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Forecasting construction demand: a vector error correction model with dummy variables

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Modelling the level of demand for construction is vital in policy formulation and implementation as the construction industry plays an important role in a country's economic development process. In construction economics, research efforts on construction demand modelling and forecasting are various, but few researchers have considered the impact of global economy events in construction demand modelling. An advanced multivariate modelling technique, namely the vector error correction (VEC) model with dummy variables, was adopted to predict demand in the Australian construction market. The results of prediction accuracy tests suggest that the general VEC model and the VEC model with dummy variables are both acceptable for forecasting construction economic indicators. However, the VEC model that considers external impacts achieves higher prediction accuracy than the general VEC model. The model estimates indicate that the growth in population, changes in national income, fluctuations in interest rates and changes in householder expenditure all play significant roles when explaining variations in construction demand. The VEC model with disturbances developed can serve as an experimentation using an advanced econometrical method which can be used to analyse the effect of specific events or factors on the construction market growth.

Keywords: Construction demand, forecasting, vector error correction model, global financial crisis.

Introduction

The construction industry is an important sector of every economy. It makes a significant contribution to the economic output in many countries; and it also provides employment and business opportunities for the people. Ofori (1990) highlighted that construction is the engine of economic growth. However, it is an industry that is greatly affected by the performance of the economy because the output of construction is a response to the demand for buildings which is a derived demand for other sectors (Hua, 1996). Changes in construction demand are affected not only by changes in the economic indicators, but also by other factors such as government policies and special global events. Ofori (1990) indicated that the effect of change in government policies on land supply, tax and in the economy can affect changes in construction demand both directly and indirectly. Global events such as the 1997 Asian financial crisis and the SARS outbreak influenced the demand for construction significantly in Hong Kong and Singapore (Hua, 2005; Fan *et al.*, 2010). Fluctuations in the construction market may be due to changes in local economic conditions, and future demand for construction may be not hard to predict as it follows a slight upward movement. However, the combined effect of the economy cycle and global economic events on the demand for construction is indeed more difficult to forecast. A dramatic change in the global economic environment such as the recent global financial tsunami would further increase the uncertainty. Therefore a more reliable forecast of construction demand would help governments and construction organizations to make apposite policies and strategies to ensure that the general economy and industry are able to develop in a more sustainable manner. As the main pillar of a country's economy, a careful and forward looking plan in the construction market can help ensure that valuable public resources can be allocated

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for the construction sectors in order to retain the labour and skills after this global recession.

Demand forecasting for the construction market has attracted considerable attention from construction economists. For example, Akintoye and Skitmore (1994) used five factors: economic conditions, construction price, real interest rate, unemployment level and profitability, to model demand for three types of construction markets in the UK. Fan *et al.* (2010) used the Box-Jenkins technique to forecast demand for commercial, industrial and residential construction in the Hong Kong market. Despite various techniques having been used to forecast construction demand in past studies, very little research has been done to analyse the effects of the recent global financial crisis on the growth of the construction market. Whether disturbances by crises should be involved in the modelling of construction demand or not has never been discussed. The recent global financial crisis happened in the late 2000s and is considered by many economists to be the worst financial crisis since the Great Depression of the 1930s. In July 2007, a liquidity shortfall in the United States banking system was caused by US investors losing confidence in the value of sub-prime mortgages and this was followed by the collapse of large financial institutions and downturns in stock markets around the world. The crisis started in 2007, but did not fully impact on the global economy until 2008/09. The annual GDP growth rates from 2007 to 2009 respectively were 3.8%, 1.6% and –2.2% for the world economy (Nayyar, 2011). The International Labour Organization claimed that unemployment worldwide rose by at least 30 million people, and reached as much as 50 million people between 2007 and 2009 (Blankenburg and Palma, 2009). At the same time, the global financial tsunami also triggered unexpected shock waves on many construction markets around the world. In Australia, construction approvals shrank by almost one-third in March 2009 as compared to their peak in March 2008, while house prices declined by 6% between March 2008 and March 2009.

The negative effects of the recent financial crisis on the construction market can be readily observed. Hence, analysing the effects of the crisis on growth in the construction market and forecasting the movement of construction demand after the crisis are extremely important. In this study, the dynamic impacts of the crisis are considered on construction demand modelling. An advanced multivariate regression modelling technique, the vector error correction model with dummy variables, was adopted to predict demand in the construction market. The choice of a reliable forecasting technique is vital for construction market researchers. The more reliable analytical technique for forecasting construction demand was identified by comparing the prediction accuracy of two forecasting models, namely the traditional VEC model and the VEC model with dummy variables. This paper continues by summarizing the forecasting techniques used in construction economics. Section three introduces the series of construction demand and key economic indicators used in this study. The model framework is outlined in the section four. Section five gives the empirical results, followed by the conclusions.

