Forecasting Private-Sector Construction Works: VAR Model Using Economic Indicators

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Abstract: Accurately modeling and forecasting construction works completed by main contractors is pivotal for policymakers, who require reliable market intelligence to adjust or develop optimal labor and housing policies. Yet, despite its importance, limited research has been conducted to systematically develop approaches to investigating future trends of works completed in the private construction sector. Against this backdrop, this paper provides a study of the annual financial value of construction work in the private residential market. A vector autoregression (VAR) model developed utilizes economic indicators (used by private financiers when making investment decisions) to estimate the value of annual construction work carried out by main contractors. Using data from the Hong Kong private residential market and constructing an accumulated impulse function, the developed model suggests that construction work completions in private residential markets can be explained by changes in economic indicators such as gross domestic product and the property price index. These economic indicators have been identified as having a large and direct effect on forthcoming construction works. The developed model also provides a high degree of accuracy (producing an adjusted R^2 value of 0.72) when simulating or forecasting future changes in the value of construction works over a short-term 5-year forecast. The output of this study contributes to the literature by systematically developing a reliable approach using economic indicators that is useful for forecasting private-sector construction completions. Such knowledge is of paramount importance when estimating the industry's future workload and supply of residential buildings. **DOI: 10.1061/(ASCE)CO.1943-7862.0001016.**

Author keywords: Construction works; Economic indicators; Granger causality; Vector auto-regression model; Quantitative methods.

Introduction

Construction is a complex and challenging industry (Agapiou et al. 1995). It not only significantly contributes to an economy's gross domestic product (GDP) but also provides basic physical and organizational structures needed for sustainable development. Because the industry represents the economic and social wellbeing of an economy, a deeper knowledge and understanding of trends in annually completed construction works is of great importance to investors and policymakers alike, for example, for developing workforce policy and highlighting new investment opportunities (Tang et al. 1990; Coulson and Kim 2000). Unfortunately, the sector's inherent and cyclical economic instability and volatility has raised concerns over the accuracy of predicting the financial value of construction works completed by main contractors, particularly in private residential development (Yiu et al. 2004). In most developed countries, over 60% of construction works completed relate to private residential development (Census and Statistics Department 2013). However, limited empirical research has been undertaken to forecast the financial value of construction works using economic indicators, despite the imperative need for such. The limited studies undertaken demonstrate an inclination to predict the demand side of residential buildings using social indicators, such as local demand among residents or the number of families considered in models. The extant literature also reveals a tendency in property market forecasting to focus mainly on commercial, industrial, and retail developments, neglecting the private residential development sector (Kling and McCue 1991; Tsolacos 1998).

This paper argues that the forthcoming completion of construction works should be based on deterministic investment decision making criteria, such as current economic conditions, property prices, credit conditions, and the balance between demand and supply of residential buildings (Mohamed and McCowan 2001). This approach would provide policymakers and stakeholders with a better understanding of the future economic value of private residential construction works slated for completion. The developed forecasting model applies a vector autoregression technique but incorporates endogenous variables related to investment decision making associated with construction activity. It is suggested that this model provides an effective tool for forecasting the annual value of construction works to be completed in the private residential sector as well as for evaluating construction workforce demand and predicting the future supply of private housing.

Theoretical Justification

Private-sector investment decisions in construction projects represent a major commitment of resources (e.g., labor, plant, and materials) and may have serious consequences for a developer's profitability and financial stability (Fewings 2013). From a normative view, a number of studies have explored the key economic factors affecting investor decision making. Green (1997) used the technique of Granger causality to measure how changes in

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Table 1. Major Studies in Estimating the Completion of Buildings through Economic Indicators

Author	Economic and social indicators	Type of property construction
Nicholson and Tebbutt (1979)	Capital utilization, index of manufacturing production, yield of government consoles	Industrial buildings
Wells (1985)	Economic growth	Industrial and residential buildings
Kling and McCue (1987)	Macroeconomy	Office buildings
Killingsworth (1990)	Industrial construction, economic shocks, sales, interest rate	Industrial buildings
Goh (1996)	GDP, building material price index, money supply, consumer price index, labor force, unemployment rate, and others	Residential buildings
Kling and McCue (1991)	Macroeconomy	Industrial buildings
Akintoye and Skitmore (1994)	Construction price, real interest rate, unemployment level, profitability	Industrial and residential buildings
Green (1997)	GDP	Industrial and residential buildings
Tsolacos (1998)	Consumer expenditure, retail return	Retail developments

an economy affect residential and nonresidential investment. Lean (2001) sought to verify whether historical variations in construction data followed or preceded those of other sectors and the aggregate economy. In addition, multivariate time series techniques, such as multiregression and vector autoregressive (VAR) approaches, were used to forecast the number of new work orders for industrial buildings and retail developments (Kling and McCue 1991). Similarly, Tsolacos (1998) developed a regression model for studying the relationship between changes in real consumer expenditures and real retail returns. Research also revealed that a VAR model could predict long-term as well as upward and downward trends of new orders for retail developments (Tsolacos 1998). Tse and Ganesan (1997) demonstrated a positive relationship between construction work and GDP using a Granger causality test, while Yiu et al. (2004) used Granger causality to examine the longitudinal relationship between construction output and the aggregate economy. Table 1 provides a summary of prior research on this topic. This prior research demonstrates that macroeconomic indicators possess information that is critical for studying the development of economic sectors, i.e., construction (Jiang and Liu 2011; Liu et al. 2014a, b).

