PRODUCTIVITY AS A DETERMINANT OF LABOUR WAGE IN NEW ZEALAND'S CONSTRUCTION SECTOR

Mustafa OZTURK[1], Serdar DURDYEV[2*],
Osman Nuri ARAS[3], Audrius BANAITIS[4]

[1]*Independent researcher, Istanbul, Turkey*
[2]*Department of Engineering and Architectural Studies, Ara Institute of Canterbury,
8011 Christchurch, New Zealand*
[3]*Faculty of Arts and Social Sciences, Nile University of Nigeria, Plot 681, Cadastral Zone C-OO,
Research & Institution Area, Jabi Airport Bypass, Abuja FCT, 900001 Nigeria*
[4]*Department of Construction Management and Real Estate,
Vilnius Gediminas Technical University, 10223 Vilnius, Lithuania*

Abstract. The empirical relationships between labour wages, unemployment rate and the labour productivity index in New Zealand's construction sector (for the period of 1983–2017) were investigated. The Johansen cointegration test and vector error correction mechanism were used to determine the existence of long-run relationships between the variables and the adjustment process of the short-run disequilibrium into the long-run equilibrium. The results show that the labour productivity index positively affects the labour wage, while the effect of unemployment rate is negative in the long run. That is, the more productive the labour, the more the wages earned. Related statistical tests on the residuals proved that the model and its findings are reliable.

Keywords: productivity, labour wage, New Zealand, construction, panel data analysis, unemployment.

JEL Classification: E10, E24, J24.

Introduction

The construction industry has a significant role in terms of growth promotion and employment generation, and it also supports other sectors to which it is linked (Durdyev & Ismail, 2016; Durdyev, Zavadskas, Thurnell, Banaitis, & Ihtiyar, 2018; Gündüz & Kaya, 2017; Nazarko & Chodakowska, 2017). Since this sector influences the growth of national economy, its productivity level is of critical importance. Studies have proved that the higher the productiv-

ity level of the construction sector, the higher the gains for other sectors, since the former feeds investments into the latter to some extent (Chia, Skitmore, Runeson, & Bridge, 2014).

An assessment of the construction industry from the economic perspective is essential to determine the national productivity level (Durdyev & Ismail, 2012). The national productivity level aims at contributing towards the gross domestic product (GDP), which is considered the main economic indicator of a nation's growth and standards of living (Durdyev & Mbachu, 2011). Productivity growth within a region or nation is an important requirement to raise the living standard of its population. Therefore, national productivity measures are typically used for comparing economic performance, for example, of regions and/or over periods. Bernold and AbouRizk (2010) state that the managerial and technological capacities of a country, which are fostered by a qualified (highly educated) workforce, are critical in driving increases in its productivity through facilitating constant improvements. Over time, factors such as incentives from stronger industries, human resource development through continued education and innovation support productivity increase. Consequently, governmental policies and cultural and institutional factors determine the success of measures to improve productivity. Further, productivity has to be measured at the industry level to observe the extent to which an industry's productivity performance affects national productivity. Such measurement is required because any industry (e.g., construction, service, manufacturing, agriculture and mining) can be considered an individual unit of the entire economy of a country. Hence, national productivity improvements depend on the productivity level of individual units, namely, industries (Bernold & AbouRizk, 2010; Han, Ko, Hong, Koo, & Lee, 2017), and such improvements are portrayed via the initial and subsequent measurements at the national and industry levels.

The relationship of the construction sector with the economy has received attention from researchers worldwide. Numerous studies have examined and reported the relationship between construction sector output and the economy (Banaitienė, Banaitis, & Laučys, 2015; Chan, 2001; Giang & Low, 2011; Ma, Liu, & Reed, 2017; Ofori, 1990; Turin, 1978), while several others (Chia et al., 2014; Y. Gang, F. Gang, & Yan, 2003) have examined the relationship between this sector's productivity performance and economic development. For instance, sufficient theoretical evidence shows that various economic parameters, such as the labour wage (LW) and unemployment rate, have either negative or positive effects on sector productivity (Yildirim, 2015). However, little attention has been paid to the impact of construction productivity on a particular economic parameter (Vergeer & Kleinknecht, 2007; Wakeford, 2004). Further, the presence of country- and industry-specific parameters means that the findings of studies on the subject are applicable within their respective economic environments (owing to political, social and institutional determinants) and hence cannot be generalised. Therefore, deeper understanding of gains and pains of the workforce from the sector's productivity performance, within the country- and industry-specific environments, is of strategic importance.

Additionally, according to growth models (Kuznets, 1961; Romer & Chow, 1996; Solow, 1956), under perfect competitive market conditions the real wage (RW) rate equals the value of the marginal product of labour at the anticipated cost per output. If the growth models are considered correct, RW should be equal to the marginal product; therefore, the long-run increase in RW should be parallel to the increase in labour productivity (LP). However, this

theoretical approach needs to be tested empirically, since many relationships exist between wage rates and productivity.