Literature review of construction demand forecasting

In the construction economics sense, statistical forecasting for construction demand can be broadly classified into two main types, namely, the univariate and the causal models (Fan *et al.*, 2010). The univariate model, which forecasts future value, is solely based on the past values of the time series. The common univariate modelling techniques employed by previous researchers include the exponential smoothing and Box-Jenkins techniques. The univariate model has been widely used for predicting construction demand, prices or activities, for example by Merkies and Poot (1990) who forecast construction activities in the Netherlands and New Zealand via an exponential smoothing technique. The Box-Jenkins technique introduced by Box and Jenkins (1970), also known as a benchmark technique, was applied to forecast construction demand, price and productivity (Hua and Pin, 2000) and construction manpower (Wong *et al.*, 2007).

In contrast, causal modelling techniques can identify the related variables affecting the predicting variable and can develop statistical models to differentiate the relationship between these variables (Fan *et al.*, 2010). The classical multi-regression and advanced multivariate regression models are the most commonly used causal models used for the prediction. Tang *et al.* (1990) forecast three different types of demand for the Thailand construction market by using the classical multi-regression technique. Neale and Ameen (2001) discussed using linear multi-regression technique to predict earthmoving productivity and bridge construction costs. In the UK, the linear multi-regression model was adopted to predict demand for the residential, commercial and industrial construction markets (Akintoye and Skitmore, 1994). Tse *et al.* (1999) discussed investment demand and traditional demand for new housing construction in Hong Kong based on the two-stage least squares and three-stage least squares regression model. The most recently used advanced multivariate models are the vector autoregressive (VAR) and the vector error correction models, which can provide prediction results of each variable based on its own lags and the lags of all the other variables. However, the vector error correction model is more suitable when used for forecasting economic variables, because it can establish a long-run equilibrium relationship between dependent and independent variables while the past equilibrium is used as explanatory variable to explain the dynamic behaviour of current variables (Fan *et al.*, 2010) as can be seen when Wong *et al.* (2007) employed a vector error correction model to predict labour demand in the Hong Kong construction market.

There has been very little research that considers the effects of global economic events and other factors in construction demand modelling and forecasting. Fan *et al.* (2010, 2011) covered the data period of the 1997 Asian economic crisis and the SARS epidemic in a study of demand forecasting. However, the authors (2010, 2011) only briefly discussed how these two events affected the construction market and ignored any consideration of the intervention of these events into the construction demand modelling process. Hua (2005) employed the intervention variable in an autoregressive-integrated-moving average (ARIMA) model to analyse the effects of the Asian financial crisis on construction demand and tender price in Singapore. Empirical studies in construction demand forecasting have shown that the accuracy performance varies with different forecasting techniques, and accuracy is the most important criterion for selecting a forecasting model. Hua (1998) compared the prediction accuracy of three forecasting models by using Singapore data. Hua (1998) found that the Box-Jenkins technique is suitable for making short-term forecasts; the multiregression technique always has a problem in modelling as the selection of indicators is affected by human judgement; and the artificial neural network technique has poor explanatory capabilities. Compared with the multi-regression technique, the Box-Jenkins technique is more reliable to forecast construction demand in Hong Kong (Fan *et al.*, 2010). Fan *et al.* (2010) claimed that the vector error correction model is more complicated and more time consuming compared with the benchmark model while the Box-Jenkins approach does not introduce too much personal bias into the forecasting process. However, the Box-Jenkins model predicts future values based on historical values and it cannot explore the factors affecting behaviour. The biggest limitation for univariate techniques is that they are only suitable for making short-term forecasts (Hua and Pin, 2000). An advanced multivariate model, such as the VEC model can help construction market researchers, policy and decision-makers to understand the relationships and interactions between related affecting variables and movement in the construction market. In addition, the VEC model can adequately deal with interactions between different construction market segments.

Key economic indicators affecting construction demand

The value of construction contract awarded or the value of construction work approved have been used to represent the demand in the construction industry because they are indicators of changes in the level of construction demand (Ofori, 1990; Hua, 2005). In this study, the value of construction work approved was adopted to represent the demand in construction because it can be explained as the total monetary cost of the construction work that clients are able and will be able to purchase in a given period.

