employment and small-employer activity, consistent with the central role of full-time employment in Malaysian SME definitions (Chin and Lim, 2018). The sectoral block captures timely real-activity signals from sectors where SMEs have meaningful presence or exposure in Malaysia. This includes construction, given its explicit policy salience (Chin and Lim, 2018), and consumer-facing activity linked to the broader services and manufacturing base of SMEs (Department of Statistics Malaysia, 2020). We include the broader macroeconomic variables to capture the well-documented sensitivity of Malaysian SMEs to systemic economic shifts (Halim et al., 2017). This choice reflects data feasibility rather than one-to-one measurement: long quarterly series on SME support measures, SME credit disbursements, or SME labour income were not yet available in a consistent form for the full sample, so the framework relies on the most interpretable SME-related proxies currently observable at quarterly frequency.

We aggregate monthly indicators to quarter using deterministic rules: simple quarterly averages for most monthly series and quarterly sums for exports and imports before QoQ transformation. Real GDP and construction output enter directly as quarterly series. We estimate all models on an expanding window. At each forecast origin, we estimate and tune the model using only data available up to that point, with the out-of-sample evaluation beginning in 2020 Q1. The target variable is quarterly real GDP growth (QoQ, NSA). The empirical design is pseudo-real-time rather than true vintage-by-vintage real-time: we estimate all models recursively using a single archived revised-data vintage timestamped 2026-03-16 20:56 (Kuala Lumpur time), while restricting the information set at each forecast origin to what would have been available up to that point.

We compare three models. The Elastic Net is a linear model that simultaneously selects and shrinks predictors, producing sparse and interpretable coefficient vectors (Zou and Hastie, 2005). Principal Component Regression with Ridge penalty compresses correlated predictors into a small number of summary components before fitting a penalised regression. The Multilayer Perceptron is a nonlinear neural network whose variable-level contributions are recovered through Integrated Gradients, implemented with the Captum library (Sundararajan et al., 2017; Kokhlikyan et al., 2020). Given the compact sample, we retain the MLP as a nonlinear challenger designed to test for coarse nonlinearities rather than as a like-for-like competitor to the parsimonious linear specifications.

We tune the hyperparameters for all three models via Bayesian optimisation (Akiba et al., 2019) on a shock-free validation window.

The primary benchmark is an AR(1) model; the secondary benchmark is a Stock-Watson diffusion-index model (Stock and Watson, 2002). We compare forecast accuracy using a Diebold-Mariano test with small-sample correction (Diebold and Mariano, 1995; Harvey et al., 1997).

We measure feature importance at the individual-variable level: mean absolute coefficients for the EN and PCR, mean absolute integrated gradients for the MLP.

The primary reporting window is Excluding-COVID (20 quarters, removing 2020 Q1–Q4); Overall (24 quarters) serves as robustness and COVID (4 quarters) as a stress test. We do not report prediction intervals: given the compact sample and the COVID disruption, interval estimates risk overstating inferential precision. For a small number of series whose monthly source coverage began after 2015, we initialize the earliest quarterly observations using the first available value; this affects only the initial in-sample period and does not enter the out-of-sample evaluation.

