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Abstract

This paper investigates the use of selected nowcasting models including ARDL, MIDAS, and U-MIDAS to nowcast the annual growth rate of gross fixed capital formation (GFCF) in private investment (PI) and its components; Structures and Machinery & Equipment (M&E) in Malaysia. High-frequency indicators, including capital imports, IPI subcomponents, and business sentiment are incorporated based on economic priors and empirical relevance. Across full-information and pseudo-out-of-sample exercises, the retained models generally outperform a naïve AR(1) benchmark, although relative performance varies across investment components and information sets. Mixed-frequency specifications deliver particularly sizeable gains for M&E, while model rankings change as additional within-quarter information becomes available. An ensemble approach provides a complementary signal by reducing reliance on any single specification. Overall, the findings support a model-toolbox approach and suggest that the proposed models may provide useful complementary signals for short-term investment surveillance.

Keywords: Nowcasting; Private Investment; Gross Fixed Capital Formation; Mixed-Frequency Models; Malaysia

JEL Classification: C53, E22, C22, E27

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Introduction

Private investment plays a central role in Malaysia's economic growth, structural transformation, and long-term competitiveness. As the largest component of Gross Fixed Capital Formation (GFCF), private investment supports capacity expansion, productivity improvements, and technological upgrading across the economy². In recent years, Malaysia has benefited from strong investment activity, driven in part by its position as a key beneficiary of the global technology upcycle, attracting investments in data centres, the electrical and electronics (E&E) industry, and other high-value activities³. These developments have contributed to a shift in the composition of investment towards machinery and equipment (M&E), digital infrastructure, and modern services, reflecting deeper integration into global value chains and accelerated digitalisation.

Despite these positive trends, investment activity remains vulnerable to changes in both the global and domestic environment, including geopolitical tensions, shifts in external demand, financial market volatility, and policy uncertainty. Assessing current investment conditions in a timely manner is therefore critical for policymakers. However, official GFCF and private investment statistics are published with a considerable lag, limiting their usefulness for real-time monitoring and policy responses. This underscores the need for timely indicators and nowcasting tools that can track evolving investment dynamics and provide early signals of turning points in investment activity.

Nowcasting frameworks can mitigate these publication lags by extracting timely signals of investment momentum from high-frequency economic indicators. By providing early indications of changes in business spending before quarterly GFCF data are released, these models complement official macroeconomic statistics and strengthen policymakers' capacity to monitor investment conditions, identify turning points and assess emerging developments. Reliable nowcasting tools are therefore increasingly relevant as investment plays a larger role in supporting Malaysia's long-term growth objectives.

² PI as a share of GFCF 2025: 77.3%; 2024: 77.4%; 2023: 77.2%. GFCF as a share of Malaysia GDP 2025: 22.2%; 2024: 21.3%; 2023: 20%

³ MIDA investment approvals in ICT: (as a proxy for data centre investment) 2025: RM154.8 bil; 2024: RM136.0 bil, 2023: RM63.7 bil. Investment approvals in information and communication activities indicate a strong project pipeline, although approvals do not necessarily translate into realised GFCF within the same period

This paper develops a toolbox of nowcasting comprising models that capture different characteristics of the available datasets. It evaluates two approaches: first, aggregating high-frequency indicators, such as monthly data, to the quarterly frequency of the target variable; and second, preserving the indicators at their original high frequency. The objective is to assess the relative performance of alternative nowcasting approaches across different investment components and information sets, while providing policymakers with a practical suite of models for assessing the near-term investment outlook. The analysis focuses on private investment (PI), which accounts for most of GFCF, while excluding public investment because it is largely shaped by the Government's policy direction and discretionary fiscal spending.

The nowcasting exercise also covers two components of GFCF: Structures, which represent the construction of physical infrastructure, and Machinery & Equipment (M&E), which captures incoming machinery for production. This distinction is particularly relevant in the context of Malaysia's current investment upcycle, where growth has increasingly been driven by high-technology manufacturing, digital infrastructure, and data-centre-related investments. Movements in M&E may therefore provide early signals of investment associated with technological upgrading and expansion in productive capacity, while Structures can offer insights into the implementation and execution of large-scale projects. Assessing these components separately allows policymakers to better understand the drivers of investment growth and the extent to which it reflects broad-based capacity expansion across the economy.

This paper makes four contributions to the literature. First, it extends the predominantly GDP-focused nowcasting literature by identifying the key factors that shape Malaysia's near-term investment outlook. Second, it assesses whether nowcasting tools can capture changes in investment momentum and intensity during periods of economic stress and uncertainty. Third, it evaluates nowcasting accuracy using different information sets, namely one-month and two-month datasets. Fourth, it develops a suite of complementary nowcasting models for Private Investment (PI), Structures, and Machinery & Equipment (M&E), providing policymakers with a systematic framework to monitor overall investment activity and its underlying composition and drivers in real time.

The remainder of the paper is organised as follows. Section 2 reviews nowcasting methods and their applications to overall GDP, investment, and the Malaysian context. Section 3 compiles relevant variables from the literature and examines their relationships with PI, Structures, and M&E. Section 4 presents the methodological setup and the criteria used to evaluate the nowcasting models. Section 5 reports and discusses the results.

1. Literature Review

1.1 General Nowcasting Literature

This section reviews three strands of literature relevant to the study. It first traces the evolution of mixed-frequency nowcasting methods, then examines their application to investment, and finally assesses the evidence available for Malaysia. Together, these strands establish the conceptual and empirical basis for comparing ARDL-Bridge, MIDAS and U-MIDAS models.

Bridge equations are among the earliest and most widely used approaches to mixed-frequency nowcasting. They link high-frequency indicators to lower-frequency target variables by first aggregating monthly indicators into quarterly measures and then estimating a forecasting relationship with the target variable (Baffigi, Golinelli & Parigi, 2004). Although basic bridge equations may be estimated using ordinary least squares, practical specifications often include lags of the dependent and explanatory variables to capture persistence and dynamic adjustment (Baffigi, Golinelli & Parigi, 2004; Schumacher, 2014). These dynamic bridge equations resemble Autoregressive Distributed Lag (ARDL) models because they combine autoregressive terms with distributed lags of the explanatory variables. The ARDL framework of Pesaran, Shin and Smith (2001) therefore provides a flexible structure for implementing such specifications.

Nevertheless, the ARDL-Bridge approach requires monthly indicators to be aggregated into quarterly measures, which may discard information on the timing of data releases within the quarter. Ghysels, Santa-Clara and Valkanov (2004) introduced the Mixed Data Sampling (MIDAS) framework to address this limitation. MIDAS regressions allow high-frequency indicators to enter the forecasting equation directly and use parsimonious lag-weighting functions, commonly based on Beta or Almon polynomials, to determine the contribution of each observation. By retaining within-quarter variation, MIDAS models may use real-time information more effectively than aggregation-based approaches, although any forecasting gain remains an empirical question.

The MIDAS framework has subsequently gained widespread application in macroeconomic forecasting and nowcasting. Empirical studies suggest that MIDAS models can outperform traditional bridge specifications when the timing of information

arrivals is important, particularly in short-term forecasting exercises involving macroeconomic and financial variables (Ghysels, Santa-Clara & Valkanov, 2004). By retaining high-frequency variation, MIDAS models may identify signals that would otherwise be obscured through temporal aggregation, although the size and consistency of these gains depend on the data, model specification and forecasting context.

However, standard MIDAS models require researchers to specify a parametric lag-weighting function. Forecasting performance may therefore become sensitive to the assumed lag structure, particularly when the underlying relationship between variables is complex or unstable. This concern motivated the development of the Unrestricted MIDAS (U-MIDAS) framework.

U-MIDAS relaxes the parametric restrictions imposed by standard MIDAS and estimates each high-frequency lag coefficient individually. As shown by Foroni, Marcellino and Schumacher (2013), this approach provides greater flexibility in capturing complex and irregular lag structures while retaining the advantages of mixed-frequency modelling. Although the larger number of estimated coefficients may increase the risk of overfitting, U-MIDAS has been shown to perform favourably when the true lag structure does not conform to a predetermined weighting scheme.