The economic indicators affecting construction demand are various, and key economic indicators were identified in order to predict the level of demand for construction in Australia. National income is the measure of the total income in an economy and a barometer of the nation's economy. The income is the sum value of the total income of householders and local governments. Any variation in the national income will affect the level of demand for construction in both the private and public sectors. Consumer demand in goods and services will soar in a period of economic prosperity, which will also trigger an increase in the level of demand for construction space (Akintoye and Skitmore, 1994). The change in household expenditure demonstrates the expectation of householders with regard to the future national economy. Increasing the expenditure of householders will lessen resources available in the construction market, which will therefore affect the level of demand for construction indirectly. A construction producer price reflects the movement of prices in the construction market for each period of time (Hua, 1998). Ball *et al.* (2000) indicated that for each market sector, construction prices should be determined by the total demand. Construction prices differ by region, partly as a result of local resources and demand as fluctuating demand will lead to fluctuating prices and vice versa (Meikle, 2001). Akintoye and Skitmore (1994) adopted construction price as one of the significant factors for modelling housing construction demand in the private sector. Demographic influences have been widely cited for modelling the construction economic indicators such as demand and prices. The growth of a population raises the basic need for new dwellings and has been identified as a key determinant of the demand for residential construction (Tang *et al.*, 1990; Hua, 1996, 1998; Fan *et al.*, 2010).

The unemployment rate is measured as the total number of people not in employment who are ready and able to work (Hua, 1998). An increase in unemployment may discourage investment in the construction market because employment is the main source of income for residents and a rise in unemployment rate represents a lowering of the purchasing power of the population as well as a lower demand. Fan *et al.* (2010) indicated that a change in interest rates can affect the lending costs of clients, contractors, developers and company profits. A lower interest rate will encourage investments in the construction market and thus raise the level of demand for construction. In contrast, an increase in interest rates will raise the cost of bank lending for construction projects and lead to a decline in purchasing power. The Australia Bureau of Statistics (ABS, 2010) indicated that the average value of exports of goods and services in Australia is more than 20% of the total GDP. This means that the export industry is a vital sector not only for the national economy but also for other sectors. The value of exports was adapted to model demand for construction in Thailand (Tang *et al.*, 1990).

The quarterly data series of selected economic indicators and the demand for construction were abstracted from ABS for the period of September 1996 to June 2010. All the data series from September 1996 to June 2009 were used to develop forecasting models. The last four data points, four quarters, were retained to evaluate the accuracy of the forecasting models. Furthermore, the data series from September 2008 to June 2009 were used to undertake an intervention analysis to analyse the impact of the recent global financial crisis on the construction market in Australia. All the time series data used in this study have been expressed as natural logarithm variables. In collecting the variables for estimation, the following important issues were taken into account (Akintoye *et al.*, 1998): economic plausibility of their leading character; availability of the time series with as few interruptions as possible; and availability of the data with minimum delay.

VEC models for forecasting construction demand

The general VEC model and the VEC model with event dummy were employed in this study to forecast the level of demand in the construction market.

Vector error correction model

The vector error correction model is a combination of the vector autoregressive model and cointegration restrictions. Cointegration, an econometric property of time series variables, is generally used to estimate the long-run relationships between non-stationary variables. If the level of time series data is not stationary but a linear combination of variables is stationary after an initial difference, then the series can be said to be cointegrated to the order one or $I(1)$. They will tend to come back to the trend in the long run, even though they deviate from each other in the short run. A prior condition for the cointegration test is that all the variables should be integrated in the same order or contain a deterministic trend (Engle and Granger, 1991; Luo *et al.*, 2007). A unit root test is conducted for each variable by using the Augmented Dickey-Fuller (ADF) unit root test and the Phillips-Perron (PP) unit root test which were introduced by Dickey and Fuller (1979) and Phillips and Perron (1988) respectively.

The general VEC model employed by Wong *et al.* (2007) is represented in Equation 1:

$$\Delta Y_t = C + \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \epsilon_t \quad (1)$$

where Y_t are the independent $I(1)$ variables being integrated to an $I(0)$ vector, C is the intercept, Γ is the matrix which reflects that the short-run dynamic relationship between the elements of Y_t, and ϵ_t is residual. $\Delta = (I–L)$, L is the lag operator, k is the number of lags, while Π is the matrix containing long-run equilibrium information. If the elements of Y_t are $I(1)$ variables and cointegrated with rank $(\Pi) = r < p$, then the rank of Π can be rewritten as $\Pi = \alpha\beta' = \alpha ecm_{t-1}, ecm_{t-1}$ is the error correction term and $\beta' Y_t$ is stationary. This implies that there exist $r < p$ stationary linear combinations of Y_t. β is a vector of cointegration relationships and α is a loading matrix defining the adjustment speed of the variables in Y to the long-run equilibria defined by the cointegrating relationships.

