MULTIDIMENSIONAL ANALYSIS OF LABOR COST PERFORMANCE IN CHINA'S REGIONAL CONSTRUCTION INDUSTRY

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Multidimensional Analysis of Labor Cost Performance in China's Regional Construction Industry

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Abstract

Labor cost estimation, control, and regulations are of great importance to achieve the final success of construction project, and sustainable development of construction industry. Cheap construction workforce underpinned by rich labor force has been regarded as a major advantage of contractors against rivals in a competitive market. The labor-intensive development of construction industry has made stable contributions to China's economic growth and social employment. Because of its close linkage with the rest of economy, construction industry is considered as an effective instrument for the government to stabilize and revitalize the economy. The development of construction industry is investment-driven by large-scale real estate development and infrastructure construction in the new century. With a rapid growth of real wage due to the increasing demands over recent decade, the affordability and availability of construction workforce has gradually become the history and exerted widespread effects on construction workforce recruitment, construction project management, and construction industry development. However, due to the limitations of data availability and model development, most of previous studies focused more on the qualitative analysis and partial evaluation of construction labor cost, few efforts have been devoted to the in-depth investigation of labor cost performance in China's construction industry.

To bridge these research gaps, the primary aim of this study is to investigate labor cost performance in China's construction industry through a multi-dimensional analysis. Four specific objectives are fulfilled and they are: (1) To investigate the relationship between construction labor cost and critical determinants across the different regions; (2) To develop an efficiency measurement for construction

industry and explore the regional differences of construction productive efficiency; (3) To identify the optimal pathways for stepwise efficiency improvement in regional construction industry; (4) To forecast the future trend of regional construction labor cost.

First, this study conducts a holistic review of construction labor cost performance from temporal and regional dimensions, then identify the critical determinant of construction labor cost based on empirical analysis of literature review and questionnaire survey. Panel data model is then developed to investigate the relationship between construction labor cost and critical determinants across different regions of China among various time periods. Second, this study develops an overall efficiency measurement for construction industry under the conceptual framework of neoclassical economic theory. Data Envelopment Analysis (DEA) model is applied to measure the performance of construction productive efficiency. Further, the causes of inefficiency and the sources of growth for regional construction industry can be identified based on the empirical results of Distance Friction Minimization (DFM) approach. Regional differences of construction productive efficiency are discussed from input optimization and output potential, respectively. Third, for those less inefficient provinces that cannot achieve the significant improvement within a short period of time, a Target-Oriented (TO) approach is adopted to set reasonable stage-wise targets according to the efficiency gaps and study period. The optimal pathways for stepwise efficiency improvement in regional construction industry can be further explored according to the results of TO-DFM model. Final, Panel Vector Error Correction (P-VEC) model is established accordingly based on identified critical determinants for regional construction labor cost forecasting. The predictability of P-VEC models is validated in comparison with that of Panel Ordinary Least Square (P-OLS) model for in-sample forecasting. Scenario analysis are further conducted based on P-VEC models to predict the future trend of regional construction labor cost in the coming periods.

This research provides a new perspective for understanding the labor cost performance in China's construction industry. Significance of this research can be summarized from theoretical and practical perspectives. Questionnaire survey can provide insights into construction migrant worker and labor cost management in real practice. In accordance with literature review and questionnaire survey, investigating the regional construction labor cost through panel data modeling can help stakeholders and policymakers understand labor cost variations in evolving construction market, provide valuable insights for contractor to formulate forward-looking market strategies and for government to fine tune economic policies. Construction industry in eastern region is more mechanized with extensive application of construction plants and equipment, offsetting the pressures of rising wage rate of skill workers. In contrast, the competitive edge of construction industry in western and midland regions is established primarily through a lower level of labor wage, underpinned by rich surplus labor force. More critically, the slow growth of labor productivity weakens the long-term competitiveness of regional construction industry.

Construction Productive Efficiency (CPE) is conceptualized under the framework of the neoclassic economic theory, benchmarked with three input and one output using DEA-based models without considering complexity in intermediate process. Construction productive efficiency in coastal areas is better than that of inland regions. Besides, Distance Friction Minimization (DFM) approach can identify the causes of inefficiency, and the sources of growth in regional construction industry. The development potential of construction industry in western region is the largest, followed by midland region and then eastern region. The inefficiency of input usages involving construction worker, real wage, construction plant and equipment, leads to diverse efficiency performance across regions. For those low efficiency provinces, the optimal pathways can be mapped out by using Target-Oriented Distance Friction Minimization (TO-DFM) model with stage-wise targets for stepwise efficiency improvement, which serves as good references for resource optimization and investment planning across different regions of China. For eastern region, investing more on construction plant and equipment for labor savings is more efficient to long-term productivity growth. The heavy reliance on cheap manpower can be gradually relieved by allocating more budgets to vocational training and education program boost quality workforce in midland region. It is more effective to raise the wage rate to retain and recruit more workforce to meet the demand of local construction in western region.

Further, regional construction labor cost forecasting can provide early information concerning the construction labor cost variations in regional market on the assumptions of two control variables. Scenario analysis is conducted based on P-VEC model to simulate the trend of construction labor cost. Due to inherent divergences of local resources and regional development, construction labor cost competitiveness can be accordingly enhanced through different ways. The forecasting results of P-VEC model provide insights into practical implications for construction labor cost estimation, construction workforce management, and construction industry development.

Publications

Refereed Journal Papers:

1. **Luo, M.**, Fan, H., & Liu, G. (2021). A target-oriented DEA model for regional construction productive efficiency improvement in China. *Advanced Engineering Informatics*, *47*, 101208.

2. **Luo, M.**, Fan, H., & Liu, G. (2019). Measuring regional differences of construction productive efficiency in China: A distance friction minimization approach. *Engineering, Construction and Architectural Management*, *27*(4), 952–974.

3. Liu, G., Yi, Z., **Luo, M.**, & Wu, W. (2017). SWOT analysis of decision making for strategic goals based on WASPAS method (in Chinese). *Science and Technology Management Research*, 37(01), 221-226.

Referred Conference Papers:

1. **Luo, M.**, Fan, H., Liu, G., Yi, Z.& Martek, I. (2019). An empirical investigation of China's construction industry development: shifts in factors of production usage from 1990 to 2014. *Proceedings of the CIB World Building Congress 2019: Construction Smart Cities*, 3232-3246.

2. **Luo, M.**, Fan, H., & Liu, G. (2019). A target-oriented data envelopment analysis for regional construction efficiency improvement in Mainland China. *Proceedings of the CIB World Building Congress 2019: Construction Smart Cities*, 2509-2520.

3. **Luo, M.**, Fan, H., & Liu, G. (2018). Comparative analysis of regional labor cost variations in China's construction industry: Panel data modeling and analysis. In *Creative Construction Conference 2018 – Proceedings*, 369-378.

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List of Abbreviations

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
AICs	Advanced Industrialized Countries
ARIMA	Autoregressive Integrated Moving Average
BOQ	Bills of Quantity
CCR	Charnes Cooper Rhodes
CE	Employed Persons in Construction Industry
CEs	Cointegration Equations
CLW	Construction Labor Wage
CLP	Construction Labor Productivity
CPE	Construction Productive Efficiency
CPI	Consumer Price Index
CVA	Construction Value Added
CV	Coefficient of Variation
CW	Floor Spare Under Construction
C-D	Cobbs-Douglas
DEA	Data Envelopment Analysis
DFM	Distance Friction Minimization
DM	Decision Maker
DMU	Decision Making Unit
DW	Durbin-Watson
FPE	Final Prediction Error
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GNP	Gross National Product
HQ	Hannan Quinn information criterion

ILO	International Labor Office
IPS	Im Pesaran Shin
KILM	Key Indicators of the Labor Market
LDCs	Less Developed Countries
LLC	Levin Lin Chu
LM	Lagarnge Multiplier
LR	Likelihood Ratio
MAPE	Mean Absolute Percentage Error
MP	Magnification Parameters
MPI	Malmquist Productivity Index
MOLP	Multiple Objective Linear Programming
NICs	Newly Industrialized Countries
OLS	Ordinary Least Square
PPP	Purchasing Power Parity
P-OLS	Panel Ordinary Least Square
P-VAR	Panel Vector Autoregressive Regression
P-VEC	Panel Vector Error Correction
SC	Schwarz information Criterion
TER	Construction Technical Equipment Ratio
TES	Target Efficiency Score
TFP	Total Factor Productivity
TI	Total Amount of Fixed Assets Investment
TO	Target Oriented
TO-DFM	Target Oriented Distance Friction Minimization
TPI	Tender Price Index
VAR	Vector Autoregressive Regression
VEC	Vector Error Correction
ULC	Unit Labor Cost

Chapter 1: Introduction

1.1 Research background

Construction industry plays an important role in boosting economic growth and social employment both directly and indirectly through its multiplier effects (Ofori, 1990). As one of pillar sectors in China's economy during the urbanization process, construction industry has been often considered as an effective tool for the government to stabilize and revitalize the economy (Giang & Pheng, 2011). The development of China's construction industry is investment-driven by large scale real estate development and infrastructure construction in the new century. It does foster economic growth with the investment of production factors, i.e. labor and capital inputs, but fails to improve productivity growth of construction industry. With the largest population in the world, construction workforce underpinned by rich labor resources across China, has been historically employed as a major advantage of contractors against rivals in international construction market. For domestic market, construction development is heavily reliant on cheap but unskilled construction manpower over the past years. China's economy has been undergoing structural reform and industry upgrade, dealing with the critical conflict between increased market demands and limited labor supply, which is a big challenge for the labor-intensive construction industry as well. The over-reliance on cheap workforce largely slows the marketization process of real wage during the periods of surplus labor force, further leads to the sluggish growth of Total Factor Productivity (TFP) in China's construction industry.

Labor cost estimation, control, and regulations are of great importance to achieve the final success of construction project. As a major component of construction cost, labor cost refers to the total amount of money paid for construction migrant workers employed in the production process. In Chinese construction industry, construction migrant workers are the mainstream that takes up over 90% of total employment (National Bureau of Statistics of China, 2020b). Also, it is noteworthy that labor cost takes up nearly 20% of the total cost of construction projects (Xu & Ji, 2010). The increasing share of construction labor cost draws extensive concerns among various participants in recent decade, such as labor-only subcontractor, contractor, stakeholder, and policymaker. Previous competitive edge based on surplus labor force has been undermined to maximize the profit margins, also exerted widespread effects towards construction workforce recruitment, construction project management, and construction industry development.

Considering that "dangerous, dirty and demanding" image of construction industry, nowadays young generations are more willing to join the service industry with better working conditions in urban areas (Ling & Ho, 2013). The ageing construction workforce can hardly meet the growing construction demands over the past decade. Labor shortage and skill crisis have emerged as a recurrent problem that hinders the sustainable development of construction workforce, construction firm, and the whole industry (Dainty et al., 2004; MacKenzie et al., 2000). Under this circumstance, the retention and attraction of construction workers becomes a focal point of contractors through the provision of a higher level of remuneration (Gruneberg, 1997), especially during the period of construction boom. Considering the one-off production nature of construction, small and medium-sized contractors tend to employ casual workers on a temporary basis as an alternative solution (Dainty et al., 2005). In addition, construction firms are reluctant to invest in machinery and new technologies for labor savings in terms of uncertainty of long-term returns (Gruneberg, 1997). The significance of construction labor cost was largely underestimated with an excess labor supply. Theoretically, the level of labor wage is determined by both labor supply and demand. Labor cost variations influences the profit margins of contractors and overall competitiveness of construction industry. Thus, a comprehensive understanding of labor cost in construction industry is essential to facilitate construction workforce management, construction project delivery, further construction investment.

Construction labor cost performance not only changes with time series but also varies greatly from region to region. After the Reform and Opening-up, the emphasis of Chinese regional development policy was shifted from equity to efficiency, which encouraged the coastal regions to "get rich first" with enormous domestic and foreign direct investment, then promoted the mutual growth of inland regions (Han & Ofori, 2001). In a stark contrast, surplus labor force was more adequate in the Midwest rather than eastern regions of China (Chi & Qian, 2013). The comparative advantage of regional development is built through gradient transfer with labor movement and capital investment across regions. The increasing differentials of labor wage are primarily due to regional gaps of TFP (Bateman et al., 1988). Regional divergences can be attributed as a combined result of unbalanced distribution of requisite local resources, and uneven allocation of industry demands (Jiang & Liu, 2014). To narrow the gaps for effective investment and productive growth across regions, it is vital to have insightful information on regional inputs and output in the construction industry. More importantly, understanding the root causes of labor cost variations across the regions can not only facilitate the recruitment and management of construction workforce, but also the adjustment of market strategies of construction firms, further policy makings of local government. It is never an easy task to capture the complicated variations of regional construction labor cost without a reliable and robust modeling technique and estimating approach. Most of previous studies focused more on the empirical analysis of construction labor cost based on the questionnaire surveys of construction workers, time series analysis of construction labor cost by using different econometric methods, whereas few efforts have been given to in-depth investigation of construction labor cost performance through a multi-dimensional analysis.

Construction labor cost is more volatile to external change due to the fragmented market. In response to seasonal fluctuations, unit rate pricing system is regularly updated by local government for labor cost estimation in construction project. It is commonly agreed that the wage level reported from contractors changes more frequently than unit wage rate in construction market. Consequently, there remains some discrepancies between estimated labor cost and actual cost in construction process, which have adverse impacts on the reasonable organization or recruitment of construction worker, the effective management of construction cost, and the successful delivery of construction project. To better understand labor cost variations in construction market, it is imperative to investigate the interplay between construction labor cost and potential factors from an overall perspective, then make timing and responsive adjustments for labor cost in construction practice.

To bridge these research gaps, this study attempts to conduct an overview of labor cost performance in China's construction industry from temporal and regional dimensions, then identify the potential determinant of construction labor cost based on a comprehensive analysis of literature review and questionnaire survey. Panel data model is then applied to investigate the relationship between construction labor cost and its explanatory variables across three regions of China with different levels of economic growth and social development over time periods. Further, Data Envelopment Analysis (DEA) model is employed to benchmark and measure the performance of construction productive efficiency based on three critical inputs of resources and one output, then explore the causes of inefficiency and the sources of growth for regional construction industry. The regional differences of construction productive efficiency are discussed from input optimization and output potential according to the results of Distance Friction Minimization (DFM) model. For those less inefficient provinces that cannot achieve significant improvement within a short period of time, a Target-Oriented (TO) approach is adopted to set the stage-wise targets according to the efficiency gaps and projection period. The optimal pathways for stepwise efficiency improvement in regional construction industry can be explored using Target-Oriented DFM (TO-DFM) model. Final, Panel Vector Error Correction (P-VEC) model is developed based on the explanatory variables to predict the future trend of regional construction labor cost. The predictability of P-VEC models is validated before conducting scenario analysis in subsequent periods, the simulation results are complementary to further in-depth discussions. The principal findings serve as strong evidence for the construction workforce management, and practical strategies for labor cost adjustments, further good references for decision support and policy making in terms of resources allocation and investment planning.

1.2 Research scope

This study conducts a multi-dimensional analysis of labor cost in China's construction industry from temporal and regional dimensions. As one of the pillar sectors in national economy, construction industry has absorbed massive surplus labor force from rural areas during the urbanization process over the past decades. Cheap workforce underpinned by rich labor force makes the construction industry show heavy reliance on migrant workers. Labor cost merely takes up a small proportion of the total cost of construction projects, which has been regarded as a major source to maximize the profit margins. According to the relevant statistics, construction migrant workers take up over 90% of the total employment in the whole industry (National Bureau of Statistics of China, 2020b). The great mobility of construction migrant workers increases the difficulty of labor cost estimation and management, meanwhile the complicated subcontracting system obscures the concept of labor cost in China's construction industry.

Unlike formal staffs with tenure contract, the temporary and casual nature of employment determine that construction migrant workers are normally paid on a daily basis in terms of completed works, a combination of both time rate and piece rate, without fringe benefits and insurances (Gruneberg, 1997). In this respect, labor remuneration can be integrated as the cost of labor per working unit in the construction industry. The rapid growth of construction labor wage draws extensive concerns in both academia and industry over the past decade. More efforts have been dedicated in exploring the underlying reasons and potential impacts of labor cost variations in China's construction industry. However, due to the limitations of data availability and model development, partial observations from a single perspective cannot provide a holistic review of labor cost performance in construction market, further insights for the references of decision making and strategic planning in construction industry.

Unit Labor Cost (ULC) is a measure of labor cost competitiveness that both considers the changes of labor wage and labor productivity in the production process (Ark et al., 2005). It is defined as the cost of labor per unit of the output produced, which can be also expressed as the ratio of labor compensation per unit and output per employed person or output per hour worked. The concept of ULC has been adopted for international comparison in terms of labor cost competitiveness. In this research, ULC is adopted as a typical proxy of labor cost performance in the construction industry. It incorporates the absolute changes of both labor compensation and construction output, providing specific information regarding the overall efficiency of labor input to created output in construction activity. Besides, selecting ULC as target variable can diminish the external differences and further facilitate the multi-dimensional labor cost analysis in China's construction industry.

1.3 Research aim and objectives

To address these research problems, the primary aim of this research is to investigate the labor cost performance of in China's construction industry through a multi-dimensional analysis.

The specific objectives of this research are as follows.

(1) To investigate the relationship between construction labor cost and critical determinants across different regions of China through panel data modeling.

(2) To develop an efficiency measurement for construction industry based on DEA and explore the regional differences of construction productive efficiency using DFM model.

(3) To identify the optimal pathways for stepwise efficiency improvement in regional construction industry using TO-DFM model.

(4) To forecast the future trend of regional construction labor cost based on P-VEC models through scenario analysis.

1.4 Research design

This research follows the process shown in **Figure 1.1** to achieve the research objectives.

First, research problems and gaps are identified based on the literature review and document analysis. Construction labor cost performance is reviewed from two perspectives of time and region, potential factors affecting labor cost are summarized from labor supply and labor demand, accompanied with the modeling techniques. The research objectives are identified based on the limitations of previous research. Chapter 2 reviews previous studies.

Based on the previous research, questionnaire survey is conducted aimed at construction migrant worker to provide an overall understanding of labor cost performance in the China's construction industry. The potential factors affecting construction labor cost are summarized based on empirical analysis of literature review and questionnaire survey. Panel data model is built to investigate the relationship between construction labor cost and its potential determinants across different regions of China with different levels of economic growth and social development over various time periods. Chapter 4 presents the research process.

