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Forecasting Office Vacancy Using Employment Indicators: A Case of the Singapore Market

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Abstract: *This study examines whether office-linked employment indicators serve as useful demand signals for capacity planning by explaining and forecasting Singapore's office vacancy rate. Two questions are addressed: whether lagged office-linked employment is associated with vacancy after controlling for supply-side change and GDP, and whether adding employment improves out-of-sample forecast accuracy relative to a baseline without it. A quarterly time-series framework is applied for 1993Q3–2025Q3 using public data, with the office vacancy rate as the dependent variable and a one-quarter-lagged office-linked employment indicator as the main predictor. Regression with ARIMA errors captures vacancy persistence alongside exogenous drivers, and forecasts are evaluated through rolling-origin, expanding-window testing at one- and four-quarter horizons using MAE, RMSE, and the Diebold–Mariano test. The findings offer only limited support for employment: at both horizons the baseline model without employment consistently outperforms the model with employment. The study contributes an operations-management lens on office vacancy as a capacity-slack measure and a transparent, replicable quarterly forecasting workflow.*

Keywords: *capacity planning; demand signals; office vacancy; ARIMAX; rolling-origin forecasting*

Abstrak: *Penelitian ini menilai apakah indikator ketenagakerjaan terkait kantor berfungsi sebagai sinyal permintaan untuk perencanaan kapasitas melalui penjelasan dan peramalan tingkat kekosongan kantor di Singapura. Dua pertanyaan diuji: apakah ketenagakerjaan terkait kantor yang dilag satu kuartal berhubungan dengan kekosongan setelah mengontrol perubahan sisi pasokan dan PDB, serta apakah memasukkan ketenagakerjaan meningkatkan akurasi peramalan luar sampel dibandingkan model dasar tanpa ketenagakerjaan. Kerangka deret waktu triwulanan diterapkan untuk 1993Q3–2025Q3 menggunakan data publik, dengan tingkat kekosongan kantor sebagai variabel dependen dan indikator ketenagakerjaan terkait kantor berlag satu kuartal sebagai prediktor utama. Regresi dengan error ARIMA menangkap persistensi kekosongan bersama penggerak eksogen, dan peramalan dievaluasi melalui pengujian rolling-origin pada horizon satu dan empat kuartal dengan MAE, RMSE, dan uji Diebold–Mariano. Temuan hanya memberikan dukungan terbatas: pada kedua horizon, model dasar tanpa ketenagakerjaan mengungguli model dengan ketenagakerjaan. Penelitian ini menyumbang perspektif manajemen operasi atas kekosongan kantor sebagai ukuran capacity slack serta alur kerja peramalan triwulanan yang transparan dan dapat direplikasi.*

Kata Kunci: *perencanaan kapasitas; sinyal permintaan; tingkat kekosongan kantor; ARIMAX; peramalan rolling-origin*

INTRODUCTION

Singapore's office market can be treated as an operations system with slow-moving capacity and cyclical demand. On the capacity side, supply is set by stock and the development pipeline, both reflecting long lead times, sunk costs, and sequencing constraints typical of capacity planning. On the demand side, utilisation is driven by the scale and composition of office-using employment such as finance, ICT, and professional services. The vacancy rate captures this capacity-to-demand interaction as a slack indicator: higher vacancy means under-utilised capacity, lower vacancy a tighter market. Singapore suits this framing because quarterly data on office availability and pipeline supply are publicly available over long horizons, enabling operations-style monitoring rather than reliance on short proprietary datasets (Stevenson & McGrath, 2003).

Because office capacity adjusts with structural inertia while demand responds quickly to macroeconomic and labour-market conditions, the mismatch creates persistent forecasting uncertainty: vacancy can rise faster than supply can be rationalised when demand weakens, and tighten before new capacity is delivered when it accelerates. Given long lead times in the built environment, better early demand signals are valuable when they inform timing decisions such as delivery phasing, retrofit scheduling, and risk buffers used by asset operators, developers, and major occupiers.

The post-pandemic period sharpened this problem. Work-from-home and hybrid practices altered office usage and how labour demand translates into space demand (Bergeaud et al., 2023), and even when employment recovers, space needs may not revert proportionally if space-per-worker assumptions shift. For Singapore, official statistics have discussed the persistence of hybrid arrangements (Monetary Authority of Singapore, 2024), reinforcing the need to treat the employment-to-vacancy link as a forecasting relationship to be tested under possible regime changes rather than assumed stable or causal.

This study frames Singapore's office vacancy rate as an operational slack metric and tests whether office-linked employment indicators function as useful demand signals for capacity planning at quarterly frequency. Using the common overlap period of 1993Q3 to 2025Q3 allows a sufficiently large sample to support time-series modelling with exogenous variables (ARIMAX), robust lag structures, and rolling out-of-sample evaluation. The goal is to improve forecast quality for planning and monitoring decisions under supply inertia and potential structural breaks in office usage patterns. Two research questions guide the study:

RQ1: What is the relationship between office-linked employment and Singapore's office vacancy rate after controlling for macroeconomic conditions and office supply?