The construction industry has a significant contribution to New Zealand's economy in terms of GDP, linkages with allied businesses and employment. While the sector's contribution, including the related services, to GDP was recorded as 8% in 2015 (PWC, 2016) and led the GDP growth by the end of 2017 (Stats NZ, 2017), it generated about 10% of total employment. When the integration with allied sectors of the economy is considered, the construction sector has even a greater impact. Given the significance of the construction sector in New Zealand in terms of employment generation and contribution to the national economy, particularly after the Canterbury earthquake, this study aims to examine the empirical relationship between RW and the productivity of this sector based on data for the 1983–2017 period. Thus, the study's contribution is to present the relationship between RW, unemployment and labour productivity within the construction industry context of New Zealand. As such, it is hoped that the study would provide implications for salary setting that are consistent with the level of productivity in the construction context of New Zealand as well as for testing economic and wage models.

The remainder of this paper is organised as follows. The next section, Section 1 presents a comprehensive literature review. Section 2 provides details on the data used and Section 3 presents the analysis results. Section 4 presents a discussion on the long-term relationships between the variables considered and Section 5, on the short-term relationships Section 6 states the results of tests on model stability. The final section provides some concluding remarks on the relationships between the empirically tested parameters as well as implications.

1. Literature review

"Productivity is not everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker".

(Krugman, 1994)

Productivity has been associated with economic growth at various levels, such as the quality of life of a society, and the quality of its services/products at the organisation level (Durdyev, 2011). Oyeranti (2000) defines it as the ability of the sector to convert inputs including material, machinery and money into outputs or a quantified ratio of inputs to outputs. Durdyev, Ismail and Kandymov (2018) define productivity as effective resource (input) utilisation to achieve set objectives (output), which also can be defined as "the ratio of output to input". In the construction sector, the built structure is an output and the major inputs are the quantity of workforce hired (worked hours) and quantity of capital and other resources utilised (e.g., energy, material and money). Durdyev and Mbachu (2018) define productivity as the measurement of the resources or inputs used to achieve the objectives or desired outputs. By focusing on creativity and innovation, the productivity aim is to accomplish higher output with fewer resources by resource optimisation through re-engineering the service delivery process.

Productivity growth within a region or nation is an important requirement to raise the living standard of its population (Bernold & AbouRizk, 2010). Therefore, national productivity measures are typically used to compare economic performance, such as between regions or periods. The input–output approach (which is the same as the general definition of productivity) is also used to measure the industry-level productivity (Huang, Chapman, & Butry, 2009). However, at this level, the input–output ratio measures the total market value (price; amount) of the services and products to the number of labourers employed by the industry. Marginal physical productivity is one of the most appropriate theoretical concepts of productivity, which is the change in output resulting from employing one more particular unit of labour. However, since such productivity cannot be readily measured, in practice, average LP is used as a productivity concept. The most common equation for calculating average LP is total output divided by total employment. From the perspective of contemporary economists, average productivity is defined as the amount of production (i.e., goods and services) per unit of labour input (Mankiw, 2017).

RW has been categorised into two types: real consumption and real product wages (Backhouse, 1991). While the former, which provides a measure for real purchasing power, is the value of wages adjusted for inflation with the consumer price index, the latter is the value of wages adjusted for inflation with the producer price index.

Several mechanisms theoretically explain the relationship between economic parameters. For instance, it has been theoretically proved that because of decrease in purchasing power, inflation is likely to have a negative impact on productivity performance. Conversely, RW is found to be a motivating factor for the labour force, which ultimately positively influences productivity performance (Karaalp-Orhan, 2017; Yildirim, 2015).

A comprehensive literature review suggests that the relationship between productivity and economic parameters, such as LWs and unemployment rate, has received broad attention from researchers, with the majority of these studies reporting a positive relationship. For instance, Wakeford (2004) reports an empirical relationship between productivity and RW in South Africa between 1983 and 2003. The findings reveal a long-run equilibrium (cointegrating) relationship among the parameters for the examined period, while revealing strong evidence of cointegration of productivity and RWs over the 1990–2002 period. Further, utilising the panel data technique, Vergeer and Kleinknecht (2007) analyse the relationships between LP growth and LW over the period of 1960–2004 in the 19 countries of the Organisation for Economic Co-operation and Development. They report that LP growth is a key determinant for wage growth but also find a causal link in the opposite direction. Yusof (2008) examines the long-run relationship between RW, employment and productivity in Malaysia's manufacturing sector. The analysis results reveal a long-run relationship among the parameters. Thus, although the theory of negative impact of RW on employment is not supported, the pay scheme theory (based on performance) is further validated.