Based on the neoclassic economic theory, DEA-based model is then applied to measure the overall performance of construction productive efficiency with three critical inputs and one output across three regions of China. The causes of inefficiency and sources of growth are explored for regional construction industry based on the empirical results of DFM model. Chapter 5 presents the research process. For the less inefficient provinces that cannot make significant improvement within a short period of time, the optimal pathway for stepwise efficiency improvement can be further identified with the stage-wise targets using TO-DFM model. Chapter 6 elaborates the research process.

Final, P-VEC model is established based on the identified critical determinants to predict the future trend of regional construction labor cost. The predictability of P-VEC model is validated with the comparison of P-OLS model for in-sample forecasting. Scenario analysis is conducted to predict the future trend of regional construction labor cost based on P-VEC model. Recommendations are made accordingly for the references of policy making and decision support. The details are presented in Chapter 7.

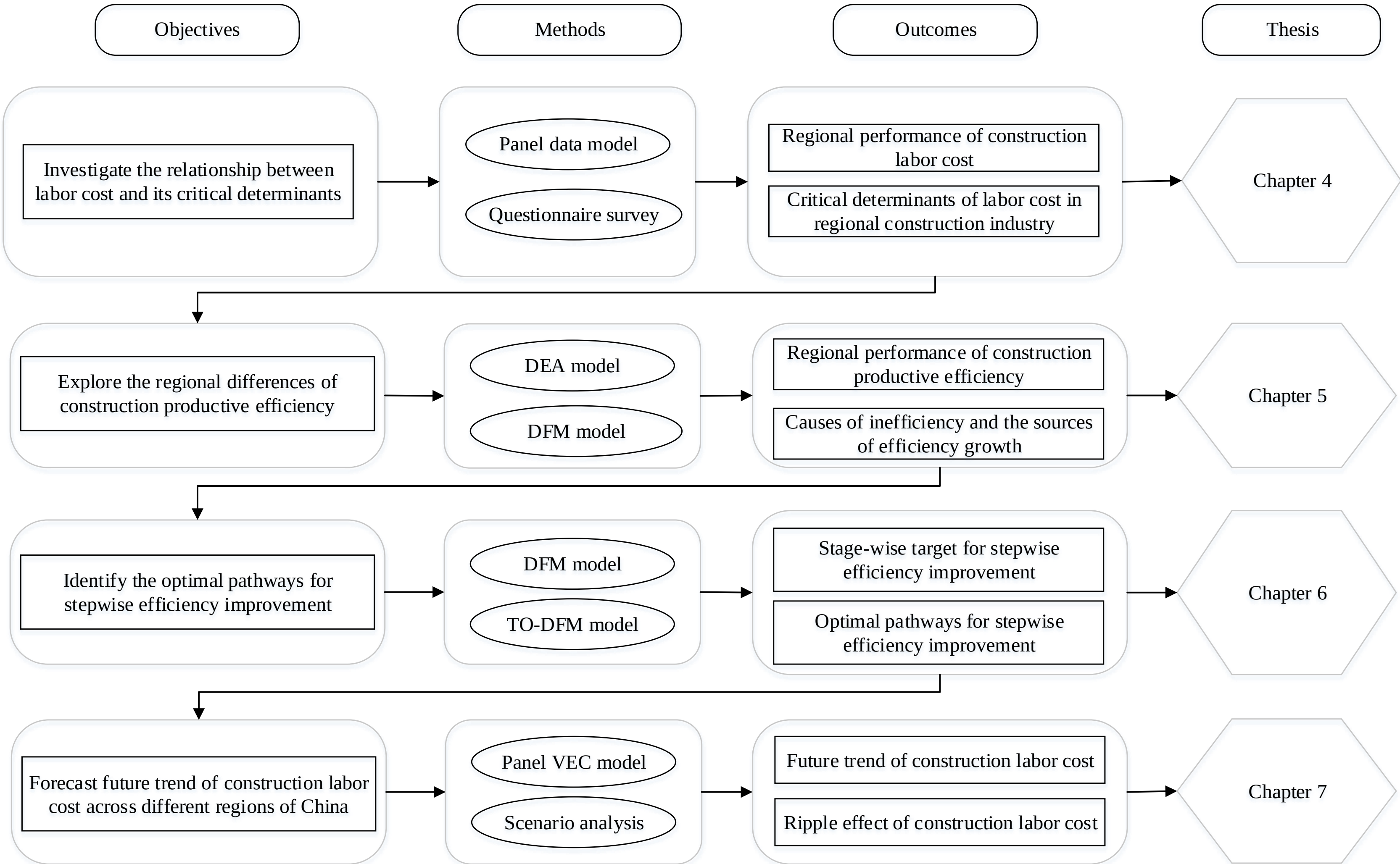

Figure 1.1 Overall research framework of the thesis

1.5 Significance of the research

This research contributes to the knowledge of labor cost studies in the China's construction industry. The theoretic and practical contributions of this research are listed as followed.

First, labor cost has undergone dramatic changes in China's construction industry over the past years. With the shift of labor supply and demand in recent decade, labor cost variations have great impacts towards different participants in regional construction industry. For comprehensive understanding, this study provides a holistic review of construction labor cost performance from both temporal and regional dimensions. Second, investigating the relationship between regional construction labor cost and its critical determinants has considerable implications for construction workforce management, and construction project delivery, further construction industry development. Third, measuring the overall performance of construction productive efficiency using the DEA-based models can provide insights into the causes of inefficiency, and the sources of growth for efficient resource planning and allocation across three regions of China, with different levels of economic growth and social development. Further, for those less inefficient provinces or municipalities identified in each region that cannot make significant improvement within a short period of time, the optimal pathways for stepwise efficiency improvement can be further mapped out under the guidance of reasonable targets, which serve as good references for making investment decisions or fine-tuning economic policies in coming periods. Final, regional construction labor cost forecasting can facilitate the recruitment and management of construction workforce, the adjustment and formulation of market strategies for construction firms, further policy making and fine-tuning for the government.

1.6 Structure of the thesis

The dissertation is organized into eight chapters.

Chapter 1 introduces the essential information of this research, including the research background, research problem and scope, research aim and objectives, research design and the structure of thesis.

Chapter 2 provides a comprehensive review of literature on labor cost in the construction industry primarily from both temporal and regional perspectives, covering labor cost definition and analysis in construction industry, relevant theories, potential factors affecting labor cost in construction industry, labor cost modeling and forecasting analysis, and total factor productivity. Moreover, research trends and gaps are discussed based on the limitations of previous studies.

Chapter 3 describes the research framework and research methodology. Research methodology comprises both qualitative method and quantitative method. Qualitative method includes literature review, document analysis, and questionnaire survey, while quantitative method consists of panel data model, P-VEC model, scenario analysis, and DEA-based models including DEA, DFM, and TO-DFM models.

Chapter 4 investigates the relationship between construction labor cost and potential determinants across three regions of China. Questionnaire survey, collected from construction migrant workers, provides additional information for an in-depth understanding of China's construction labor cost. Potential factors affecting labor cost in construction industry are summarized with considerations of literature review and questionnaire survey. Panel data model is then developed to identify the critical determinants of construction labor cost across different regions of China over the past two decades.

Chapter 5 explores the regional gaps of construction productive efficiency. DEA model is applied to measure the overall performance of construction productive efficiency across three regions of China. Based on the results of DEA model, DFM approach is used to explore the regional differences of construction productive efficiency. The causes of inefficiency and sources of growth for regional construction industry are discussed from input optimization and output potential, respectively.

Chapter 6 identifies the stepwise improvement pathways of construction productive efficiency across three regions of China. The less inefficient provinces are identified from each region based on the DFM modeling results, which require a stepwise planning for efficiency improvement. The stage-wise targets are set according to the efficiency gaps and study period. The optimal pathways are explored by using TO-DFM model for stepwise efficiency improvement in the coming periods.

Chapter 7 develops the P-VEC models based on the identified critical determinants to predict the future trend of construction labor cost across different regions of China. The predictability and reliability of regional construction labor cost forecasting models are validated and compared with other econometric methods. Regional construction labor cost is further predicted by conducting scenario analysis underlying the assumptions of critical bidirectional variables in P-VEC models. Recommendations are made accordingly for the references of policy making and decision support in construction industry.

Chapter 8 summarizes the primary research findings and examines the achievement of the research objectives proposed in Chapter 1. The contributions and limitations of this research are highlighted, also future directions of this study are recommended.

1.7 Summary of the chapter

The chapter outlines the overall picture of this research, including research background, research scope, research aim and objectives, research design, and significance of this research.

Chapter 2: Literature Review

2.1 Introduction

This chapter reviews empirical studies concerning labor cost in the construction industry, including labor cost definition and analysis in construction industry, relevant theories of research, potential factors affecting construction labor cost, labor cost modeling and forecasting in construction industry, total factor productivity, research trends and gaps.

2.2 Labor cost performance definition of construction industry

Labor is one of the essential production factors that determine the progress, productivity, and performance in the production process (Gruneberg, 1997). The cost of labor refers to the sum of money paid for employees as well as payroll tax, supplement pay, subsidy, staff welfare, insurance and so forth (International Labor Office, 2020). Construction industry is labor intensive that has absorbed massive unskilled migrant workers from the rural areas. Due to the one-off nature of construction product, construction workers are dismissed on completion of a project and move to another construction site. There is a high proportion of self-employed workers in the construction industry (National Bureau of Statistics of China, 2020b). The great mobility of construction migrant workers may increase the difficulty of labor cost estimation and management. In this respect, labor cost refers to the total expenditure of construction workers in construction process. As the dominant component of construction labor cost, labor remuneration is measured on daily completed works in real project, a combination of time rate and piece rate methods, which determines the performance of labor productivity as well as unit labor cost in construction activities.

Unit Labor Cost (ULC) is the cost of labor of output produced per unit, which can reflect both wage rate and labor productivity in a particular sector or economy (Ark et al., 2005). It is calculated by dividing the cost of labor by the value of output produced, also expressed as the ratio of labor wage per unit and output per employed person or per hour worked, shown in **Formula 2.1**.

$$Unit\ labor\ cost = \frac{labor\ wage\ per\ unit}{output\ per\ employed\ person} = \frac{real\ wage}{labor\ productivity} \tag{2.1}$$

ULC is measured in index and percentage changes, included in Key Indicator of the Labor Market (KILM) of International Labor Office (ILO) for international comparison of cost competitiveness across sectors and economies. It is an overall measure of cost competitiveness that can consider both wage rate and productivity level in the production process. The change of ULC contributed by productivity gains or wage moderation has considerable implications for construction workforce and cost management, further construction industry development (Ark et al., 2005). Raising labor wage can attract more workers, however, reduce profit margins of construction firms. An alternative strategy to offset the rising remuneration is to improve labor productivity. However, ULC is more sensitive to the labor cost variations, compared with slow productivity growth in the labor-intensive construction industry. Contractors are more inclined to minimize the labor costs with management skills to remain competitive in a tight labor market (Gruneberg & Francis, 2019). In addition, ULC can be also used to estimate the capacity of construction industry to accommodate for the changes in labor wage to output created per unit. A country or region characterized with a high level of ULC is normally regarded as uncompetitive in construction market. In this context, an increasing use of new technology and technical equipment is to reduce the demand of site workers for a higher level of productivity against the labor shortage in some construction works (Chia et al., 2012). This study attempts to use an overall indicator of ULC for conducting a multidimensional investigation of labor cost performance in China's regional construction industry.

The great difficulty in ULC estimates, particularly the developing economies, is the data availability concerning real wage and labor productivity in a specific industry. China is not included in KILM database due to lack of adequate information in labor market, notwithstanding with large share of self-employed persons in the informal sectors (Ark et al., 2005). For statistical purpose, the reliable sources of labor wage and productivity is critical to the accurate estimation of ULC in construction industry. Given the mainstream of construction workers in total employment, labor compensation is represented by the remuneration of construction workers on either monthly or yearly basis. Besides, measuring the labor productivity on the basis of working hours per unit is more difficult due to the complexity in construction process. Instead, productivity is often estimated by dividing value added by the total number of employed persons in construction industry.

$$Productivity = \frac{value\ added}{labor\ units \times time\ periods}\ \ or\ \ \frac{value\ added}{total\ labor\ inputs} \tag{2.2}$$

For international comparison, both labor remuneration and value added need to be converted with the exchange rate and Purchasing Power Parity (PPP) across countries and regions (Ark et al., 2005). In this research, ULC is measured and compared across different regions of China. The effect of Consumer Price Index (CPI) can be indirectly eliminated in the normalization process of ULC on the base year. In terms of regional disparities of economic growth and industry development, ULC can incorporate absolute changes of labor compensation and productivity in construction, providing specific information concerning the labor cost competitiveness in construction practice. Meanwhile, selecting ULC as the target variable of construction labor cost can automatically diminish external impacts caused by market changes, further facilitates the multidimensional analysis of labor cost performance in China's construction industry.

2.3 Labor cost analysis in construction industry

Construction industry is one of the pillar sectors in Chinese economy, contributing more than 5% value added in Gross Domestic Product (GDP) and job opportunities in total employment over the past decades (National Bureau of Statistics of China, 2020a). Because of its widespread linkages to the rest of the economy, construction investment is often adopted as an effective instrument to stabilize and regulate the economy, particularly during the economic downturn (Ofori & Han, 2003). The rapid development of China's construction industry is sustained by cheap workforce over the past years, underpinned by surplus labor force. China's dual economic structural reform has been accelerated by a demographic transition, characterized with the slow growth of labor supply and strong demand for labor (Fang & Yang, 2011). Because of the existing income gaps between rural and urban areas, high remuneration is the primary driving force to attract surplus migrant workers for the increased demands over the past years, although labor wage in construction industry is still far away from the average level in national economy (National Bureau of Statistics of China, 2020a). Further, construction demand is very sensitive to the economy at both regional and province levels, given the investment-driven nature of China's construction industry (Chen, 1998). Construction industry plays a distinct role in various regions with different levels of economic development across China (Han & Ofori, 2001). Construction migrant workers tend to move and work in where better salaries can be offered. In light of these observations, a multi-dimensional review of construction labor cost performance from both temporal and regional perspectives is theoretically and practically essential.

2.3.1 Temporal characteristics of construction labor cost

Labor cost has been one of the major advantages of Chinese contractors in both domestic and international construction market. It has not drawn extensive attention until the outbreak of labor shortage over recent decade. Construction industry has made extensive use of migrant workers during the rapid urbanization process, addressing the employment issues of surplus labor force but showing more reliance on cheap workforce in construction works. Labor cost has been largely underestimated and minimized for profit gains in the period of excess labor supply. With the rapid growth of construction works created by enormous public investment, the labor-intensive development of construction industry cannot be sustained with a slow growth of migrant workers, shown in **Figure 2.1**. Construction labor wage achieves an incremental growth in the past decade with a large share of labor cost of building project (National Bureau of Statistics of China, 2020a), sometimes occupying more than 20% of the total construction cost in some developed regions.

Figure 2.1 Annual salary and total employment in construction industry

(Source: National Bureau of Statistics of China, 2020a)

Construction migrant worker becomes a major source of the employed persons in the construction industry (National Bureau of Statistics of China, 2020b). Owing to the inherent restrictions of "hukou" system, construction migrant workers cannot easily settle down in urban areas and are normally paid by labor-only subcontractors or foremen on a daily or monthly basis without contract. The informal recruitment of temporary labor, complicated by the subcontracting system in labor market, obscures the concept of labor wage in China's construction industry. According to relevant statistics shown in **Figure 2.2**, the real wage of construction industry is the second highest with steady growth of all sectors for migrant workers (National Bureau of Statistics of China, 2020b). However, most construction migrant workers were unskilled due to limited education and training, often they improved skills through the on-the-job training or apprenticeship on construction sites (Gruneberg, 1997). Given the informal contract and low status of migrant workers, the wage rate of construction workers was lower than the average level in the economy. In terms of poor image of construction industry, young generations are more willing to undertake other sectors in urban areas, although respectable earnings can be offered in construction activities. Under this circumstance, the ageing construction workforce can hardly satisfy the strong market demands without adequate supplement of new blood, thus presenting a declining supply of construction migrant workers after 2014.

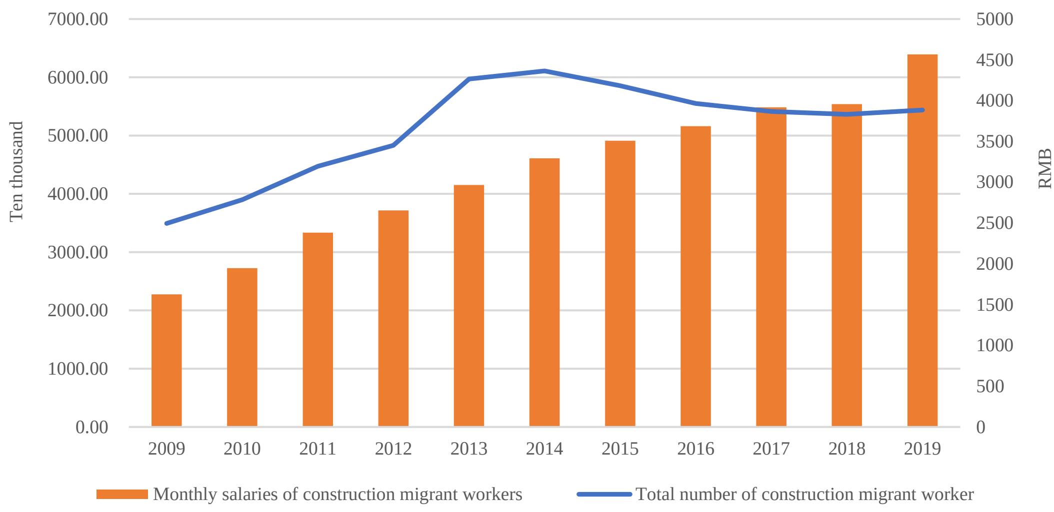

Figure 2.2 Monthly salary and total number of construction migrant workers in China

(Source: Ministry of Housing and Urban-Rural Development of PRC, 2020)

In response to the labor shortage, contractors usually tend to raise the wage level to attract additional workers from labor pool in the short term. Rising labor cost would have a great impact towards the operation and management of construction project, and further the performance of profits margins. Compared with other sectors, the job turnover of construction workers is relatively high with little loyalty to contractors (Ive & Gruneberg, 2000). Thus, there is little incentive for construction firms to train the causal workers. Skill shortages are the result of insufficient investment in the vocational training program. Migrant workers are reluctant to attend the training programs unless financed by government or institutions. Faced with the decreasing labor supply, contractors are also reluctant to use construction plant and equipment for labor savings due to high up-front investment (Gruneberg & Francis, 2019). The increasing use of new technologies and advanced equipment for labor savings has been an alternative response to wage increase. However, low profit gains imply that construction machinery and equipment is a risky investment for contractors with the consideration of long-term returns. Instead, they prefer to use the subcontracting work packages to lower down the cost of labor for maintaining the level of profitability.