A better understanding of the dynamics of construction works completed annually would assist with the development and implementation of appropriate labor and housing policies. Unlike previous research, this paper attempts to connect four key economic factors, namely: (1) economic conditions, (2) credit conditions, (3) profit earning, and (4) demand and supply of residential construction. The study's findings prove that through the VAR model, economic indicators can be used to forecast future private building work completed and accurately capture the long-term trend and turning points.

Methodology

To forecast annual construction works, a VAR model is developed. Given a set of K time-series variables (or endogenous variables), $Y_t = (y_{1\,t}, y_{2\,t}, \ldots, y_{Kt})$, the basic p-lag VAR [VAR(p)] model has the form

$$Y_t = c + \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \ldots + \prod_p Y_{t-p} + \varepsilon_t \qquad (1)$$

where $\prod_i = (n \times n)$ coefficient matrices; c = constant vector; and ε_t = an $(n \times 1)$ unobservable zero-mean white-noise vector process with time-invariant covariance matrix. The model is stable if $\det(I_k - \prod_1 z_1 - \ldots - \prod_p Z_p) \neq 0$ for $|z| = 1$.

The VAR is a popular and straightforward method for the analysis of multivariate time series and is especially useful for describing the dynamic behavior of economic and financial time series (McQuarrite and Tsai 1998; Atsushi and Lutz 2013). However, the variables to be included in the VAR are rarely known beforehand. Because this research focused on how business investment decisions affect construction output in private residential development, subsequent modeling is limited to variables that are related to indicators of economic growth and profit making sourced from the extant literature (Lean 2001; Yiu et al. 2004). Further, the vacancy rate, representing the number of unoccupied residential flats, is also included to incorporate the imbalance between demand and supply of private housing into the VAR model (cf. Stevenson and Young 2013). The overarching VAR model development is diagrammatically depicted in Fig. 1 to accompany the narrative,

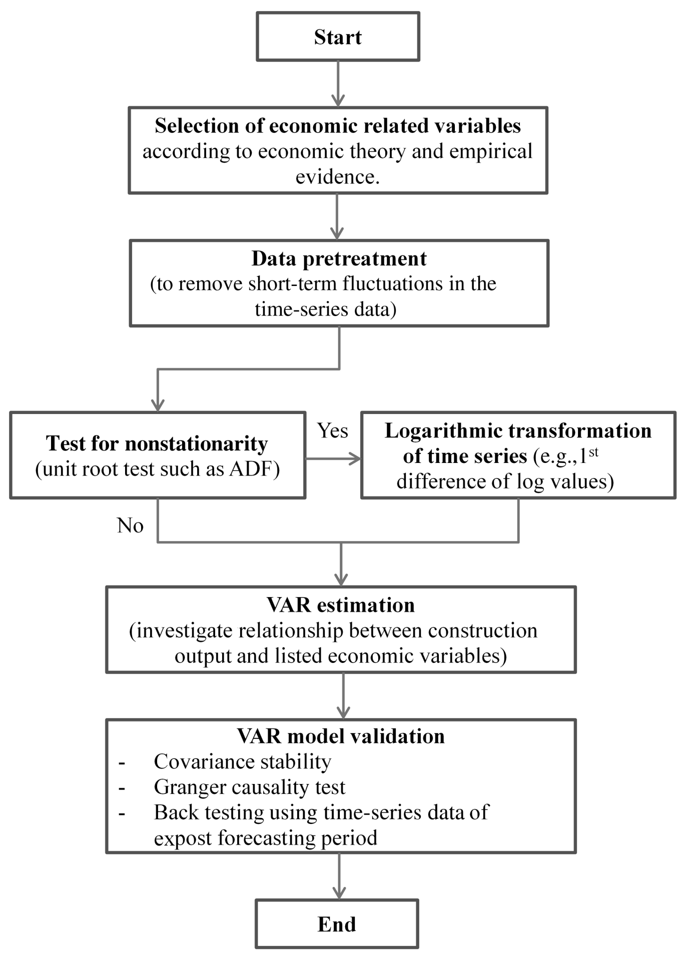

Fig. 1. VAR model development

and a detailed discussion of the selected economic variables is presented as followins.

Construction Works and Output (in Dollar Terms)

The term *construction works* describes the creation of physical infrastructure (Wells 1985), and for this study, construction works completed annually by main contractors were measured by their gross value [in Hong Kong dollars (HK$)]. Fig. 2 identifies the pattern of private-sector construction works completed in the period 1989–2013 in Hong Kong, within which four distinct time periods are apparent. From 1989 to 1993, construction works completed rose steadily until 1993, when a drop in output occurred due to economic recession. From 1994 to 1998, a series of large-scale infrastructure projects commenced and business confidence improved, which led to a rise in completed construction works until 1999. During the period 1999–2006, investment dropped dramatically as a result of the Asian financial crisis that occurred in 1997. A gradual increase in the amount of completed construction work was thereafter experienced from 2007 to 2009, though levels were considerably lower than at the 1990s peak.

Economic Conditions, As Measured by Gross Domestic Product

A positive statistical correlation exists between construction activity and economic conditions (Kling and McCue 1987). Research reveals that construction business cycles are also closely aligned with prevailing economic conditions, which influence investors' expectations and their intention to participate in development projects (Tse and Ganesan 1997). During periods of economic expansion, investors invariably become optimistic about the extent to which growth can be sustained and, consequently, borrow money to make construction investments (Baumohl 2012). Conversely, when an economy contracts, such investments are significantly reduced. This business cycle is primarily measured and tracked in terms of GDP (Fleurbary and Blanchet 2013). GDP per se represents the health of an economy in monetary terms; examples of business cycle perturbations include the Asian financial crisis in 1997, which caused the Hong Kong construction industry to contract between1999 and 2006.