RQ2: Does incorporating employment indicators into ARIMAX models significantly improve out-of-sample accuracy of office vacancy forecasts compared to baseline models without employment indicators?

The contribution is threefold: it extends operations-management thinking into commercial real estate by framing office vacancy as a capacity-slack outcome; it tests whether a theoretically plausible demand signal, office-linked employment, adds practical value once persistence and core controls are included; and it provides a transparent, replicable quarterly forecasting workflow using public Singapore data under disciplined rolling-origin testing.

LITERATURE REVIEW

Operations Management and Capacity Planning

Operations management (OM) creates value by transforming inputs into outputs through the systematic design, direction, and control of processes (Heizer et al., 2017). Central to OM are capacity decisions under uncertainty: capacity is not merely a throughput concept but an economic commitment shaping fixed-cost exposure, responsiveness, and risk. Contemporary research treats capacity planning under limited information as a core problem, emphasising the trade-off between under-capacity (service losses, missed growth) and over-capacity (inefficiency and slack) (Anand et al., 2023).

OM is increasingly applied to asset-heavy service systems where capacity is embodied in long-lived assets and where short-run adjustments are limited. Capacity typically exhibits inertia because assets cannot be scaled up or down quickly without financial and operational friction. Empirical work on capacity and flexibility planning under demand uncertainty reinforces that capacity choices interact with flexibility strategies and uncertainty characteristics, affecting performance outcomes and highlighting the need to model the demand to capacity interface explicitly (Hamidian et al., 2021).

This broad OM foundation motivates viewing office markets through an OM lens: office supply behaves like slow-moving capacity, office demand varies with economic conditions, and vacancy can be interpreted as an observable indicator of slack or under-utilised capacity.

Theoretical Foundations

Four operations-management theories anchor the study. First, capacity planning theory treats capacity as a costly, partially irreversible, timing-dependent commitment, so the task is to set the size, type, and timing of capacity under uncertain demand (Van Mieghem, 2003); office stock and the pipeline are slow-moving capacity, and vacancy is the visible result of capacity-demand alignment. Second, demand forecasting theory positions forecasting as a planning function whose value lies in decision-relevant accuracy, benchmarked against credible alternatives and judged out of sample (De Gooijer & Hyndman, 2006; Makridakis et al., 2018), motivating the test of employment as a candidate predictor rather than assuming its usefulness.

Third, resource allocation theory frames slack as under-utilised capacity acting as either costly inefficiency or a protective buffer, so persistent slack signals structural imbalance and makes demand monitoring central to leasing, phasing, and rationalisation decisions (Babai et al., 2022; Van Mieghem, 2003); office vacancy is thus a resource-allocation signal, not merely a ratio. Fourth, operations strategy theory links these to longer-horizon choices, treating information quality and analytics as complements to process discipline (Choi et al., 2018). Together, these theories justify treating vacancy as a capacity-slack outcome, employment as a testable demand signal, and disciplined forecast evaluation as the criterion for operational value.

Office Vacancy as a Capacity-Slack Metric

Office vacancy can be interpreted as a practical measure of capacity slack in an asset-heavy service system. Office space is costly to develop, slow to adjust, and subject to leasing frictions, so the vacancy rate provides a visible indicator of the extent to which available capacity is under-utilised relative to realised demand. Under this interpretation, high vacancy reflects excess capacity and low vacancy reflects a tighter market with less slack. This framing is consistent with classic office-market research showing that vacancy is central to understanding the cyclical behaviour of office markets rather than merely a passive descriptive outcome (Wheaton, 1987).

Vacancy adjusts gradually rather than instantaneously, shaped by construction lags, staggered lease expiries, relocation frictions, and delayed absorption that make it persistent. Wheaton identifies recurrent construction-vacancy cycles, while Grenadier shows demand uncertainty, adjustment costs, and development lags generate prolonged real-estate cycles (Grenadier, 1995). The natural or equilibrium vacancy rate further supports interpreting vacancy as a market-balance indicator, including in Singapore (Khor et al., 2000); comparative work shows vacancy reflects rental adjustment, speculative development, and frictions (Sanderson et al., 2006), and the natural rate can vary over time with labour-market and real-estate conditions (Black et al., 2021).

Employment Indicators as Demand Signals

Employment indicators can serve as demand signals because labour input is closely tied to workspace requirements: demand for space derives from the scale, composition, and growth of firms needing office functions. The argument is stronger when employment is operationalised as office-linked employment, i.e. changes in industries directly tied to office occupancy such as finance, ICT, professional services, and related business services (Foo & Higgins, 2007). Office-market adjustment studies show employment is part of the mechanism through which demand, rents, absorption, and vacancy evolve (Hendershott et al., 1999; Tse & Webb, 2003).