2.3.2 Regional performance of construction labor cost

China is the largest developing country with the most population in the world, regional inequality is an overall result in terms of economic growth, resource allocation, investment planning and so forth (Chang et al., 2002). China has been undergoing the transition process from a planned economy into a market-oriented economy after the Reform and Open-up since 1978. Under the planned economy framework, regionalization schemes are tailored by the central government with considerable implications for economic growth and industry development. The definition and specification of regionalization depends on the economies of scale and development policies of the government (Ofori & Han, 2003). The emphasis of regional development is mapped out according to the distributions of local resources. The coastal regions were encouraged to get rich first with strong support of the government, whereas regional development in inland regions was resource-oriented with primary focus on traditional second industries (Han & Ofori, 2001). As a consequence, regional gaps were partly the overall results of unbalanced allocation of capital investment and key resources. The expansion of Chinese economy at regional and province levels has been invariably began with large-scale investment through the creation of construction works. As the major engine of economic growth, construction industry plays an important role in boosting regional development and performs as a good example to illustrate regional divergencies, evidenced by its contributions to GDP and total employment in the economy (Ofori & Han, 2003).

Based on the arguments of Bon's curve shown in **Figure 2.3**, there remains an inverted U-shaped relationship between the share of construction activities and the level of economic development based on the observations of a number of countries and regions over time (Bon, 1992). The selected countries and regions are classified into the three clusters according to the level of per capita Gross National Product (GNP), i.e. Less Developed Countries (LDCs), Newly Industrialized Countries (NICs), and Advanced Industrialized Countries (AICs). The share of construction activities increases in the early stage of development and then starts to decline at the latter stage of mature (Bon, 1992; Ruddock & Lopes, 2006). As one of the evolving economies in global market, China's construction industry has been achieving a rapid growth with an increasing share of GDP over the past years. The inverse U-shaped pattern can partly explain the regional development of construction industry in China.

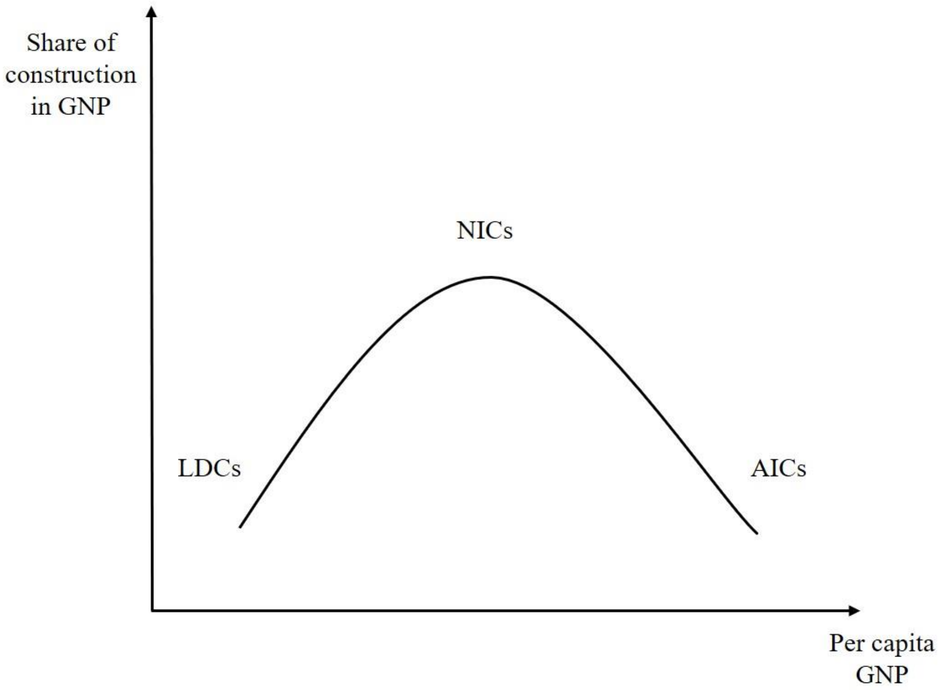

Figure 2.3 Share of construction in GNP and per capita GNP

(Source: Bon, 1992)

In coastal areas, construction industry is more developed with a large volume of construction output, but most provinces in eastern region register a smaller value in the contribution of construction to GDP (Han & Ofori, 2001). In contrast, inland regions, i.e. western and central regions, are recorded with a high proportion of the construction value added to GDP, due to the small size of regional economies (Han & Ofori, 2001). Likewise, the proposition of 'volume follows share' could well explain the regional performance of employment level, construction investment and other aspects in China's construction industry. The rapid growth of construction industry has become an important consideration in determining the policy formulation and capital investment (Mayo & Liu, 1995). Overinvestment in construction activities does not necessarily boost the efficient economic growth, however, may drive up the costs of production factors, e.g. labor, materials, and equipment in construction process, thus influencing the availability of inputted resources that would ultimately restrict further growth of the economy. Labor shortage is a recurrent problem perplexing the industry, regional labor cost performance has considerable implications for the sustainable development of construction industry.

China's construction industry has achieved a rapid growth with the reliance on cheap labor over the past decades. Geographically, capital investment is mainly allocated in coastal areas with the lower transportation cost and better economic performance, whereas abundant labor resources are widely distributed in inland areas (Chang et al., 2002). Given the labor-intensive nature of the construction industry, migrant workers from the remote areas tend to move and work in developed coastal areas, where a high level of remuneration is provided for meeting the increasing demands. Labor migration can facilitate the process of resource optimization, but the enlarging regional gaps of construction labor cost exacerbate the dependence on cheap but unskilled workforce in construction activities. Labor cost is calculated on the basis of unit rate pricing system, in accordance with the actual usage of labor in Bill of Quantities (BOQs). Unit rate pricing system is standardized with considerations of productivity and periodically updated by official authorities according to the real-time changes in construction labor market. Regional divergences can be observed in the wage rate of construction worker according to the unit rate pricing standard. The different calculation basis takes accounts of factors with respect to labor market, subsistence level, and so forth. As is shown in **Figure 2.4**, the daily wage of construction worker in eastern region is basically higher than that of western and midland regions, nearly double of that in some central cities from inland regions over recent years (Ministry of Housing and Urban-Rural Development of PRC, 2020).

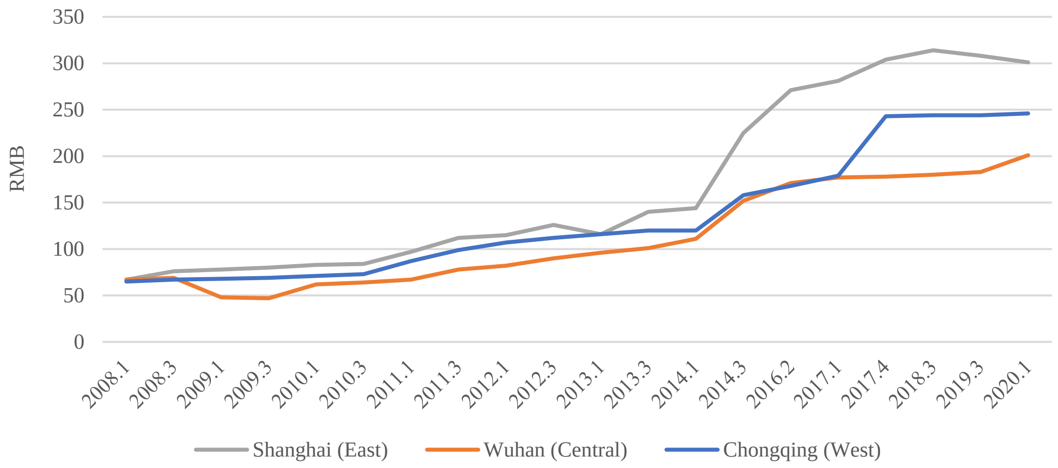

Figure 2.4 Average daily wage of construction workers in three cites from different regions

(Source: Ministry of Housing and Urban-Rural Development of PRC, 2020)

In practices, construction site workers tend to work intensively for more earnings, usually more than 8 hours each day. The actual calculation of labor cost takes account into a series of other factors including the overtime working, holidays subsidies and so forth. The extra pays can explain the gaps of unit wage rate across three typical cities from different regions of China, shown in **Figure 2.5**.

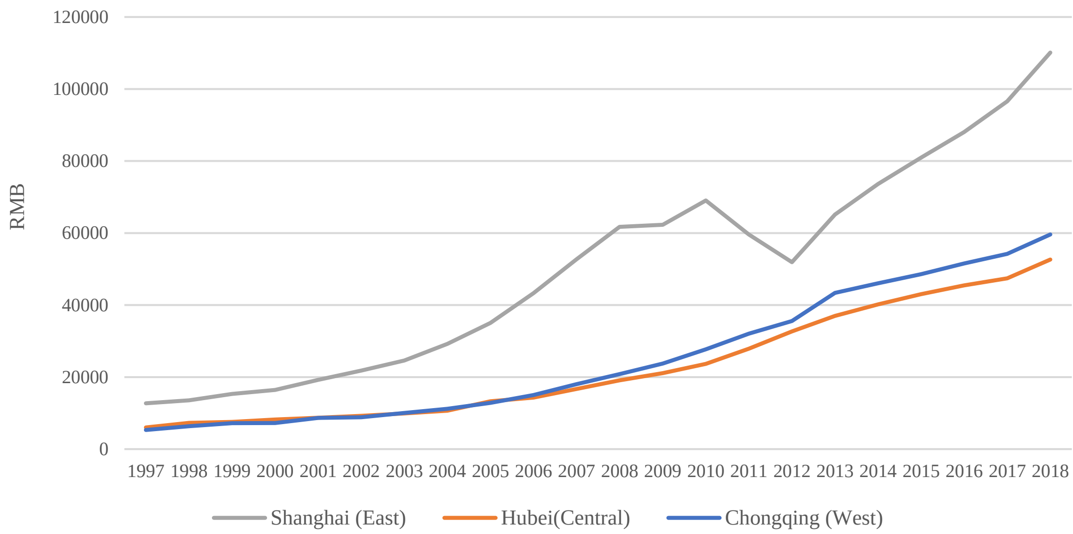

Figure 2.5 Average annual salary of construction workers in three cities from different regions

(Source: National Bureau of Statistics of China, 2020a)

On the other hand, the shortages of some skilled trades lead to a continuous growth of real wage in construction domain. Detailed information concerning real wage across various trades is presented in **Figure 2.6**. 2016 is taken as an example year for the illustration, significant regional differences of skilled workers' compensation are clearly captured across different trades. The monthly salary of formwork erector is the highest of three regions. For regional comparison, the real wage of skilled worker in eastern region is the highest of all in each trade. In contrast, there are some differences in several skill trades between western region and midland region, but overall level is nearly the same. Although the wave of massive construction enables the government raising the updating frequency of local unit wage rate across different regions, this by-product in the planned economy cannot well react to the dynamic changes in labor market, and ultimately increase the possibility of cost overruns or lower the profitability of construction projects.

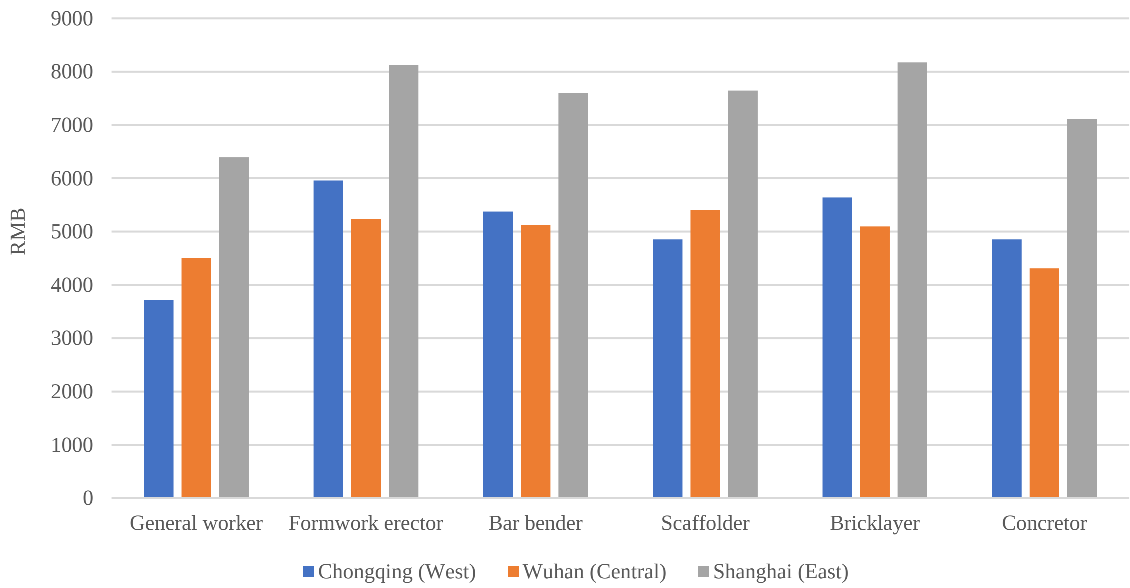

Figure 2.6 Monthly salary of construction workers across various skills trades in different regions

(Source: Ministry of Housing and Urban-Rural Development of PRC, 2020)

Under this circumstance, labor cost information derived from construction project turns to be more objective and accurate. It can be also anticipated that the growing labor cost takes up a bigger share of the total cost of construction projects. Based on the summary of collected information in building projects shown in **Table 2.1**, labor cost proportion maintained a slow growth and sometimes exceeded 20% of building projects in the central cities from developed eastern region. In comparison, labor cost percentage varied within a range from 10% to 20% in hinterland construction market due to the availability of cheap manpower. In response to the rising labor wage, new technologies and some equipment have been applied for labor saving in construction works, e.g. prefabricated and precast components. The labor-saving effects of advanced equipment and new techniques can be indirectly measured by the indicator of labor usage in construction works. It is interesting to note that the average labor usage of building project is less than 5 man-days of each square meters in developed eastern region, while the ratio remains high in underdeveloped western region as well as developing central region. As such, construction labor cost performance can be characterized with different indicators and expressed by several forms at various levels. Undoubtedly, labor cost is an indispensable element in establishing the competitiveness of contractors in regional construction market.

Table 2.1 Case studies of regional construction labor cost performance in building projects

Region	**Unit project cost (RMB)**	**Unit labor cost (RMB)**	**Labor cost percentage (%)**	**Labor usage (Man-day / m^2)**
Shanghai (East)	3604.75	559.79	15.53%	4.72
Wuhan (Central)	1407.90	178.10	12.65%	5.12
Chongqing (West)	1569.65	158.06	10.07%	5.40

2.4 Theories of this research

2.4.1 The law of labor supply and demand

The level of real wage is primarily determined by the law of labor supply and demand. As is shown in **Figure 2.7**, the two lines of labor supply and demand intersect is the equilibrium wage in theory, where the number of employed persons in the industry is nearly equal to the number of job vacancies required in construction activities. To this intersection, the equilibrium wage can be integrated as a reasonable remuneration level in a competitive market.

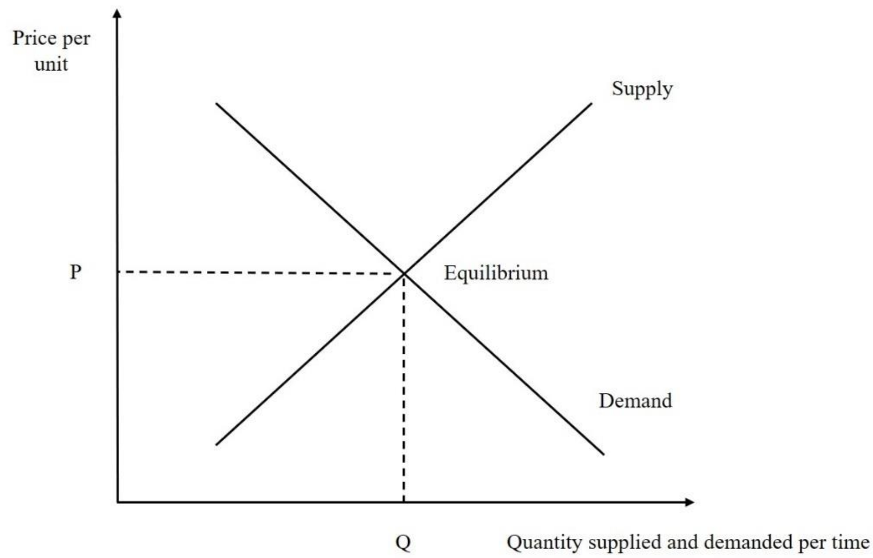

Figure 2.7 The laws of labor supply and demand

For the side of labor supply, the total number of people entering the market depends largely on the demographic factors and participate rate (Ive & Gruneberg, 2000). China's construction industry has enjoyed surplus labor force and made extensive use of migrant workers with unformal contracts. Compared with other labor-intensive sectors, low threshold and respectable salaries are two major priorities that attract migrant workers to participate in construction industry (National Bureau of

Statistics of China, 2020b). Construction industry is ranked as one of the most dangerous sectors with the occurrence of many accidents every year. They are less subject to the competition from urban residents, although most migrant workers are unskilled without the formal training. This can partly explain the relatively high remuneration for construction migrant worker (National Bureau of Statistics of China, 2020b). On the other hand, late payment is a perennial social issue besetting the construction migrant workers, particularly for temporary worker with limited individual capability of wage bargaining. Migrant workers are in a weak position to enforce their claims and rights in terms of wage arrears, as contractors are liable to retain some profits at the expense of labor cost and keep competitive for the lowest price bid (Gruneberg, 1997). With more skill requirements of construction worker and rapid growth of construction demand, the effective supply of labor relies more on the number of skilled workers at a given wage rate.

For the side of labor demand, it can be interpreted as a derived demand of construction. In the neoclassical economies, labor demand mainly depends on a combination of three factors, i.e. the quantity of fixed capital asset, the technology level embodied in plant and machinery, and the wage rate (Ive & Gruneberg, 2000). Capital intensity is the ratio of capital to labor input that can reveal the volume of plant and equipment per person employed. When the level of labor wage is relatively high, construction firms tend to increase the investment in construction plant and equipment to save the utilization of construction manpower for higher labor productivity. The growing demand backed by capital investment can be fulfilled through the greater application of machinery and technology rather than the employment of additional labor. When the wage rate is low, the incentive to substitute labor with machinery and equipment is reduced, labor demand is more responsive to market changes created by capital assets. Against this background, additional construction workers can be attracted if better salaries are offered.