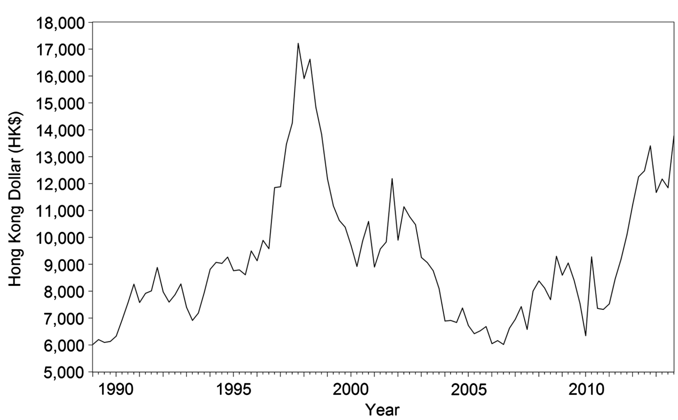

Fig. 2. Gross value (nominal value in Hong Kong dollars) of construction works completed in private sector (data from Census and Statistics Department 2012)

Credit Conditions, As Measured by the Best Lending Rate BLR

Construction projects are typically financed by commercial banks and insurance companies, and interest payments on a loan can determine the project viability (Gruneberg 1997; Collier et al. 2008). In Hong Kong, for example, the interest payment may account for more than 20% of the total development costs (Census and Statistics Department 2012). When interest rates are low, developers borrow money more cheaply, thereby providing an incentive to invest. In contrast, when interest rates are high, an investment becomes more expensive. Then developers are likely to eschew investment in building developments, resulting in a fall in the construction work completed in later years. For the VAR model developed in this paper, the best lending rate (BLR) published by the Hong Kong Monetary Authority was used to represent credit conditions for private residential developments.

Profit Earnings, As Measured by the Property Price Index

Private residential developers are mainly interested in the profit margin they might gain from land development. To capture this factor in an investor's decision-making process, a property price index (PPI) is used to measure profits earned in the VAR model, where the PPI represents a measure of the change in value of residential buildings for a specific year (Wilson et al. 2002). PPI attempts to aggregate market information by providing a more accurate representation of underlying real estate asset performance (Diewert et al. 2013). The methodology for constructing the PPI is derived from an analysis of all effective transactions in a given period. It therefore enables developers to improve their investment decision making. The PPI time series used in this research is derived from reports on property published by the rating and valuation department (RVD) of the Hong Kong Government.

Demand and Supply of Private Residential Building, As Measured by Vacancy Rate

The vacancy rate (VR) determines the supply and demand conditions in the real estate market (Benjamin et al. 1998). For instance, if the demand increases and supply remains stable, vacancies will decrease. Based on this knowledge, property developers can determine the market's profit-making potential and make an effective decision as to whether to invest.

Model Development and Validation

Data Pretreatment and Methods

The data used in this study include quarterly time series for completed construction works (in Hong Kong dollars, PCW), GDP, BLR, PPI, and VR from January (Q1) 1989 to December (Q4) 2013. To prevent any random short-term fluctuations, a centered four-quarter moving-average technique is applied to smooth the trend of the raw data in the presence of quarterly seasonality [Eq. (2)]

$$\widehat{y}_i = \frac{y_{i+2} \cdot 1/2 + y_{i+1} + y_i + y_{i-1} + y_{i-2} \cdot 1/2}{4} \qquad (2)$$

where $y = \{\mathrm{PCW}, \mathrm{GDP}, \mathrm{BLR}, \mathrm{PPI}, \mathrm{VR}\}$.

For annual construction works completed in the private residential sector, statistics from the *gross value of private construction works (nominal value) performed by main contractors (PCW)* (as published by the Hong Kong Census and Statistics Dept.) were collected (Census and Statistics Department 2013); this data set includes the number of construction works completed from the entire private sector, including residential, commercial, and industrial building development. Thus, to calculate the proportion of residential building development within these published data, secondary data sets that contain the monetary value of contractors' earnings are used and derived from the *Report on the Annual Survey of the Building, Construction, and Real Estate Sectors* (Census and Statistics Department 2009) and *Key Statistics on Business Performance and Operating Characteristics of the Building, Construction, and Real Estate Sectors* (Census and Statistics Department 2012). The tender price index (TPI), which measures the trend of contractors' price level for new projects, is used as a deflator to obtain real construction work output (RCWO) from the nominal PCW [Eq. (3)]. Similarly, the nominal GDP value from the government of Hong Kong was also deflated by the GDP implicit deflator to obtain real GDP (RGDP) [Eq. (4)] so as to eliminate the effect of price inflation.

With the aforementioned statistics, the output for residential building development is expressed as

$$\mathrm{RPCW}_t = \alpha_t \cdot \frac{\mathrm{PCW}_t}{\mathrm{TPI}_t} \tag{3}$$

where PCW_t = nominal value of construction works (HK$) completed in the private sector at time t; α = share of residential building development derived from the *Report on the Annual Survey of the Building, Construction, and Real Estate Sectors*; RPCW_t = real value of private construction output in private residential development; and TPI_t = tender price index

$$\mathrm{RGDP}_t = \frac{\mathrm{GDP}_t}{ID_t} \tag{4}$$

where GDP_t = nominal GDP at time t; ID_t = GDP implicit deflator; and RGDP_t = real GDP.