Timing also matters: employment changes do not translate into occupancy immediately, since firms adjust space through lease renewals, relocations, consolidation, and staged expansion. The effect of employment is therefore more plausibly lagged than contemporaneous, consistent with dynamic evidence that vacancy responses to fundamentals unfold gradually (Ho et al., 2014), which supports using lagged office-linked employment indicators.

Structural Shifts: Remote and Hybrid Work

Remote and hybrid work introduced after 2020 represent a structural shift that may alter the labour-to-space relationship. Hybrid arrangements can reduce space intensity per worker by changing attendance, desk-sharing, and workplace strategies (Van Nieuwerburgh, 2023); they have remained materially above pre-pandemic norms (Barrero et al., 2023), telework is associated with weaker office-market outcomes and reduced construction (Bergeaud et al., 2023), and job-posting evidence shows work-from-home opportunities stayed elevated after the shock (Adrjan et al., 2025).

This potential structural change means forecasting models should not assume a constant relationship without testing. If the employment-to-space link weakened after 2020, models fit over long samples may overstate earlier stability and understate regime-dependent forecast risk (Hewamalage et al., 2023), justifying robustness checks and regime-aware interpretation.

Predictive Modelling with Exogenous Drivers (ARIMAX)

Predictive modelling in operations management often needs to capture two features at once: persistence in the outcome and the influence of external drivers (De Gooijer & Hyndman, 2006). ARIMAX, or regression with ARIMA errors, models the dependent variable as a function of external drivers while capturing residual persistence through an ARIMA process (Hyndman & Khandakar, 2008), retaining economic interpretation while respecting the properties of persistent series. Office vacancy is persistent through lease structures, staggered expiries, and gradual absorption, yet also influenced by labour-market, supply, and macroeconomic conditions, so ARIMAX offers a parsimonious way to test demand and supply signals as incremental predictors.

A key issue is forecast evaluation: predictors should not be assumed to improve forecasts merely because they are theoretically meaningful. Their value must be shown under time-consistent out-of-sample procedures reflecting the information available at the forecast origin. This matters especially in nested settings, where an augmented model may cut in-sample error without genuine predictive gain (Clark & West, 2007), and performance should be judged against the actual evaluation design rather than full-sample averages (Giacomini & White, 2006), motivating the rolling-origin evaluation used here.

Conceptual Framework and Hypotheses

Bringing these together, the study models office vacancy as a persistent capacity-slack outcome driven by a demand signal (lagged office-linked employment) and two controls (pipeline-supply change and GDP growth), with persistence captured through an ARIMA error structure. Figure 1 summarises this framework: the demand signal and controls enter an ARIMAX model whose output, the vacancy rate, is assessed for in-sample association (RQ1) and out-of-sample accuracy (RQ2). Consistent with the expectation that stronger office-linked labour demand coincides with lower vacancy, two directional hypotheses are tested:

H1: After controlling for change in pipeline supply, GDP growth, and vacancy persistence, lagged office-linked employment is negatively associated with the office vacancy rate.

H2: **A**dding lagged office-linked employment to an ARIMAX model improves the out-of-sample forecast accuracy of office vacancy relative to a baseline model that excludes employment.

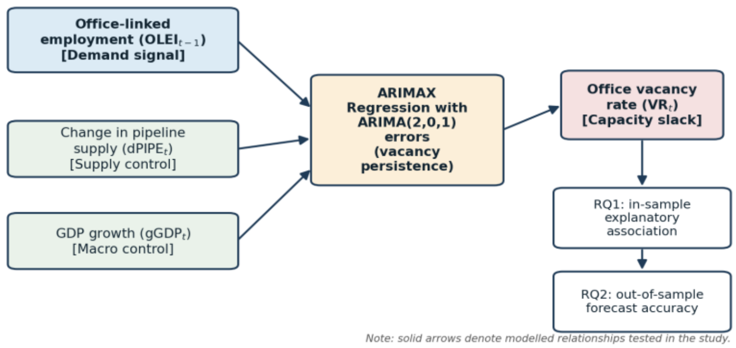

Figure 1. Conceptual Framework of the Study

METHODOLOGY

Research Design

A quantitative quarterly time-series methodology assesses whether employment-based demand signals improve the prediction of office vacancy in Singapore. The orientation is both explanatory and predictive: explanatory structure comes from a demand signal (office-linked employment), a supply control (pipeline supply), and a macroeconomic control (GDP growth), while predictive validity is established through time-consistent out-of-sample evaluation rather than in-sample fit. A regression-with-ARIMA-errors framework jointly addresses two properties of vacancy series: persistence and sensitivity to external fundamentals.

The study uses a longitudinal secondary-data design with quarterly observations from 1993Q3 to 2025Q3 for the Singapore national office market. The dependent variable is the office vacancy rate, a system-level measure of capacity slack. The main predictor is an office-linked employment indicator (quarterly employment change in office-using industries), entered at a one-quarter lag to reflect delayed adjustment; supply is controlled by the quarter-on-quarter change in pipeline supply and macro conditions by year-on-year GDP growth. The study proceeds through six stages: data preparation, descriptive analysis, RQ1 in-sample analysis, RQ2 out-of-sample evaluation, robustness and structural-change checks, and a summary of findings.