Taken together, ARDL-Bridge, MIDAS and U-MIDAS provide alternative ways of addressing mixed-frequency data in nowcasting. ARDL-Bridge models prioritise simplicity and interpretability by aggregating high-frequency indicators, whereas MIDAS and U-MIDAS preserve information at its original frequency. The literature does not establish that one approach consistently dominates across applications, as relative performance depends on the information set, lag structure and stability of the underlying relationships. This motivates an empirical comparison of the three approaches for investment, a volatile component for which the timing of incoming information may be particularly important.

1.2 Investment Nowcasting Literature

Among the expenditure components of GDP, investment activity, commonly measured by Gross Fixed Capital Formation (GFCF), is one of the most volatile and difficult variables to forecast. Investment decisions are inherently forward-looking and

depend on expectations regarding future demand, financing conditions, profitability, business sentiment and economic uncertainty. Consequently, investment growth tends to exhibit substantially greater cyclical fluctuations than household consumption or government expenditure, while official investment statistics are often subject to sizeable revisions as additional information becomes available. Galvão and MacQueen (2023), for example, document that revisions to UK investment growth are considerably larger than revisions to consumption, highlighting the challenges associated with measuring and forecasting investment developments in real time.

These characteristics make investment particularly suitable for mixed-frequency nowcasting. A wide range of monthly and higher-frequency indicators become available well before official quarterly investment statistics are released. Such indicators include industrial production, construction activity, vacancy data, lending and credit measures, stock market performance and business confidence surveys. Since these variables often capture firms' investment intentions and financing conditions before they materialise in national accounts data, they can provide valuable signals regarding current-quarter investment developments.

A growing literature has therefore applied mixed-frequency techniques specifically to investment nowcasting. Degiannakis (2022) shows that daily financial market information improves nowcasts of investment across several European economies, suggesting that asset prices contain forward-looking information regarding future investment behaviour. Similar conclusions emerge in emerging market economies. Using Indonesia as a case study, Tarsidin, Idham and Rakhman (2018) develop a Dynamic Factor Model for nowcasting investment and find that indicators such as cement sales, motor vehicle production, electricity consumption, outstanding loans and money supply contain useful information for assessing current investment conditions before official data releases become available.

Recent studies further emphasise the value of sectoral and real-time indicators. Galvão and MacQueen (2023) show that monthly sectoral output components and vacancy-related indicators improve nowcasts of UK investment, particularly during periods of heightened economic volatility such as the COVID-19 pandemic. Their findings suggest that sector-specific information can capture rapid turning points in investment activity more effectively than simple autoregressive benchmarks.

Beyond the choice of indicators, recent research also highlights the importance of allowing predictor relevance to vary across economic conditions. Hlouskova and Fortin (2026) demonstrate that regime-dependent MIDAS models outperform conventional linear specifications when nowcasting Austrian investment. Their results show that labour market variables are among the most important predictors of investment activity and that forecasting performance improves when financial uncertainty and business-cycle regimes are incorporated explicitly. Moreover, the study finds that hard economic indicators become relatively more informative during periods of economic stress, whereas survey-based indicators play a larger role during more stable conditions.

Overall, the literature identifies three reasons why mixed-frequency methods are well suited to investment nowcasting. First, timely production, labour market, financial and sentiment indicators provide signals before official investment data are released. Second, the usefulness of these indicators can vary across economic conditions, particularly during periods of heightened volatility. Third, retaining high-frequency information may improve the detection of turning points that temporal aggregation could obscure. Comparing ARDL-Bridge, MIDAS and U-MIDAS therefore provides a direct test of whether these informational gains translate into more accurate investment nowcasts.

1.3 Malaysia Nowcasting Literature

Empirical evidence on nowcasting in Malaysia remains relatively limited, particularly for GDP expenditure components. Most studies focus on aggregate GDP growth and seek to identify high-frequency indicators that provide timely signals of current economic activity.

Jamilat (2022) develops a Dynamic Factor Model for Malaysian GDP using 103 economic indicators. Indicators related to industrial production, external trade, banking activity and financial conditions display the strongest correlations with GDP growth, with 78 variables meeting the study's inclusion threshold. Forecast evaluation using root mean squared prediction error indicates that the model outperforms autoregressive benchmarks during periods of disruption, particularly the COVID-19 recession. The findings highlight the usefulness of broad, timely information sets for real-time assessment of the Malaysian economy.

The indicators identified by Jamilat (2022), particularly industrial production, external trade, banking activity and financial conditions, are also closely linked to investment activity. They therefore provide a useful starting point for selecting candidate predictors in a Malaysian investment nowcasting exercise. Their predictive contribution to Malaysian investment, however, must be evaluated directly rather than inferred from their relationship with aggregate GDP.

Despite these advances, Malaysian nowcasting research has paid limited attention to mixed-frequency regression approaches such as ARDL-Bridge, MIDAS and U-MIDAS. Existing work has also focused predominantly on aggregate GDP growth rather than Gross Fixed Capital Formation (GFCF). This leaves two related questions unresolved: whether monthly indicators improve real-time estimates of Malaysian investment, and whether preserving their original frequency yields forecasting gains over conventional temporal aggregation. Addressing these questions is particularly relevant because investment is volatile and responds to developments in construction activity, industrial production, financing conditions and business sentiment.

Accordingly, this study evaluates ARDL-Bridge, MIDAS and U-MIDAS models for nowcasting Malaysian GFCF using monthly indicators of production, construction, trade and financial activity. The comparison assesses whether preserving monthly information improves forecasting performance relative to temporal aggregation and whether these gains differ across available information sets. The results provide evidence on the practical suitability of mixed-frequency methods for monitoring Malaysian investment in real time.

2. Variable Selection

This paper uses monthly and quarterly macroeconomic variables to estimate the ARDL-Bridge, MIDAS and U-MIDAS models. The selected indicators are motivated by both economic theory and the empirical nowcasting literature, which suggests that investment activity responds to developments in production, construction activity, financing conditions, external demand and business expectations. Given that Gross Fixed Capital Formation (GFCF) is highly sensitive to changes in economic conditions and is often released with a significant delay, the use of timely monthly indicators can improve the assessment of current-quarter investment activity before official statistics become available. Recent studies find that industrial production, labour market indicators, financial conditions and business sentiment measures contain valuable information for tracking investment developments in real time.

Table 2: Indicators used in the nowcasting models

Category	Indicator	Frequency	Source
Structures	Outstanding Loans (Investment-Related)	Monthly	BNM
	Construction-Related Industrial Production Index (IPI)	Monthly	DOSM
Machinery and Equipment (M&E)	Capital Imports	Monthly	DOSM
	Export-Oriented IPI	Monthly	DOSM
External conditions	Export-Weighted Global Growth	Quarterly	IMF
Sentiments	DOSM Business Tendency Survey	Quarterly	DOSM
	Global Purchasing Managers' Index (PMI)	Monthly	S&P Capital
	RES Balance of Scoring (BOS)	Quarterly	BNM

Source: DOSM, Bank Negara Malaysia, S&P Capital IQ

Structures

Construction-related indicators are included because structures investment is closely linked to activity in the construction sector. Construction-related Industrial Production Index (IPI) provides a direct measure of ongoing building and infrastructure activity, while investment-related outstanding loans capture financing conditions faced by firms undertaking construction and development projects.

Machinery and Equipment (M&E)

Capital imports and export-oriented industrial production are used as proxies for machinery and equipment investment. As Malaysia imports a substantial proportion of its capital goods, capital imports provide a timely signal of firms' investment expenditure on machinery and productive assets. Similarly, export-oriented manufacturing activity reflects expectations of future demand, which can influence firms' incentives to expand productive capacity through investment. Studies of investment nowcasting have consistently found that production and trade-related indicators contain valuable information regarding future investment behaviour.

External Conditions

Investment decisions are influenced not only by domestic economic conditions but also by developments in external demand. Stronger global growth increases export opportunities and improves expected profitability, thereby encouraging expansion of productive capacity. Export-weighted global growth is therefore included as a proxy for external demand conditions facing Malaysian firms.