2.4.2 Neoclassical economic theory

In neoclassical economic theory, labor is one of the indispensable inputs producing output in the production process. The wage rate is the most visible factor reflecting labor movement in terms of regional division. Technology is a possible alternative against expensive labor, with a high level of unionization and social relations. If technical process can be sufficiently mechanized to permit the use of unskilled and cheap labor, enterprises can seek the place where the reproduction cost of labor force is low. Besides, as the level of living cost grows, the average labor cost tends to exceed the increase in real wage. Therefore, enterprises are more inclined to mass production, mechanization, deskilling of labor, and the concentration of capital (Gruneberg & Ive, 2000). In terms of regional development theory, a major component of theoretical grounds in the neoclassical economic theory is that free market economies tend to move towards equilibrium, with an optimal distribution of economic activity, employment, and income (Higgins & Savoie, 1997). Regional gaps can be reduced with the movements of production factors including labor, capital, and technology through appropriate intervention in free market. Theoretically, labor can move to richer regions for meeting industry demand, while capital can flow into poorer regions to take advantage of low wage rates. The optimization process results in more efficient resource allocation across regions with different levels of economic development under reasonable development policies.

2.5 Potential factors affecting labor cost in construction industry

Based on the theory of labor wage, real wage is determined by the interactions between labor supply and demand in construction market. Given the complexity and diversity of construction market, a comprehensive review is conducted under the framework of labor supply and demand, and potential factors affecting construction labor cost is reviewed from the side of labor supply and demand, respectively.

2.5.1 Factors affecting construction labor demand

For the demand of labor in construction works, it can be also interpreted as construction demand in broad terms, particularly for a pillar sector in the developing economy. The positive relationship between construction sector and the economy provides strong evidence for boosting the economic growth through the output of construction activities in different phases (Tse & Ganesan IV, 1997; Wong et al., 2008). The growth rate of GDP stimulates the growth of construction output with a diminishing marginal return over time (Yiu et al., 2004). The development of construction industry is attributable to capital accumulation, and construction demands are created by a vast amount of physical investment to regulate and revitalize the economy (Ozkan et al., 2012). In this regard, construction output can quantify the amount of construction demands, whilst real GDP serves as a barometer of economic climate that would influence the potential demands of construction works.

The employment level in construction is essential to maintain the development of construction industry. The unemployment rate is measured as the proportion of unemployed persons who are ready and able to work. It serves as a signal indicating the stability and healthiness of an economy. An increase in unemployment rate might discourage further investment in construction and related activities (Hannikainen, 2008). Although construction industry provides enormous job opportunities for migrant workers with few requirements, it is unattractive for young people as an alternative career choice even offered with desirable labor wage (Ling & Ho, 2013). On the other hand, a high unemployment rate may denote the period of economic austerity, thus lower the purchasing power of residents with a decreasing income. Under this circumstance, new construction demands can hardly be accommodated unless with a loose credit policy. Interest rate is a macroeconomic variable that reflects the economic landscape and investment environment. It can be also interpreted as the lending rate, which affects the lending costs of different participants involved in construction projects. As construction project management is necessarily operated by loans from the financial institutions, fluctuations in interest rate may exert great impact on the management of cash flow, the achievement of profit gains, and the desire of further investment (Gruneberg & Francis, 2019). A lower interest rate implies a cheaper lending cost and hence encourages more spare money inflow into the construction market. Generally, the emergence of construction boom is sustained with the policy support of a low interest rate, national income supports the purchasing power of households and residents for construction demand. In contrast, a high level of interest rate would undermine the confidence of investors and the volume of construction demand.

In building projects, material cost is a key contributor that takes up over half of the total construction cost. Variations in major material price not only affect the demands of labor and equipment, but also the control of construction cost, and the amount of construction demand. Since the costs of labor and equipment are another two major components of construction cost. The continuous growth of labor cost might result in an increasing application of construction plant and machinery, and further improvement in construction workforce management. The aim of substituting expensive labor by equipment is to improve the performance of labor productivity through labor savings, then satisfy the labor demand for further development (Tan, 1996). The machine-for-labor substitution has been adopted as an alternative long-term strategy for addressing skill shortage after the tradeoff between labor input and equipment input among the industry (Goodrum & Haas, 2004). Therefore, labor productivity is a typical proxy for capturing the pace of technological changes as well as the progress of management practices. All these factors would determine the labor demand in construction works, and further demand of the whole industry.

2.5.2 Factors affecting construction labor supply

For the supply of labor in construction sector, the population size and structure determine the pool and capacity of construction workforce (Agapiou et al., 1995). The population growth results from interactions between fertility, immigration, and death in society, which also affects the demands for residential building. The development of construction industry initially relies on the availability of construction workers. The employment-generating capability of construction sector is enhanced to address the problem of unemployment through its multiplier effects in national economy. To define the participation of labor force in construction domain, participate rate is introduced to specify the percentage of population aged over 18 years who are active in labor market. More specifically, it also depends on the age and sex distribution of the population, further the individual decision and preference to seek a possible job in certain field (Uwakweh & Maloney, 1991). Compared with other sectors, construction industry is unattractive for urban residents due to poor industry image. Because of the dualism between urban and rural development, the tide of migrant worker flowing into urban areas fills the gap of labor demand and promotes the rapid growth of construction industry during the urbanization process. Another major driving force to absorb additional workforce is to increase remuneration (Agapiou et al., 1995). Alternatively, vocational education and training program is necessary for the long-term development of adequate construction workforce, and the improvement of working skills to meet the growing demands of construction industry (Agapiou et al., 1995).

2.6 Total factor productivity (TFP)

In the neoclassical growth theory, labor, capital, and TFP are the main drivers of growth. Based on the Cobbs-Douglas (C-D) production function, Solow residual approach is built on the assumptions of labor and capital inputs in the production process that has a positive but diminishing marginal utility with constant returns to scale (Solow, 1956). Due to the model restrictions, growth driven by technology is exogenous and can be merely achieved through the changes of TFP. Besides, as one of the key endogenous variables, labor is normally underestimated in contrast with capital (Kim & Lau, 1994). The growth contributed by capital input is stable but shows obvious regional disparities. This can partly explain the difficulty of attaining equilibrium in terms of regional development over time. In contrast, TFP is of immense significance to promote the economic growth based on the combination of labor, capital, and other production factors (Chau & Walker, 1988). Essentially, TFP is a result of cumulative accumulation of different production factors, it serves as a comprehensive indicator measuring the efficiency of resource allocation and utilization in an economy or industry. For construction sector, TFP can provide insights into the performance of productivity, as well as the underlying information regarding the overall competitiveness and development pattern.

China’s construction development is mainly investment-driven with the undesirable performance of labor productivity over the decades. Central government uses the infrastructure investment as a vital instrument to boost the economic growth and minimize the regional divergence (Shi et al., 2017). However, excessive investment in infrastructure cannot always translate into a faster growth and sometimes even be detrimental to economic structure regardless of the absorptive capacity (Shi et al., 2017). Due to the regional gaps of economic growth and fixed assets investment, migrant workers are inclined to move to regions where a high level of remuneration can be provided, leading to the imbalanced labor share across regions (Chi & Qian, 2013). The increasing regional gaps in income per capita were primarily due to differentials in TFP (Bateman et al., 1988). The income gap influences TFP through labor supply and market demand, exhibiting an inverted U-shaped trend of "first increase and then decrease" from least developed economies to developed economies (He et al., 2020).

Unlike manufacturing products, construction activity requires the coordination and cooperation of various inputs and participants on site. Construction is universally characterized with instability, insecurity, and unpredictability in the process of any project, these drawbacks inevitability increase the difficulty of measuring the productivity in construction. To overcome the challenge, the concept of TFP was proposed to estimate the level of production efficiency though a comparison between input and output without considering complexity in the intermediate process. To the best of our knowledge, numerous methods have been applied to measure the TFP in construction domain. The measurement methods can be further divided into two major types, i.e. parametric method and non-parametric method. Solow residual approach and DEA model are the typical approaches of these two methods, respectively. Solow residual approach focuses on the time series or discrete analysis of TFP growth with only one Decision Making Unit (DMU), while DEA is a popular benchmarking method for conducting the cross-section analysis by comparisons of multiple DMUs. A systematic review of related literature indicate that these two types of methods have been commonly used to evaluate the performance of construction industry TFP based on a summary of critical factors from different perspectives, shown in **Table 2.2**.

Solow residual approach is a useful descriptive tool to identify the sources of productivity growth over time (Solow, 1957). The growth accounting framework is appropriate for conducting discrete analysis at national or industry level. Wang et al. (2020) applied the Solow residual approach to evaluate the performance of Chinese construction industry development. The foremost contribution of TFP to final output suggested that China's construction industry was upgrading from a labor-intensive industry to a knowledge-based and technology-intensive industry (Wang et al., 2020). Ye et al. (2019) used the Solow residual approach to measure the impact of migrant workers on TFP in Chinese construction industry by comparisons of two scenarios. In addition, the growth accounting framework was also adopted for the investigation of construction industry TFP in Hong Kong (Chau & Walker, 1988) as well as Singapore (Tan, 1996, 2000; Zhi et al., 2003), and other developed economies (Abdel-Wahab & Vogl, 2011). As construction activities are volatile to the investment environment, the TFP growth of construction industry tends to move in accordance with business cycle, thus subject to fluctuations on time series data impacted by the occurrence of great event. Besides, the estimation of productivity growth is constrained by implicit assumptions on constant returns to scale, perfect competition, and the C-D specifications in the production process (Abdel-Wahab & Vogl, 2011). Consequently, Solow residual approach is restrictive to measure construction industry TFP at micro level, and less effective to explain cross-section differences particularly in terms of regional performance.

DEA-based model has advantages of benchmarking the performance of TFP based on cross-section data with common inputs and outputs at different levels. The Malmquist Productivity Index (MPI) is often adopted in DEA model to estimate the performance of construction industry TFP over the time period (Chancellor & Lu, 2016; Hu & Liu, 2018; Wang et al., 2013; Xue et al., 2008). Xue et al. (2008) and Chancellor & Lu (2016) measured the Chinese construction industry TFP at regional level, the increasing gaps were clearly identified between coastal region and inland region. The overall performance of TFP improved steadily primarily due to the economies of scale, less progress in equipment and technology (Wang et al., 2013), with the most productive eastern region and the least western region (Chancellor & Lu, 2016; Hu & Liu, 2018; Wang et al., 2013; Xue et al., 2008). Regional disparities on economic climate, organization structure and technology level influence the productivity performance of the China's construction industry (Chen et al., 2018), and further hinder the effective resource allocation and utilization (Wang et al., 2013). However, the decomposition of TFP can merely delivery information pure efficiency, technological progress, and the economies of scale. The traditional DEA-based model cannot provide insights into the efficient use of inputs to produce desirable output under full efficiency. Thus, further adjustments cannot be simply obtained from the production factors of inputs and outputs themselves, because of the model restrictions.

Table 2.2 Review of literature on TFP measurement in construction domain

Author	Country / Region	Method	Level	Input / Output Factors
Chau and Walker (1988)	Hong Kong	Production function	Industry	4 inputs: labor, material, plant and equipment, overheads; 1output: gross output
Tan (2000)	Singapore	Production function	Industry	2 inputs: labor (labor hours), capital (fixed assts); 1 output: total value added
Zhi et al. (2003)	Singapore	Production function	Industry	3 inputs: labor (hours worked), capital (fixed assets), intermediate (real value); 1 output: total value added
Xue et al. (2008)	China	DEA-Malmquist	Region	2 inputs: labor (number of employees), capital (fixed assets); 1 output: total value added
Li and Liu (2010)	Australia	DEA-Malmquist	State	2 inputs: labor (number of employees), capital (construction work done); 1 output: total value added
Wang et al. (2013)	China	DEA-Malmquist	Region	3 inputs: labor (number of employees), capital (fixed assets), equipment (total power of machinery and equipment owned); 2 outputs: total value added and output value
Chancellor (2015)	Australia	DEA	State	2 inputs: labor (hours worked), capital (capital stock); 1 output: total value added
Chancellor and Lu (2016)	China	Fare-Primont DEA	Region	4 inputs: labor (number of employees), capital (total assets and paid up total capital), equipment (total power of machinery and equipment owned); 2 outputs: total floor space and output value
Liu et al. (2016)	China	DEA-Malmquist	Region	2 inputs: capital (total assets and operational investment); 2 outputs: total pre-tax profits and profits of project settlement accounts
Lee at el. (2016)	Korea	Malmquist	Firm	2 inputs: labor (number of employees), capital (total assets); 2 outputs: total revenue, market share
Hu and Liu (2018)	China	Two-stage DEA	Region	3 inputs: labor (number of staff and workers), capital (fixed assets), equipment (number and power of machinery and equipment owned); 3 outputs: total value added, gross output value, total profits
Chen et al. (2018)	China	DEA-Malmquist	Region	2 inputs: labor (number of employees), equipment (total power of machinery and equipment owned); 3 outputs: total value added, gross output value, total pre-tax profits

2.7 Labor cost modeling and forecasting in construction industry

Faced with the rising labor wage over recent decade, it is essential to have insights into the future development of labor wage and responsive adjustments for construction workforce. As the dominant component of labor cost, it is of great significance to investigate the causes and effects of labor wage for effective control and management of construction workforce. In terms of the complexity of labor market, a dearth of studies has been conducted to explore the relationship between construction labor cost and its explanatory variables. Instead, previous studies focused mainly on the estimation and forecasting analysis of construction labor supply and demand, respectively.

2.7.1 Construction labor supply model

Uwakweh & Maloney (1991) proposed a diagnostic model of construction manpower planning by considering potential factors for labor supply and demand in developing countries. The conceptual frameworks for forecasting construction labor supply and demand are outlined according to the condition of labor market, the nature of the industry, and the level of economic activity. Based on the human capital approach, Agapiou et al (1995) presented an aggregate supply model for operative trainee entrants to the UK construction industry. The modeling results indicated that real craft wage and construction output are two major determinants of construction labor supply, meanwhile the demographic trend and socioenvironmental factors affects the choices of new entrants. Similarly, Sing et al (2012) developed a labor supply using a stock-flow approach for predicting labor supply in Hong Kong construction industry. To enhance the predictive ability of modeling, qualitative data obtained from interviews and questionnaire surveys is also incorporated for forecasting labor supply and demand of construction workers (Sing et al., 2012) and technicians (Sing et al., 2014). Besides, considering the complex nature of labor flow, a system dynamics model is developed by Sing et al (2016) to simulate the impact of external changes through the interconnections and feedback loops in infrastructure projects. These developed models of construction manpower planning can well assist the construction workforce management and the decision making of construction investment. However, the forecasting accuracy of construction labor supply model is subject to the quality and the availability of research data on construction workers in a changing labor market.

2.7.2 Construction labor demand model

Compared with the instability of construction labor supply model, labor demand with close linkages of construction demand has been estimated by a set of related variables based on different types of models. Rosenfeld & Warszawski (1993) proposed a conceptual framework for construction labor demand in various skills, and the strengths and weaknesses of different forecasting models were highlighted with the detailed discussion of major factors. Wong et al (2007) applied a Vector Error Correction (VEC) model to investigate the long-run relationship between construction labor demand and a group of associated variables including construction output, real wage, material price, bank rate and labor productivity. Construction output and labor productivity were the two most significant factors determining construction manpower demand in Hong Kong. To capture the external impact towards construction labor demand, Liu et al (2015) added a dummy variable to describe the changes of economic climate based on the VEC model in Australian construction industry. Besides, the forecasting results of multiple regression model and exponential smoothing techniques were also performed using the same factors (Wong et al., 2009). In comparison with the Box-Jenkins approach, VEC modeling technique and multiple regression analysis can better capture the casual interactions between labor demand and explanatory variables. In terms of the forecasting accuracy, multiple regression analysis was proved to be the highest of the all three models (Wong et al., 2011). The predictive capability of these models depends largely on the amount and quality of research data. Gray model is able to forecast the time series performance based on a limited amount of available data. Based on the theory of gray system, Ho (2010) used the gray model to predict the labor demand in Hong Kong construction industry. However, the forecasting method is applicable to other time series data, except for the frequent emergence of turning points. In contrast to the traditional model that is not adaptable to the changing economic conditions, a mathematical model of labor demand forecasting was built by Sing et al (2012) using a distributed lag model and labor multiplier approach for public and private sectors in Hong Kong construction industry. For labor demand at project level, it depends on several qualitative variables covering construction cost, project complexity attributes, physical site condition, and project type (Wong, et al., 2008). A labor demand forecasting model was established based on collected information of construction projects, multiple regression analysis was then applied for predicting the total labors and ten essential trades in Hong Kong construction industry (Wong, et al., 2008). To sum up, the major forecasting models of construction labor demand can be accordingly categorized into the following four groups, i.e. time series model, bottom-up coefficient approach, top-down forecasting model, and market signal approach (Wong et al., 2012).