Variable Definitions

The variables used in this study are defined to reflect the main elements of the office-market capacity-planning problem: vacancy as the utilisation outcome, employment as the demand-side signal, pipeline change as the supply-side control, and GDP growth as the macroeconomic control.

The dependent variable is the office vacancy rate (VR_t). It is constructed as the ratio of vacant private office space to available private office space in quarter t, as taken from Wheaton (1987) and Khor et al., (2000).

$$VR_t = VOS_t / AOS_t \qquad (1)$$

where VOS_t is vacant private office space and AOS_t is available private office space. This variable is interpreted as a measure of capacity slack in the office market. The main demand-side variable is the office-linked employment indicator ($OLEI_t$). It refers to the sum of quarterly employment changes across selected office-using industries in finance, professional services, information and communications, telecommunications, and real estate-related activities. To reflect delayed adjustment between labour-market conditions and office occupancy, the main model uses the one-quarter lag of this variable, denoted $OLEI_{t-1}$.

The supply-side variable used in the final model is the quarter-on-quarter change in office pipeline supply, denoted $dPIPE_t$. Referenced from Box & Jenkins (1976), it is defined as:

$$dPIPE_t = PIPE_t - PIPE_{t-1} \tag{2}$$

where $PIPE_t$ is total office space in the pipeline at quarter t. This specification is used instead of the pipeline level because the level series showed non-stationary behaviour, while the differenced series was more appropriate for modelling and remained economically interpretable. The macroeconomic control is GDP year-on-year growth, denoted $gGDP_t$, used to capture broader business-cycle conditions. The variables and their roles in the study are summarised in Table 1.

Table 1. Variables and Their Roles

Variable	Symbol	Definition / construction	Role in study	Frequency
Office vacancy rate	VR_t	VOS_t / AOS_t	Dependent variable; capacity-slack measure	Quarterly
Office-linked employment	$OLEI_t$	Sum of quarterly employment changes across office-using industries	Demand-side signal	Quarterly
Lagged employment	$OLEI_{t-1}$	One-quarter lag of $OLEI_t$	Main demand-side regressor	Quarterly
Change in pipeline supply	$dPIPE_t$	$PIPE_t - PIPE_{t-1}$	Supply-side control	Quarterly
GDP YoY growth	$gGDP_t$	Year-on-year GDP growth	Macroeconomic control	Quarterly

Source: Author's elaboration (2026)

Data Preparation

All datasets are converted to a common year-quarter index and merged by quarter. The vacancy rate is constructed from the vacant and available private office space series, and the office-linked employment indicator by filtering the employment-change-by-industry data to office-using industries (financial institutions and services, insurance, legal, accounting and management, architectural and engineering, other professional services, IT and information services, telecommunications, broadcasting and publishing, and real-estate-related services) and summing quarterly changes, then taking a one-quarter lag for the main models.

Total office pipeline supply is extracted from the raw pipeline dataset; because the level series was unsuitable in raw form, the final specification uses its quarter-on-quarter change, and GDP is retained as year-on-year growth. The sample is restricted to quarters with the dependent variable and all regressors available, giving a model-ready dataset from 1993Q3 to 2025Q3.

Model Specification

This study uses regression with ARIMA errors (ARIMAX) to combine interpretable external drivers with the dynamic behaviour of office vacancy. The general model structure expresses the dependent variable as a linear function of selected exogenous regressors plus an ARIMA error term. Specifically, the office vacancy rate VR_t is modelled as a function of explanatory variables $X_{k,t}$ (for k = 1, ..., n) with coefficients βk and an error term u_t , taken from Hyndman & Khandakar (2008):

$$VR_t = \beta 0 + \Sigma\beta k\, X_{k,t} + u_t \qquad (3)$$

Vacancy is highly persistent over time, so the error term is modelled using an ARIMA structure. An AR(1) error was used as the initial starting point, but alternative ARIMA error structures were compared when diagnostics showed remaining serial dependence. In the final implemented models, the retained error structure was ARIMA(2,0,1).

Model Specification for RQ1

RQ1 examines whether office-linked employment is associated with office vacancy after controlling for supply-side change and macroeconomic conditions under time-series dependence. The final RQ1 model, adopted from Hyndman and Khandakar (2008), is:

$$VR_t = \beta 0 + \gamma\, OLEI_{t-1} + \beta 1\, dPIPE_t + \beta 2\, gGDP_t + u_t \qquad (4)$$

In the final implemented analysis, the error term u_t is modeled using ARIMA(2,0,1). This allows the model to account for the strong persistence observed in office vacancy while testing whether lagged employment adds explanatory value beyond supply-side change and macroeconomic conditions. The coefficient on lagged employment is interpreted as a predictive association rather than a causal effect.