One study on Australia analyses the empirical relationship between LP, inflation and RWs during 1965–2007 utilising Granger causality, cointegration and, most importantly, structural change tests (Kumar, Webber, & Perry, 2012). The results reveal a positive relationship among the parameters in the manufacturing sector. Tipper (2012) investigates the impact of labour age structure on productivity and RWs, as well as the productivity–RW gap between 2001 and 2007 in New Zealand. The results reveal no significant differences between LP and work-

force age structure at the industry level; however, the study finds that the younger workforce is paid lower RW than the older workforce. Further, the productivity–RW gap is not found to be applicable for the older workforce but exists for the younger workforce, which is paid less in comparison to its productivity.

Rosenberg (2010) examines the long-run relationship between RWs and LP in New Zealand using data for the 1978–2006 period. According to the results over a variety of business cycles, increase in RW varies widely owing to LP increases. Conway, Meehan and Parham (2015) test the relationship between labour income share and productivity growth over 1978–2010 in New Zealand. The results indicate consistency in growth of RWs and productivity as well as the lack of a systemic relationship between significant growth of productivity and decreases in labour income share.

A recent study on Nigeria investigates both long- and short-run relationships in the 1981–2012 period between inflation, RW and LP (Iheanacho, 2017). For further cointegration analysis, the study utilises the bound testing, autoregressive distributed lag and error correction approaches. The findings reveal a significant and positive long-run relationship between the tested parameters and that a positive short-run relationship does coexist, which confirms the dual impact of RW on productivity.

A strong relationship between LP, wages and unemployment has been reported by various studies worldwide. However, the findings reported from other countries cannot be generalised and further country- and industry-specific investigation is required on the relationship between the aforementioned parameters. In addition, although some studies have considered the topic in the New Zealand context, it is necessary to revisit the topic and examine the empirical relationships between LWs, LP and unemployment rates, particularly in the construction sector. Thus, this study aims at empirically testing these relationships in the New Zealand construction industry context for the 1983–2017 period.

2. Research data

The variables used in the model are weekly wage, unemployment rate and labour productivity index (see Table 1), all of which are annual time series retrieved from the Stats NZ Tatauranga Aotearoa databank and New Zealand Yearbooks. The series are available only from 1983 to 2017; therefore, this study is limited to this period.

Logarithmic values of the variables are used in the model. First, the augmented Dickey–Fuller (ADF) test is used to determine whether all the variables are stationary, following the recommendations of Dickey and Fuller (1979). Next, the vector error correction model (VECM) is used to estimate the speed of adjustment of the short-run disequilibrium into

Table 1. Utilized variables

Variables	Code	Type
Labor Wage (weekly)	Ln WAGE	Endogenous
Unemployment	Ln UNIMP	Endogenous
Labor Productivity Index	Ln LAPROD	Endogenous

the long-run equilibrium among the cointegrated variables. Finally, to check how stable and desirable the model is, the residuals of the VECM are tested via serial correlation LM, Breusch–Pagan–Godfrey heteroscedasticity and histogram normality tests.

3. Data analysis and results

3.1. Unit root test

The statistical properties of a stationary time series, such as mean, variance and autocorrelation, are all constant over time. If nonstationary time series are regressed, the results may be meaningless and biased. Therefore, regressions based on the nonstationary time series are called spurious regressions. Elimination of trend and seasonal effects from the series, filtration of it and obtaining its logarithmic values are the ways to convert a nonstationary series into a stationary one. In cointegration tests, all variables are added in the model at their base level I (0) if they all are stationary at the same level. Hence, the variables are checked via the ADF test using Equations (1) and (2), which are the equations for the stationary series without and with trend, respectively (Dickey & Fuller, 1979):

$$\Delta X_t = a + \alpha X_{t-1} + \beta \sum_{i=1}^{m} \Delta X_{t-i} + e_t; \tag{1}$$

$$\Delta X_t = a + bt + \alpha X_{t-1} + \beta \sum_{i=1}^{m} \Delta X_{t-i} + e_t. \tag{2}$$

The null hypothesis is H_0: $\alpha = 0$ and $b = 0$, which means the X_t series is not stationary. In case the null hypothesis (H_0) is rejected, the alternative hypothesis (H_1) that the series is stationary is accepted. The ADF unit root test results indicate that the series are not stationary in their base level I (0), but they become stationary after differencing I (1) (Phillips & Perron, 1988).

Table 2 presents the ADF test results based on the Akaike information criterion (AIC) for eight lags. Although none of the variables are stationary in their base level at 1% significance, they are stationary in their first differences with two stages, for with and without trend.

Table 2. Stationarity of the variables

Variable code	Without trend					With trend				
	τ	%1	%5	%10	Prob.	τ	%1	%5	%10	Prob.
Ln WAGE	–4.07	–1.95	–2.64	–1.95	0.000	–2.93	–4.34	–3.55	–3.20	0.016
ln UNIMP	–3.43	–2.64	–1.95	–1.61	0.001	–3.47	–4.27	–3.56	–3.21	0.060
ln LAPROD	–8.09	–2.63	–1.95	–1.61	0.000	–8.43	–4.24	–3.54	–3.21	0.000

3.2. Selection of the VAR lag order

In line with the recommendation of Speed and Yu (1993) and Dickey and Fuller (1981), the likelihood ratio, final prediction error, AIC, Schwarz information criterion and Hannan–Quinn information criterion are applied to determine the optimum lag order for the cointegration of the variables. The optimum lag order is 1 according to all criteria.