Sentiment Indicators

Investment decisions are inherently forward-looking and depend heavily on business expectations regarding future economic conditions. Consequently, several sentiment indicators are considered. The DOSM Business Tendency Survey and Bank Negara Malaysia's Regional Economic Survey (RES) Balance of Score (BOS) measure firms' assessments of current and future business conditions, while the Global Purchasing Managers' Index (PMI) provides a timely signal of international manufacturing and business activity. The investment nowcasting literature highlights that survey-based indicators often capture changes in investment intentions before they become observable in official investment statistics. However, recent evidence also suggests that the predictive importance of sentiment indicators may vary across economic conditions, with hard indicators such as industrial production becoming relatively more informative during periods of economic stress.

3. Methodology

3.1 Empirical Strategy

This study develops a suite of models to nowcast quarterly growth in Private Investment (PI), Structures and Machinery & Equipment (M&E). The empirical framework is designed to address two features of the nowcasting problem. First, the target variables are observed at a quarterly frequency while several potentially informative indicators are available monthly. Second, these indicators are released at different points within the quarter, resulting in an incomplete or ragged-edge information set when a nowcast is produced.

Three approaches are considered. The ARDL-Bridge model aggregates monthly indicators to quarterly frequency before estimation, providing a relatively parsimonious and transparent specification. MIDAS preserves the monthly frequency of the indicators while imposing a restricted lag-weighting structure, allowing information released at different points within the quarter to receive different weights. U-MIDAS similarly retains monthly observations but estimates their coefficients without imposing a parametric lag-weighting function. Comparing these approaches allows the analysis to assess whether preserving within-quarter information improves nowcast accuracy relative to temporal aggregation.

All three approaches are evaluated against an AR(1) benchmark, which captures the historical persistence of the target variable without incorporating additional economic indicators. Forecast gains relative to this benchmark therefore provide an indication of the incremental predictive information contained in the selected high-frequency indicators.

3.2 Treatment of Ragged-Edge Data

Monthly indicators used in the nowcasting exercise are released according to different publication schedules. Consequently, information for the latest quarter may be incomplete at the time a nowcast is produced. This creates a ragged-edge problem, whereby observations are available for some indicators but not for others.

To obtain a balanced information set for model estimation, unavailable end-of-sample observations are projected using univariate ARIMA models. Importantly, ARIMA is used solely as a data-completion procedure and not as a competing nowcasting model. Each projection relies only on the historical behaviour of the respective indicator, thereby avoiding the introduction of additional cross-variable information into the subsequent nowcasting models.

This treatment is applied consistently according to the information assumed to be available under the one-month, two-month and full-quarter exercises described in Section 5.

3.3 Model Setup

The nowcasting exercises employed in this paper follow similar methodologies as discussed in the literature review section.

i. **Benchmark Autoregressive Model of Order 1 (AR1)**

$$y_t = \mu + \phi y_{t-1} + \varepsilon_t$$

Where:

- y_t denotes the target variable (Private Investment, Structures Investment, or Machinery and Equipment Investment) at quarter t
- μ is a constant
- ϕ_i is the autoregressive coefficients
- ε_t is the error term

Following common practice in the nowcasting literature, an autoregressive benchmark model is employed as the baseline specification against which more sophisticated mixed-frequency models are evaluated. Autoregressive models capture the persistence inherent in macroeconomic variables by relying solely on their historical behaviour. This approach has been widely adopted in studies assessing the predictive contribution of higher-frequency indicators, including Clements and Galvão (2008) and Galvão and MacQueen (2023). If the ARDL-Bridge, MIDAS or U-MIDAS specifications fail to outperform the AR benchmark, then the inclusion of monthly indicators provides little additional information beyond that already contained in past

investment dynamics. Conversely, superior performance would indicate that high-frequency indicators contribute incremental predictive content

ii. Autoregressive Integrated Moving Average (ARIMA)

$$\Delta^d x_t = \alpha + \sum_{i=1}^p \phi_i \Delta^d y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where:

- $\Delta^d y_t$ is the d-th backward difference
- ϕ_i = AR coefficients
- θ_j = MA coefficients
- $\varepsilon_t \sim \text{i.i.d.}(0, \sigma^2)$

The ARIMA specification is used to project unavailable end-of-sample observations for monthly indicators as part of the ragged-edge treatment described in Section 4.2. These projections are used solely to complete the contemporaneous information set and are not treated as competing nowcasts of investment.

iii. Bridge – Autoregressive Distributed Lags (ARDL)

Step 1: Bridge Equations

Following the bridge-equation literature, monthly indicators are first converted into quarterly proxies before being linked to the quarterly target variable (Baffigi, Golinelli and Parigi, 2004). Bridge equations traditionally operate by forecasting or aggregating high-frequency indicators and subsequently relating them to lower-frequency macroeconomic variables. The approach remains widely used by central banks due to its transparency and ease of implementation.

Bridge 1: Using average of monthly indicators

$$x_t^Q = \frac{1}{3}(x_{3t} + x_{3t-1} + x_{3t-2})$$

Bridge 2: Using sum of monthly indicators

$$x_t^{(Q)} = x_{3t} + x_{3t-1} + x_{3t-2}$$

The quarterly average is used for stock variables, growth rates and diffusion indices where the level observed throughout the quarter is of primary interest. Examples include outstanding loans, business sentiment indicators and Purchasing Managers' Indices (PMIs). Conversely, the quarterly sum is employed for flow variables such as capital imports and credit disbursements, where economic activity accumulates over the quarter.

This conversion creates a bridge between monthly indicators and the quarterly target variable, allowing variables sampled at different frequencies to be incorporated into a conventional time-series framework.

Step 2: ARDL with Bridge Equation

$$y_t = \alpha + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=0}^q \beta_j x_{t-j}^{(Q)} + \varepsilon_t$$

Where:

- y_t : Quarterly target variable
- $x_t^{(Q)}$: Monthly indicator aggregated into quarterly frequency using either the *average* or *sum* bridge equation.
- ϕ_i : Autoregressive (AR) coefficients capturing persistence in target variable.
- β_j : Distributed-lag coefficients measuring the contemporaneous and lagged impact of the bridged indicator on target variable.
- p, q : Number of AR and indicator lags, respectively.
- $\varepsilon_t \sim i.i.d.(0, \sigma^2)$: Error term capturing unexplained quarter-to-quarter variation

The ARDL specification extends the traditional bridge equation by allowing both the target variable and the explanatory indicator to exert dynamic effects over multiple quarters. The autoregressive component captures the persistence frequently observed in investment activity, reflecting the gradual implementation of investment projects and adjustment costs faced by firms.

Meanwhile, the distributed lag structure accommodates delayed responses of investment to changes in financing conditions, external demand, construction activity and business sentiment.

Consequently, the ARDL-Bridge model provides a flexible framework for nowcasting investment while maintaining the simplicity and interpretability of traditional bridge equations.

iv. **Mixed Data Sampling (MIDAS)**

Unlike Bridge models, MIDAS regressions retain indicators at their native monthly frequency and incorporate them directly into a quarterly forecasting equation. This allows the model to preserve information contained in the timing and sequence of monthly releases without requiring temporal aggregation. As discussed by Ghysels, Santa-Clara and Valkanov (2004), this feature is particularly advantageous when newly released information arrives throughout the quarter and may contain differing levels of predictive content.

The MIDAS specification estimated in this study is given by:

$$y_t = \alpha + \sum_{i=1}^p \phi_i y_{t-i} + \beta \sum_{k=0}^K \tilde{w}(k; \theta) x_{t-\frac{k}{m}} + \varepsilon_t$$

where the normalised Almon weights are:

$$\tilde{w}(k) = \frac{w(k)}{\sum_{j=0}^K w(j)}$$

A key feature of MIDAS is the use of a parsimonious lag-weighting structure. Rather than estimating a separate coefficient for every monthly observation, the Almon polynomial imposes a smooth weighting pattern across monthly lags. This substantially reduces the number of parameters that must be estimated while allowing observations released at different points in time to exert different influences on the nowcast.

For investment nowcasting, this approach is particularly relevant because firms respond gradually to changes in financing conditions, external demand and business sentiment. Consequently, information released later within the quarter may contain different predictive signals from information released earlier. By allowing lag weights to vary systematically across observations, the MIDAS framework can capture these dynamics while avoiding the dimensionality problems often associated with unrestricted lag specifications.