Test for Nonstationarity

The validity of the VAR model depends on whether the time series are stationary or exhibit periodic fluctuations (Koop 2013; Woodward et al. 2012). For example, when two different unrelated nonstationary series are regressed on each other, a so-called spurious regression is produced, in which the ordinary least-squares (OLS) estimates and t-statistics indicate that a relationship exists when, in reality, no such relationship does. Results obtained are therefore erroneous. Fig. 3 provides time-series plots of variables considered in the VAR model. It demonstrates a notable pattern of

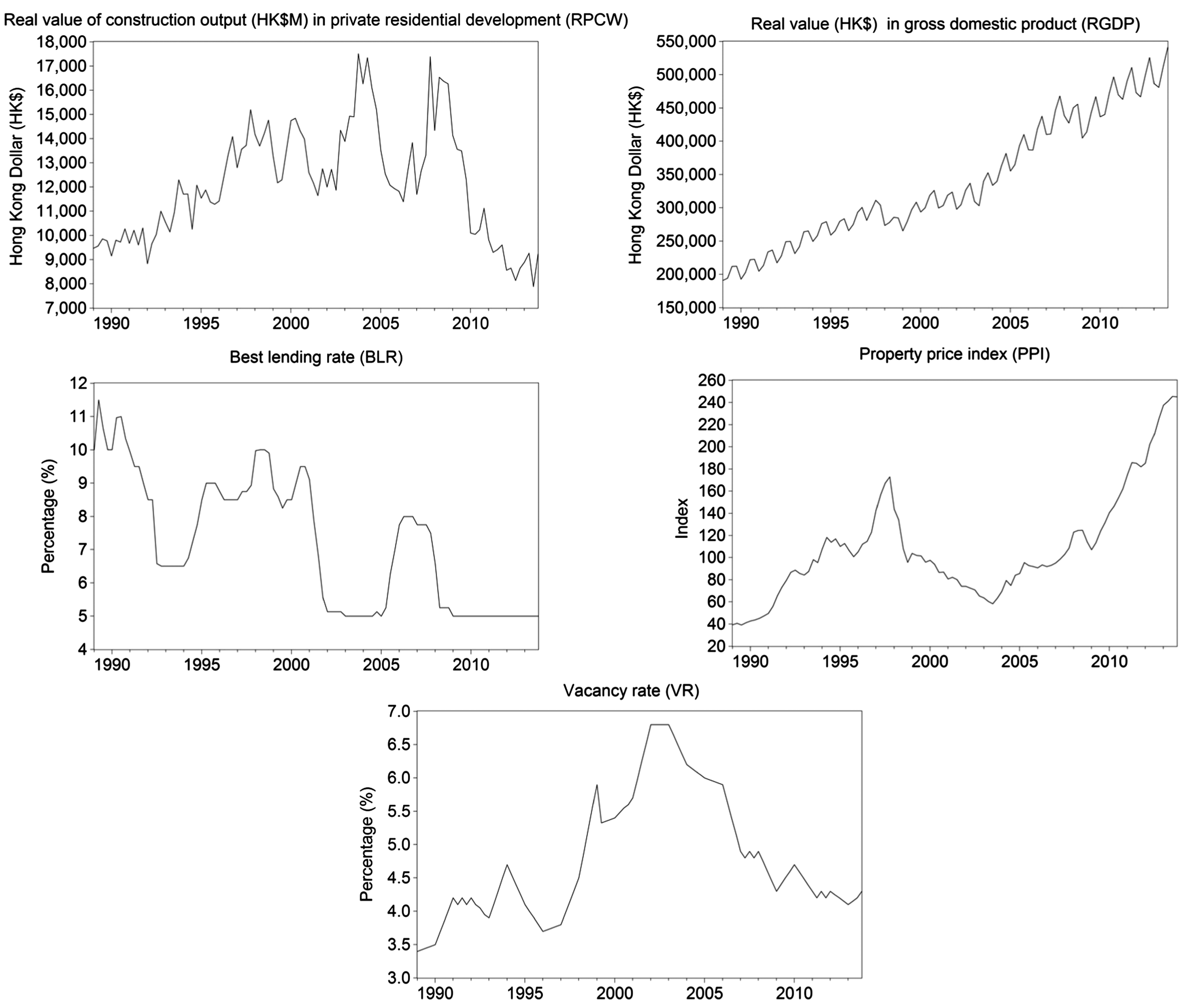

Fig. 3. Time series variables in VAR model

Table 2. Augmented Dickey–Fuller (ADF) Unit Root Tests

Time series variables	Level		First difference in log levels	
	Model specification	Test statistic	Model specification	Test statistic
$RPCW_t$	Trend and intercept	−2.5119	Intercept	−3.944211[a]
$RGDP_t$	Trend and intercept	−1.4620	Intercept	−3.4860[b]
PPI_t	Trend and intercept	−0.9057	Intercept	−6.4534[a]
BLR_t	Trend and intercept	−3.1125	Intercept	−6.2738[a]
VR_t	Trend and intercept	−1.4472	Intercept	−5.5575[a]

Note: According to Mackinnon (1991), the critical value of the ADF test is −4.0575 at a 1% level of significance and −3.458 at a 5% level of significance.
[a]Indicates significant at 1% level.
[b]Indicates significant at 5% level.

trend and periodic fluctuation and the likelihood that nonstationarity may exist among the time-series data.