Visual Appendix

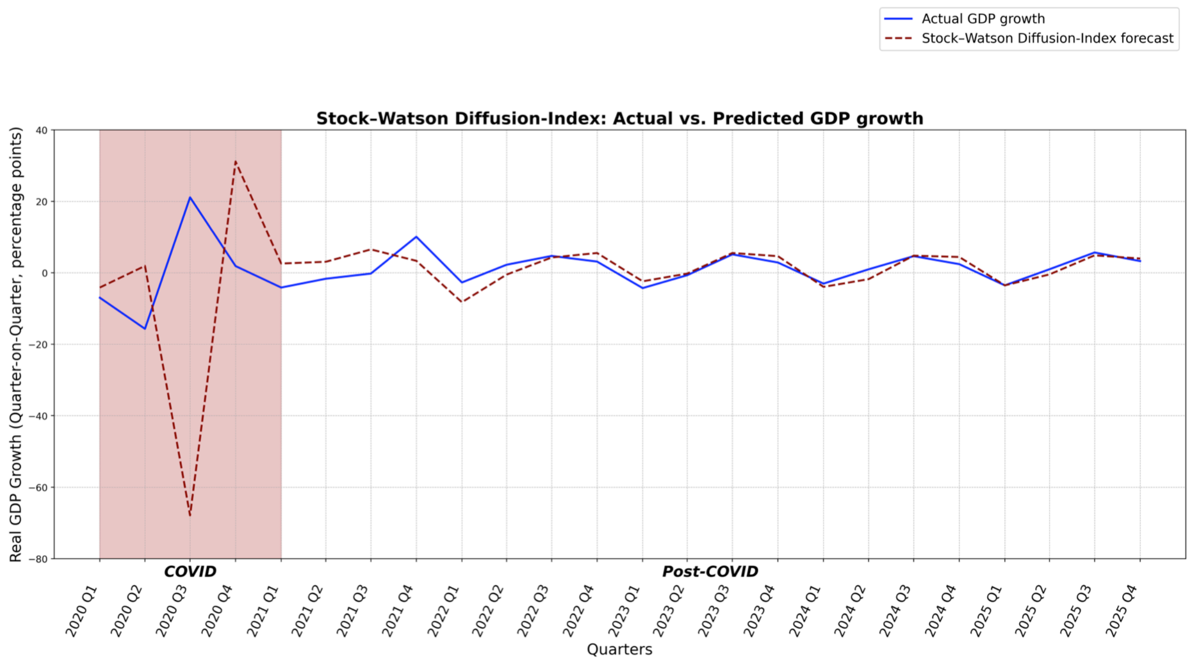

Figure A1. Actual GDP growth versus Stock-Watson diffusion-index nowcast, 2020 Q1–2025 Q4
Note: Actual quarterly real GDP growth (QoQ, NSA) against the nowcast from the Stock-Watson diffusion-index benchmark. Shading denotes the COVID period (2020 Q1–Q4). The large deviations during COVID quarters illustrate why the diffusion-index benchmark is treated as a secondary reference with a more lagged information set.
Source: DOSM/OpenDOSM (actual GDP); Author's calculations (SW-DI nowcast).

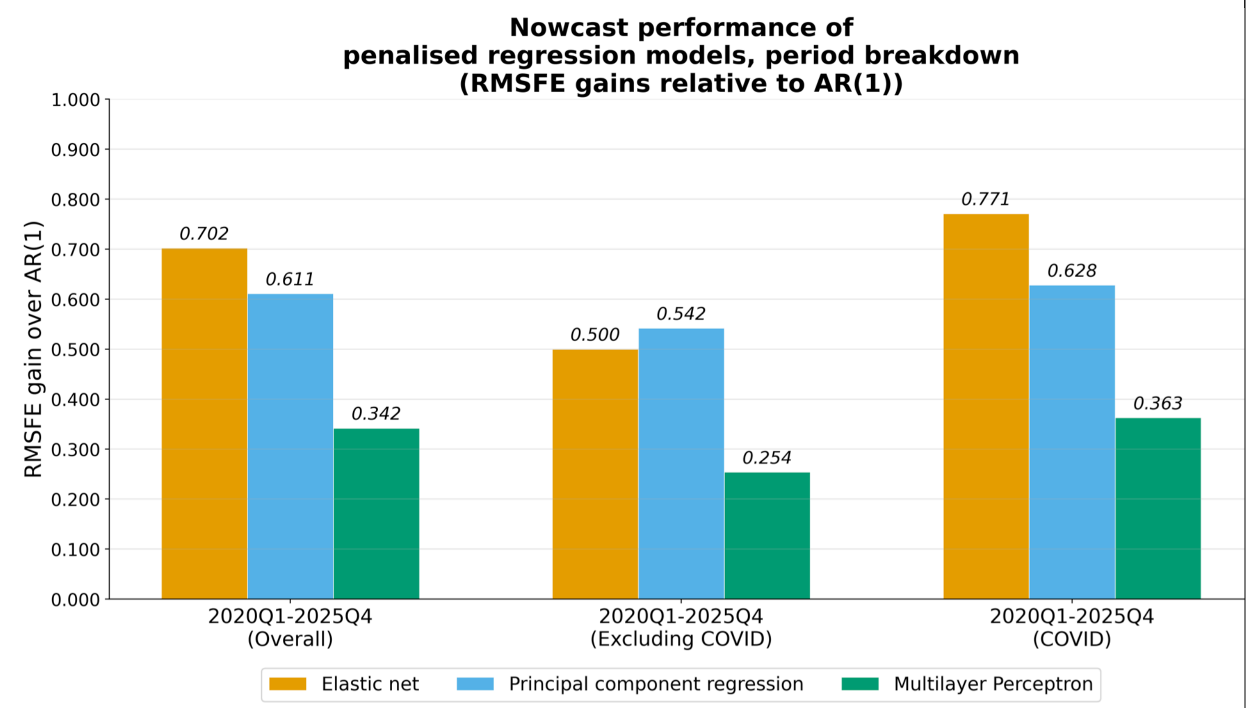

Figure A2. RMSFE gain of nowcasting models over AR(1) benchmark, by reporting window
Note: Each bar shows the proportional reduction in forecast error relative to the AR(1): gain = 1 − (model RMSFE / AR(1) RMSFE). A value of 0.50 means the model reduces forecast error by 50%. Three reporting windows are shown: Overall (24 out-of-sample quarters), Excluding-COVID (20 quarters, removing 2020 Q1–Q4), and COVID (4 quarters, 2020 Q1–Q4 only).
Source: Author's calculations based on DOSM/OpenDOSM and BNM data.