The Johansen cointegration test was introduced by Johansen and Juselius (1990) who conducted the multivariate maximum likelihood approach in order to reveal the number or cointegration equations without using arbitrary normalization rules. There are five models in the Johansen cointegration test. Model one represents all series having a zero mean. Model two represents deterministic data with an intercept but no trend in the cointegration equations (CE). Model three suggests that data have a linear trend with an intercept but no trend in the CE. Model four has a linear trend with both an intercept and a trend in the CE while model five suggests a quadratic data trend with an intercept and a trend in the CE. This paper only analyses three different specifications in the

Johansen cointegration estimation, because models 1 and 5 are usually excluded from the estimation as they are not practical in real life (Hui and Yue, 2006). The lag length of the VEC model is selected for a time series in VAR modelling on the basis of the sequential modified likelihood ratio test statistic (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ). The test results of the lag length selection are then inputted into the Johansen cointegration test to construct the VEC models with different combinations between construction demand and each economic indicator. Once all variables are proved to be stationary and cointegrated, a vector error correction model can be formulated.

Specifically the VEC model for construction demand (CD_t) can be written as

$$\begin{aligned}\Delta CD_t &= C + \alpha(ecm_{t-1}Y_{t-1} + \rho_0) \\ &\quad + \sum_{i=1}^{k}\theta_{1,i}\Delta CD_{t-i} + \sum_{i=1}^{k}\theta_{2,i}\Delta NI_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{3,i}\Delta HHE_{t-i} + \sum_{i=1}^{k}\theta_{4,i}\Delta CPPI_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{5,i}\Delta UR_{t-i} + \sum_{i=1}^{k}\theta_{6,i}\Delta POP_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{7,i}\Delta IR_{t-i} + \sum_{i=1}^{k}\theta_{8,i}\Delta VOE_{t-i} + \varepsilon_t \end{aligned} \quad (2)$$

where α is the adjustment coefficient, ρ_0 is the intercept of cointegrating equations, $Y_{t\text{-}1}$ are the $I(1)$ vectors at time t-1. $\theta_{j,i}$ reflects the short-run aspects of the relationships between the independent variables and the target variable. At time t, NI_t is the national income, HHE_t is the household expenditure, $CPPI_t$ is the construction producer price index, UR_t is the unemployment rate, POP_t is the size of population, IR_t is the interest rate and VOE_t is the value of exports.

Vector error correction model with dummy variables

The VEC model containing exogenous variables was earlier used by Ramey (1993) for analysing the effect of seasonality and monetary policy disturbance on the money market. As types of exogenous variables, dummy variables have been involved in the VEC model to estimate the impacts of the 1985 United Airlines strike and the 1991 Persian Gulf War on the tourism demand and supply for Hawaii (Bonham *et al.*, 2009). Some of these previous applications of an event dummy analysis have been studied and used to analyse the impact of the 1997 Asian financial crisis, the 2000 Sydney Olympic Games, and the Bali bombing in 2005 on the housing market and tourism industries (Hua, 2005; Yap and Allen, 2011).

Based on Equation 1, the VEC model with dummy variables can be represented in Equation 3

$$\Delta Y_t = C + \Pi Y_{t-1} + \sum_{i=1}^{k-1}\Gamma_i \Delta Y_{t-i} + \sum_{j=1}^{n}\Theta_N D_{j,t} + \varepsilon_t \quad (3)$$

where $D_{j,t}$ is dummy variable j at time t, N is the number of endogenous variables, n is the number of dummy variables, Θ_k are $n \times N$ vectors. In this research, only recent global financial crises have been considered, hence $n = 1$.

The VEC model using the late 2000s financial crisis dummy variable (D_t) for construction demand can be constructed in Equation 4:

$$\begin{aligned}\Delta CD_t &= C + \alpha(ecm_{t-1}Y_{t-1} + \rho_0) \\ &\quad + \sum_{i=1}^{k}\theta_{1,i}\Delta CD_{t-i} + \sum_{i=1}^{k}\theta_{2,i}\Delta NI_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{3,i}\Delta HHE_{t-i} + \sum_{i=1}^{k}\theta_{4,i}\Delta CPPI_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{5,i}\Delta UR_{t-i} + \sum_{i=1}^{k}\theta_{6,i}\Delta POP_{t-i} \\ &\quad + \sum_{i=1}^{k}\theta_{7,i}\Delta IR_{t-i} + \sum_{i=1}^{k}\theta_{8,i}\Delta VOE_{t-i} \\ &\quad + \delta D_t + \varepsilon_t \end{aligned} \quad (4)$$