Model Specification for RQ2

RQ2 tests whether lagged office-linked employment improves out-of-sample forecast accuracy relative to a baseline model without employment. A two-model design, adopted from Tashman (2000), is used.

Model A (baseline without employment):

$$VR_t = \beta 0 + \beta 1\, dPIPE_t + \beta 2\, gGDP_t + u_t \qquad (5)$$

Model B (test model with employment):

$$VR_t = \beta 0 + \gamma\, OLEI_{t-1} + \beta 1\, dPIPE_t + \beta 2\, gGDP_t + u_t \qquad (6)$$

Both models use the same ARIMA(2,0,1) error structure, so the comparison isolates the incremental contribution of employment rather than differences in dynamics. Forecasts are evaluated using a rolling-origin, expanding-window design in which, at each origin, models are estimated on data available up to that point and forecasts generated one and four quarters ahead. Accuracy is measured by MAE and RMSE, with a Diebold-

Mariano test as a supplementary comparison.

Structural Change and Robustness

Because office demand may have changed after 2020, structural change is treated as a modelling risk and assessed two ways. For RQ2, forecast performance is reported separately for pre- and post-2020 periods; for RQ1, an interaction model tests whether the employment-to-vacancy relationship shifted after 2020. Following the regime-aware evaluation logic advocated for forecasting work (Hewamalage et al., 2023), the robustness specification is:

$$VR_t = \beta 0 + \gamma\ OLEI_{t-1} + \theta\ D_{post,t} + \delta\ (D_{post,t} \times OLEI_{t-1}) + \beta 1\ dPIPE_t + \beta 2\ gGDP_t + u_t \quad (7)$$

Where $D_{post,t}$ is a dummy variable that equals 1 for quarters from 2020Q1 onward and 0 otherwise. In this model, γ captures the employment effect before 2020, θ captures any general post-2020 shift in vacancy, and δ captures whether the employment effect changed after 2020. The robustness model uses the same ARIMA(2,0,1) errors; a meaningful interaction implies a regime-dependent relationship, otherwise the conclusions are stable across pre- and post-2020 periods. All analyses are implemented in R using a reproducible workflow of data ingestion, quarterly alignment, variable construction, lag generation, estimation, diagnostics, and rolling-origin evaluation.

RESULTS AND DISCUSSION

Data Construction and Descriptive Results

The analysis draws on four quarterly inputs representing the market's utilisation outcome, supply, demand, and macroeconomic conditions: private-sector office space statistics for the vacancy rate, office pipeline supply for supply-side pressure, employment change by industry for the office-linked employment indicator, and GDP year-on-year growth as the macro control. After cleaning, reshaping, and alignment, the four series were merged into a single master quarterly dataset. The research flow from raw data to final analytical model is shown in Figure 2.

Descriptive statistics for the final variables are reported in Table 2. The vacancy rate averages 0.1204 and ranges from 0.0588 to 0.1861, indicating substantial variation in capacity slack. Lagged office-linked employment varies widely with both negative and positive values, reflecting contraction and expansion in office-using employment; pipeline change is volatile, consistent with cyclical development activity, and GDP growth shows the widest dispersion.

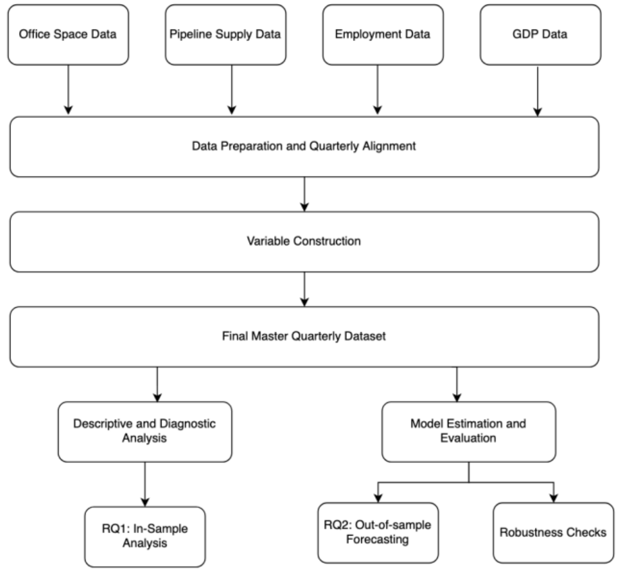

Figure 2. Research Flow from Raw Data to Final Analytical Model

Source: Author's elaboration (2026)

Table 2. Descriptive Statistics of Final Variables (1993Q3 to 2025Q3, N = 129)

Variable	N	Mean	Std. Dev.	Min	Median	Max
vr	129	0.1204	0.0257	0.0588	0.1208	0.1861
olei_l1	129	3.9256	4.6719	−8.0000	2.4000	19.7000
d_pipe	129	−12.6202	113.2511	−303.0000	−14.0000	365.0000
gdp_yoy	129	6.0852	6.6186	−21.2069	6.0794	44.9828

Source: Author's calculation in R based on the final master quarterly dataset (2026)

The quarterly series show that office vacancy is persistent, adjusting gradually rather than sharply from quarter to quarter, consistent with slow-moving changes in occupancy, leasing, and absorption. From an operations management view, this indicates capacity utilisation is not instantly responsive to short-run demand, supporting a modelling framework that accounts for persistence while testing external drivers. Figure 3 presents the office vacancy rate over time and Figure 4 the lagged office-linked employment indicator.