Unit root tests, such as the augmented Dickey–Fuller (ADF), can establish whether the trending data should be first differenced or regressed on deterministic functions of time to render the data stationary (Kirchgassner and Wolters 2007). The null hypothesis is that a unit root at some level of confidence exists in a nonstationary trend. ADF test results (Table 2) are compared with the critical values given in Mackinnon (1991). The analysis reveals that $RPCW_t$, $RGDP_t$, PPI_t, BLR_t, and VR_t had been nonstationary level terms, but the series became stationary in their first difference of its log-level (i.e., percentage change) terms, where a stationary series is a requirement of VAR modeling (Koop 2013). This study therefore applies a logarithmic transformation of the time series being studied.

VAR Model Estimation

To investigate the relationship between construction output in private residential development and the listed economic variables, the VAR(8) model used in this empirical analysis can be written as

$$Y_t = c + \sum_{k=1}^{8} \prod_k Y_{t-k} + \varepsilon_t \tag{5}$$

where $Y_t = \{\Delta \log(\mathrm{RPCW})_t, \Delta \log(\mathrm{RGDP})_t, \Delta \log(\mathrm{PPI})_t, \Delta \log(\mathrm{BLR})_t, \Delta \log(VR)_t\}$; $\prod = 8 \times 5$ coefficient matrices; $c = 8 \times 1$ constant coefficient vectors; and ε = error term of 8×1 vectors. Hence, the VAR of Eq. (5) can be represented as follows:

$$\begin{aligned}\Delta \log(\mathrm{RPCW})_t &= c + \sum_{k=1}^{8} \Pi_{1,8} \Delta \log(\mathrm{RPCW})_{t-8} \\ &+ \sum_{k=1}^{8} \Pi_{2,8} \Delta \log(\mathrm{RGDP})_{t-8} + \sum_{k=1}^{8} \Pi_{3,8} \Delta \log(\mathrm{PPI})_{t-8} \\ &+ \sum_{k=1}^{8} \Pi_{4,8} \Delta \log(\mathrm{BLR})_{t-8} + \sum_{k=1}^{8} \Pi_{5,8} \Delta \log(VR)_{t-8} + \varepsilon_t\end{aligned} \tag{6}$$

In the VAR framework, each endogenous variable is explained and forecasted by lags of its own values together with lags of all other variables within a simultaneous equation system. To determine the lag length in Eq. (5), the lagged effect between the construction output and the decision to initiate projects must be considered. The design and construction sequences often begin after an investment decision has been made, and the time taken to implement a project can vary dramatically (Killingsworth 1990; Goh 2000). A time lag therefore exists between the decision to build and construction project completion and can be modeled using a logarithm of construction costs (Chan 1999). It is proposed that the mean of construction duration (from the decision to build) is around 0.7 and 2.3 years. Based on Chan's (1999) work, a lag length of 2 years ($t = 8$ quarters) is selected in the preliminary VAR model. According to Claeskens and Hjort (2008), a valid VAR structure is one with a minimum Akaike information criterion (AIC) value. The decision of $t = 8$ yielded the lowest AIC value and thus fulfills the criteria for building a valid model structure.

Unlike the coefficient of determination (R^2), the adjusted R^2 value will increase only if a new data point actually improves the regression and will provide a better understanding of the relationship between dependent variables and independent variables (Johnson and Kuby 2012). The adjusted R^2 value in the proposed model is 0.72, suggesting that 72% of the variation in construction output can be explained by the aforementioned economic variables. The VAR model's estimation coefficients for construction output in private residential development are not discussed in this paper because it is extremely difficult to interpret the coefficient of the endogenous variables in a VAR model that includes many variables and lags (Stock and Watson 2007; Atsushi and Lutz 2013). Instead, an accumulated impulse function is used to trace the responses of endogenous variables, RGDP, BLR, VR, and PPI, to a unit shock (or one standard deviation increase) in the dependent variable of RPCW. Results are depicted graphically to visually show the dynamic relationship within the system. Fig. 4 tracks the responses of construction output (in the residential development) over time to a positive shock of one standard deviation to GDP, BLR, VR, and PPI.

1. Accumulated response of RPCW to a positive shock on RGDP: Positive economic conditions (shock to GDP value) would impact construction output positively but not immediately. An increase in output would commence from the fourth quarter of every year (after 1 year). A plausible explanation is that there is always a lagged effect between the decision to commence a project and project completion.
2. Accumulated response of RPCW to a positive shock to BLR: A shock that produces a high lending rate would negatively impact future construction output. The drops in construction output started from the first, sixth, and tenth quarters and are most likely due to higher lending rates, which would increase project costs. Such a financial circumstance would suppress developers' intentions to initiate new construction projects unless the internal rate of return (IRR) remained positive.
3. Accumulated response of RPCW to a positive shock to VR: Of interest is the nonpronounced effect of a VR shock on the RPCW. Theoretically, a rise in VR would cause a decrease in future construction output because demand for private housing would similarly decrease. However, this relationship is not reflected in the developed VAR model, and though this is somewhat puzzling, it can be explained by the VR thresholds in Hong Kong. The VR has been historically maintained at a very low level over the last 24 years (that is, 1989–2013). The mean VR value over this period is 4.8, and one standard deviation is 0.94 (Fig. 5). Such a low VR has encouraged private developers to invest in residential projects in Hong Kong (Ho 1998). Therefore, even if there is a shock of one positive standard derivation to the response function, the VR would only increase to $4.8 + 1 \cdot \sigma = 5.74$, which is still very low. This explains why the accumulated response function remains positive when a positive shock to the VR occurs. The demand for residential housing is always greater than the available supply.