where δ is the coefficient of the dummy variable, and D_t is the dummy variable for an one-off event. The one-off event dummy is an exogenous variable which indicates the presence or absence of the intervention in the variation of construction demand. The intervention remains at 1 for the duration of the presence of the event otherwise the intervention is 0 during the period of the absence of event. The first sign of a deterioration in Australia's construction market was in the second half of 2008 when the demand for construction declined over 29% during these six months. At the same time, the first significant policy response to the global financial crisis came from the Australian Commonwealth Government. The government announced it would guarantee all bank deposits, and an economic stimulus package worth AU$10.4 billion was announced. In this package, AU$1.5 billion was allocated to support housing construction. This announcement could be considered as an ideal indicator that denoted when the financial crisis started to affect the Australian economy. Through a series of effective boost strategies, the approvals in the Australian construction market reached the same level in the September quarter of 2009 as at the beginning of the global financial crisis, and the Australian government was able to announce that the economy of Australia had recovered from the late 2000s global financial crisis (Henry, 2009). At the same time, the Reserve Bank of Australia (RBA) announced it would raise the cash rate by 25 base points. Indeed, the period of the late 2000s global financial crisis that affected the Australian economy can be defined as starting in September 2008 and finishing in September 2009.

Techniques for evaluating prediction accuracy

After constructing the two prediction models, the out-of-sample testing was carried out. The prediction accuracy was estimated by comparing the predicted values with the actual values. The two testing techniques mainly used for forecasting reliability were applied: the mean absolute percentage error (MAPE) and the Theil's inequality coefficient *U*. Generally, any result of the MAPE test smaller than 10% is considered as acceptable, while the closer the Theil's inequality coefficient *U* value is to 0 the better the prediction results achieved (Fan *et al.*, 2010, 2011). The characteristics of these measures have been elaborated in other studies (such as Hua and Pin, 2000; Wong *et al.*, 2007; Fan *et al.*, 2010). In brief, these measures can be explained as follows,

The mean absolute percentage error is computed by Equation 5:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|e_t|}{Y_t} * 100 \tag{5}$$

Where $e_t = Y_t - Y_t$, e_t is the forecast error term at time t, Y_t, is the forecast value of Y_t at period t, Y_t is the actual value at time t. T is the total number of periods.

The Theil's inequality coefficient U is computed by Equation 6:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t - Y_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t)^2}} \tag{6}$$

where Y_t is the actual value at time t, Y_t is the forecast value of Y_t at period t. T is the total number of periods. The coefficient U can only occur between 0 and 1. If U equals 0, then the predicted value perfectly fits

Table 1 Summarized results of ADF and PP unit root tests

Indicators	ADF unit root test				PP unit root test			
	Level		First difference		Level		First difference	
	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value
CD	2.02	0.99	−8.62	0.00**	−1.25	0.65	−11.95	0.00**
NI	0.34	0.98	−4.92	0.00**	0.41	0.98	−6.01	0.00**
VOE	2.47	1.00	−8.12	0.00**	−1.87	0.34	−8.79	0.00**
HHE	−1.73	0.41	−6.35	0.00**	−1.74	0.41	−6.27	0.00**
CPPI	2.43	1.00	−3.18	0.03*	−0.26	0.92	−3.18	0.03*
UR	−1.12	0.24	−4.11	0.01*	−1.26	0.19	−4.11	0.01*
POP	1.97	0.99	−3.68	0.03*	1.18	1.00	−7.54	0.00**
IR	−0.38	0.54	−4.63	0.00**	−0.75	0.39	−4.49	0.00**

Notes: CD, construction demand; NI, national income; VOE, value of export; HHE, household expenditure; CPPI, construction producer price index; UR, unemployment rate; POP, size of population; IR, interest rates. * denotes rejection of null hypothesis of unit root based on their P-value at the 0.05 significance level.

** denotes rejection of null hypothesis of unit root based on their P-value at the 0.01 significance level.

with the actual value during the forecasting period. If U equals 1, then the performance of the predicting mode is as poor as it can be (Fan *et al.*, 2010).

Empirical results

Before conducting each of the regression models, all the variables should be integrated at the same order or contain a deterministic trend. The ADF and PP unit root tests were carried out to test stationary for all the variables. The results are summarized in Table 1 and suggest that all the variables were stationary after the first difference at the 0.01 and 0.05 significance levels. Based on the VAR lag length selection system, the smallest values of the LR, FPE, AIC, SC and HQ tests indicate that the lag length for the VEC models was three. After that, cointegration tests were carried out, and the results of the trace statistics indicate that each variable Y_t has a linear trend with an intercept but construction demand has no trend in the cointegrating relation. The deterministic trend in model three and one cointegration relationship were identified and implemented into the VEC models.