Table 3. VAR lag order

Lag	LogL	LR	FPE	AIC	SC	HQ
0	149.4537	NA	8.24e-09	−10.10026	−9.958813	−10.05596
1	**168.5155**	**32.86520***	**4.14e-09***	**−10.79418***	**−10.22840***	**−10.61698***
2	171.5773	4.645400	6.39e-09	−10.38464	−9.394530	−10.07455
3	177.6126	7.908391	8.31e-09	−10.18018	−8.765738	−9.737196
4	184.2017	7.270683	1.10e-08	−10.01391	−8.175133	−9.438028
5	192.8427	7.747070	1.39e-08	−9.989149	−7.726039	−9.280371

Note: *selected lag order based on the criterion.

4. Long-term relationships between labour wage and productivity variables

4.1. Cointegration test

Cointegration is a technique that allows determining the relationships between two or more nonstationary variables. Although two or more variables might not be stationary, the variables are cointegrated if their linear combinations are stationary (Granger, 1988). A nonstationary series may not have stochastic processes, and hence, analysis with such a series could produce a spurious relationship. However, the cointegration models allow displaying genuine relationships between the variables. While the Engle–Granger (Engle & Granger, 1987) cointegration model displays a single cointegrating relationship), Johansen's (1988) model allows for multiple relationships. Thus, the equation of the latter model is provided as follows:

$$x_t = \left[\mu + \Pi\right] x_{t-1} + \ldots\ldots\ldots + \Pi_k x_{t-k} + \varepsilon_t, \tag{3}$$

ε_t is error term and μ, $\Pi_1 \ldots \Pi_k$ are restricted parameters that are estimated via the vector auto regressive model:

$$\Delta x_t = \mu + \Gamma_1 \left[\Delta x\right]_{t-1} + \ldots + \Gamma_{k-1}\left[\Delta x\right]_{t-k+1} + \left[\Pi x\right]_{t-1} + \varepsilon_t. \tag{4}$$

Since the series have a unit root in their base level, they became stationary after first difference. This operation transforms Equation (3) into Equation (4).

$$\Gamma_i = -\left(I - \Pi_1 - \ldots \Pi_i\right) \; i = 1, \ldots k - 1 \text{ and } \Pi = -\left(I - \Pi_1 - \cdots \ldots\ldots \Pi_k\right). \tag{5}$$

With this operation, the coefficient matrix is checked for information about the relationships of the variables and the data vector. The coefficient matrix may have one of three possible values (Johansen & Juselius, 1990):

Rank (Π) = 0. Coefficient matrix (Π) is zero and Equation (3) is suitable for the traditional time series differential vector. It does not fit the cointegration structure.

Rank (Π) = p. The rank of coefficient vector (Π) is a whole and X_t process vector is stationary.

$0 <$ Rank (Π) = $r < p$ means that the variables are cointegrated and have long-run associations. In other words, there are α and β matrixes such that Π is equal to the multiplication of α and β' ($\Pi = \alpha\beta$') and β'X_t is stationary.

Since all variables are of the same order, the Johansen cointegration test is utilised to determine if these are integrated. There is at least a unilateral causality between the variables in case the variables are integrated (Granger, 1969). Hence, the causality between the variables is checked via the standard Granger test (Granger, 1969). Then, the VECM is set to determine how many periods later the disequilibrium between the variables changes into equilibrium (Granger, 1988). Tables 5 and 6 present the results of the trace and maximum eigenvalue tests, respectively, applied to determine the number of cointegrating vectors between the variables.

Cointegration models are established based on five assumptions about whether data have a deterministic trend and intercept. 'Intercept (no trend) in CE and test VAR' option of the linear deterministic trend in data is the most appropriate assumption for the cointegration equation.

The trace statistic value in Table 4 is bigger than the critical value at the 0.03% level of significance in the first line. Therefore, the null hypothesis is rejected; hence, the variables are not cointegrated. However, the second line shows that the trace statistic is less than the critical value at 56.7% level of significance; hence, the null hypothesis cannot be rejected and reveals that there is at most one cointegration equation.

The maximum eigenvalue (ME) statistic in Table 5 shows that there is at least one cointegration equation between the variables and they are correlated in the long run.

The ME statistic in the first line is bigger than the critical value at the 1.5% level of significance, and hence, the null hypothesis (there is no cointegration between variables) is rejected. Conversely, the ME statistic in the second line is less than the critical value at 53.7% level of significance; hence, the null hypothesis is not rejected.