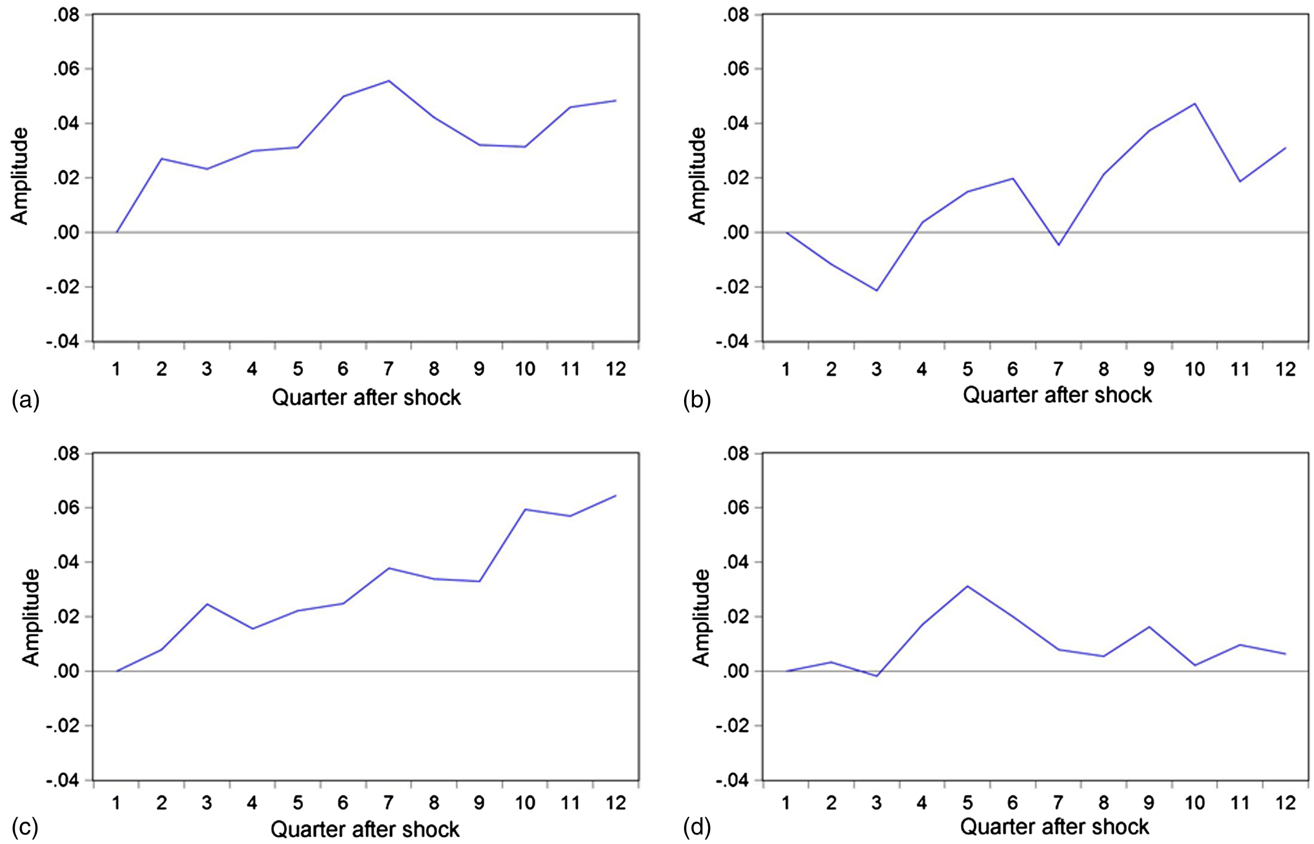

Fig. 4. Accumulated impulse response of RPCW to a one positive standard derivation shock on (a) RGDP; (b) BLR; (c) VR; (d) PPI

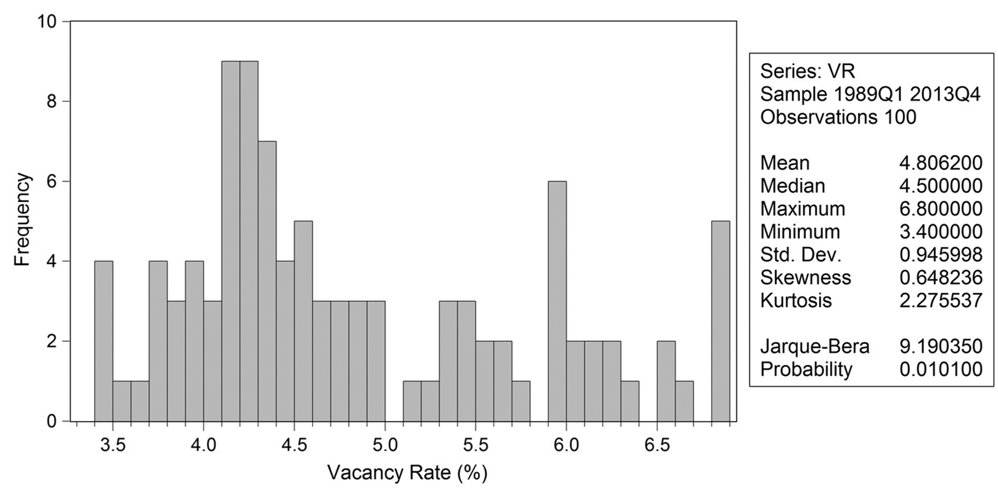

Fig. 5. Descriptive statistics on vacancy rate

4. Accumulated response of construction output in RPCW to a positive shock to PPI: A shock that leads to a high PPI would positively impact construction output in private residential building starting from the fourth quarter. However, the upward trend in construction output would start to decelerate over the sixth quarter owing to the effect of the shock's fading.