Table 2.3 Summary of explanatory variables for construction labor supply and demand modeling and forecasting

Author	**Target**	**Method**	**Country / Region**	**Level**	**Factor**
Goh (1996)	Construction demand	ANN, Multiple regression	Singapore	Industry	national income, population size, lending rate, GDP, unemployment rate, material price, household savings, GFCF
Goh (1999)		Multiple regression	Singapore	Sectoral	population size, national savings, TPI, unemployment rate, lending rate, housing stock, GFCF
Hua and Pin (2000)		Box-Jenkins	Singapore	Industry	residential demand
Goh (2005)		Box-Jenkins	Singapore	Industry	value of contract awarded
Wong et al. (2005)		Box-Jenkins	Hong Kong	Industry	construction employment, labor productivity, unemployment rate, underemployment rate, real wage
Fan et al. (2010)		Box-Jenkins	Hong Kong	Sectoral	residential demand, commercial demand, industrial demand, total construction
Fan et al. (2011)		VEC, Multiple regression	Hong Kong	Industry	GDP, interest rate, population growth rate, unemployment rate
Jiang and Liu (2011)		VEC, VEC-D	Australia	Industry	national income, population size, household expenditure, construction price index, export value, interest rate
Jiang and Liu (2014)		Panel VEC	Australia	Regional	construction price, state income, population size, unemployment rate, interest rate
Tan et al. (2015)		Grey model	Hong Kong	Sectoral	gross value of construction works performed by main contractors
Sing et al. (2015)		VAR	Hong Kong	Industry	GDP, best lending rate, property price index, vacancy rate

Table 2.3 Summary of explanatory variables for construction labor supply and demand modeling and forecasting (To be continued)

Author	**Target**	**Method**	**Country / Region**	**Level**	**Factor**
Wong et al. (2007)	Labor demand	VEC	Hong Kong	Industry	construction output, real wage, labor productivity, interest rate, material price
Wong et al. (2008)		Multiple regression	Hong Kong	Project	construction cost, project complexity attributes, physical site condition, project type
Wong et al. (2009)		VEC, Box-Jenkins, Multiple regression	Hong Kong	Industry	construction output, real wage, labor productivity, interest rate, material price
Ho 2010		Gray model	Hong Kong	Industry	employed persons in construction industry
Wong et al. (2011)		VEC, Box-Jenkins, Multiple regression	Hong Kong	Industry	construction output, real wage, labor productivity, interest rate, material price
Sing et al. (2012)		Multiplier model	Hong Kong	Project	GDP, construction output, unemployment rate, working days
Liu et al. (2015)		VEC-D	Australia	Industry	construction output, real wage, labor productivity, interest rate, material price
Uwakwen and Maloney (1991)	Labor supply	Multiplier model	Developing countries	Industry	population size, participate rate, estimated size of labor force, enrolment in training programs, skill bases
Agapiou et al. (1995)		Multiple regression	United Kingdom	Industry	population size, participate rate, real wage, construction output
Sing et al. (2012)		Stock flow model	Hong Kong	Industry	trade classification, new entrants, retirement rate, attrition ratio, skill trade, labor working overseas
Liu and Xiang (2009)	Labor cost	VAR	China	Sectoral	labor productivity
Yang and Guo (2014)		VAR	China	Industry	labor productivity
Liu et al. (2015)		VAR, Box-Jenkins	China	Industry	construction output, CPI

2.8 Research trends and gaps

Most of previous studies focused more on empirical analysis of labor cost performance in China's construction industry, involving the causes and effects of rising labor cost, the issues of construction migrant worker, the effective measures of construction workforce management and so forth. Wu et al., (2014) investigated the major reasons for rising labor cost from the viewpoint of market supply and demand, found the driving force came from the demand of economic growth with increasing levels of CPI and inflation rate. On the other hand, labor shortage and skills crisis became the main barrier slowing the continuous growth of construction development, with a decreasing supplement of new blood into the industry. Liu & Xiang (2009) adopted VAR model to explore the relationship between labor wage and labor productivity in China's construction industry. Rising living cost and strong demand were two major determinants for rising construction labor cost (Liu et al., 2015). The growth of labor productivity was partly attributable to the increase of labor wage (Liu & Xiang, 2009). To understand the real situation of construction migrant worker, questionnaire surveys were distributed for construction migrant workers on sites in several provinces or cities across regions of China.

An accurate construction labor cost estimation and forecasting becomes quite crucial in enhancing the competitiveness of contractors and the possibility of winning construction project bids in a tight market. Liu et al., (2015) used ARIMA model to predict the future trend of labor cost development in China's construction industry. Liu & Diao (2014) applied the gray model to forecast the daily wage of construction worker, revealing that CPI, construction demand, and technology progress were the main contributors to rising labor cost in construction industry. More importantly, the shift of labor supply and demand was the root cause for labor cost variations. Ye & Zhang (2018) applied a multiplier model to conduct scenario analysis of labor supply and demand under different hypotheses in China's construction industry. It was anticipated that construction labor cost would keep an upward trend in the coming period, rising labor cost would promote the application of labor saving and new technologies in construction activities, as the short supply of construction migrant workers cannot fully satisfy the growing demands created by public investment. The unbalanced distribution of public investment leads to regional differences in terms of economic growth and construction demand.

Considering the significance of labor cost performance in construction industry, it is inconclusive to explore the variations and impacts of construction labor cost without considerations of regional differences. Regional divergences of labor cost are the combined results of uneven labor supply and demand, as the disparities will lead to fluctuating labor wage and vice versa. However, a paucity of research has considered the impact of regional disparities and movements of construction workers through a comprehensive modeling of regional construction labor cost performance in China. In view of relationship between construction labor wage and construction productivity, it is essential to investigate productivity changes and have insightful information on regional inputs and outputs in construction industry for strategic planning and investment making. A paucity of research has considered the regional diversities from the perspective of resource allocation and optimization, although there have been numerous studies concerning the construction industry TFP. In addition, the movements of labor, capital and equipment inputs allocated across regions are also crucial in determining the regional performance. Exploring the causes of inefficiency in different regions can provide insights into the disequilibrium of wage growth and the sources of productivity growth in regional construction industry. The principal findings of resource allocation and optimization have considerable implications for fine-tuning economic policies and making investment decisions at both national and regional levels.

2.9 Summary of the chapter

The chapter reviews literature on labor cost in construction industry. The definition of labor cost in construction industry is first introduced, and labor cost performance in China's construction industry is examined from two dimensions, i.e. time and region. Given that labor wage and labor productivity are the main components determining the competitiveness of unit labor cost in construction industry, the grounded laws determining the level of labor wage is reviewed from the side of labor supply and demand. The neoclassic economic theory is also reviewed with the concept of TFP. The potential factors affecting labor cost in the construction industry are summarized under the framework of labor supply and demand, respectively. Further, research methodologies of modeling and forecasting construction labor supply and demand are illustrated, research trends and gaps are also discussed.

Chapter 3: Research Design and Methodology

3.1 Introduction

This chapter first presents the design of research framework including research objectives, research methods, and analysis techniques. Research methodologies are then discussed from the viewpoint of qualitative and quantitative, respectively. To realize the research objectives, an overview and explanation of the research methodologies used in this study is also provided.

3.2 Research framework

The study has four research objectives. For each research objective, detailed information regarding analysis methods and techniques is presented in **Table 3.1**. The qualitative research methods and quantitative analysis techniques applied in this study are elaborated as follows.

Table 3.1 Research methodology for research objectives

Research objectives	Analysis methods	Analysis techniques
1. To investigate the relationship between construction labor cost and its critical determinants across regions	1. Document analysis 2. Questionnaire survey 3. Data analysis	1. Literature review 2. Panel data model
2. To explore the regional differences of construction productive efficiency	1. Document analysis 2. Data analysis	1. Literature review 2. DEA 3. DFM
3. To identify the stepwise improvement pathways for construction productive efficiency across regions	1. Document analysis 2. Data analysis	1. Literature review 2. DEA 3. TO-DFM
4. To forecast future trend of construction labor cost across regions	1. Document analysis 2. Data analysis	1. Literature review 2. Panel VEC model 3. Scenario analysis

For the first research objective, considering the variations and fluctuations of construction labor cost and potential factors across regions over time periods, panel data model is able to capture both time series dynamics and cross-section changes, even with some missing data. Unlike other econometric methods focus merely on one dimension, the multi-dimensional structure of the panel data model provides the possibilities of controlling individual heterogeneity and overcoming multicollinearity among variables. Using panel data model can effectively capture the labor cost variations of regional construction industry, then identify the critical determinants from both horizontal and longitudinal perspectives for further comparison and discussion in Chapter 4.

For the second research objective, although DEA has been widely applied to benchmark the overall performance of construction industry TFP based on the production factors at various levels, it fails to provide insights into the causes of inefficiency and the sources of growth under a full efficiency, which is of immerse importance for stakeholders or decision makers to make effective adjustments. To fill this gap, as one of the DEA-based models, DFM approach is therefore adopted to identify the shortest pathway for inefficient DMUs to the efficient frontier, further indicating the inefficiency of inputs and output potential across three regions. Regional differences of construction productive efficiency can be then quantified based on the empirical results of DFM modeling in Chapter 5. For those less inefficient provinces that cannot make significant productivity improvement within a short period of time, target efficiency score can be further defined using TO approach according to the efficiency gap and projection period. The combination of TO approach and DFM model can map out the optimal pathway for stepwise efficiency improvement in coming periods, which facilitate strategic planning or policy making for regional development of construction industry in Chapter 6.

For the last research objective, time series model is largely dependent on historic data, particularly over recent periods, which limits the medium and long-term forecasting accuracy of the model. The cross-sectional techniques cannot explore the intertemporal causal relationship among variables, without underlying information regarding short-term dynamics and long-term equilibrium. With this respect, panel VEC model is a combination of panel data model and VEC model that considers both temporal and regional variations of labor cost in changing construction market. The predictability of established panel VEC models is validated through in-sample forecasting analysis in comparison with that of panel OLS model. Scenario analysis is further conducted to simulate the impacts of scenario variables towards regional construction labor cost in Chapter 7.

3.3 Research methods

3.3.1 Literature review

Literature review is a major type of analysis method that is often used to understand existing body of knowledge, empirical findings, theoretical and practical contributions in a specific research field. In this study, an extensive review of literature on labor cost in construction domain was reviewed to identify research gaps, a theoretic framework of this research was accordingly established based on the grounded theory. Statistics yearbook, official report and other publications issued by different government and institutions from various sources were also reviewed to serves as strong evidence for an in-depth analysis throughout the whole study.

3.3.2 Document analysis

Document analysis is designed to address research problems by investigating different types of recorded information, professional reports, and published documents. It is a qualitative method that incorporates content analysis and data analysis based on existing documents. The content analysis is to make inferences by systematically referencing from a theoretical viewpoint (Dane, 1990). Besides, document analysis can supplement additional information through the collection of certain types of data, such as background information and present situation. It is proven to be more reliable and plausible than observations, interviews, and questionnaires. In this research, document analysis was adopted to understand the state-of-the-art of labor cost performance in China's construction industry. Document analysis can also assist to identify the current issues and extensive impacts of labor cost in construction domain, facilitating the identification of potential factors affecting labor cost in construction industry, and further discussions of construction labor cost forecasting.

3.3.3 Questionnaire survey

Questionnaire survey is a cheap way of survey consisting of standardized questions for respondents. It might hardly attain the desired purpose to gather effective information with a complicated design and limited response (Brace, 2008). In this study, construction migrant worker is the respondent of questionnaire. Considering education background and harsh working environment, questionnaire is designed simply with ten questions, covering the basic personal information, education background, skill trade, real wage, method of labor payment, and related information. To have a comprehensive understanding of real wage and related information of construction migrant worker, questionnaires were distributed on construction site and completed by construction workers during their spare time.

The empirical results of questionnaire survey can be referenced to identify potential factors affecting construction labor cost, also validate some findings of this study.

3.4 Analytical techniques

3.4.1 Panel data model

Panel data refers to the pooling of time series observations of a number of individuals or entities. Panel data model can incorporate more informative data covering both cross-section and time-series data. The multi-dimensional structure of panel data model provides the possibilities of controlling individual heterogeneity and overcoming multicollinearity among variables (Baltagi, 2014). Time series model is subject to the availability of data and the impact of omitted variables. The predictive capability of time series modeling is limited in the medium and long-term, especially around the turning points. On the other hand, cross-sectional model cannot investigate the intertemporal causal relationship between dependent variable and independent variable, also the underlying information regarding dynamic equilibrium relationships is not included.

Previous studies focused more on investigation and estimation of construction industry performance using time-series models, whereas the effects of regional differences were seldom considered in the models. Therefore, apart from simply time series model or cross-sectional model, this study attempts to incorporate the diverse variations in regional market to investigate and forecast construction labor cost performance across different regions of China. It should be noted that panel data model can better deal with uncertainty and complexity of construction labor cost in a changing market than other methods or modeling techniques.

3.4.2 Data envelopment analysis (DEA)

DEA is a non-parametric assessment methodology based on linear programming for measuring the relative efficiency of a set of comparable DMUs with common inputs and outputs. DEA was first proposed by Charnes et al. (1978), which has evolved with a collection of models and extensions to the original works within the framework of Farrell (1957). DEA models have been developed to estimate the efficiency performance in various domains. The popularity of DEA-based model is reflected by many successful applications for comprehensive evaluation (Lotfi et al., 2010), target setting (Lotfi et al., 2010; Malekmohammadi et al., 2011; Sadjadi et al., 2011; Yang et al., 2009) and resource allocation (Bi et al., 2011), on multiple inputs and multiple outputs without any preassigned weights.

In the standard DEA model, a DMU located on the production frontier is efficient with an efficiency score of 1.0, whereas a DMU off the frontier is inefficient with an efficiency score below 1.0. An inefficient DMU can attain full efficiency through a radial projection curve to the efficient frontier, with a uniform reduction in all inputs or a uniform increase in all outputs. In principle, there are a variety of projected routes for an inefficient DMU to reach the efficiency frontier. The improvement projection of conventional DEA model has only one possible solution, which might not be the best one (Suzuki et al., 2010). This is because traditional DEA model does not include decision maker's (DM) preference information or value judgement during the process of evaluating the efficiency. In this study, DEA model is first applied to develop an efficiency measurement for China's construction industry under the framework of TFP, based on common input and output, then assess the regional performance of construction productive efficiency.

3.4.3 Data friction minimization (DFM) approach

DEA was initially developed by Charnes et al. (1978). The classic DEA model, named after its three founders including Charnes, Cooper, and Rhodes (CCR), has the capability of measuring the relative efficiency of multiple input and output by establishing a piecewise linear production frontier along the most efficient DMU, then determining the efficiency performance of other comparable DMUs. As original DEA model does not include the decision maker's preferences in evaluating efficiency and setting targets, integrated methods with the combination of DEA and Multiple Objective Linear Programming (MOLP) have emerged to address the critical issue for both management control and resource planning during the past decades. In DEA-MOLP studies, a radial projection has been used in most of the studies, which indicates that a proportional change in input level or output level of an inefficient DMU to reach the efficiency frontier. However, from the planning perspective, it is not an optimal choice for decision makers to identify alternative targets and make further adjustment simply through a radial projection (Seiford & Zhu, 2003).

Alternatively, Suzuki et al. (2010) proposed a DFM model with a non-radial improvement projection for inefficient DMUs. To avoid the subjectivity of preferences, DFM approach employs the optimum weights for input and output variables that are automatically generated by the CCR-Input (CCR-I) model. A generalized distance function is built to identify the shortest path for an inefficient DMU towards the efficient frontier (Suzuki et al., 2010). The simultaneous treatment of input reduction as well as output augmentation is a main advantage of DFM model over the traditional DEA model. It contributes to the body of knowledge with respect to productivity improvement for decision making and strategic planning under a novel assessment method framework. Further, the usefulness of

DFM-based model has extended to a variety of domains or application areas (Kourtit et al., 2017; Nijkamp & Suzuki, 2009; Suzuki et al., 2015; Suzuki & Nijkamp, 2016). More details of the DFM model can be referred to Suzuki et al. (2010).

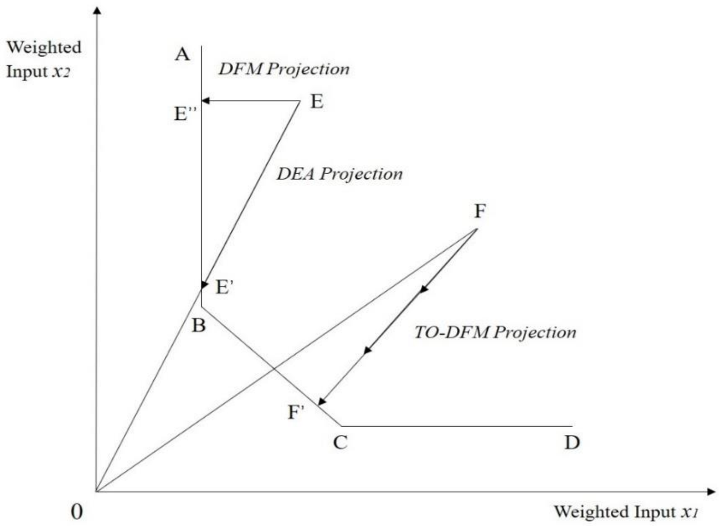

Figure 3.1 Illustrations of differences among DEA, DFM and TO-DFM projections

(Source: Suzuki et al. 2010)

3.4.4 Target-oriented DFM (TO-DFM) model

DFM model retains the original advantage of DEA model, also maps out the optimization route for an inefficient DMU with overall consideration of both input and output sides. DMU that is close to the efficient frontier can search for an optimal route towards the efficient frontier. But in some cases, this may be quite difficult and unrealistic for less inefficient DMUs, particularly those located far away from the efficient frontier. Therefore, Target-Oriented (TO) approach is developed within the framework of DFM model (Suzuki et al., 2015), the definitions and steps are herein presented to illustrate the mathematical procedures of TO-DFM model.

Target Efficiency Score (TES) is a milestone on the non-radial projection of DFM model. It is first defined by the decision maker (DM), according to efficiency gap and projection period. The value of TES determines the type of efficiency projection for an inefficient DMU. There are three types of DFM improvement projections to the efficient frontier. **Figure 3.2** shows the differences of three types of DFM improvement projections. If the value of $\mathrm{TES} = 1$, it equals to the normal DFM projection and reaches the efficient frontier; If the value of $\mathrm{TES} > 1$, the projection type is super-efficient. Since it is beyond the efficient frontier, this is available for efficient DMUs that are already on the efficient frontier and project the efficient points to the extended line of efficient frontier; If the value of $\theta^* < \mathrm{TES} < 1$, it belongs to non-attainment DFM projection that inefficient DMUs are below the efficient frontier, which require a stepwise improvement projection to the efficient frontier, especially for the low efficiency production units. The detailed discussions focus on non-attainment DFM projection for stepwise efficiency improvement according to the TES value in coming periods. The steps of TO-DFM model are briefly presented.