As cointegration relationships were found between the construction demand and selected economic indicators, the general VEC model and the VEC model with global event dummy were constructed based on Equations 2 and 4 respectively. The estimates of the general VEC model and the VEC model with dummy variables for construction demand are reported in Table 2 and Table 3 respectively. The specifications of two VEC models show that the construction demand was affected by the national income, household expenditure, the construction producer price index, population, interest rates and the value of exports. Additionally, a growth in population, a change in national income, a variation of interest rate and a change in householder expenditure play key roles in explaining movement in construction demand. The general VEC model and the VEC model with the global event dummy were examined for their model fit based on the values of R-squared, sum square residue, Standard Error (SE) of the equation and log likelihood. The VEC model with the crisis dummy variable has a higher R-square value with 0.75 than the general VEC model does with 0.68. This suggests that approximately 75% of the variations in Australian

Table 2 Estimation results for construction demand by using the general VEC model

Variables	ΔCD_t		
$CD_{t\text{-}1}$	1		
$NI_{t\text{-}1}$	29.19 (5.71)***		
$HHE_{t\text{-}1}$	−6.35 (−1.79)**		
$CPPI_{t\text{-}1}$	4.63 (4.36)***		
$UR_{t\text{-}1}$	1.06 (1.15)		
$POP_{t\text{-}1}$	−166.20 (−8.11)***		
$IR_{t\text{-}1}$	−2.14 (−5.15)***		
$VOE_{t\text{-}1}$	4.20 (4.79)***		
C	1281.55		
CointEq1 (α)	0.18 (1.55)*		
ρ_0	−0.54 (−1.50)*		
Error correction	*t*-1	*t*-2	*t*-3
ΔCD	−0.31 (−1.30)	−0.39 (−2.26)**	−0.01 (−0.03)
ΔNI	−7.01 (−2.02)**	−6.21 (−1.94)**	−4.14 (−1.46)*
ΔHHE	2.54 (0.80)	7.62 (2.35)**	−0.54 (−0.14)
$\Delta CPPI$	3.74 (1.03)	−0.46 (−0.11)	−2.57 (−0.62)
ΔUR	0.54 (−0.62)	−0.35 (−0.42)	0.06 (0.08)
ΔPOP	85.25 (1.67)*	90.26 (1.70)**	49.82 (1.21)
ΔIR	0.34 (1.15)	0.39 (1.24)	−0.22 (−0.73)
ΔVOE	0.32 (0.48)	−0.43 (−0.62)	0.22 (0.29)
R-squared	0.68		
Sum sq. residue	0.17		
S.E. equation	0.09		
Log likelihood	67.69		

Notes: CD, construction demand; NI, national income; VOE, value of export; HHE, household expenditure; CPPI, construction producer price index; UR, unemployment rate; POP, population; IR, interest rates. 'Δ' is the first difference operator. Values in parenthesis are *t*-statistics.

* denotes *t*-statistics significant at 0.1 level.

** denotes *t*-statistics significant at 0.05 level.

*** denotes *t*-statistics significant at 0.01 level.

construction demand could be captured by the VEC model with event dummy. A rise in the unemployment rate represents a lowering of the purchasing power of the population as well as a lower demand. However, the estimates of the VEC model without event dummy indicate the changes of unemployment rates cannot affect the level of demand in the construction market significantly. It may be due to the variation of construction demand caused by external impacts such as the deep recession of the global economy, bankruptcy of financial facilities, etc., while the relationships among economic indicators and construction demand cannot be estimated correctly. In contrast, the changes of unemployment rates can significantly affect construction demand in the VEC model with event dummy and the relationships among construction demand and economic indicators can be more reliably estimated after considering external interventions. The global financial crisis dummy variable performs a negative coefficient in the model with –0.25, which confirms that construction demand in Australia received a significant negative impact from the recent global financial crisis. In the Australian construction market, the total actual value added of construction work approved had a negative value of AU$5052 million during the crisis period (ABS, 2010). The Australian government would encourage investment in the construction market of no less than AU$5052 million to correct the effect of the financial tsunami.

Validations on the general VEC model and VEC model with dummy variables were carried out to verify the assumptions of statistical soundness. These techniques include serial correlation Lagrange multiplier tests (LM) for up to fourth, eighth and twelfth order respectively, White's test for heteroskedasticity (White) in the residual and for model misspecification, and the Jarque-Bera test for normality of the residual (Jarque-Bera). The results of model validations are summarized in Table 4, which indicates that the two VEC models passed all validation tests at the 5% significance level. Therefore, there is no evidence of problems related to serial correlation, heteroskedasticity and non-normal errors.