According to normalized co-integrating coefficients presented in Table 6, the coefficients of ln LAPROD and ln UNIMP are –2.6 and 0.34, respectively, which estimate the long-run elasticities. Thus, every increase in ln LAPROD reflects in ln WAGE by 260% in the long run, and every increase in ln UNIMP reflects ln WAGE by –34%.

Table 4. Unrestricted Co-Integration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None * (R = 0)	0.526639	31.77027	29.79707	0.0292
At most 1 ($r \leq 1$)	0.181442	7.089689	15.49471	0.5672
At most 2 ($r \leq 2$)	0.014521	0.482717	3.841466	0.4872

Notes: *the hypothesis is rejected at 0.05 significance level; **MacKinnon-Haug-Michelis (1999) p-values.

Table 5. Unrestricted Co-Integration Rank test (ME)

Hypothesized No. of CE(s)	Eigenvalue	ME Statistic	0.05 Critical Value	Prob.**
None * (R = 0)	0.526639	24.68058	21.13162	0.0151
At most 1 ($r \leq 1$)	0.181442	6.606972	14.26460	0.5366
At most 2 ($r \leq 2$)	0.014521	0.482717	3.841466	0.4872

Notes: *the hypothesis is rejected at 0.05 significance level; **MacKinnon-Haug-Michelis (1999) p-values.

Table 6. Normalized vector

Ln WAGE	Ln LAPROD	Ln UNIMP
1.000000	−2.605217	0.346929
	(0.69140)	(0.16736)

Increase in unemployment may lead the labour force to consent to lower wages to find a job or to retain the existing job because of strong competition in the labour market. Conversely, the more productive the workers become, the more wages they will demand. Therefore, the positive relationships between wages and labour productivity that this empirical study finds.

4.2. Vector Error Correction Model

According to the cointegration theory, the short-run disequilibrium between the variables may have a tendency to change into the long-run equilibrium. Cointegration models help identify long-run associations of variables while they have short-run deviations. Hence, it is possible to find the number of periods required to adjust short-run deviations into long-run equilibrium. The VECM is used to determine the number of periods for this equilibrium process, and the model's formula is as follows:

$$\Delta \ln \text{WAGE}_t = \propto_0 + \sum_{i=1}^{n} \propto_{1i} \Delta \ln \text{WAGE}_{t-i} + \sum_{i=1}^{n} \propto_{2i} \Delta \ln \text{UNIMP}_{t-1} +$$
$$\sum_{i=1}^{n} \propto_{3i} \Delta \ln \text{LAPROD}_{t-1} + \gamma \text{ECM}_{t-1} + \varepsilon_t,$$

where:

$\Delta \ln \text{WAGE}_{t-i}$ = change in labour wage in the period $t-1$;

$\Delta \ln \text{UNIMP}_{t-1}$ = change in the Unemployment rate in the period $t-1$;

$\Delta \ln \text{LAPROD}_{t-1}$ = change in Labour Production index in the period $t-1$;

ECM_{t-1} = error terms of the co-integration model in the period $t-1$;

μ_{1i}, μ_{2i} and μ_{3i} = coefficients or the short-term parameters affecting the dependent variables.

The long-run associations of the variables can be obtained provided that the error term is negative in sign in the VECM. According to the VECM model shown in Table 7, the ECM_{t-1} coefficient is negative in sign and statistically significant at the 0.01% level, which reveals the existence of long-run causality from the input productivity indexes to Labour Wages. The coefficient of ECM_{t-1} estimated for error correction is in between 0 and −1; hence, this reveals that the deviations among the variables gradually diminish in the short run and the model approaches the equilibrium level in the long run. The adjustment speed from short-run disequilibrium to long-run equilibrium is calculated as follows (Johansen & Juselius, 1990):

$$1 / \text{ECM}_{t-1} = 1 / 0.08255 = 12.11.$$

This result shows that the cointegration equilibrium can be obtained in approximately 12 periods.

Table 7. Vector Error Correction Model

Dependent Variable: Δ ln WAGE$_t$				
	Coefficient	Std. Error	t-Statistic	Prob.
ECM$_{t-1}$	−0.082550	0.018419	−4.481738	0.0001
Δ ln WAGE$_{t-1}$	0.297473	0.133714	2.224693	0.0343
Δ ln UNIMP$_{t-1}$	−0.161652	0.090292	−1.790318	0.0842
Δ ln LAPROD$_{t-1}$	−0.042880	0.024199	−1.771990	0.0873
ε_t	0.029938	0.006622	4.520669	0.0001
R-squared	0.732812	Mean dependent variance		0.041136
Adjusted R-squared	0.694642	S.D. dependent variance		0.035162
S.E. of regression	0.019430	Akaike info criterion		−4.905251
Sum squared residual	0.010571	Schwarz criterion		−4.678508
Log likelihood	85.93665	Hannan-Quinn criterion		−4.828959
F-statistic	19.19877	Durbin-Watson statistic		1.832934
Prob (F-statistic)	0.000000			

Vector Error Correction Model also displays the short run associations between the dependent and the independent variables as well as it displayed the speed of adjustment between variables in the long run. T statistics and their corresponding probability values show that only one lagged value of the wage affects the wage itself at the 5% significance level in the short run.