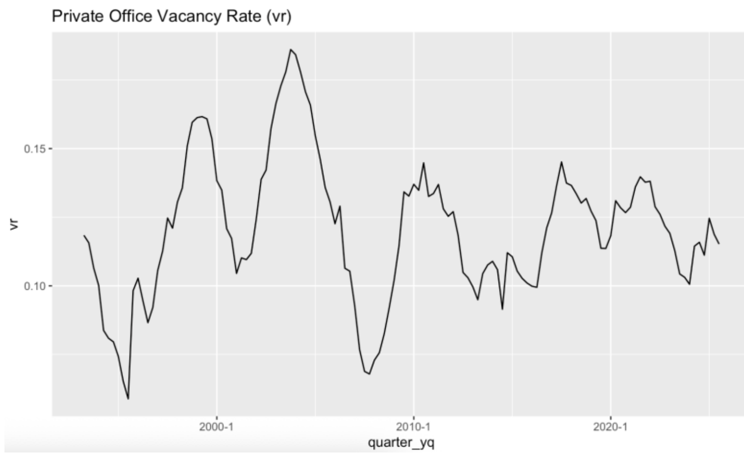

Figure 3. Office Vacancy Rate Over Time
Source: Author's calculation in R (2026)

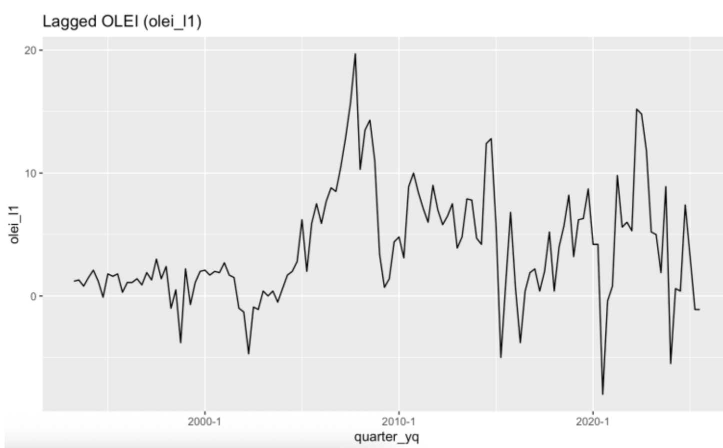

Figure 4. Lagged Office-Linked Employment Indicator Over Time
Source: Author's calculation in R (2026)

Preliminary Diagnostic Checks

Before estimating the main model, the final variables were checked for suitability. Office vacancy, GDP growth, and pipeline change all showed acceptable properties, and lagged office-linked employment produced weaker but still acceptable evidence for inclusion, so the variables were retained without further transformation. The checks also confirmed that using the change in pipeline supply rather than the level was appropriate. Table 3 summarises the preliminary diagnostic checks.

Table 3. Summary of Preliminary Diagnostic Checks

Variable	ADF result	KPSS result	Overall assessment
vr	Stationary ($p < 0.01$)	Stationary ($p > 0.10$)	Suitable for modelling
olei_l1	Stationary at 5% ($p = 0.044$)	Borderline ($p = 0.052$)	Acceptable for inclusion
gdp_yoy	Stationary ($p < 0.01$)	Stationary ($p > 0.10$)	Suitable for modelling
d_pipe	Stationary ($p < 0.01$)	Stationary ($p > 0.10$)	Suitable for modelling
OLS benchmark residuals	Not applicable	Ljung–Box $p < 2.2e-16$	OLS inadequate due to serial dependence

Source: Author's calculation in R based on the final master quarterly dataset (2026)

Office-Linked Employment and Office Vacancy

RQ1 examines whether office-linked employment is associated with vacancy after controlling for supply change and macroeconomic conditions under time-series dependence. An initial AR(1) error structure proved too simple, so alternative ARIMA error structures were tested; the ARIMA(2,0,1) specification performed best, achieving the lowest AIC and being the only candidate to pass the residual autocorrelation check at conventional levels.

Table 4 reports the final RQ1 model. In the ARIMA(2,0,1)-error specification, the coefficient on lagged office-linked employment remained negative, consistent with expectation, but was not statistically significant: once persistence and controls were accounted for, employment showed no robust in-sample association with vacancy. Pipeline change was significant but negatively signed, suggesting it captures market timing rather than immediate supply pressure, and GDP growth was insignificant. The autoregressive and moving-average terms were all highly significant, indicating vacancy is driven mainly by its own persistence and short-run dynamics.