The predicted values of construction demand generated by the two forecasting models are plotted in Figure 1 in comparison with the actual data. The MAPE and Theil's inequality coefficient U were employed to evaluate the predictive ability of the two

Table 3 Estimation results for construction demand by using the VEC model with dummy variables

Variables	ΔCD_t		
CD_{t-1}	1		
NI_{t-1}	2.97 (1.82)**		
HHE_{t-1}	−4.66 (4.55)***		
$CPPI_{t-1}$	−1.46 (−5.36)***		
UR_{t-1}	0.54 (1.91)**		
POP_{t-1}	−28.27 (−4.18)***		
IR_{t-1}	−0.33 (2.54)***		
VOE_{t-1}	2.15 (1.66)*		
C	179.27		
CointEq1 (α)	0.10 (0.27)		
ρ_0	−0.13 (−1.27)		
DUMMY	−0.25 (−2.54)***		
Error correction	*t*-1	*t*-2	*t*-3
ΔCD	−0.41 (−1.12)	−0.51 (−2.02)	−0.09 (−0.38)
ΔNI	−1.68 (−0.72)	−2.67 (−1.09)	−2.08 (−0.85)
ΔHHE	−1.04 (−0.35)	4.98 (1.78)**	0.62 (0.18)
$\Delta CPPI$	2.34 (0.65)	0.59 (0.16)	−4.60 (−1.51)*
ΔUR	0.50 (0.81)	−0.38 (−0.50)	0.15 (0.23)
ΔPOP	10.23 (0.39)	37.24 (1.58)*	30.53 (1.02)
ΔIR	−0.10 (−0.39)	−0.01 (−0.02)	−0.42 (−1.44)*
ΔVOE	0.49 (0.80)	−0.19 (−0.31)	−0.26 (−0.38)
R-squared	0.75		
Sum sq. residue	0.13		
S.E. equation	0.08		
Log likelihood	73.59		

Notes: CD, construction demand; NI, national income; VOE, value of export; HHE, household expenditure; CPPI, construction producer price index; UR, unemployment rate; POP, population; IR, interest rates. 'Δ' is the first difference operator. Values in parenthesis are *t*-statistics.

* denotes *t*-statistics significant at 0.1 level.

** denotes *t*-statistics significant at 0.05 level.

*** denotes *t*-statistics significant at 0.01 level.

Table 4 Model validation

Modelling technique	VEC	VEC with dummy
LM(4)	76.02 (0.14)	86.97 (0.08)
LM(8)	73.99 (0.18)	75.33 (0.16)
LM(12)	70.97 (0.26)	56.89 (0.72)
White	0.66 (0.83)	0.81 (0.68)
Jarque-Bera	88.35 (0.09)	96.24 (0.18)

Notes: LM(p) is the Lagrange multiplier test for residual serial correlation with p lag length; White is White's test for heteroskedasticity; Jarque-Bera is the Jarque Bera test for normality of the residuals; figures in parentheses denote probability values.

models. The figure reflects that the previous deviation between actual value and predicted value of construction demand is adjusted quarterly towards the equilibrium by 31%. This implies that the process of adjustment in the level of demand for the construction market is precarious and sensitive. The predictive adequacy of the two forecasting models was further evaluated by comparing them with the actual construction demand over the forecasting period as shown in Table 5. The values of the MAPE test of the two models are both less than 10% absolute percentage error and the coefficients U are all close to 0, which indicates that the general VEC model and the VEC model with dummy variables are both acceptable for predicting the level of demand for construction. Furthermore, the results of the evaluation of prediction accuracy suggest that the VEC model with event dummy gives a better prediction result in construction demand forecasting compared with the general VEC model by achieving a lower MAPE and Theil's inequality coefficient U statistics i.e. 3.58% and 0.0262 respectively.

Many construction economists have adopted the ARIMA model to predict demand, prices or productivity in the construction market. Some of them claimed that the ARIMA models could provide better prediction results than using observed variables to capture the movement of construction demand (Hua and Pin, 2000; Fan *et al.*, 2010). However, compared to the dynamic regression models, the VEC model can preserve the information relating to the key economic indicators and construction demand. In this study, the general VEC model and the VEC model with dummy variables were proved to be acceptable for forecasting construction economic indicators, while the VEC model when considering external impacts, compared with the general VEC model, is a more reliable and robust approach for forecasting demand in the Australian construction market. The VEC model with dummy variables provides a valuable future direction for construction developers, policy-makers and stakeholders to project the growth of the construction market and to formulate appropriate development strategies.