5. Model stability

Reliability of the model results depends on the stability of the model. Residuals of unstable models have several problems, such as heteroscedasticity, serial correlation and abnormal distribution, which adversely affect the accuracy of the model results. The first condition of model stability is that the residuals should be normally distributed.

Jarque-Berra statistic and the corresponding probability value (JB = 2.97 < 22.6 or Prob = 22.6 > 0.05) support the null hypothesis that the residuals of the model are normally distributed (see Table 8).

The second condition for model stability is that the variables should be homoscedastic, namely, they should have the same finite variance. The null hypothesis of the Hetereskedasticity ARCH test rejects the heteroscedasticity of the variables).

Table 8. Histogram normality test

Mean	: −2.44e-17	Skewness	: 0648096
Median	: −0.002797	Kurtosis	: 3.693324
Maximum	: 0.052844	Jarque-Berra	: 2.971119
Minimum	: −0.037031	Probability	: 0.226376
Std. Dev.	: 0.018175		

Table 9. Heteroskedasticity test: ARCH

F-statistic	0.341867	Prob. F(12,12)	0.5631
Obs. R-squared	12.58418	Prob. Chi-Square (12)	0.5482

Table 10. Breusch-Godfrey serial correlation LM test

F-statistic	0.432387	Prob. F(2,12)	0.5164
Obs*R-squared	0.520143	Prob. Chi-Square(2)	0.4708

The test results in Table 9 reveal that the model is homoscedastic. The chi-square value supports the null hypothesis at the 54.8% significance level.

The third condition for model efficiency is that the residuals of the model should not be serially correlated. The Breusch–Godfrey serial correlation LM test rejects the hypothesis that the residuals of the model are serially correlated (Breusch, 1978; Godfrey, 1978).

The results of this test in Table 10 indicate that the residuals are not serially correlated, and the equation is appropriate for hypothesis tests and forecasting.

Conclusions

The construction sector is a sector that significantly contributes to New Zealand's economy. Thus, the existence of intersectoral linkages means that any improvement in the sector is positively reflected in other sectors – for instance, because this sector is an infrastructure provider to other sectors. Moreover, increase in the quality and productivity of labour positively affects the construction sector quality because of its labour-intensive nature. Thus, increase in labour wage (LW) based on productivity growth encourages labour to be more productive.

New Zealand is a high-income country, and the construction sector is the fourth largest contributor to the national economy. The share of the construction sector in the GDP and its contribution to national economic growth is worthy of attention, and hence a motivating point for this study utilising the statistical data recorded by Statistics New Zealand. Therefore, this study examined the relationships between labour productivity, unemployment and LW. The Johansen cointegration test proved that LW, unemployment and the labour productivity (LP) index are cointegrated. According to the Vector Error Correction Mechanism, short-run deviations between the variables move towards long-run equilibrium in 12 periods. Normalised cointegrating coefficients showed that the LP index positively affects LW, while the effect of unemployment rates is negative. These results showed that the more productive the labour, the more the wages earned. However, the short run associations of the variables showed that only the one lagged values of the labour wages affected the current values of the LWs themselves. Nevertheless, although similar studies have been undertaken, assessment of the relationships between the LP and LW in the construction context of New Zealand is of utmost significance. Further, the outcomes of the model are sufficiently justified by the theory that the change in unemployment rates is negatively reflected in the wages, while LP affects the wage positively. Thus, since it is the first study of its kind undertaken in the New Zealand construction context, the authors believe that the findings of this short scoping study would

provide implications for salary setting that are consistent with the level of productivity in the construction context as well as for testing economic and wage models. Although the aim of the study was achieved, the results are limited to the data obtained from the Statistics New Zealand, therefore cannot be generalised and should be treated with caution.

Acknowledgments

Author contributions

Mustafa Ozturk and Osman Nuri Aras together carried out the data analysis, Serdar Durdyev designed and wrote the introduction and literature review of the paper, Audrius Banaitis provided extensive advice throughout the study regarding the abstract, introduction, literature review, research methodology, data analysis, results and discussion, and conclusions of the manuscript. The discussion was a team task. All authors have read and approved the final manuscript.

Conflicts of interest

The authors declare no conflict of interest.