VAR Model Validation

Covariance stability is a crucial condition for the validity and consistency of the VAR model. The covariance stability of a VAR can be examined by calculating the inverse roots of

$$\left(I_n - \prod_1 L - \prod_2 L^2 - \ldots\right) \cdot Y_t = \prod(L)Y_t \tag{7}$$

The lag operator, L, can be calculated using $LY_t = Y_{t-1}$. Given an 8×5 square matrix, there is a scalar λ and a vector $c \neq 0$ such that $\prod c = \lambda c$; then λ is an eigenvalue (or inverse root) of $\prod$. Then there will be up to 40 eigenvalues in the developed VAR model, which will give up to 40 linearly endogenous associated eigenvectors such that

$$Ac - \lambda Ic = 0 \Rightarrow [A - \lambda I]c = 0 \tag{8}$$

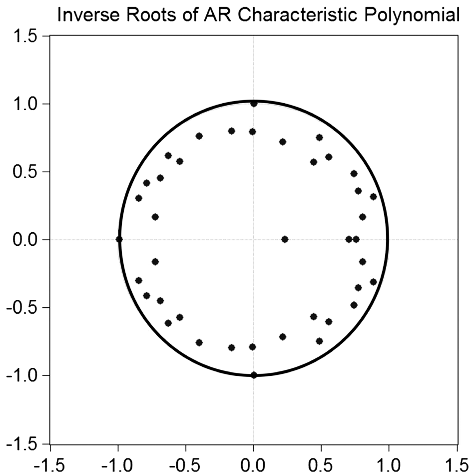

Fig. 6. Inverse root of VAR(8) model

The λ_i are interpreted as eigenvalues (or inverse roots) of Π in a VAR(8) model [as shown by Eqs. (5) and (6)]. In particular, the VAR model is stable if it only has inverse roots of $\lambda_i < 1$. Graphically, Fig. 6 illustrates that all λ_i lie within the circle (<1), and this confirms the stability of the developed VAR model.

Apart from the covariance stability test, the VAR model's structure was further validated through the Granger causality test, which measures whether one time-series variable consistently and predictably changes before other variables (Stock and Watson 2007). The absence of Granger causality between variables X and Y can be tested by estimating the following VAR model

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \ldots + \beta_p Y_{t-p} + \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + \varepsilon_t \quad (9)$$

For example, the null hypothesis should be tested if the coefficients of the lagged variables X all equal zero. If the t-statistic is statistically significant, it can be concluded that the null hypothesis should be rejected and X Granger-caused Y. Granger causality is important because it allows one to analyze which variable precedes or leads the other as well as confirming the validity of the VAR model structure. Table 3 summarizes the Granger causality test results and suggests that the endogenous and economic variables identified in Eq. (5) are significant for the change in construction output in private residential development at the 1 and 5% significant levels.

The VAR model's predictive accuracy is further evaluated by comparing the actual and forecast values for construction output over the ex post forecasting period (Q3 2010–Q4 2013) (Table 4). In addition, the mean absolute percentage error (MAPE) is used to quantify the prediction accuracy of the model. MAPE is the mean of the absolute percentage errors of forecasts for each time period, e.g., quarterly data in the VAR model [Eq. (10)]. Using the actual and forecast figures of construction output over the ex post forecasting period (Q3 2010–Q4 2013) as stated in Table 4, the MAPE of the proposed VAR model is approximately 5.46%. Because this equates to less than 20%, the proposed model is identified as having strong predictability with a high level of accuracy (Lewis 1982). The actual, estimated (over the ex post simulation period Q2 1992–Q2 2010) and forecast values (over the ex post forecasting period Q3 2010–Q4 2013) are plotted in Fig. 7 and reveal that the developed model can accurately capture the long-term trend and turning points in construction output in private residential development.

The MAPE formula is as follows:

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{F_t - A_t}{A_t}\right| \quad (10)$$

where F_t = forecast value at time t; A_t = actual value at time t; and N = number of time-series data in ex post forecasting period.

Table 3. VAR Granger Causality/Block Exogeneity Tests

Dependent variable	Independent variable	Chi-square	Degree of freedom	P-value	Null hypothesis
$\Delta \log(\text{RPCW})$	$\Delta \log(\text{RGDP})$	41.63	8	0.00	Reject
	$\Delta \log(\text{BLR})$	38.13	8	0.00	Reject
	$\Delta \log(\text{PPI})$	17.24	8	0.04	Reject
	$\Delta \log(\text{VR})$	22.27	8	0.03	Reject

Note: P-values denote probability values.