Table 4. Final RQ1 Model Results: Regression with ARIMA(2,0,1) Errors

Variable	Estimate	Std. Error	z-statistic	p-value
AR(1)	1.8414	0.0588	31.304	<0.001
AR(2)	−0.8878	0.0546	−16.263	<0.001
MA(1)	−0.7223	0.0916	−7.886	<0.001
Intercept	0.1223	0.00523	23.388	<0.001
Lagged employment (olei_l1)	−0.000153	0.000169	−0.906	0.365
Change in pipeline (d_pipe)	−0.0000179	0.00000457	−3.920	<0.001
GDP growth (gdp_yoy)	−0.0000667	0.000170	−0.391	0.696

Source: Author's calculation in R based on the final master quarterly dataset (2026)

Taken together, much of the explanatory power in office vacancy comes from its own dynamic structure rather than from the employment indicator, so the evidence for RQ1 is limited and employment does not emerge as a statistically robust in-sample factor.

The final model suggests office-linked employment carries some directional information but not enough for a robust in-sample relationship once persistence is modelled. The negative coefficient is consistent with the expectation that stronger office-linked labour demand should lower vacancy (Foo & Higgins, 2007; Ho et al., 2014), yet weaker than a simple demand-signal view. As Hendershott et al. (1999) and Tse & Webb (2003) note, employment operates within a wider system of rents, absorption, supply responses, and market timing, so it remains economically relevant but is not a statistically robust standalone factor.

This is supported by wider office-market research showing that theoretically relevant demand-side variables do not always retain explanatory power once local market dynamics are modelled (Brounen & Jennen, 2009; Öven & Pekdemir, 2006). Notably, changes in the share of employees working from home did not produce statistically significant effects on office rents and vacancy in a European time-series framework (Morawski, 2022), reinforcing that labour-related demand indicators may remain economically plausible yet empirically weak.

The significant but negatively signed pipeline change variable indicates that supply-side movements matter, but not as a simple increase in supply raising vacancy. A plausible interpretation is that pipeline expansion often occurs in stronger market conditions, when developers respond to favourable expectations and vacancy is still low, so the variable reflects market timing rather than mechanical supply pressure. This is consistent with real-option views of office development, in which construction timing responds to expected future demand and uncertainty (Fu & Jennen, 2009), and with dynamic models in which supply responses lag demand and may not carry the expected sign in a single reduced-form equation (Hendershott et al., 1999).

A further RQ1 result is the strong persistence in vacancy: the significant ARIMA dynamic terms indicate that vacancy behaves as a slow-moving capacity-slack variable rather than a short-run response to individual drivers. For operations management, this implies office-market slack should be monitored as a dynamic system variable shaped largely by its own past, with external signals such as employment and supply operating within that broader adjustment process.

Overall, RQ1 receives limited support, but this does not invalidate the broader thesis: a variable can fail to explain in-sample variation strongly yet still improve forecast performance if it carries incremental predictive information.

Further Considerations for Multicollinearity, Structural Break, Hybrid Work and Lag Length

Four further issues bear on the RQ1 results. First, on multicollinearity, the model has only three economically distinct regressors with low pairwise correlations, lagged office-linked employment, pipeline-supply change, and GDP growth and variance-inflation factors well below the conventional threshold of five, so multicollinearity is not material and does not explain the insignificant employment coefficient.

Second, on structural breaks, the Equation (7) interaction model and an event-based extension across the Asian Financial Crisis, Global Financial Crisis, and post-2020 period were estimated. No employment-crisis interaction was significant, and recursive and rolling estimates of the employment coefficient stayed near zero with confidence bands including zero in most windows, so the weak effect is stable across crisis and non-crisis subperiods rather than an averaging artefact.

Third, on hybrid work, the implied post-2020 employment effect turned only marginally positive and stayed insignificant, consistent with remote and hybrid arrangements softening the mapping from headcount growth to office absorption (Barrero et al., 2023; Bergeaud et al., 2023; Van Nieuwerburgh, 2023): firms may add employment without proportionate occupancy. The evidence points to a gentle softening rather than a sharp break.

Fourth, regarding delayed adjustment of more than one quarter, the main model uses a one-quarter lag for parsimony, but since office space adjusts through multi-quarter leasing and fit-out cycles, longer-lag and distributed-lag specifications were considered. Extending the lag reduces the effective sample and, given that recursive and rolling estimates already show the coefficient near zero throughout, did not strengthen the employment signal, so the one-quarter lag was retained and the conclusion is robust to the lag choice.

Employment Indicators and Out-of-Sample Forecast Accuracy

RQ2 examines whether adding office-linked employment improves out-of-sample forecast accuracy relative to a baseline without it, using the rolling-origin, expanding-window design described above at one-quarter (short-term) and four-quarter (medium-term) horizons. Performance is assessed using MAE and RMSE, with Diebold-Mariano tests as supplementary comparisons (Hyndman & Koehler, 2006). Model A is the baseline with pipeline change and GDP growth and ARIMA(2,0,1) errors; Model B adds lagged office-linked employment.