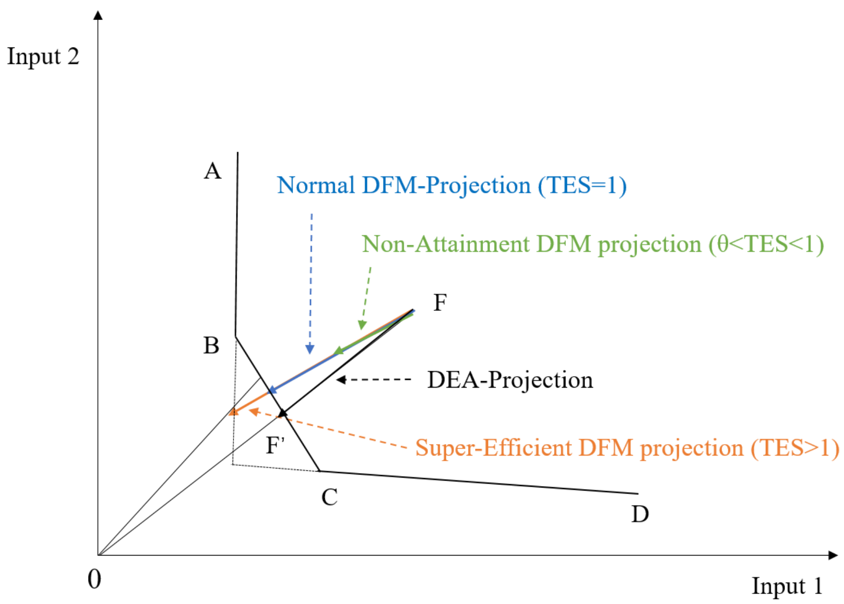

Figure 3.2 Three types of DFM projections for efficiency improvement

(Source: Suzuki & Nijkamp, 2016)

According to the **formula 3.1**, θ^* refers to the efficiency score of a DMU. TES_0 is obtained after defining the value of MP_0.MP_0 is short of Magnification Parameter and set by the decision maker in advance, which serves to adjust the targets of both input reduction and output increase in **formulas (3.5) and (3.6)**. The performance of both input reduction target and output increase target determines the TES_0 defined in **formula 3.1**, and further stepwise projection path for a DMU.

$$\mathrm{TES}_0 = \frac{\theta^* + MP_0(1-\theta^*) \times \dfrac{\theta^*}{(1+\theta^*)}}{1 - MP_0(1-\theta^*) \times \dfrac{\theta^*}{(1+\theta^*)}} \tag{3.1}$$

In this case, v_m^* and u_s^* are the optimal weights for input item *m* and output item *s*, which are calculated by the CCR-I model. The distance functions Fr^x and Fr^y are specified in **formulas (3.2) and (3.3)** by using a Euclidean distance in weighed spaces.

$$\min Fr^x = \sqrt{\sum\nolimits_m (v_m^* x_{mo} - v_m^* d_{mo}^x)^2} \tag{3.2}$$

$$\min Fr^y = \sqrt{\sum\nolimits_s (u_s^* y_{so} - u_s^* d_{so}^x)^2} \tag{3.3}$$

The aim of these two functions is to find an optimal solution that minimize the sum of input reduction distance and output increase distance.

$$\text{s.t.} \quad \mathrm{TES}_0 = \frac{\sum_s u_s^*(y_{so} + d_{so}^y)}{\sum_m v_m^*(x_{mo} - d_{mo}^x)} \tag{3.4}$$

The constraint **functions (3.5) and (3.6)** refer to the target values of both input reduction and output augmentation, respectively.

$$\sum\nolimits_m v_m^*(x_{mo} - d_{mo}^x) = 1 - MP_0(1-\theta^*) \times \frac{\theta^*}{(1+\theta^*)} \tag{3.5}$$

$$\sum\nolimits_s u_s^*(y_{so} + d_{so}^y) = \theta^* + MP_0(1-\theta^*) \times \frac{\theta^*}{(1+\theta^*)} \tag{3.6}$$

Balance of stepwise improvement contributions is distributed accordingly from input and output sides to fill the possible efficiency gap on the assumptions of **(3.7) to (3.9)**.

$$x_{mo} - d_{mo}^{x} > 0 \tag{3.7}$$

$$d_{mo}^{x} \geq 0 \tag{3.8}$$

$$d_{so}^{y} \geq 0 \tag{3.9}$$

Finally, the optimal solutions for both input and output can be obtained using **formulas (3.2) to (3.9)**. The degree to which the efficiency score is improved depends largely on MP_0 set by the DM, which directly determines the target setting and resource allocation.

3.4.5 Panel vector error correction (P-VEC) model

P-VEC model is a combination of panel data model and VEC model that consider both time series dynamics and cross-sectional changes over time. P-VEC model is established based on the temporal and regional performance of labor cost in China's construction industry. To establish a reliable and robust P-VEC model for dynamic modeling and further forecasting analysis, a series of necessary statistics tests including panel unit root test, panel cointegration tests, and dynamic panel causality tests need to be conducted between target variable and explanatory variables. In this research, the critical factors identified based on panel data modeling results are the major inputs for forecasting regional construction labor cost in the P-VEC model. The details of P-VEC modeling process are described as follows.

Step 1 Panel unit root test

Since the null hypothesis of non-stationary time series data would result in a spurious estimation of

P-VEC model, therefore, the stationary properties of variables must be tested by using several panel unit root tests including Levin-Lin-Chu (LLC) (Levin et al., 2002), Breitung, Im-Pesaran-Shin (IPS) (Im et al., 2003), based on the principle of the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979). For a robustness check, two other tests are also included, i.e. Fisher-ADF and Fisher-Phillips-Perron (Fisher-PP). Panel unit root tests are performed on each of variables on both level and first differences, and then examined the order of integration to attain stationarity. Unit root tests in panel data analysis are based on the following autoregressive model:

$$Y_{i,t} = \rho_i Y_{i,t-1} + \delta_i X_{i,t} + \varepsilon_{i,t} \ (t = 1, \dots, N; i = 1, \dots, N) \tag{3.10}$$

Where $i = 1,2, \dots, N$ represents provinces observed over periods $t = 1,2, \dots, N$. $X_{i,t}$ are exogenous variables in the model including any fixed effects or individual trends, ρ_i are the autoregressive coefficients, $\varepsilon_{i,t}$ are the stationary error terms. If $\rho_i < 1$, $Y_{i,t}$ is said to be weakly trend stationary. Otherwise, if $\rho_i = 1$, then $Y_{i,t}$ contains a unit root.

Step 2 Panel cointegration tests

Panel cointegration tests are conducted to determine if there is a long-run equilibrium relationship between non-stationary variables, with the integration of order one to be stationary. Otherwise, a panel VAR model should be built in case of no cointegration. This test can be realized by using the Johansen and Juselius maximum likelihood approach to identify the number of cointegration relationship among selected variables (Johansen & Juselius, 1992). The empirical model for this test can be written as:

$$Y_{i,t} = \alpha_i + \delta_i t + \beta_1 X_{1,i,t} + \beta_2 X_{2,i,t} \dots + \beta_n X_{n,i,t} + \varepsilon_{i,t} \;\; (t = 1, \dots, T;\; i = 1, \dots, N) \quad (3.11)$$

Where $Y_{i,t}$ and $X_{n,i,t}$ are dependent variables and independent variables, $\varepsilon_{i,t}$ is the estimated residual standing for deviations from long-run equilibrium relationship, α and δ are provinces and time fixed effects, respectively. There are several panel cointegration tests that can be divided into two broad groups, i.e. residual based and the likelihood tests. For overall consideration, this study uses both Kao and Pedroni panel cointegration tests. The Kao test assumes homogenous or a common cointegration vector (Kao, 1999), whilst Pedroni test considers a set of seven tests, four of which based on pooling the residuals of regression along the within-dimension of the panel, and the other three are based on pooling the residuals of regression along the between-dimension of the panel (Pedroni, 2001).

Step 3 Panel causality tests and P-VEC model

Panel Granger causality tests are sensitive to lag lengths, the selection of optimal lag would largely determine the results of P-VEC modeling. The most common lag length selection methods are the Akaike information criterion (AIC) (Akaike, 1974) and the Schwarz information criterion (SC) (Schwarz, 1978). In this study, we will use SC, AIC, and other criteria to determine the optimal lag in the unrestricted VAR model. The causality test is critical in determining the usefulness of time series projection in forecasting process. The standard two-step Eagle-Granger or Granger causality tests are two primary forms of causality tests using error correction or vector error correction model (Engle & Granger, 1987; Granger, 1988). In this research, panel Granger causality test was conducted to examine the presence of short-term relationship between regional construction labor cost and its explanatory variables over time. The long-run equilibrium for P-VEC model can be obtained from the estimated residuals in **Equation 3.12**. P-VAR model can be interpreted as the equation without the presence of error correction component (Granger, 1988). The P-VEC model can be therefore expressed as follows:

$$\Delta Y_{i,t} = \alpha_{i,t} + \lambda_i ecm_{i,t-1} + \sum_{k=1}^{h} \theta_{1,i,k}\, \Delta Y_{i,t-k} + \sum_{k=1}^{h} \theta_{2,i,k} \Delta X_{n,i,t-k} \dots + \sum_{k=1}^{h} \theta_{n+1,i,k} \Delta X_{n,i,t-k} + \varepsilon_{i,t} (t = 1, \dots, T, i = 1, \dots, N) \quad (3.12)$$

When Δ means the first difference of the variables, h is the optimal lag length, $ecm_{i,t-1}$ is the serially uncorrelated error correction term, θ is the coefficient of estimated parameters, others are the same with prior description in **Equation 3.12**. The short-run relationship among variables can be achieved by checking the significance of the coefficients of the independent variables. Likewise, the presence of long-term effect can be estimated by examining the coefficient of the error correction term. Final, the established P-VEC model should be validated by running serial correlation Lagarnge multiplier (LM) tests, White's heteroskedasticity (White) test and Jarque-Bera normality (Jarque-Bera) test to verify the assumption of statistical soundness of the proposed P-VEC model.

3.4.6 Scenario analysis

Scenario analysis is a projection process of future trend by considering alternative possible outcome (Huss, 1988). Unlike Box-Jenkins and Gray models, the projection is not based on extrapolation of its own historic trends, but a scope of possible future performance underlying the assumptions of control variables. The simulation results generated by scenario analysis based on the P-VEC model can provide good references for strategic planning and effective adjustments of construction labor cost in regional market.

3.5 Summary of the chapter

This chapter presents the research framework and elaborates the research methodologies for each research objective. The research methods and analysis techniques are illustrated from the viewpoint of qualitative and quantitative in research design. The research methods include document analysis, literature interview, and questionnaire survey. Analytical techniques incorporate panel data model, P-VEC model, scenario analysis, DEA-based models, including DEA, DFM, and TO-DFM models. Research methods and analytical techniques are discussed and organized to accomplish the research objectives.

Chapter 4: Regional Determinants of Construction Labor Cost

4.1 Introduction

The aim of this chapter is to investigate the relationship between construction labor cost and critical determinants across the different regions of China over time. The chapter first analyzes the empirical results of questionnaire surveys aimed at construction migrant workers. In accordance with literature review and questionnaire survey, critical determinants affecting construction labor cost performance are identified for panel data modeling in regional construction industry. Five factors are selected as the explanatory variables to investigate the construction labor cost variations across three regions of China with different levels of economic growth and social development. Panel data model is then established on the assumptions of selected provinces from three regions over time periods. Regional comparisons of construction labor cost performance are discussed according to the empirical results of panel data models.

4.2 Questionnaire survey

Since migrant workers are the mainstream of total employment in construction industry. Compared with formal technical or managerial staffs, investigating the labor cost performance of construction migrant worker has a profound effect on the identification of potential factors affecting labor cost in construction industry. Considering the mobility of labor and the availability of data, questionnaire survey is the most effective way to collect the labor cost information regarding construction migrant worker. Based on previous studies, questionnaire surveys were conducted mostly in coastal areas of China, such as Jiangsu, Zhejiang, Guangzhou, Anhui provinces and Beijing municipality. In contrast, the developing and underdeveloped provinces or central cities was seldom included. To fill this gap, a specific questionnaire of construction labor cost was therefore designed to have a comprehensive understanding of construction migrant workers covering following aspects, including basic personal information, education background, skill trade, real wage, and related information. Details of this questionnaire are attached in **Appendix I**.

Similar with the questionnaire surveys in other regions or cities of China, this survey was conducted in Chongqing municipality from western region in late 2014. Over 700 valid questionnaires were received from construction site workers. The response rate was over 90%, additional feedbacks were collected through short conversations with migrant workers on site. Besides, construction project manager was also interviewed to share practical experience of construction workforce recruitment and management. The empirical analysis of questionnaire survey serves as strong evidence to the identification of key elements influencing labor cost in regional construction industry.

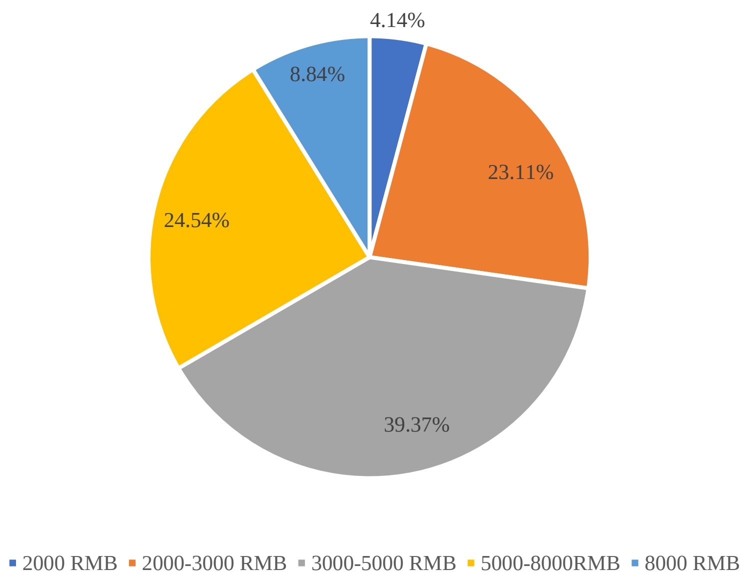

Figure 4.1 Monthly salary of the surveyed construction workers

According to the results of questionnaire survey, the average monthly salary of construction worker was 4538 RMB in the first quarter of 2014, nearly the same level of monthly salaries of construction site workers reported from labor-only subcontractors. More specifically, the monthly salaries of carpenter and bar bender were the highest among various trades. The wage rate is closely related to the working experience and skills of construction migrant workers. More than 54% of the surveyed workers stayed in the construction industry for at least five years.

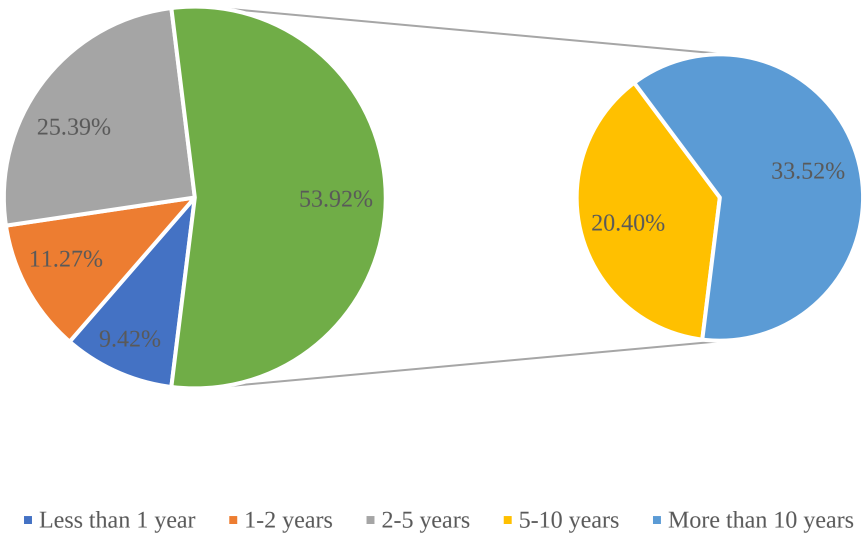

Figure 4.2 Working experience of the surveyed construction workers

Most of construction migrant workers dropped out of middle school and improved their working skills through the apprenticeship program in real practice. The experienced migrant workers were normally paid with a higher wage rate, particularly in several trades such as plasterer, carpenter, and bar bender. It takes several years for a general worker to become a skilled worker through informal on-the-job training in construction practice. However, merely 30% of construction workers attended the pre-job training, often they were reluctant to participate in vocational training program unless financed by local government. Besides, it is relatively difficult to measure the skill development of training program for construction workers. Instead, they were willing to work more hours to make up for the losses due to low productivity. According to the statistics results of questionnaire survey, construction workers normally worked 10 hours every day, and sometimes more than 12 hours. Compared with other occupations, competitive wage is the primary driving force for migrant worker to undertake construction activities even with high risk on sites. Nearly 70 % of the surveyed migrant workers were satisfied with their monthly income, and usually they collected their salaries from the foremen each month. The one-off nature of construction project determines the flexibility of migrant workers. Owing to the increasing demand backed by massive investment, they tended to move on another site after the completion of one project under the leadership of foremen. The rapid wage growth results in a relatively high job turnover rate among migrant workers across regions. However, the surveyed construction workers preferred their children to seek jobs in an alternative sector. This can partly explain the ageing process and short supply of construction workforce in recent years.

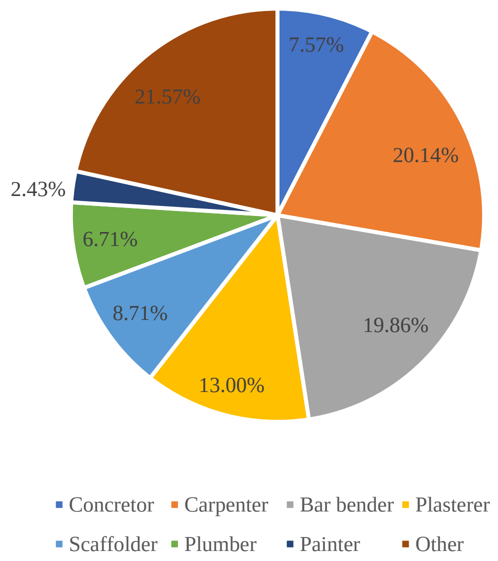

Figure 4.3 Skilled trades of the surveyed construction workers

In contrast with similar surveys conducted from other regions of China, rising labor demand is a common reason for the rapid growth of construction labor cost, particularly in coastal areas where additional workers are mainly recruited from central region and western region. The number of construction workers in coastal areas is nearly half of the total employment in China's construction industry, due to the strong performance of construction development (National Bureau of Statistics of China, 2020a). It cannot deny that the majority of construction migrant workers are untrained without formal skill certificates, especially for the new entrants. Main contractor merely provides necessary safety training before construction. Skill development of construction worker is mainly improved with the accumulation of experience in real practice. Since construction migrant workers are arranged and managed by the labor-only subcontractors or foremen. Site management would to some extent determine the productivity of migrant workers, which is associated with the wage level. With the ageing process of construction workforce, skill shortages would lead to growing labor cost as well as difficulties in applying new technologies for labor saving (Gruneberg, 1997). Because of the expense of machinery, there is little incentive for small-and-medium sized contractors to invest in construction plant and equipment for slow productivity growth in the long term (Dainty et al., 2005). Raising wages for the adequate recruitment of construction workers is more economical and practical in terms of cost and benefit (Gruneberg, 1997). Overall, construction labor cost is more sensitive to the labor demand if the pocket of surplus labor remains (Fang & Yang, 2011). With decreasing labor supply and ageing workforce in buoyant construction industry, an increasing use of construction plant and equipment and new technologies has been part of the response to expensive labor in construction activities (Goodrum & Gangwar, 2004). However, the application of new technology and advanced equipment depends on the extent of labor savings in construction practice.