Unrestricted Mixed Data Sampling (U-MIDAS)

While MIDAS provides a parsimonious framework for incorporating high-frequency indicators, its performance depends on the appropriateness of the assumed lag-weighting function. If the true relationship between monthly indicators and quarterly investment does not follow the imposed polynomial structure, the resulting forecasts may be suboptimal.

To address this limitation, Foroni, Marcellino and Schumacher (2015) propose the Unrestricted MIDAS (U-MIDAS) framework, which removes the parametric lag restrictions and estimates each monthly lag coefficient separately. The U-MIDAS specification is given by:

$$y_t = \alpha + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{k=0}^K \beta_k x_{t-\frac{k}{m}} + \varepsilon_t$$

Where:

- y_t : Quarterly target variable
- $x_{t-k/m}$: Monthly (high-frequency) indicator at lag k , with $m = 3$ months per quarter
- ϕ_i : AR coefficients on quarterly lags of the target variable
- β_k : Unrestricted coefficient associated with the k -th monthly lag of the high-frequency indicator.
- K : Maximum number of monthly lags included
- $\varepsilon_t \sim i.i.d. (0, \sigma^2)$: Error term

By estimating each lag separately, U-MIDAS provides greater flexibility in capturing complex and irregular relationships between monthly indicators and quarterly investment activity. This may be particularly beneficial when investment responds unevenly to changes in economic conditions or when the timing of information arrivals varies across indicators.

The main drawback of U-MIDAS is the larger number of parameters that must be estimated. As the number of monthly lags increases, the model becomes more susceptible to overfitting, particularly in relatively short samples. Nevertheless, previous studies have shown that U-MIDAS can outperform conventional MIDAS models when the underlying lag structure deviates substantially from the smooth weighting patterns imposed by polynomial functions.

In the context of this study, U-MIDAS provides a useful benchmark against which the performance of restricted MIDAS specifications can be assessed. Comparing the results of MIDAS and U-MIDAS allows an evaluation of whether imposing a parsimonious lag structure improves forecasting performance or whether Malaysian investment activity exhibits a more irregular high-frequency response pattern.

Collectively, the ARDL-Bridge, MIDAS and U-MIDAS specifications represent three alternative approaches to mixed-frequency nowcasting. The ARDL-Bridge model aggregates monthly information into quarterly series before estimation, whereas MIDAS and U-MIDAS preserve the original monthly frequency. Comparing their forecasting performance provides a direct assessment of whether retaining higher-frequency information improves the accuracy of nowcasts for Malaysian investment activity.

4.4 Model Specification and Selection

The specification of the ARDL-Bridge, MIDAS and U-MIDAS models follows a structured approach that balances economic relevance, parsimony, statistical adequacy and predictive performance. Candidate indicators are first identified based on the economic relationships discussed in Section 3. Alternative specifications are subsequently estimated using different combinations and lag structures of these indicators.

Within the estimation sample, the Akaike Information Criterion (AIC) and adjusted R-squared are used to assess model fit and parsimony, while residual diagnostics are used to identify potentially misspecified models. These measures are treated as specification-screening criteria rather than direct measures of forecasting ability. The ultimate assessment of the nowcasting models is based on their pseudo-out-of-sample predictive performance, as described in Section 4.3.

Table 3: Criteria for Model Selection

Criteria	Definition
i. Akaike Information Criterion (AIC)	AIC evaluates a specification's in-sample goodness of fit while penalising excessive complexity. A lower AIC indicates that the model achieves a better balance between explanatory power and parsimony.
ii. Adjusted R-squared	Adjusted R-squared measures the proportion of variation in the target series explained by the predictors, explicitly correcting for the number of regressors. Unlike the standard R-squared, it decreases when irrelevant predictors are added. A higher adjusted R-squared indicates that the included indicators contribute meaningful explanatory content for the nowcast.
iii. Durbin-Watson (DW) Statistic	The DW statistic provides an initial indication of residual serial correlation. More comprehensive residual diagnostics are subsequently reported in the robustness analysis.

4.5 Pseudo-Out-of-Sample Nowcast Evaluation

The predictive performance of the selected models is evaluated using a pseudo-out-of-sample nowcasting exercise. The exercise is designed to approximate the information constraints faced by policymakers at different points within the quarter and to assess whether the inclusion of higher-frequency indicators improves the assessment of current-quarter investment growth relative to a simple autoregressive benchmark.

Specifically, the evaluation considers three information sets: one-month, two-month and full-quarter information. The one-month information set represents the earliest assessment of investment conditions, when only the first month of current-quarter information is available. The two-month information set incorporates information for the first two months of the quarter, while the full-quarter information set represents the case in which information for all three months is available. Where observations required to complete the monthly information set are unavailable because of the ragged-edge structure of the data, the missing observations are projected using the ARIMA procedure described in Section 4.2.

Forecast performance is evaluated recursively. At each evaluation point, the models are estimated using the historical observations available within the estimation sample and used to generate a nowcast for the target quarter. The estimation sample is subsequently expanded and the procedure repeated for the next evaluation period. This expanding-window approach allows model parameters to adapt progressively as additional observations become available while preserving the temporal ordering of the forecasting exercise.

The pseudo-out-of-sample exercise is conducted separately for Private Investment, Structures and Machinery & Equipment (M&E). The AR(1) specification serves as the naïve benchmark, allowing the analysis to assess whether the incorporation of economic indicators provides incremental predictive information beyond that contained in the target variable's own historical dynamics.

Forecast accuracy is primarily assessed using the root mean squared error (RMSE). To facilitate comparison across specifications, the RMSE of each model is also expressed relative to the RMSE of the AR(1) benchmark:

$$RMSE\ Ratio_m = \frac{RMSE_m}{RMSE_{AR(1)}}$$

where $RMSE_m$ denotes the RMSE of model m . A ratio below one indicates that the model outperforms the AR(1) benchmark, while a ratio above one indicates weaker predictive performance.

To ensure comparability across approaches, all models are estimated using a common recursive expanding-window framework. Forecasts are generated recursively beginning from an initial estimation sample that satisfies the minimum data requirements of all model specifications. Model parameters are subsequently re-estimated as additional observations become available, and forecasts are generated using only information available at each forecast origin.

4. Results

The forecast evaluation yields three broad findings. First, the inclusion of timely economic indicators generally improves nowcast accuracy relative to the autoregressive benchmark, indicating that the selected indicators contain incremental information about current-quarter investment activity. Second, the gains from mixed-frequency modelling differ across investment components, with particularly strong improvements observed for M&E. Third, no single specification dominates across all information sets and investment components. Model performance changes as additional within-quarter information becomes available, supporting the use of a suite of complementary models rather than reliance on a single specification.

The following sections examine these findings across the full-quarter, one-month and two-month information sets.

4.1 Forecast Evaluation Across Information Sets

The results are evaluated according to the sequential arrival of information within the quarter. This allows the analysis to assess not only overall nowcast accuracy, but also how the predictive performance of alternative models changes as the information set expands. The one-month exercise captures early-quarter conditions, the two-month exercise incorporates a broader set of observed monthly information, while the full-information exercise evaluates performance when all three months of within-quarter information are available. Comparing model performance across these information sets therefore provides evidence on the incremental value of newly available information and whether the preferred model changes over the course of the quarter.

4.2 Full Information Set Results

Table 4: Nowcast models evaluation with complete data (RMSE ratio*)

RMSE Ratio	AR1	ARDL**	MIDAS	U-MIDAS**	Ensemble ⁴
Private Investment	1.0	0.659	0.811	0.199	0.251
GFCF: Structures	1.0	0.750	0.933		0.828
GFCF: M&E	1.0		0.211	0.121	0.128

Source: DOSM, staff estimates

Note: *The RMSE ratio denominator is the RMSE for the naïve benchmark, i.e. the AR1 model

**For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively.

Table 5: Nowcast models evaluation with complete data (absolute RMSE)

RMSE	AR1	ARDL	MIDAS	U-MIDAS	Ensemble	Long-Run Standard Deviation (2011-19)
Private Investment	2.281	1.503	1.849	0.455	0.573	6.548
GFCF: Structures	3.689	2.767	3.442		3.054	7.111
GFCF: M&E	7.056		1.492	0.856	0.906	9.115

Source: DOSM, staff estimates

Note: For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively.