At the one-quarter-ahead horizon the baseline outperformed the employment model on both measures: Model A recorded an MAE of 0.00473 and RMSE of 0.00671, against 0.00512 and 0.00729 for Model B, and won more periods (16 versus 13). The Diebold-Mariano test gave no strong evidence of superior accuracy for the employment model, so adding employment did not improve short-horizon forecasting (Figure 5).

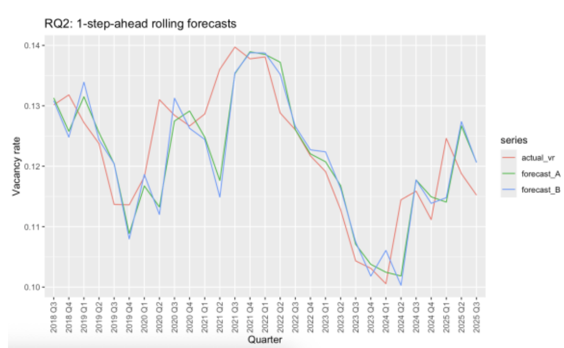

Figure 5. Actual vs Forecasted Vacancy, 1-Quarter-Ahead

The four-quarter-ahead horizon showed the same pattern: Model A produced an MAE of 0.01121 and RMSE of 0.01267 versus 0.01141 and 0.01298 for Model B, and won more often (14 versus 12). The Diebold-Mariano test was again clearly not significant, so adding lagged office-linked employment did not improve forecast performance even at the longer planning horizon (Figure 6).

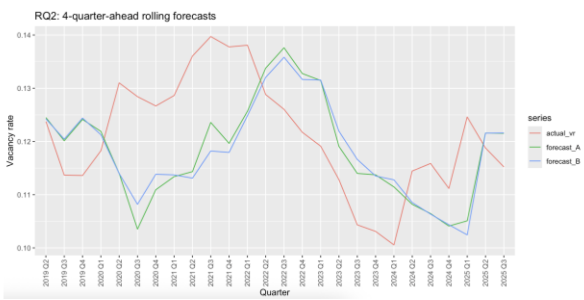

Figure 6. Actual vs Forecasted Vacancy, 4-Quarter-Ahead

Across both horizons the baseline without employment performed slightly but consistently better, so the employment variable added no incremental predictive information; forecasts were driven by the baseline controls and vacancy persistence. The differences were modest, and the Diebold-Mariano results gave no strong evidence of a meaningful gain (Diebold & Mariano, 1995; Hewamalage et al., 2023; Tashman, 2000).

This is consistent with nested-model forecast research: Clark & McCracken (2001) show that when one model nests another, out-of-sample comparisons are hard to interpret because the larger model may fit history more flexibly without genuine predictive gains. The selected employment indicator is therefore not a strong standalone forecasting signal for Singapore office vacancy under the final specification.

One plausible explanation is that post-pandemic hybrid and remote work weakened the traditional link between office-linked employment and physical office demand, which earlier translated more directly into absorption. Such arrangements have remained materially above pre-pandemic norms (Barrero et al., 2023; Bergeaud et al., 2023; Van Nieuwerburgh, 2023), and work-from-home job postings stayed elevated after restrictions eased (Adrjan et al., 2025). If firms expand employment without proportionate office occupancy, an employment-based indicator becomes less informative as a forecasting input.

CONCLUSION

This study examined whether office-linked employment functions as a useful demand signal for capacity planning by explaining and forecasting Singapore's office vacancy rate, framing the market as an asset-heavy operations system with slow capacity, faster demand, and vacancy as observable slack. Using quarterly data over 1993Q3–2025Q3 with regression-with-ARIMA-errors and rolling-origin evaluation, the evidence offers only limited support. For RQ1, lagged employment kept the expected negative sign but was insignificant once persistence, pipeline change, and GDP were controlled; vacancy is explained mainly by its own dynamics. For RQ2, the baseline without employment gave lower MAE and RMSE and more wins at both horizons. Robustness checks across crisis and post-2020 regimes pointed to the same weak, stable effect.

The main implication is that office vacancy in Singapore should be monitored as a dynamic capacity-slack variable rather than a point-in-time response to one indicator, emphasising persistence, supply timing, and macroeconomic conditions. Office-linked employment is best treated as a supplementary signal, and forecasting frameworks should rest on disciplined baselines, adding variables only when they demonstrably improve out-of-sample performance.

The study contributes by extending operations-management thinking into commercial real estate, by showing that theoretical plausibility and empirical usefulness are distinct, and by providing a transparent, replicable quarterly workflow. Its limitations indicate clear next steps: the employment indicator is only a proxy for office demand, the analysis is at the national level, and the post-2020 sample is still evolving, so future work could use more direct measures of office use, disaggregate by submarket and building grade, and revisit the models as more post-2020 data accumulate.

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