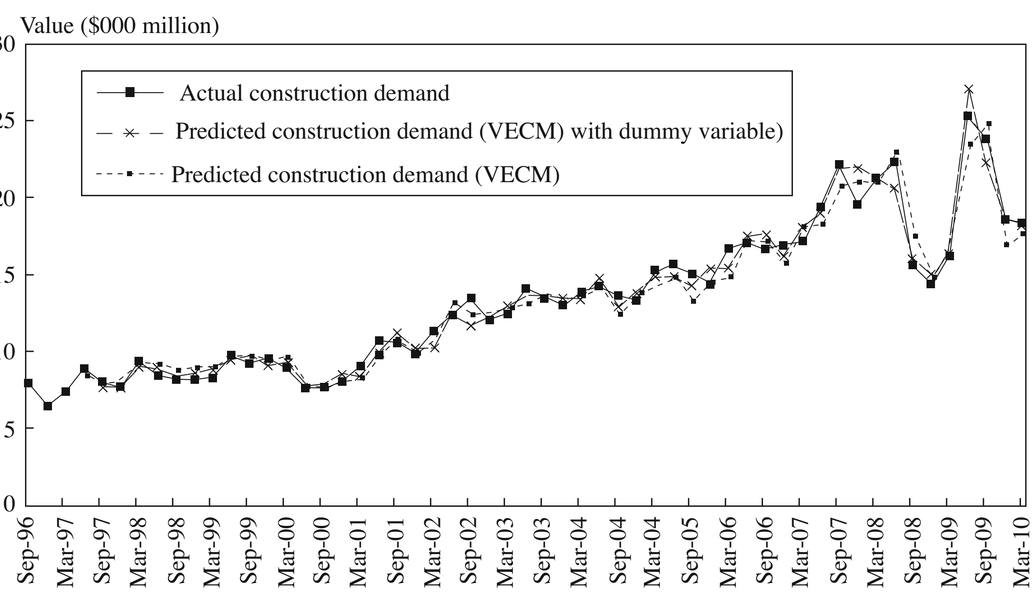

Figure 1 Comparison of actual construction demand and prediction of two forecasting models

Table 5 Summarized results of evaluating prediction accuracy

Period	Actual values	Predicted values			
		VEC	Percentage error	VEC with dummy	Percentage error
2009Q3	25 305	23 477	−7.22%	26 988	6.65%
2009Q4	23 800	24 807	4.23%	22 279	−6.39%
2010Q1	18 581	16 970	−8.67%	18 569	−0.06%
2010Q2	18 397	17 709	−3.74%	18 169	−1.24%
		MAPE =	6.00%	MAPE =	3.58%
		U =	0.0318	U =	0.0262

The recovery of Australia's economy and construction market from the recent global economic recession was successful but would not have worked without a series of corrective and effective stimulating strategies put in place by the Australian government. During the period of the 2008–09 crisis, these policies included the first home buyer's grant, which encouraged residents to buy their first property, and an increase in investment in public facilities. Together, these effectively created growth in construction demand in Australia. For example, the approved value of non-residential construction projects rose almost four times from AU$1650 million in December 2008 to AU$5793 million in August 2009 (ABS, 2010). At the same time, the rise in investment in the construction market triggered growth in the Australian economy, enabling it to recover from the recession. The responses of the Australian government to the late 2000s global financial crisis, especially the stimulation policies enacted in the construction market, set a good example for other organizations and provide a good solution for similar cases.

Conclusions

An empirical study of the use of advanced multivariate techniques, namely the general VEC model and the VEC model with an event dummy, has been presented to model and forecast the level of demand in the Australian construction market. The impact of the late 2000s global financial crisis was developed as an intervention in the forecasting model to evaluate the dynamic effects of the recent crisis on the variation in the construction market and construction demand projection. The out-of-sample forecasts during the September quarter 2009 and the June quarter 2010 provided a basis for assessing the predictive performance of these two models.

The estimates of the two forecasting models both indicated that the growth in population is the most significant factor that can affect construction demand positively, compared with other selected macroeconomic indicators. It is important for construction contractors, tenders and developers to observe the fluctuation of growth in the population, any change in national income, variations in interest rates and changes in household expenditure in order to predict the future level of demand for construction in Australia. The estimation results of the event dummy variable revealed that the effect of the late 2000s global financial crisis on the demand for construction was negative and statistically significant. Although the general VEC model has been proved to be reliable in previous studies in forecasting techniques, a better prediction performance can be achieved by inserting dummy variables into the general VEC model to involve the dynamic impact of special global events in the forecasting model. Hence, the VEC model with the event dummy is valid for application to a global event period as well as to a period of change in government policy, which could be valuable for construction policy-makers, developers and stakeholders in order to forecast the future growth of the construction market and to develop the industry in a sustainable manner.

The impact of the recent global financial crisis is the single external influence considered in this study. Further research may be expanded to involve other global events and factors such as the 1997 Asian Financial Crisis, the 2000 Sydney Olympic Games, the September 11 attacks and seasonality, etc. The VEC model developed in this research may also be used to analyse the effect of national events and factors such as changes in Australian government policies.

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