⁴ The ensemble nowcast is constructed as an equal-weight average of the retained model nowcasts for each target variable and information set.

Tables 4 and 5 report pseudo-out-of-sample performance when information for all three months of the quarter is incorporated. Most retained specifications record lower RMSEs than the AR(1) benchmark, suggesting that the selected indicators provide useful predictive information beyond the target variable's own historical dynamics.

For aggregate private investment, U-MIDAS records the lowest forecast error, with an RMSE ratio of 0.199, compared with 0.659 for ARDL-Bridge and 0.811 for MIDAS. The strong relative performance of U-MIDAS suggests that allowing greater flexibility in the relationship between monthly indicators and quarterly investment may be useful when a complete within-quarter information set is available.

The forecasting gains are particularly pronounced for M&E, where MIDAS and U-MIDAS register RMSE ratios of 0.211 and 0.121, respectively. This is consistent with the timely nature of the monthly indicators used for M&E, including capital imports and export-oriented industrial production. In contrast, the improvement for Structures is comparatively more modest, suggesting that the available monthly indicators provide a comparatively weaker short-term predictive signal for Structures investment.

Overall, the full-information results indicate that retaining monthly information can provide meaningful predictive gains, particularly for M&E and aggregate private investment. Nevertheless, the relative performance of the models differs across investment components, reinforcing the importance of evaluating model suitability separately for each target variable.

4.3 One Month Information Set Results

Table 6: Nowcast models evaluation with 1-month data (RMSE ratio*)

RMSE Ratio	AR1	ARDL**	MIDAS	U-MIDAS**	Ensemble
Private Investment	1.0	0.959	0.484	0.458	0.471
GFCF: Structures	1.0	1.350	0.959		1.096
GFCF: M&E	1.0		0.895	0.587	0.723

Source: DOSM, staff estimates

Note: *The RMSE ratio denominator is the RMSE for the naïve benchmark, i.e. the AR1 model

**For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively

Table 7: Nowcast models evaluation with 1-month data (absolute RMSE)

RMSE	AR1	ARDL	MIDAS	U-MIDAS	Ensemble	Long-Run Standard Deviation (2011-19)
Private Investment	2.281	2.187	1.105	1.044	1.074	6.548
GFCF: Structures	3.689	4.982	3.537		4.043	7.111
GFCF: M&E	7.056		6.316	4.144	5.099	9.115

Source: DOSM, staff estimates

Note: For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively

Tables 6 and 7 evaluate nowcast performance when only the first month of current-quarter information is available. This represents the most information-constrained exercise and is therefore particularly relevant for assessing the usefulness of the models for early-quarter surveillance.

Even at this early stage, the retained models generally improve upon the AR(1) benchmark. For private investment, U-MIDAS and MIDAS register RMSE ratios of 0.458 and 0.484, respectively, compared with 0.959 for ARDL-Bridge. The relatively strong performance of MIDAS-based models suggests that retaining the timing of monthly observations may be particularly valuable when the available information set remains limited.

A similar pattern is evident across the investment components, although the gains are less uniform. For Structures, MIDAS records an RMSE ratio of 0.959, marginally outperforming the AR(1) benchmark, while ARDL-Bridge performs worse than the benchmark. For M&E, U-MIDAS performs best, with an RMSE ratio of 0.587, compared with 0.895 for MIDAS. These results indicate that useful signals about current-quarter investment conditions are already present in the earliest monthly releases, although the magnitude of the gains varies across investment components and model specifications.

Importantly, these findings should not be interpreted as implying that incomplete monthly data are sufficient to determine the quarter's investment outcome. Rather, they suggest that the models can extract useful early signals from the limited information available at this stage of the quarter.

4.4 Two-Month Information Set Results

Table 8: Nowcast models evaluation with 2-months data (RMSE ratio*)

RMSE Ratio	AR1	ARDL**	MIDAS	U-MIDAS**	Ensemble
Private Investment	1.0	0.745	1.335	1.320	0.996
GFCF: Structures	1.0	0.815	0.861		0.821
GFCF: M&E	1.0		0.8	0.658	0.710

Source: DOSM, staff estimates

Note: *The RMSE ratio denominator is the RMSE for the naïve benchmark, i.e. the AR1 model

**For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively

Table 9: Nowcast models evaluation with 2-months data (absolute RMSE)

RMSE	AR1	ARDL	MIDAS	U-MIDAS	Ensemble	Long-Run Standard Deviation (2011-19)
Private Investment	2.281	1.700	3.046	3.011	2.271	6.548
GFCF: Structures	3.689	3.006	3.175		3.030	7.111
GFCF: M&E	7.056		5.642	4.646	5.013	9.115

Source: DOSM, staff estimates

Note: For Structures and M&E, out-of-sample results for U-MIDAS and ARDL models did not outperform naïve benchmarks (AR(1)) respectively

Tables 8 and 9 assess model performance after information for the second month of the quarter becomes available. The additional information materially changes the relative ranking of some specifications, illustrating that the usefulness of alternative model structures varies as the within-quarter information set evolves.

The most notable result is observed for aggregate private investment, where ARDL-Bridge records the lowest reported RMSE ratio of 0.745, compared with 1.335 for MIDAS and 1.320 for U-MIDAS, both of which underperform AR(1). This contrasts with the one-month exercise, in which the MIDAS-based specifications perform more strongly. One interpretation is that the relative advantage of retaining individual monthly observations may diminish as the information set becomes more complete, although this result should be interpreted as specific to the evaluation sample rather than as evidence of a general property of ARDL models.

For Structures, ARDL and MIDAS record broadly similar RMSE ratios of 0.815 and 0.861, respectively, while U-MIDAS remains the best-performing retained specification for M&E, with an RMSE ratio of 0.658.

Overall, the two-month exercise reinforces an important practical finding: the preferred model may change as additional within-quarter information becomes available. This reduces the case for relying on a single specification throughout the quarter and provides a rationale for monitoring signals across multiple models.

4.5 What Do the Forecasting Results Tell Us?

Taken together, the pseudo-out-of-sample exercises highlight three findings.

First, higher-frequency indicators add useful predictive information. Relative to a benchmark based solely on the historical dynamics of investment, the retained specifications generally produce lower forecast errors across the reported information sets. This supports the use of timely production, trade, financing and sentiment indicators for assessing current-quarter investment conditions.

Second, the value of mixed-frequency information differs across investment components. M&E shows particularly sizeable gains from specifications that retain monthly information, consistent with its close association with timely indicators such as capital imports and industrial production. Structures displays comparatively smaller and less uniform gains, suggesting that short-term indicators may provide a weaker signal for investment characterised by longer implementation cycles.

Third, model rankings change as information accumulates within the quarter. MIDAS-based specifications perform relatively strongly when information is limited, whereas ARDL-Bridge becomes competitive for some targets when a larger share of the quarter's information is available. Consequently, the results do not identify a universally dominant specification.

From a surveillance perspective, these findings favour a model-toolbox approach. Rather than selecting one model for all stages of the quarter, policymakers can assess signals from several complementary specifications, with the ensemble providing an additional benchmark that reduces reliance on any single model.

Robustness and Model Diagnostics

The robustness of the retained specifications is assessed through a combination of residual diagnostics, parameter-stability tests and alternative model specifications. The diagnostic assessment considers residual normality, serial dependence, heteroskedasticity and functional-form specification, where applicable to the respective model structures. Parameter stability is additionally examined for the ARDL specifications using CUSUM and CUSUMSQ tests. Given the mixed-frequency structure of MIDAS and U-MIDAS, some conventional single-frequency diagnostic tests are not directly applicable and are therefore not reported for these models.

Overall, the residual diagnostics do not point to material specification concerns in the retained models. The Jarque-Bera tests do not provide evidence against residual normality at the 5% significance level. For the ARDL specifications, the Ramsey RESET tests do not indicate functional-form misspecification, while the Breusch-Pagan-Godfrey tests do not provide evidence of heteroskedasticity at the reported significance level. Residual correlograms for ARDL, MIDAS and U-MIDAS similarly do not indicate strong evidence of persistent serial dependence over the reported lags. However, the Q-statistic probabilities should be interpreted cautiously, as the estimation output indicates that these probabilities may not be valid for the respective equation specifications.