Table 4. Actual and Forecast Value (Ex Post Forecasting Period of Q3 2010–Q4 2013) on Construction Output (Millions of Hong Kong Dollars) in Private Residential Development

Year (quarter)	Actual value (millions of Hong Kong dollars)	Forecast value (millions of Hong Kong dollars)	Difference (%)
2010 (Q3)	10,232	10,563	3.24
2010 (Q4)	11,126	11,470	3.10
2011 (Q1)	9,821	9,962	1.44
2011 (Q2)	9,303	8,708	−6.39
2011 (Q3)	9,415	8,311	−11.72
2011 (Q4)	9,610	8,934	−7.03
2012 (Q1)	8,564	7,995	−6.64
2012 (Q2)	8,654	7,790	−9.98
2012 (Q3)	8,139	7,586	−6.79
2012 (Q4)	8,648	8,271	−4.35
2013 (Q1)	8,892	8,528	−4.09
2013 (Q2)	9,267	9,189	−0.83
2013 (Q3)	7,890	8,355	5.90
2013 (Q4)	9,233	9,686	4.92

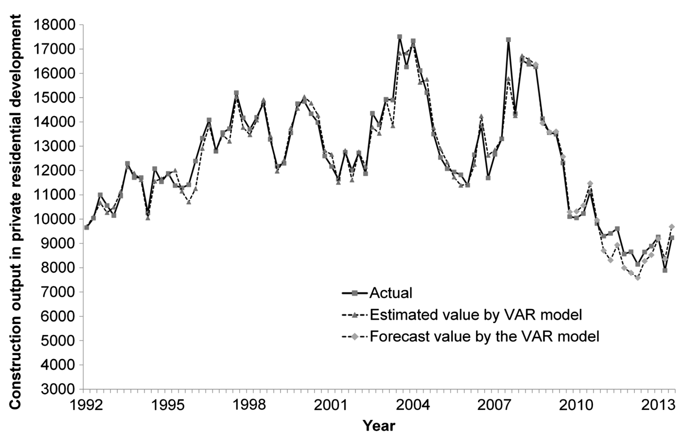

Fig. 7. Comparisons between actual value, estimated value, and forecast value by VAR model

Practical Implications

At the outset of this research, the fundamental objective was to accurately model *workforce demand* and *housing supply in the private sector* to provide pragmatic tools for investors and policymakers. Both models are now discussed in further detail.

Workforce Demand Forecasting

To deliver construction projects within a targeted schedule and budget, sufficient workforce supply is of paramount importance. The strength of training policy for the supply pool can only be imposed if reliable workforce demand forecasting is made (Park et al. 2008; Sing et al. 2012b, 2014). Many researchers have focused on demand forecasting of the construction workforce (Briscoe 1990; Brandenburg et al. 2006; Wong et al. 2011). The labor multiplier approach is commonly adopted in both simple and sophisticated workforce demand modeling (Sing et al. 2012a). It generally makes use of the correlation between the construction works completed and workforce demand per dollar (or labor multiplier) and can be expressed mathematically by Eq. (11).

For private residential development,

$$D = \sum_{i=1}^{k} M_i \cdot \mathrm{RPCW} \tag{11}$$

where D = projected workforce demand; RPCW = projected construction output; i = trade; and M_i = labor multiplier of work trade i.

In Eq. (9), the labor multiplier, M_i, can be derived from the contractor's labor deployment records. However, an accurate estimate of workforce demand, D, on the left-hand side of Eq. (9) is highly dependent on the estimate of RPCW. To ensure the reliability of the labor multiplier approach in Eq. (9), the modeling works presented in this paper provide a reliable forecast of future construction work completion and work with the labor multiplier to evaluate the industry's future workforce demand. By comparing the forecast demand and the existing workforce supply pool, the shortage or surplus of construction workers can be identified in advance. This information would be critical in formulating labor and training policy in order to avoid possible skill mismatches, maintain an optimal workforce, and promote sustainable development for the industry.

Housing Supply Estimation in Private Sector

Housing policy is one of the critical components in community development. The demand side of the housing market is much better understood than the supply side in the private sector. From the literature review, the supply of housing in any period can derive from new housing construction that may arise via the investment decisions of builders (Baer 1986; Mayer and Somerville 2000). According to Arnott (1987) and DiPasquale and Wheaton (1994), a strong relationship exists between the construction completion rate and the number of flats/units available on the market. A reliable forecast of construction works completed in residential development (as put forth in this paper) can be used to evaluate the supply of new housing in the private sector.

Conclusions

This paper has proposed a VAR model augmented by economic variables for estimating construction completion rates (in dollar terms) in private residential development. Unlike models proposed in the literature, four key economic variables were used to forecast construction work completion: (1) GDP; (2) PPI; (3) credit conditions; and (4) VR. This deterministic approach provided a systematic analysis of the time-series data set to capture long-term trend turning points in the market (producing an adjusted R^2 value of 0.72). With a full understanding of future trends in construction work completion in private residential development, the government, policymakers, and investors can accurately estimate future workforce demand, which will enable them to deliver planned projects and attune future housing policy to societal demand.

The output of this study provides a systematic development of a reliable approach (i.e., methodology and applied model) that is useful for forecasting private-sector construction completion. While the proposed model structure has demonstrated a high degree of accuracy and reliability, future research will be required to expand and more finely granulate the model's usage to encapsulate the different classes of residential buildings. The significant key economic variables may well vary between these different classes, and therefore, comprehensive time-series data are required (e.g., PPI for luxury or middle-income residential buildings). Unfortunately, such information is currently unavailable from the government or other sources. Although the developed VAR model can yield a satisfactory and reasonable output on the basis of Hong Kong's property construction market, its performance is unknown when data obtained from other regions or countries are used. Given this limitation, a comparative study between different regions or countries using the proposed models is recommended and will be completed as part of future research in this novel area of construction/civil engineering management science.

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