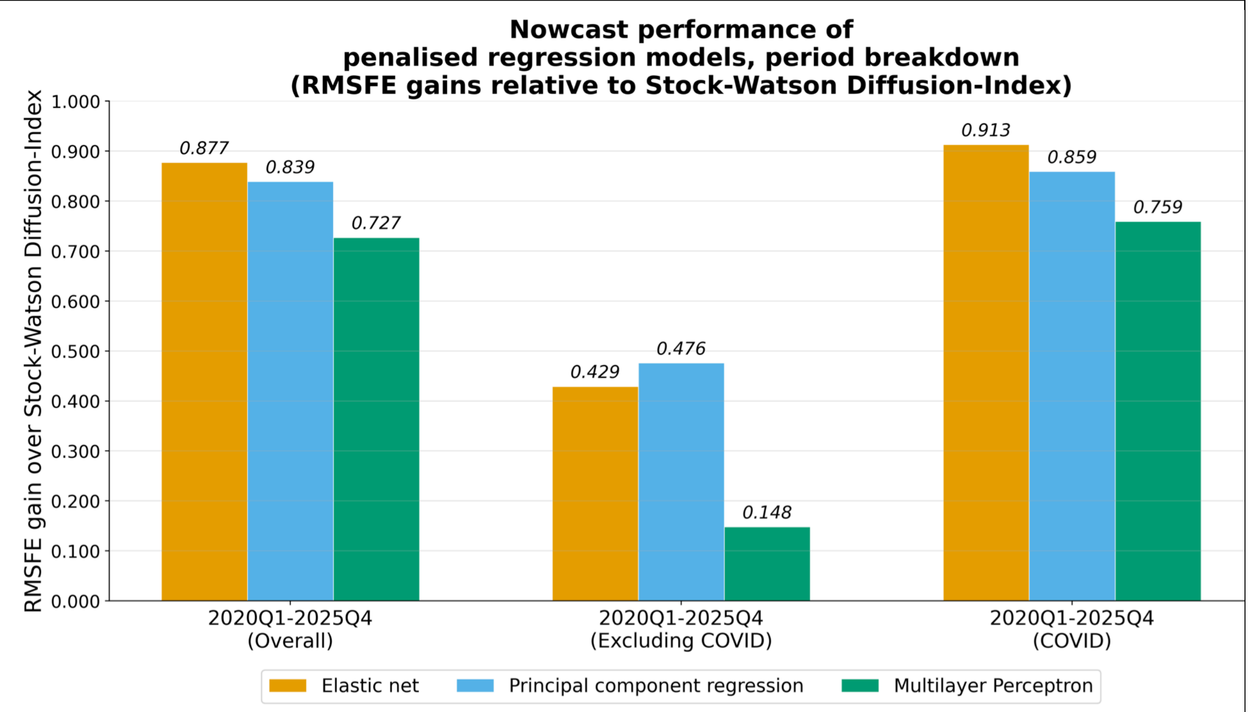

Figure A3. RMSFE gain of nowcasting models over Stock-Watson diffusion-index benchmark, by reporting window

Note: Each bar shows the proportional reduction in forecast error relative to the Stock-Watson diffusion-index: gain = 1 − (model RMSFE / SW-DI RMSFE). A value of 0.50 means the model reduces forecast error by 50%. Three reporting windows are shown: Overall (24 out-of-sample quarters), Excluding-COVID (20 quarters, removing 2020 Q1–Q4), and COVID (4 quarters, 2020 Q1–Q4 only). Source: Author's calculations based on DOSM/OpenDOSM and BNM data.

Table A1. RMSFE for all models and benchmarks (AR(1), Stock-Watson DI, EN, PCR, MLP) across three reporting windows (Excluding-COVID, Overall, COVID).

Model	**Excluding-COVID (20 quarters)**	**Overall (24 quarters)**	**COVID (4 quarters)**
Benchmarks			
AR(1)	3.834	8.161	18.060
Stock-Watson DI	3.355	19.715	47.705
Nowcasting models			
EN	1.917	2.433	4.141
PCR	1.757	3.179	6.722
MLP	2.858	5.374	11.507

RMSFE is the root mean squared forecast error; lower values indicate more accurate nowcasts. Excluding-COVID evaluates 20 out-of-sample quarters after removing the four COVID quarters (2020 Q1–Q4); Overall evaluates all 24 out-of-sample quarters; COVID evaluates the four COVID quarters only. The Stock-Watson diffusion-index benchmark draws on a more lagged information set than the three nowcasting models.