The parameter-stability diagnostics provide a more nuanced picture. For private investment, the CUSUM and CUSUMSQ tests indicate instability around 2Q2020, while the Structures specification shows evidence of parameter instability during 2018–2021. These periods encompass substantial changes in the economic environment, although the diagnostic tests themselves do not establish the underlying causes of the instability.

These findings suggest that the relationships between investment and its predictors may not remain constant throughout the sample. The expanding-window estimation approach allows parameter estimates to be updated as additional observations become available but does not eliminate the possibility of structural change. Accordingly, the pseudo-out-of-sample results are interpreted alongside the stability diagnostics rather than relying solely on in-sample goodness of fit. This also

supports the use of several complementary specifications rather than treating the performance of any individual model as structurally invariant.

Robustness is further assessed by considering alternative indicator sets and alternative treatment of the pandemic period. Specifications incorporating additional indicators, including ALR, RAM BCI and MCU, do not yield systematic improvements in model fit or nowcast performance relative to the retained specifications. Similarly, extending the duration of the COVID-19 dummy variables does not materially improve performance. These alternative specifications are therefore excluded from the baseline model suite in favour of more parsimonious specifications.

Taken together, the diagnostic and sensitivity exercises provide reasonable support for the retained specifications, while also highlighting the importance of interpreting their performance in the presence of potential parameter instability and a relatively limited forecast-evaluation sample. The models are therefore best viewed as complementary quantitative signals for investment surveillance, with their predictive performance periodically reassessed as additional observations become available.

5. Conclusion

This paper examines a range of nowcasting techniques to improve the real-time assessment of investment activity in Malaysia. It contributes to the literature by extending existing techniques that have traditionally focused on overall GDP nowcasting to the investment component. By applying both single and mixed-frequency modelling frameworks to investment data, the analysis demonstrates how high-frequency indicators can be systematically incorporated to provide earlier and more granular insights into investment dynamics. In doing so, the paper enhances the understanding of short-term investment developments and offers a complementary tool for monitoring domestic demand conditions ahead of official data releases.

The results yield three main findings. First, timely monthly indicators generally contain useful incremental information for assessing current-quarter investment conditions, although the magnitude of the forecasting gains varies across information sets. Second, preserving monthly information generates particularly sizeable gains for M&E. Third, model rankings change as information accumulates within the quarter,

with no single specification consistently dominating across investment components and information sets. These findings support a model-toolbox approach to investment surveillance rather than reliance on a single model throughout the quarter.

As with all empirical models, several limitations remain. The performance of the nowcasts is sensitive to data revisions, model specification choices, and the availability and timeliness of high-frequency indicators, which may affect real-time accuracy. Differences in data release calendars and subsequent revisions can introduce uncertainty into early estimates, particularly when information sets are incomplete. In addition, structural changes in investment behaviour—arising from shifts in technology, policy regimes, or global economic conditions—may alter the underlying relationships captured by the models over time, potentially reducing their predictive stability. These considerations underscore the importance of continuous monitoring, periodic re-evaluation of model specifications, and the use of complementary approaches when interpreting nowcasting signals.

Moving forward, continued monitoring and periodic re-evaluation of these models will be crucial to ensure that they remain relevant, reliable, and well aligned with evolving economic conditions. As data availability, release calendars, and investment structures change over time, model specifications and indicator choices may need to be updated to preserve predictive accuracy. Future research could extend the framework by incorporating a broader set of high-frequency indicators, exploring more granular, sector-specific nowcasts, or integrating machine-learning techniques to further enhance predictive performance. Such enhancements could further improve the timeliness and robustness of real-time investment assessments.

Overall, the framework developed in this paper provides a practical and informative tool to support pre-emptive policy analysis and to strengthen the surveillance of investment activity in Malaysia.

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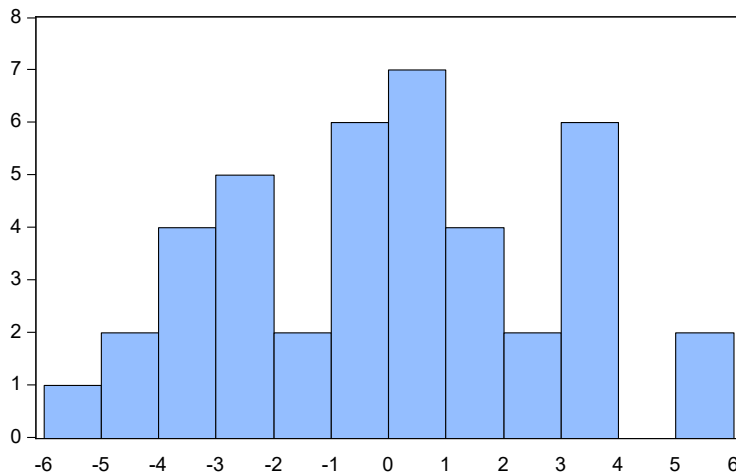
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Appendix I: Diagnostic tests and robustness checks

1) Normality of residuals (Jarque-Bera Test)

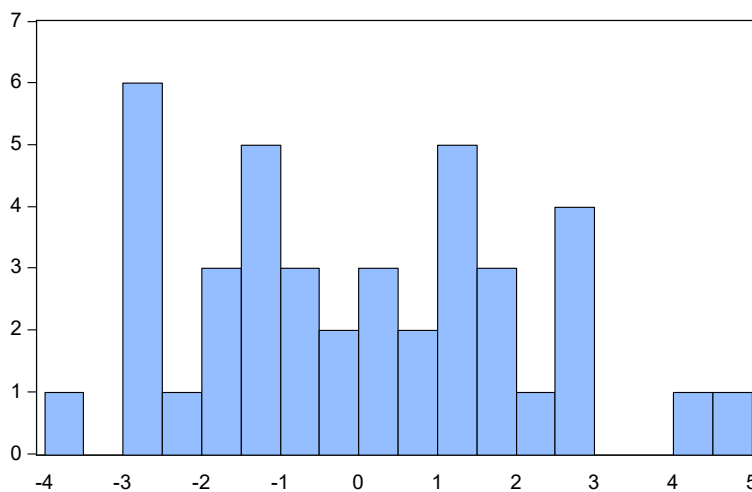
a. ARDL



Series	Residuals
Sample	2014Q3 to 2024Q3
Observations	41
Mean	-1.08e-16
Median	0.033412
Maximum	5.529971
Minimum	-5.202733
Standard Deviation	2.814749
Skewness	0.020871
Kurtosis	2.147138
Jarque-Bera Probability	1.245572 0.536448

The Jarque-Bera statistic is 1.2456 with a p-value of 0.5364, which is greater than 0.05. This indicates that we fail to reject the null hypothesis of normality, suggesting residuals are approximately normal.

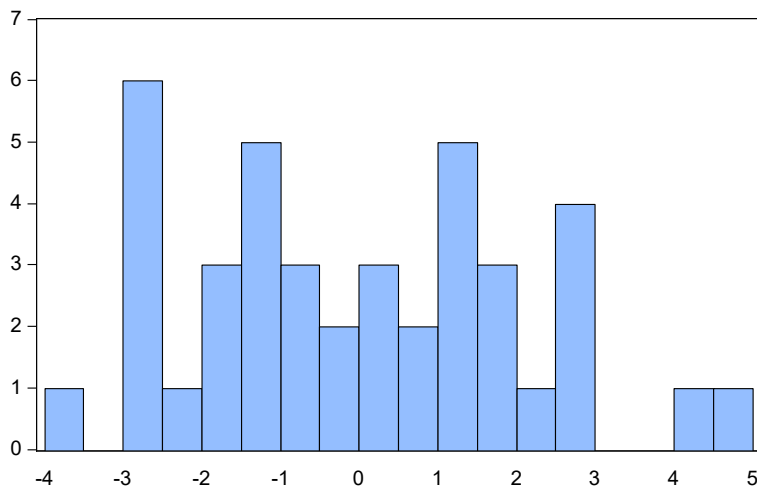
b. MIDAS



Series	Residuals
Sample	2010Q1 to 2024Q3
Observations	41
Mean	-3.06e-13
Median	-0.282071
Maximum	4.631110
Minimum	-3.626461
Standard Deviation	2.099232
Skewness	0.285879
Kurtosis	2.2661370
Jarque-Bera Probability	1.490488 0.474618

The Jarque-Bera statistic is 1.490488 with a p-value of 0.474618, which is greater than 0.05. This indicates that we fail to reject the null hypothesis of normality, suggesting residuals are approximately normal.

c. U-MIDAS



Series	Residuals
Sample	2010Q1 to 2024Q3
Observations	43
Mean	1.78e-15
Median	-0.020910
Maximum	6.252225
Minimum	-6.689584
Standard Deviation	2.994822
Skewness	-0.038969
Kurtosis	2.380807
Jarque-Bera Probability	0.697809
	0.705461

The Jarque-Bera statistic is 0.697809 with a p-value of 0.705461, which is greater than 0.05. This indicates that we fail to reject the null hypothesis of normality, suggesting residuals are approximately normal.