References

Backhouse, R. (1991). *Applied UK macroeconomics*. Oxford, UK: Basil Backwell. Retrieved from http://www.socscistaff.bham.ac.uk/backhouse/homepage/aukm/Prelims.pdf

Banaitienė, N., Banaitis, A., & Laučys, M. (2015). Foreign direct investment and growth: analysis of the construction sector in the Baltic States. *Journal of Civil Engineering and Management*, *21*(6), 813-826. https://doi.org/10.3846/13923730.2015.1046478

Bernold, L. E., & AbouRizk, S. M. (2010). *Managing performance in construction*. Hoboken, NJ: John Wiley and Sons Inc. https://doi.org/10.1002/9780470638996

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers*, *17*(31), 334-355. https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

Chan, S. L. (2001). Empirical tests to discern linkage between construction and other economic sectors in Singapore. *Construction Management and Economics*, *19*(4), 355-363. https://doi.org/10.1080/01446190010022686

Chia, F. C., Skitmore, M., Runeson, G., & Bridge, A. (2014). Economic development and construction productivity in Malaysia. *Construction Management and Economics*, *32*(9), 874-887. http://dx.doi.org/10.1080/01446193.2014.938086

Conway, P., Meehan, L., & Parham, D. (2015). *Who benefits from productivity growth? The labour income share in New Zealand* (New Zealand Productivity Commission Working Paper 2015/1 February 2015). Retrieved from https://www.productivity.govt.nz/sites/default/files/research-who-benefits-from-productivity-growth.pdf

Dickey, D. A., & Fuller ,W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427- 431. https://doi.org/10.2307/2286348

Dickey, D., & Fuller, W. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*(4), 1057-1072. https://doi.org/10.2307/1912517

Durdyev, S., & Ismail, S. (2016). On-site construction productivity in Malaysian infrastructure projects. *Structural Survey*, *34*(4/5), 446-462. https://doi.org/10.1108/SS-12-2015-0058

Durdyev, S. (2011). *Pareto analysis of on-site productivity constraints and improvement techniques in New Zealand building industry* (Master thesis). School of Engineering and Advanced Technology, College of Sciences, Massey University at Albany, New Zealand.

Durdyev, S. & Ismail, S. (2012). Pareto analysis of on-site productivity constraints and improvement techniques in construction industry. *Scientific Research and Essays*, *7*(7), 824-833. https://doi.org/10.5897/SRE12.005

Durdyev, S., Ismail, S., & Kandymov, N. (2018). Structural equation model of the factors affecting construction labor productivity. *Journal of Construction Engineering and Management*, *144*(4), 1-11. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001452

Durdyev, S., Zavadskas, K. E., Thurnell, D., Banaitis, A., & Ihtiyar, A. (2018). Sustainable construction industry in Cambodia: Awareness, drivers and barriers. *Sustainability*, *10*(2), 392. https://doi.org/10.3390/su10020392

Durdyev, S., & Mbachu, J. (2011). On-site labour productivity of New Zealand construction industry: Key constraints and improvement measures. *Construction Economics and Building*, *11*(3), 18-33. https://doi.org/10.5130/AJCEB.v11i3.2120

Durdyev, S., & Mbachu, J. (2018). Key constraints to labour productivity in residential building projects: Evidence from Cambodia. *International Journal of Construction Management*, *18*(5), 385-393. https://doi.org/10.1080/15623599.2017.1326301

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, *55*(2), 251-276. https://doi.org/10.2307/1913236

Gang, Y., Gang, F., & Yan, L. (2003). A theoretical analysis on economic growth in China and total factor productivity. *Economic Research Journal*, 2003-8.

Giang, D. T., & Low, S. P. (2011). Role of construction in economic development: review of key concepts in the past 40 years. *Habitat International*, *35*(1), 118-125. https://doi.org/10.1016/j.habitatint.2010.06.003

Godfrey, L. G. (1978). Testing for multiplicative heteroscedasticity. *Journal of Econometrics*, *8*(2), 227-236. https://doi.org/10.1016/0304-4076(78)90031-3

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424-438. shttps://doi.org/10.2307/1912791

Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of Econometrics*, *39*(1-2), 199-211. https://doi.org/10.1016/0304-4076(88)90045-0

Gündüz, U., & Kaya, T. (2017). Regional employment generation potential of the Turkish labor market: an inter-sectoral perspective. *Technological and Economic Development of Economy*, *23*(5), 726-741. https://doi.org/10.3846/20294913.2015.1015110

Han, S., Ko, Y.-H., Hong, T., Koo, C., & Lee, S. (2017). Framework for the validation of simulation-based productivity analysis: focused on curtain wall construction process. *Journal of Civil Engineering and Management*, *23*(2), 163-172. https://doi.org/10.3846/13923730.2014.992468

Huang, A. L., Chapman, R. E., & Butry, D. T. (2009). *Metrics and tools for measuring construction productivity: Technical and empirical considerations*. National Institute of Standards and Technology,

Gaithersburg, USA. Retrieved from https://www.nist.gov/publications/metrics-and-tools-measuring-construction-productivity-technical-and-empirical https://doi.org/10.6028/NIST.SP.1101

Iheanacho, E. (2017). Empirical review on the relationship between real wages, inflation and labour productivity in Nigeria: ARDL bounds testing approach. *International Economics and Business*, *3*(1), 9-29.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on co-integration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169-210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x

Johansen, S. (1988). Statistical analysis of co-integrated vectors. *Journal of Economic Dynamics and Control*, *12*(2-3), 131-154. https://doi.org/10.1016/0165-1889(88)90041-3

Karaalp-Orhan, H. S. (2017). Labour productivity, real wages and unemployment: An application of bounds test approach for Turkey. *Journal of Economic and Social Development*, *4*(2), 11-22.