Source: Author's calculations based on DOSM/OpenDOSM and BNM data.

Table A2. Diebold-Mariano test with small-sample correction, full results.

Sample	Model vs. Benchmark	DM statistic	Degrees of freedom	p-value (one-sided)	p-value (two-sided)	Significance (two-sided)
Excluding-COVID (20 quarters)	PCR vs. AR(1)	3.344	19	0.002	0.003	***
	EN vs. AR(1)	3.323	19	0.002	0.004	***
	MLP vs. AR(1)	1.861	19	0.039	0.078	*
Excluding-COVID (20 quarters)	PCR vs. Stock-Watson DI	1.612	19	0.062	0.123	
	EN vs. Stock-Watson DI	1.559	19	0.068	0.136	
	MLP vs. Stock-Watson DI	0.668	19	0.256	0.512	
Overall (24 quarters)	MLP vs. AR(1)	1.639	23	0.057	0.115	
	EN vs. AR(1)	1.538	23	0.069	0.138	
	PCR vs. AR(1)	1.497	23	0.074	0.148	
Overall (24 quarters)	EN vs. Stock-Watson DI	1.114	23	0.139	0.277	
	PCR vs. Stock-Watson DI	1.107	23	0.140	0.280	
	MLP vs. Stock-Watson DI	1.105	23	0.140	0.280	

Note: The Diebold-Mariano test with small-sample correction compares the mean squared forecast error of a nowcasting model with that of the benchmark. The one-sided p-value tests H□: the model has lower average squared error than the benchmark. Significance stars are based on the two-sided p-value: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Long-run variance estimation follows a conservative heteroskedasticity and autocorrelation consistent specification appropriate for the compact sample. Excluding-COVID removes 2020 Q1–Q4; Overall includes all 24 out-of-sample quarters.

Source: Author’s calculations based on DOSM/OpenDOSM and BNM data.

References

Akiba, T., Sano, S., Yanase, T., Ohta, T. and Koyama, M. (2019). Optuna: A next-generation hyperparameter optimization framework. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2623–2631.

Chin, Y.-W. and Lim, E.-S. (2018). SME Policies and Performance in Malaysia. *ISEAS Economics Working Paper*, No. 2018-3.

Department of Statistics Malaysia (DOSM). OpenDOSM: Open Data Portal. Available at: https://open.dosm.gov.my

Department of Statistics Malaysia (DOSM) (2020). Small and Medium Enterprises (SMEs) Performance 2019. Available at: https://www.dosm.gov.my/portal-main/release-content/small-and-medium-enterprises-smes-performance-2019

Diebold, F.X. and Mariano, R.S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253–263.

Government of Malaysia (data.gov.my). Monthly Currency in Circulation. Available at: https://data.gov.my/data-catalogue/currency_in_circulation

Government of Malaysia (data.gov.my). Monthly Interest Rates. Available at: https://data.gov.my/data-catalogue/interestrates

Halim, F.A., Malim, M.R., Derasit, Z., Rani, R.M. and Rashid, S.S. (2017). The impact of macroeconomic variables on SMEs in Malaysia. *Journal of Physics: Conference Series*, 890, 012138.

Harvey, D., Leybourne, S. and Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, 13(2), 281–291.

Kokhlikyan, N., Miglani, V., Martin, M., Wang, E., Alsallakh, B., Reynolds, J., Melnikov, A., Kliushkina, N., Araya, C., Yan, S. and Reblitz-Richardson, O. (2020). Captum: A unified and generic model interpretability library for PyTorch. arXiv preprint arXiv:2009.07896.

Stock, J.H. and Watson, M.W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2), 147–162.

Sundararajan, M., Taly, A. and Yan, Q. (2017). Axiomatic attribution for deep networks. In Proceedings of the 34th International Conference on Machine Learning, *Proceedings of Machine Learning Research*, 70, 3319–3328.

Vaghefi, N. and Yap, J. (2021). Helping Small and Medium Sized Enterprises rise to challenges posed by the Covid-19 pandemic. *Penang Institute ISSUES*, February 2021.

World Bank Group (2020). Malaysia's Experience with the SME Masterplan: Lessons Learned. Available at: https://www.worldbank.org/en/country/malaysia/publication/malaysias-experience-with-the-sme-masterplan-lessons-learned

Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67(2), 301–320.