2) Specification (Ramsey RESET Test)

a. ARDL⁵

Ramsey RESET Test

Equation: FINAL_ARDL_EQ2_BEST

Omitted Variables: Squares of fitted values

Specification:

GRPI GRPI(-1) XGG XGG(-1) XGG(-2) BTS GKIMPORTS

GOUTLOANS GOUTLOANS(-1) GOUTLOANS(-2) C

	Value	df	Probability
t-statistic	0.871115	30	0.3906
F-statistic	0.758841	(1,30)	0.3906
Likelihood ratio	1.024184	1	0.3115
F-test summary:			
	Sum of Sq.	df	Mean Squares
Test SSR	7.818444	1	7.818444
Restricted SSR	316.9124	31	10.22298
Unrestricted SSR	309.0940	30	10.30313
LR test summary:			
	Value		
Restricted LogL	-100.1001		
Unrestricted LogL	-99.58798		

⁵ This test cannot be applied to MIDAS and U-MIDAS given that the models uses mixed-frequency datasets

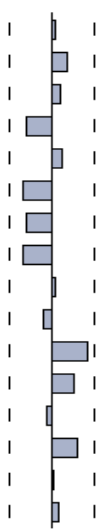
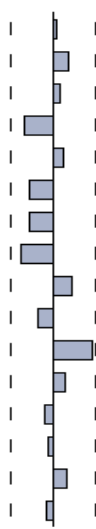
3) Autocorrelation (Q-Statistics Test)

a. ARDL

Date: 11/17/25 Time: 21:47

Sample (adjusted): 2014Q3 2024Q3

Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.025	0.025	0.0269	0.870
		2	0.108	0.108	0.5586	0.756
		3	0.058	0.053	0.7130	0.870
		4	-0.193	-0.210	2.4889	0.647
		5	0.069	0.070	2.7247	0.742
		6	-0.206	-0.178	4.8700	0.561
		7	-0.186	-0.180	6.6693	0.464
		8	-0.208	-0.230	8.9885	0.343
		9	0.025	0.132	9.0240	0.435
		10	-0.066	-0.111	9.2683	0.507
		11	0.257	0.282	13.135	0.285
		12	0.166	0.083	14.809	0.252
		13	-0.035	-0.065	14.885	0.315
		14	0.183	-0.033	17.072	0.252
		15	0.016	0.106	17.088	0.314
		16	0.050	-0.047	17.268	0.368

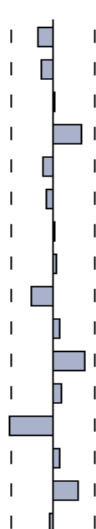
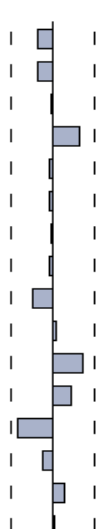
*Probabilities may not be valid for this equation specification.

b. MIDAS

Date: 11/17/25 Time: 21:47

Sample (adjusted): 2014Q3 2024Q3

Q-statistic probabilities adjusted for 2 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.108	-0.108	0.5101	0.475
		2	-0.097	-0.110	0.9341	0.627
		3	0.010	-0.013	0.9391	0.816
		4	0.207	0.201	2.9828	0.561
		5	-0.078	-0.032	3.2825	0.657
		6	-0.049	-0.026	3.4037	0.757
		7	0.013	-0.010	3.4121	0.844
		8	0.025	-0.022	3.4461	0.903
		9	-0.164	-0.150	4.9259	0.841
		10	0.042	0.022	5.0268	0.889
		11	0.230	0.229	8.1261	0.702
		12	0.061	0.137	8.3513	0.757
		13	-0.330	-0.258	15.216	0.294
		14	0.044	-0.068	15.341	0.355
		15	0.187	0.086	17.711	0.278
		16	-0.026	0.009	17.760	0.338

*Probabilities may not be valid for this equation specification.

c. U-MIDAS

Date: 11/17/25 Time: 21:46

Sample (adjusted): 2014Q3 2024Q3

Q-statistic probabilities adjusted for 2 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.075	-0.075	0.2622	0.609
		2	-0.089	-0.095	0.6383	0.727
		3	0.038	0.024	0.7072	0.872
		4	-0.243	-0.251	3.6408	0.457
		5	0.157	0.135	4.8945	0.429
		6	0.068	0.037	5.1352	0.527
		7	-0.215	-0.184	7.6250	0.367
		8	-0.222	-0.335	10.346	0.242
		9	0.050	0.055	10.488	0.312
		10	-0.105	-0.165	11.132	0.347
		11	0.213	0.126	13.872	0.240
		12	0.168	0.098	15.629	0.209
		13	-0.310	-0.191	21.817	0.058
		14	0.048	-0.097	21.970	0.079
		15	0.101	0.104	22.670	0.091
		16	-0.034	-0.073	22.754	0.120

*Probabilities may not be valid for this equation specification.

4) Heteroskedasticity⁶ (Breusch-Pagan-Godfrey Test)

a. ARDL

Heteroskedasticity Test: Breusch-Pagan-Godfrey

Null hypothesis: Homoskedasticity

F-statistic	0.371771	Prob. F(9,31)	0.9399
Obs*R-squared	3.994171	Prob. Chi-Square(9)	0.9118
Scaled explained SS	1.309689	Prob. Chi-Square(9)	0.9983

⁶ This test cannot be applied to MIDAS and U-MIDAS given that the models uses mixed-frequency datasets

5) Model Stability (CUSUM and CUSUMSQ)