Krugman, P. (1994). *The age of diminishing expectations*. Retrieved from http://www.oecd.org/sdd/productivity-stats/40526851.pdf

Kumar, S., Webber, D. J., & Perry, G. (2012). Real wages, inflation and labour productivity in Australia. *Applied Economics*, *44*(23), 2945-2954. https://doi.org/10.1080/00036846.2011.568405

Kuznets, S. (1961). Economic growth and the contribution of agriculture: notes on measurement. *International Journal of Agrarian Affairs*, *3*(2). Retrieved from https://econpapers.repec.org/scripts/redir.pf?u=http%3A%2F%2Fpurl.umn.edu%2F229152;h=repec:ags:iaaeaa:229152

Ma, L., Liu, C., & Reed, R. (2017). The impacts of residential construction and property prices on residential construction outputs: an inter-market equilibrium approach. *International Journal of Strategic Property Management*, *21*(3), 296-306. https://doi.org/10.3846/1648715X.2016.1255675

Mankiw, N. G. (2017). *Principles of macroeconomics*. Cengage Learning. USA.

Nazarko, J., & Chodakowska, E. (2017). Labour efficiency in construction industry in Europe based on frontier methods: data envelopment analysis and stochastic frontier analysis. *Journal of Civil Engineering and Management*, *23*(6), 787-795. https://doi.org/10.3846/13923730.2017.1321577

Ofori, G. (1990). *The construction industry: Aspects of its economics and management*, Singapore: Singapore University Press.

Oyeranti, O. A. (2000). *Concept and measurement of productivity in productivity and capacity building in Nigeria*. Paper presented at Proceedings of the Ninth Annual Conference of the Zonal Research Units of the Central Bank of Nigeria, 12 June 2000, Abeokuta, Nigeria.

Phillips, P. C. B., & Perron, P. (1988). Testing for unit roots in time series regression. *Biometrika*, *75*(2), 335-346. https://doi.org/10.2307/2336182

PwC. (2016). *Valuing the role of construction in the New Zealand economy*. A report to the Construction Strategy Group in association with Construction Industry Council BRANZ. Retrieved from https://www.pwc.co.nz/pdfs/CSG-PwC-Value-of-Construction-Sector-NZ.pdf

Romer, D., & Chow, C. (1996). *Advanced macroeconomic theory*. Mcgraw-Hill, USA.

Rosenberg, B. (2010). Real wages and productivity in New Zealand. *Labour, Employment and Work in New Zealand*. https://doi.org/10.26686/lew.v0i0.1714

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65-94. https://doi.org/10.2307/1884513

Speed, T. P., & Yu, B. (1993). Model selection and prediction: Normal regression. *Annals of the Institute of Statistical Mathematics*, *45*(1), 35-54. https://doi.org/10.1007/BF00773667

Stats NZ. (2017). *Construction leads GDP growth*. Retrieved from https://www.stats.govt.nz/news/construction-leads-gdp-growth

Tipper, A. (2012). *Labour productivity, real wages, and workforce age structure.* Paper presented at 53rd New Zealand Association of Economists Conference, Palmerston North. Retrieved from https://www.nzae.org.nz/wp-content/uploads/2012/06/Tipper-productivity-real-wages-and-workforce-age-structure-final.pdf

Turin, D. A. (1978). Construction and development. *Habitat International, 3*(1/2), 33-45. https://doi.org/10.1016/0197-3975(78)90032-2

Vergeer, R., & Kleinknecht, A. (2007). *Jobs versus productivity? The causal link from wages to labour productivity growth.* TU Delft Innovation Systems Discussion Papers, IS, 1. Retrieved from https://www.fep.up.pt/conferencias/eaepe2007/Papers%20and%20abstracts_CD/Vergeer.pdf

Wakeford, J. (2004). The productivity–wage relationship in South Africa: an empirical investigation. *Development Southern Africa, 21*(1), 109-132. https://doi.org/10.1080/0376835042000181444

Yildirim, Z. (2015). Relationships among labour productivity, real wages and inflation in Turkey. *Economic Research-Ekonomska Istraživanja, 28*(1), 85-103. https://doi.org/10.1080/1331677X.2015.1022401

Yusof, S. A. (2008). The long-run and dynamic behaviors of wages, productivity and employment in Malaysia. *Journal of Economic Studies, 35*(3), 249-262. https://doi.org/10.1108/01443580810887805