4.3 Potential variables affecting construction labor cost

With the ever-increasing labor cost across China's construction industry over the past years, it has become a main concern of construction development, and even drawn widespread public attention on construction migrant workers. Based on previous review of literature on construction labor cost, potential factors affecting construction labor wage are listed from the sides of both labor supply and demand, presented in **Table 4.1**.

Table 4.1 Potential factors affecting labor cost in construction industry

Target	Side	Factor	Author
Labor wage	Labor demand	Construction output	Wong et 2007, Wong et 2009, Wong et al 2011, Liu et 2015
		GDP	Goh 1996, Sing et al 2015, Fan et 2011
		Labor productivity	Wong et 2007, Wong et 2009, Wong et al 2011, Liu et 2015
		Interest rate	Wong et 2007, Wong et 2009, Wong et al 2011, Liu et 2015
		Material price	Wong et 2007, Wong et 2009, Wong et al 2011, Liu et 2015
		Gross fixed capital formation	Goh 1996 &1999
		CPI	Goh 1996 &1999, Jiang and Liu 2011& 2014, Sing et al 2015, Liu et al 2015, Song et al 2015
		Unemployment rate	Goh 1996 &1999, Fan et 2011, Jiang and Liu 2011& 2014,
	Labor supply	Population size	Uwakwen and Maloney 1991, Agapiou et al 1995, Goh 1996 & 1999, Fan et al 2011, Jiang and Liu 2011, 2014
		Participate rate	Uwakwen and Maloney 1991, Agapiou et al 1995
		Unemployment rate	Song et al 2015
		Construction output	Agapiou et al 1995

Construction output and unemployment rate are two important factors that significant influence both sides of labor supply and demand (Agapiou et al., 1995; Wong et al., 2007, 2011, 2009). As a pillar contributor to the economy, construction development is boosted by enormous public investment.

Enormous amount of fixed assets have been invested to maintain the economic growth through the creation of construction demands and employment opportunities. The investment program initiated by government is used as a counter-cyclical instrument against the pressures of economic downturn (Giang & Pheng, 2011). The changes of total amount of construction works created by fixed assets investment will presumably alter the balance of supply and demand of construction workers, further influence the labor wage level in construction market. In this context, the total amount of fixed assets investment is adopted as a barometer of economic climate and job-seeking environment (Bee-Hua, 1999; Hua, 1996). Also, the unbalanced distribution of fixed assets investment leads to regional differences in terms of economic growth and industry development. Construction value added is introduced to quantity the overall output of construction industry (Liu et al., 2015; Wong et al., 2007, 2011, 2009). Besides, physical output is applied to improve the accuracy and rationality of the measurement of construction demand. In contrast with construction value added, floor space under construction can better capture the volume of construction works that might not be easily affected by price differentials in regional construction market (Bee-Hua, 1999).

With more contributions of construction industry to regional development, construction demand can be integrated as the demand of labor, respectable remuneration is provided for labor recruitment and attraction in a competitive market. Faced with the rising labor cost and decreasing manual workers, labor savings by investing more on construction plants and equipment is an irresistible trend against the frequent emergences of labor shortage in the industry. Applying advanced equipment and new technology can attain multiple objectives of labor, cost, and time savings if reasonably managed and operated. Higher technical equipment ratio in construction industry implies more investment and utilization of modern machinery and technical equipment in construction process, with less labor usage and hence higher labor productivity (Goodrum & Haas, 2004). However, the role of construction site worker cannot be easily replaced by construction plant and equipment, particularly in some skilled works. Wage differentials of skilled workers can reflect the emerging skills shortage among construction workers, e.g. bar bender, formwork erector, plasterer, carpenter and so forth. In contrast with the unemployment rate estimating the availability of labor pool, the indicator of the employed persons in construction industry is more overall and accurate to reflect the labor supply in construction works. In accordance with the comprehensive analysis of questionnaire survey and literature review, this study attempts to adopt the following five potential factors including the value added of the construction industry, the employed persons in construction industry, construction technical equipment ratio, total amount of fixed assets investment, and floor spare under construction, for further investigation across different regions of China, shown in **Table 4.2**.

Table 4.2 Critical determinants of labor cost in China's construction industry

Variable	**Abbreviation**	**Side**	**Source**
Construction value added	CVA	Labor demand	L & R
Total amount of fixed assets investment	TI	Labor demand	L & R
Floor space under construction	CW	Labor demand	L & R, Q & S
Employed person in construction industry	CE	Labor supply	L & R, Q & S
Construction technical equipment ratio	TER	Labor supply	L & R

Note: literature review (L & R), questionnaire survey (Q & S).

4.4 Specifications of panel data model

4.4.1 Data source

Unit Labor Cost (ULC) is a measure of labor cost competitiveness that considers the changes of labor wage and labor productivity simultaneously in the production process. Based on a systematic review of literature, five critical determinants of labor cost in the construction industry, including construction value added (CVA), the employed persons in construction industry (CE), construction technical equipment ratio (TER), the total amount of fixed assets investment (TI), and the floor spare under construction (CW), for investigating the labor cot variations in construction industry across three regions of China. The annual data of these key indicators can be acquired from the National Statistics Yearbooks from 1998 to 2018 (National Bureau of Statistics of China, 2020a), covering 31 provinces, municipalities, or autonomous regions (hereafter provinces) in Mainland China.

According to the administrative layout and geographic distribution shown in **Figure 4.4**, China can be categorized into three regions with different levels of economic growth and social development, i.e. underdeveloped western region, developing central region, and developed eastern region. Construction sector plays a different role in boosting the regional economy. The division rules are illustrated as follows: economic growth and construction development is combined with geographic distribution, giving priority to construction industry performance.

Western region stands for underdeveloped economics with a level of low income in the remote areas of China. There are 12 provinces in Western China, i.e. Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Guangxi, Inner Mongolia, Gansu, Ningxia, Xinjiang, Qinghai, and Tibet provinces. Central region consists of 6 provinces, most belong to the developing economies with a middle-income level, i.e. Hubei, Henan, Hunan, Anhui, Shanxi, and Jiangxi provinces. Eastern region refers to the developed economies most in coastal areas, such as Hainan, Guangdong, Fujian, Zhejiang, Jiangsu, Shanghai, Shandong, Hebei, Tianjin, Beijing, Liaoning, Jilin, and Heilongjiang provinces.

In line with the rules above, the representative provinces are accordingly selected from each region of China for further discussion. For better comparison of regional performance, six typical provinces are chosen from each region to offset the biases of heterogeneity within region. For example, Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Shandong provinces are selected as the representatives of developed eastern region. These first-class provinces located in coastal area are the economic hubs of the subregion or economic circle. The average GDP per capita in these places are much higher than that in northeast region where the second sector acts as the contributor of regional development. Similarly, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, and Guangxi provinces are selected on behalf of underdeveloped western region, the rest of provinces are less developed with limited market demands, few construction activities are created in the remote areas except for infrastructure construction. Therefore, the original six provinces in central region would represent the developing economies.

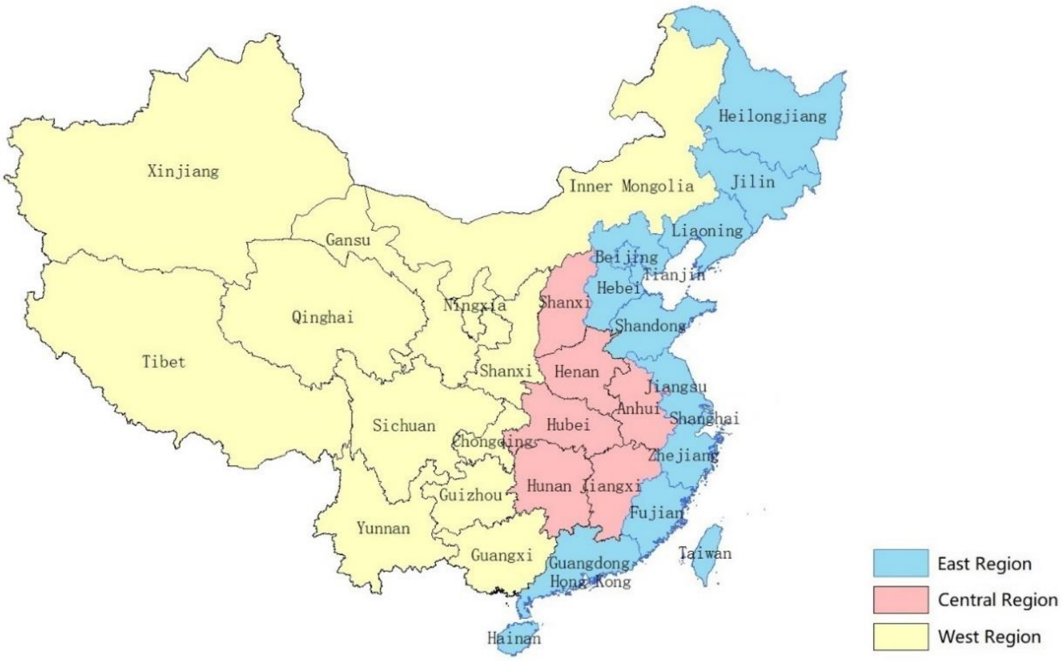

Figure 4.4 Geographic map and regional division of China

(Source: Luo et al., 2019)

4.4.2 Model specification

For diverse performance of construction labor cost across three regions, panel data model is thereby used to explore the relationship between target variable and its explanatory variables, covering both horizontal and longitudinal dimension for overall examination. Meanwhile, panel data model is able to control the impact of omitted variables arising from unobserved variables through constants that are over time periods and across regions (Hsiao, 2007). Besides, panel data model allows some missing observations in the modeling process, given the sample size and data availability. In addition, the balanced panel has all observations covering variables from either each time or each entity, otherwise the data set would be unbalanced. Basically, there are two types of panel data model, i.e. random effects model and fixed effects model (Baltagi, 2014). The type of the econometric model is determined whether the likelihood ratio test can be passed or not. If regression coefficients under fixed effects model or random effects model are statistically different from each other, fixed effects model will be preferred after conducting the Hausman test. Otherwise, random effects model is more suitable for further estimation. Compared with fixed effects model, random effects model has more degrees of freedom, but the unobserved impacts of omitted variables need to be assumed with target variable in advance (Studenmund, 2013). Therefore, the Hausman test is first conducted to examine whether there is correlation between α_i and X_{it} in the equations before the establishment of panel data model.

For this study, as labor cost performance not only changes over time, but also varies greatly from region to region in the China's construction industry. Hence, both region and time fixed effects of unobservable variables will be considered in the panel data modeling. The combined effects of panel data model for regional construction labor cost can be written as follows.

$$Y_{it} = \beta_1 X_{it} + \alpha_i + \lambda_t + \mu_{it} \quad (i = 1, \dots, N; t = 1, \dots T) \tag{4.1}$$

Where Y is dependent variable, X_{it} are independent variables, subscript i represents the cross-section dimension, subscript t denotes the time-series dimension. The unobserved effects μ_{it} are captured including time fixed effects λ_t and region fixed effects α_i , characterized by the structural parameter β. The coefficients β can be estimated using Ordinary Least Square (OLS) by including additional time and region binary variables. The calculation process of panel data modeling will be solved on the platform of EViews software, and empirical results of regional construction labor cost are then compiled for further discussion.

4.4.3 Study period

The model specification is divided into several steps before conducting panel data analysis. First, target variable and explanatory variables needs to be normalized in real terms on the baseline year of 1997. As is shown in **Figure 4.5**, regional construction labor cost performance is obtained via the calculations of provincial performance. For the comprehensive analysis, the study period is further divided into three stages: 1997 – 2003 (Stage 1), 2003 – 2009 (Stage 2), and 2009 – 2017 (Stage 3).

There are several reasons for such division: First, all three regions show an overall upward trend of construction unit labor cost during the entire period from 1997 to 2017, but slight fluctuations are observed due to the abrupt changes of several provinces around the turning points in 2003 and 2009. Besides, China's construction industry development peaked in 1997 before the emergence of Asian Financial Turmoil. Afterwards, it declined and touched the trough around 2003, with the outbreak of SARS. Third, the occurrence of Global Subprime Mortgage in late 2008 led to another wave of economic downturn, particularly among developed economies worldwide. In response to economic crisis, Chinese government had initiated a 'Four Trillion Fiscal Stimulus Package' to revitalize the economy, particularly in the Midwest. Fixed assets were invested in the major domains of real estate development and infrastructure construction, both of which have close linkages with construction industry development across different regions of China.

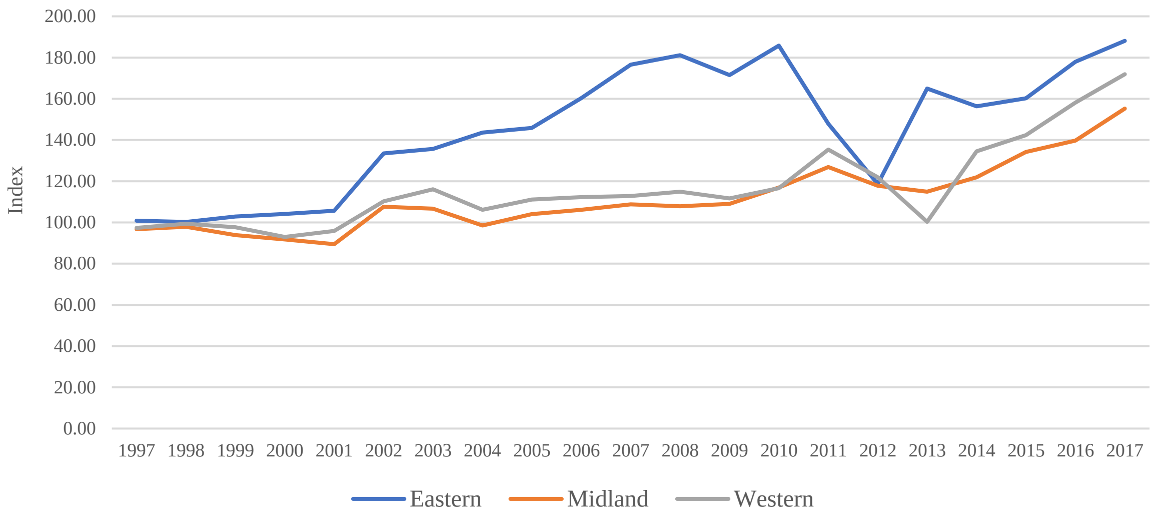

Figure 4.5 Unit labor cost of regional construction industry in China (baseline 1997 = 100)

4.5 Regional comparison and analysis

According to the results of panel data model in **Table 4.3**, the established econometric models can fit regional performance of construction labor cost well. The P-values are all less than 1% in the Hausman test for three established panels, which indicates fixed effects model is more appropriate than random effects model to illustrate the variations of regional construction labor cost. In addition, F-test and Durbin-Watson statistics tests are conducted to determine the validity and feasibility of the panel data models. F-test is a type of statistics test that is often used to identify whether the model best fits the sample data. In the three panels, the F-tests are all passed at the 1% significance level, which can be referenced to explain the significant relationship between target variable and explanatory variables across regions of China. Durbin-Watson statistics test is a test of statistic to detect the presence of autocorrelation at lag 1 in the residuals from a regression analysis. The values of Durbin-Watson statistics tests are less than 2 in all three panels, which reveals that no significant autoregression problems are found in the three datasets with avoidance of spurious regression.

Table 4.3 Panel data analysis: determinants of unit labor cost in China's construction industry (1997-2017)

Variable / Region	All	West Region	Central Region	East Region
CVA	0.022425[b]	-0.072046[a]	0.076326[a]	0.006673
CE	0.0000315[a]	0.0000338[a]	0.0000223[b]	0.0000251[b]
CW	-0.000973[a]	-0.001114[c]	-0.002114[a]	-0.000595
TI	-0.000447	0.008411[a]	-0.001637[b]	-0.000104
TER	0.000816[a]	0.000698	0.00106[c]	0.000881[b]
Constant	83.227[a]	93.039[a]	71.506[a]	101.68[a]
R-squared	0.568	0.636	0.567	0.475
F-statistics	21.219	20.109	15.062	10.426
DW statistics	0.635	1.240	0.795	0.581

Note: DW = Durbin-Watson statistics.
[a] Denotes significance at 1% level.
[b] Denotes significance at 5% level.
[c] Denotes significance at 10% level.

The employment level in construction is found to be the common significant determinants of ULC across three regions. Positive coefficient of CE is the biggest in west region, also gradually increases from central region to east region. This indicates that regional construction development is labor-intensive, and existing differences might be an overall result of diverse performance of real wage and labor productivity in regional construction industry among different development stages. It can be evidenced by the positive coefficients of TER in both central region and eastern region, apart from western region, which implies that the application of plant and equipment in construction practice, further reflects reliance upon construction workers for meeting the regional construction demands. In contrast, the coefficients of CVA and TI are significantly associated with ULC in both western region and central region. With an increasing amount of fixed assets investment, construction industry plays a more important role in revitalizing the economy through real estate development and infrastructure construction over the past decade. As a result, ULC is largely driven by growing labor demands in the Midwest, where cheap workforce is a major advantage in meeting the demand of local construction. However, the over-reliance on unskilled migrant workers hampers the progress of construction productivity in the long term.