a. ARDL

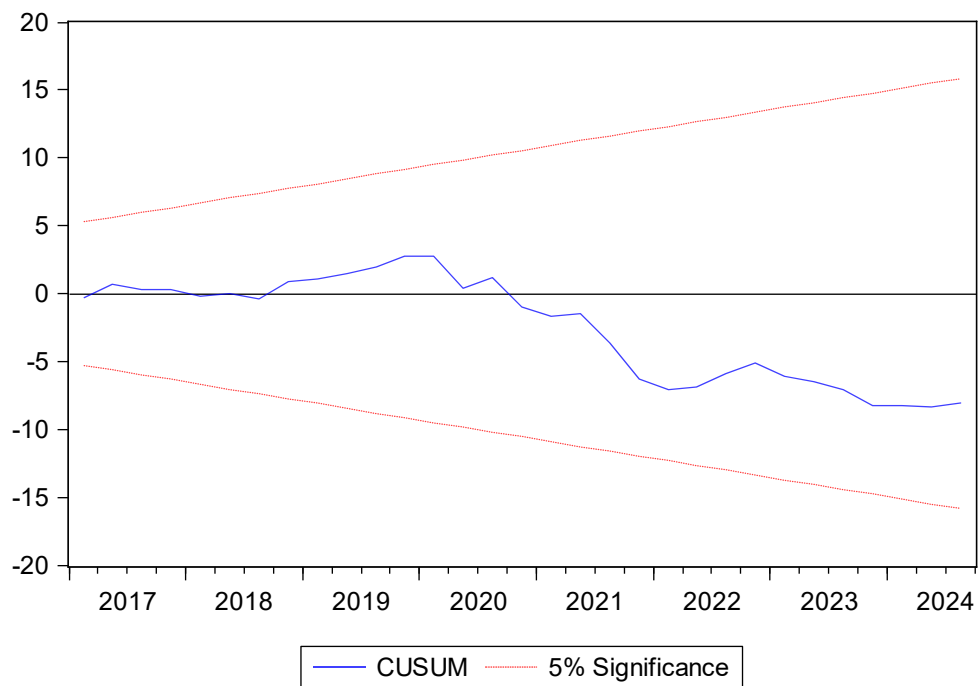
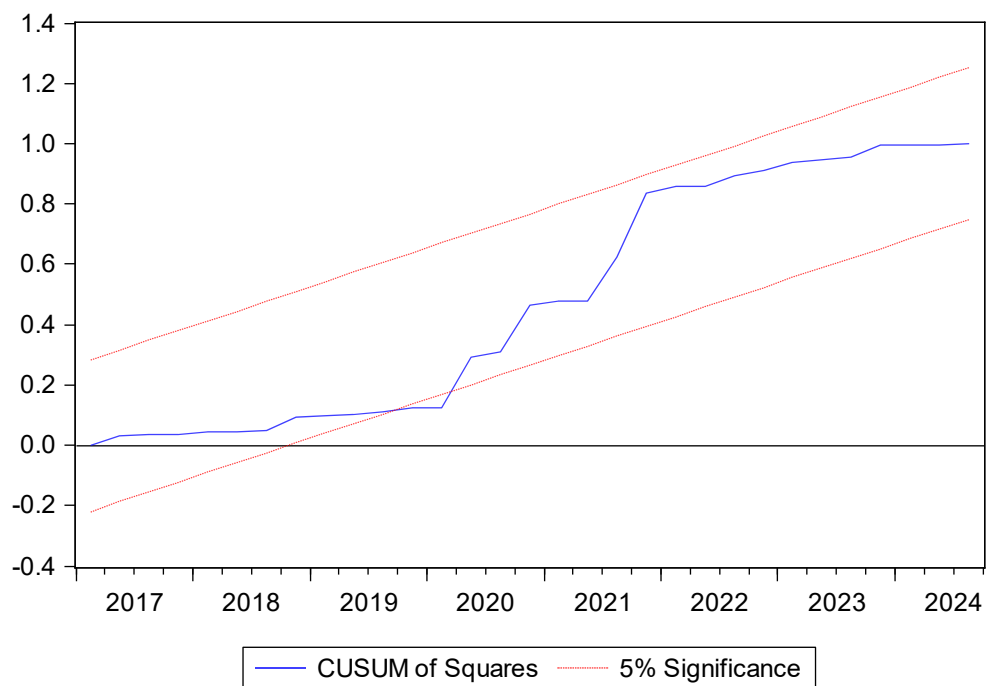


Table 10: Diagnostic Tests and Robustness Checks (PI)

	ARDL	MIDAS	U-MIDAS
Variables	<ul style="list-style-type: none"> • Lags of PI • Global Growth • DOSM BTS • Capital Imports* • Outstanding Loans* 	<ul style="list-style-type: none"> • Lags of PI • Global Growth • DOSM BTS • Capital Imports* • Outstanding Loans* • Global PMI* 	<ul style="list-style-type: none"> • Lags of PI • Global Growth • DOSM BTS • Capital Imports* • Outstanding Loans*
Normality of residuals (<i>Jarque-Bera Test</i> ***)	No evidence against residual normality at the 5% significance level (<i>JB test statistic</i> = 1.25)	No evidence against residual normality at the 5% significance level (<i>JB test statistic</i> = 1.49)	No evidence against residual normality at the 5% significance level (<i>JB test statistic</i> = 0.70)
Specification (<i>Ramsey's RESET Test</i> ***)	RESET test does not indicate functional-form misspecification at the 5% significance level (<i>F-stat</i> = 0.76)	N/A**	N/A**
Autocorrelation (up to 16 lags)	Residual correlogram does not indicate strong serial dependence over the reported lags.		
Heteroskedasticity (<i>Breusch-Pagan-Godfrey Test</i> ***)	No evidence of heteroskedasticity at the 5% significance level (<i>F-stat</i> = 0.37)	N/A**	N/A**
Model stability (<i>CUSUM and CUSUMSQ</i>)	Evidence of parameter instability; expanding-window estimates allow for recursive updating.	N/A**	N/A**
Robustness check	<ul style="list-style-type: none"> ▪ Inclusion of additional variables (ALR, RAM BCI, MCU etc.) do not improve model fit or nowcast performance. ▪ Longer COVID-19 dummies do not improve performance. 		

Note: *Indicates monthly variables

**Certain diagnostic tests are not applicable for mixed-frequency models such as MIDAS and U-MIDAS

***All diagnostic tests are evaluated at the 5% significance level, where applicable

Source: Staff estimate

Table 11: Diagnostic Tests and Robustness Checks (GFCF: Structures)

	ARDL	MIDAS	U-MIDAS
Variables	<ul style="list-style-type: none"> • Lags of Structures • Global Growth • DOSM BTS* • IPI • Construction* • Outstanding Loans* 	<ul style="list-style-type: none"> • Lags of Structures • Global Growth • DOSM BTS • Outstanding Loans* • Global PMI* 	
Normality of residuals (<i>Jarque-Bera Test***</i>)	No evidence against residual normality at the 5% significance level (<i>JB test statistic = 0.07</i>)	No evidence against residual normality at the 5% significance level (<i>JB test statistic = 1.27</i>)	
Specification (<i>Ramsey's RESET Test***</i>)	RESET test does not indicate functional-form misspecification at the 5% significance level (<i>F-stat = 1.62</i>)	N/A**	
Autocorrelation (<i>up to 16 lags</i>)	Residual correlogram does not indicate strong serial dependence over the reported lags.		
Heteroskedasticity (<i>Breusch-Pagan-Godfrey Test***</i>)	No evidence of heteroskedasticity at the 5% significance level (<i>F-stat = 0.459</i>)	N/A**	
Model stability (<i>CUSUM and CUSUMSQ</i>)	Evidence of parameter instability; expanding-window estimates allow for recursive updating.	N/A**	
Robustness check	<ul style="list-style-type: none"> ▪ Inclusion of additional variables (ALR, RAM BCI, MCU etc.) do not improve model fit or nowcast performance. ▪ Longer COVID-19 dummies do not improve performance. 		

Note: *Indicates monthly variables

**Certain diagnostic tests are not applicable for mixed-frequency models such as MIDAS and U-MIDAS

***All diagnostic tests are evaluated at the 5% significance level, where applicable

Source: Staff estimate

Table 12: Diagnostic Tests and Robustness Checks (GFCF: M&E)

	ARDL	MIDAS	U-MIDAS
Variables		<ul style="list-style-type: none"> • Lags of M&E • Global Growth • RES BOS • Capital Imports Growth* • Outstanding Loans* • IPI Export-Oriented* 	<ul style="list-style-type: none"> • Lags of M&E • Global Growth • DOSM BTS • Capital Imports Growth* • Global PMI* • IOWT Machineries*
Normality of residuals (<i>Jarque-Bera Test***</i>)		No evidence against residual normality at the 5% significance level (<i>JB test statistic = 1.70</i>)	No evidence against residual normality at the 5% significance level (<i>JB test statistic = 0.54</i>)
Specification (<i>Ramsey's RESET Test***</i>)		N/A**	N/A**
Autocorrelation (<i>up to 16 lags</i>)		Residual correlogram does not indicate strong serial dependence over the reported lags.	
Heteroskedasticity (<i>Breusch-Pagan-Godfrey Test***</i>)		N/A**	N/A**
Model stability (<i>CUSUM and CUSUMSQ</i>)		N/A**	N/A**
Robustness check	<ul style="list-style-type: none"> ▪ Inclusion of additional variables (ALR, RAM BCI, MCU etc.) do not improve model fit or nowcast performance. ▪ Longer COVID-19 dummies do not improve performance. 		

Note: *Indicates monthly variables

**Certain diagnostic tests are not applicable for mixed-frequency models such as MIDAS and U-MIDAS

***All diagnostic tests are evaluated at the 5% significance level, where applicable

Source: Staff estimate