4.5.1 Western region

Coefficients of construction value added, employment level in construction industry, and fixed assets investment are statistically significant in western region. Owing to the distinctive contributions from construction industry to regional economic development, massive construction investment promotes an incremental growth of construction labor cost, associated with living standard. However, regional construction industry in western region is heavily reliance upon cheap workforce, whereas surplus labor force tends to move towards the coastal areas for better remuneration (Liu & Xiang, 2009). Although the employment generation potential of construction industry has been effectively utilized particularly in the period of construction boom, the labor-intensive pattern in construction activity hinders efforts toward the growth of labor productivity, also the rationalization of labor wage. The profit gains of contractors are achieved at the sacrifice of low labor cost for a long period of time. Contractors are inclined to reduce the budget for construction site workers, and even delay payoffs to relieve the pressure of cash flow for project cost management (Gruneberg, 1997), primarily due to the low social status of construction migrant workers, and few barriers to the industry (Goodrum et al., 2012), especially when labor supply exceeds the market demand. However, the situation and mechanism has been gradually improved with the emergence of labor shortage in the industry, partly with surging construction demands created by public investment. Besides, the insecure employment, and negative aspects of working conditions weakens the attractiveness of construction industry, particularly for the young generation (Goodrum & Gangwar, 2004). To overcome the challenge, contractors have to pay disproportionally high wages to recruit adequate workers for the soaring construction demands, sometimes relying on untrained and little experienced laborers, despite the continued efforts to develop a core of local workforce in the period of planned economy. Moreover, the inadequacy of vocational training programs and education mechanism resulted in an acute shortage of skilled workers but required a high level of site management capability and skills for project manager. Under this circumstance, the development and proper deployment of a well-trained and competent construction workforce is quite important for the well-being of construction industry, given the contributions to regional economic growth.

Table 4.4 Panel data analysis: determinants of unit labor cost in west region (1997 - 2017)

West Region	**1997 - 2017**	**1997 - 2003**	**2003 - 2009**	**2009 - 2017**
CVA	-0.072046[a]	-0.061208	-0.128651[c]	-0.081657[a]
CE	0.0000338[a]	0.0000593	0.0000006	0.000059[a]
CW	-0.001114[c]	-0.002889	0.004570[b]	-0.000139
TI	0.008411[a]	0.033909	0.003399	0.009562[a]
TER	0.000698	0.003163[b]	0.002689	0.000620
Constant	93.039[a]	56.16[a]	89.41[b]	60.57[a]
R-squared	0.636	0.666	0.549	0.743
F-statistics	20.109	6.192	3.774	12.475
DW statistics	1.240	1.092	1.348	1.798

[a] Denotes significance at 1% level.
[b] Denotes significance at 5% level.
[c] Denotes significance at 10% level.

4.5.2 Central region

Unlike considerable fluctuations of construction labor cost in other regions, labor cost performance in central region is much smoother with an upward trend over years, except for slight fluctuations. The instability of construction labor cost is recognized as a result of fluctuations in the demands for investment, which gives a strong impetus to construction development (Ofori, 1990). Construction sector is regarded as an important instrument for government to regulate the economy, and more knowledge is required about the way that public works as a major participant in the regional market (Giang & Pheng, 2011). Fixed assets investment is initial positively correlated with unit labor cost, then shifts into negative relationship later. The industry is operating below the capacity and performs as a main contributor in the past. With more capital inflow into the midland region, some underlying mismatches between the levels of construction labor wage and construction development spring out. This implies the urgent need to raise the wage level for attracting additional workers to satisfy the growing demands (Agapiou et al., 1995). As one of the labor-intensive sectors, construction industry has absorbed massive labor force not only from labor pool but also other industries, making the industry even more fragmented with great mobility. The overall level of efficiency in construction process would fall and the quality of workmanship suffer with a slow growth of real wage. In terms of availability of skilled workers in shrinking labor market, plus limited new blood into construction industry over recent decade, labor substitution by construction equipment and technology seems to be an inevitable trend that should be reasonably considered and carefully managed (Gruneberg & Francis, 2019), e.g. prefabricated components and off-site construction. Apart from the significant coefficients in western region, construction technical equipment ratio is identified to be positively with unit labor cost in midland region. In some regional central cities, governments have introduced some incentive mechanism over a certain segment of construction activities to promote the adoption of new technology and construction equipment, reducing inherent reliance on labor inputs. On the other hand, labor cost needs to be well estimated and managed in relation with the dynamics of real wage in construction market. Otherwise, negative effects are to emerge soon once the balance of market supply and demand is altered, due to external impacts of great events or promulgation of regional policies and strategic planning.

Table 4.5 Panel data analysis: determinants of unit labor cost in central region (1997 - 2017)

Central Region	**1997 - 2017**	**1997 - 2003**	**2003 - 2009**	**2009 - 2017**
CVA	0.076326[a]	-0.120178	-0.014813	0.069382[b]
CE	0.0000223[b]	0.0000939[a]	-0.0000131	0.0000551[a]
CW	-0.002114[a]	-0.009543[a]	0.000969	-0.001518[b]
TI	-0.001637[b]	0.118082[b]	0.000455	-0.002237[b]
TER	0.00106[c]	0.001263	0.002234[c]	0.000327
Constant	71.506[a]	50.085[a]	97.132[a]	24.636[a]
R-squared	0.567	0.740	0.359	0.744
F-statistics	15.062	8.983	1.736	12.549
DW statistics	0.795	1.781	1.359	1.61

[a] Denotes significance at 1% level.
[b] Denotes significance at 5% level.
[c] Denotes significance at 10% level.

4.5.3 Eastern region

Similar with the performance of central region, construction technical equipment ratio and total employment in construction are positively to construction labor cost in eastern region. However, the big differences lie in less dependence on cheap unskilled labor, and more reliance on construction plant and equipment. The heavy dependence on casual laborers hampers the creation of a pool of experienced workers and introduction of new techniques, further investment in construction plant and equipment. Coupled with uncertainty about the nature and size of construction workload, this has reinforced the unwillingness of contractors to acquire new technology and advanced equipment.

Meanwhile, it is closely related to the total volume and development stage that regional construction industry lies in. There is no doubt that construction development in coastal area is superior to inland regions of China, no matter from the market structure and development pattern (Ofori & Han, 2003). As the leadership of national economy and construction industry performance, regional construction development has been seeking the shift from labor-intensive pattern towards technology-intensive pattern, seizing the transition opportunities accompanied with the rapid development of real estate industry since 2003, and the implementation of 'Four Trillion Fiscal Stimulus Package' released in 2009. From a holistic view, construction labor cost in eastern region is higher than that of hinterland and stays a moderate level except for some ups and downs around the turning points. Regional construction industry becomes more mechanized with desirable performance of labor productivity in the face of labor shortage, evidenced by the negative coefficient of TER over the recent decade. Construction labor cost is less subject to external shocks that can better respond to changing market environment. High levels of remuneration and motivation of career development become effective measures in a tight labor market. In addition, labor cost development in competitive construction market can facilitate the efficient project management, further influence alternative strategies over the recruitment and retainment of skilled workers. It is also an epitomize that does determine the final success of industry upgrade and transformation from life-cycle perspective, provide a paradigm how to deal with the critical conflict between rising labor cost and restricted available construction manpower under different conditions.

Table 4.6 Panel data analysis: determinants of unit labor cost in east region (1997 - 2017)

East Region	**1997 - 2017**	**1997 - 2003**	**2003 - 2009**	**2009 - 2017**
CVA	0.006673	0.040453	-0.023797	-0.032629
CE	0.0000251[b]	0.0000506	0.000108	0.0000379[a]
CW	-0.000595	-0.001679	-0.003824	-0.000749
TI	-0.000104	-0.009602	0.002068	0.002407
TER	0.000881[b]	0.004229[a]	0.002368	-0.001496[a]
Constant	101.68[a]	29.124[a]	34.516[a]	142.899[a]
R-squared	0.475	0.729	0.826	0.728
F-statistics	10.426	8.339	14.784	11.557
DW statistics	0.581	1.95	0.664	2.026

[a] Denotes significance at 1% level.

[b] Denotes significance at 5% level.

[c] Denotes significance at 10% level.

4.6 Summary of the chapter

This chapter first analyzed the empirical results of questionnaire surveys, accordingly identified the explanatory factors of construction labor cost based on the empirical analysis of literature review and questionnaire survey. To investigate the regional performance of construction labor cost, panel data model is built on the assumptions of study period and selected provinces from three regions with different levels of economic growth and social development. The panel data modeling results are then discussed for regional comparison and analysis over different stages. The principal findings can well assist understand the critical determinants of construction labor cost across three regions, further provide valuable insights for contractors to formulate forward-looking market strategies, and for government to fine tune economic policies.

Panel data model estimates indicate that regional development of construction industry is overall labor intensive, and regional differences of labor cost is an overall result of diverse performance of real wage and labor productivity. Unlike the inland regions with heavy reliance on cheap labor and fixed assets investment, construction industry in eastern region becomes more mechanized with extensive application of plants and equipment in construction activities, offsetting the pressure of rising wage rate of skilled workers. More critically, the slow growth of construction productivity weakens the labor cost competitiveness. In contrast, the competitive edge of construction industry in both western and midland regions is established primarily through a lower level of labor wage. Increasing construction demands supported by the large amount of fixed assets investment promote a stable growth of real wage of construction workers in the Midwest. Compared with central region, construction development is more investment-driven in western region, primarily in the field of infrastructure construction. Labor-intensive pattern of construction development hinders efforts towards productivity improvement, although western region has abundant construction workers. The undesirable performance of construction productivity can be also explained by the limited adoption of plants and equipment in construction activities, which is not conductive to establish the long-term competitiveness of regional construction industry.

Chapter 5: Regional Differences of Construction Productive Efficiency

5.1 Introduction

This chapter elaborates the measurement of construction productivity and the conceptualization of construction productive efficiency. Based on the framework of Solow growth theory, an overall efficiency measurement is developed for regional construction industry based on the review of literature and findings of previous chapter. DEA-based models are specified with three inputs and one output to measure the overall performance of construction productive efficiency across three regions of China, with different levels of economic growth and social development, i.e. developed eastern region, developing midland region, and underdeveloped western region. Based on the empirical results of DFM models, the causes of inefficiency and the sources of growth are identified for regional construction industry from the viewpoint of input optimization and output potential.

5.2 Measurement of construction productivity

Based on the major findings from previous chapter, construction productivity is critical to sharpen the competitiveness of labor cost in construction industry. A wealth of research has been conducted from various levels, covering industry, project, and activity levels, to benchmark and assess the performance of construction productivity. However, there is not a clear definition of productivity in construction domain, due to difficulty and inconsistency of measurement from different perspectives (Carson & Abbott, 2012). There are two major ways in terms of productivity definitions, i.e. single factor productivity and total factor productivity. Labor productivity is a type of single factor productivity estimated purely on labor inputs for final output. One of the common measurements that is widely used at either project level or activity level is the basis of hourly output, where the working hours and physical output of construction workers need to be clearly figured out. In real practice, the discrete performance of construction productivity can hardly provide an accurate estimation of construction manpower performance during the process of construction project. Alternatively, the employed number of total persons and value added in construction industry is often used as input and output for productivity measurement in construction industry. Publications released by official authorities or professional institutions prefer to adopt this statistics method for estimating the productivity level in construction industry. Owing to the uncertainty of statistics and mobility of labor, some abnormal points can be occasionally observed that might mislead the understanding of production efficiency and investment returns in construction activities. Thus, an overall and accurate measurement of labor productivity in construction industry is prerequisite for identifying the root causes and the optimal pathways of further improvement, particularly in the developing economies characterized with low productivity.

5.3 Conceptualization of construction productive efficiency

Productivity is a technical concept which can be integrated as a ratio of output to input. Unlike the single factor productivity, TFP concept takes into account the overall factors of production proxied as multiple inputs to calculate the level of production efficiency in construction industry. According to the neoclassical economic theory, labor, capital, and equipment element are three main inputs to determine the capacity of industry output. Moreover, the production factor of labor, capital, and equipment input should be considered in measuring the overall performance of construction industry TFP, regardless of the complexity of intermediate inputs in the lengthy production process.

$$TFP = \frac{Output}{Input} = \frac{Y}{f(L,K)} = \frac{Y}{L \times f(1, K/L)} = \frac{Y}{L \times f(1, \frac{K_1}{L} + \frac{K_2}{L})} \tag{5.1}$$

$$L: labor, K_1 = capital\ investment\ in\ labor, K_2 = capital\ investment\ in\ equipment$$

Based on a review of literature on the TFP measurement, Solow residual approach and DEA model have been widely applied and acknowledged as the representatives of the parametric methods and non-parametric methods, respectively. Solow residual approach focuses more on time series analysis and discrete analysis with only one DMU (Solow, 1957), while DEA model is an objective and comprehensive evaluation tool for cross-section analysis through comparisons of multiple DMUs with common inputs and outputs (Charnes et al., 1978). DEA-based models have been commonly used in measuring the TFP performance in various domain due to its simplicity of modeling. One of the critical factors in measuring the construction industry TFP is the selection of input and output factors. For the construction industry, a systematic overview of important factors and indicators is summarized from the sides of input and output presented in **Table 2.3**. From the viewpoint of input, labor compensation tends to move in tandem with labor productivity in construction activities. Further, the increasing gaps of income per capita across regions are mainly due to differentials in TFP (Bateman et al., 1988), which delivers the underlying information on industry competitiveness and economic development. Therefore, the average employee cost of construction workers, i.e. real wage in construction industry, are thereby adopted as the reflection of capital input towards labor recruitment and management. In accordance with the empirical results of panel data modeling, the total number of employed persons in construction industry and construction technical equipment ratio are also adopted as the typical proxies of labor and equipment inputs based on the inferences of **Formula 5.2**. For industry output, construction value added is preferred instead of construction output to avoid the double counting of intermediate inputs for the DEA-based measurement of construction industry TFP.

$$TFP = \frac{construction\ value\ added}{f(labor, capital, equipment)} = \frac{Y}{L * (1 + \frac{K}{L} + \frac{T}{L})} = \frac{CVA}{f(CE, CLW, TER)} \qquad (5.2)$$

DEA model has gained popularity in numerous studies concerning benchmarking assessment and efficiency evaluation across a variety of industries and fields, which provides valuable information assisting decision making and policy design to boost the economic growth and industry performance (Charnes et al., 1978). Further, DEA-based models have been extensively applied to benchmark and evaluate the efficiency performance of construction industry covering different aspects. However, TFP decomposition can merely provide limited information regarding pure efficiency, technological progress, and economies of scale due to the inherent restrictions of traditional DEA model. Further adjustments from factors of inputs and outputs cannot be obtained for efficiency improvement by using conventional DEA model due to a uniform radial projection. Since there are no “one size fits all” solutions to efficiency improvement considering uneven regional development of construction industry, formulating development policies and strategic planning for regional construction industry is pivotal to foster the industry development and productivity growth. In light of above observations, this study attempt to develop the DEA-based models to overcome that challenge.

As one of the DEA-based optimization methods, DFM approach was developed by Nijkamp & Suzuki (2009) on the basis of the standard DEA model. With the definition of non-radial directional distance frictions shown in **Table 3.1**, DFM model can find the shortcut for inefficient DMUs to reach the efficient frontier, further indicating the inefficient use of input resources and potential of output growth with a full efficiency. Due to the complex nature of construction industry, it is difficult for inefficient provinces or regions to improve the efficiency performance of construction industry within a short period of time. Against this background, a stepwise efficiency improvement planning is more applicable for sluggish construction industry, particularly for those less inefficient provinces (Suzuki et al., 2015). The annual efficiency target for stepwise improvement can be set according to the efficiency gaps and study period within the framework of DEA model. Setting reasonable and appropriate targets can well track the process of resource allocation and optimization, meanwhile assist the unproductive provinces to achieve the stepwise improvement of construction productive efficiency, according to regional development and strategic planning.

5.4 Specifications of DEA-based modeling

5.4.1 Data source

Based on literature review and empirical analysis, three input and one output indicators are selected to benchmark the performance of construction productive efficiency in China's construction industry. All input data and output data are obtained from the China Statistics Yearbook (National Bureau of Statistics of China, 2020a), published annually during the study period. As described above, the input variables are chosen from three types of critical resource in the production process, i.e. labor, capital, and equipment. First, labor input is represented by the total number of employed persons in the construction industry at the end of each year (Li & Liu, 2010; Wang et al., 2013; Xue et al., 2008). Second, capital input can be represented by investment in both labor and machinery in construction industry. Average annual salary of construction worker is used as an indicator to capture the wage rate of construction worker, also reflect labor supply and demand in construction market (Chancellor, 2015; Park et al., 2015). It is a part of capital investment can directly or indirectly affect the levels of labor cost, productivity, and other intangible inputs. Third, the input of equipment is proxied by the capacity of construction plant and equipment as a major part of capital formation. Construction technical equipment ratio refers to the value of machinery and equipment owned per capita in construction industry, which is a technical proxy to measure the investment and application of technical plant and equipment in construction activities, also the potential of labor savings in the industry (Chancellor & Lu, 2016; Wang et al., 2013). The output variable is characterized by the value added of the construction industry (Li & Liu, 2010; Wang et al., 2013; Xue et al., 2008).

China is the largest developing country with an imbalanced economy and resource distribution across regions. There is a total of 31 provincial administrative units (hereafter provinces) in China. Regional disparity can be clearly observed in construction industry development, due to the different levels of resource allocation and fiscal public investment over the past decades (Han & Ofori, 2001). The coefficient of variation (CV) is defined as the proportion of an indicator's standard deviation and value. It is commonly used to measure the regional inequality and unbalanced development (Huo et al., 2020; Wang et al., 2013) .

$$\mathrm{CV} = \frac{1}{Y}\left[\frac{1}{n}\times\sum_{i=1}^{n}(Y_i-\bar{Y})^2\right] \tag{5.3}$$

$\bar{Y}$ refers to the mean value of efficiency score, Y_i refers to the efficiency score of a DMU, and n is the number of DMUs. If the value of CV is greater, this indicates the difference of efficiency score among DMUs is greater. This research attempts to use this indicator to explore the efficiency gap of construction industry among provinces and regions over the study period.

5.4.2 Research target

The levels of input and output are strongly related to the geographic location and administrate layout. The level of economic prosperity and the maturity of construction industry exhibits a seemingly decreasing pattern from East China to West China. In this study, 30 provinces are selected excluding Tibet due to data unavailability. Besides, these provinces with similar levels of economic strength and technology development will be classified into the same group from the perspective of regional economy. In line with these principles, this study divides 30 provinces into three clusters shown in **Figure 5.1** , i.e. developed eastern region (Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Fujian, Guangdong, Shandong, and Hainan), developing central/northeast (hereafter central) region (Jiangxi, Shanxi, Anhui, Hubei, Hunan, Henan, Heilongjiang, Jilin, and Liaoning), and underdeveloped western region (Sichuan, Chongqing, Shanxi, Yunnan, Guizhou, Xinjiang, Gansu, Ningxia, Qinghai, Guangxi, and Inner Mongolia).

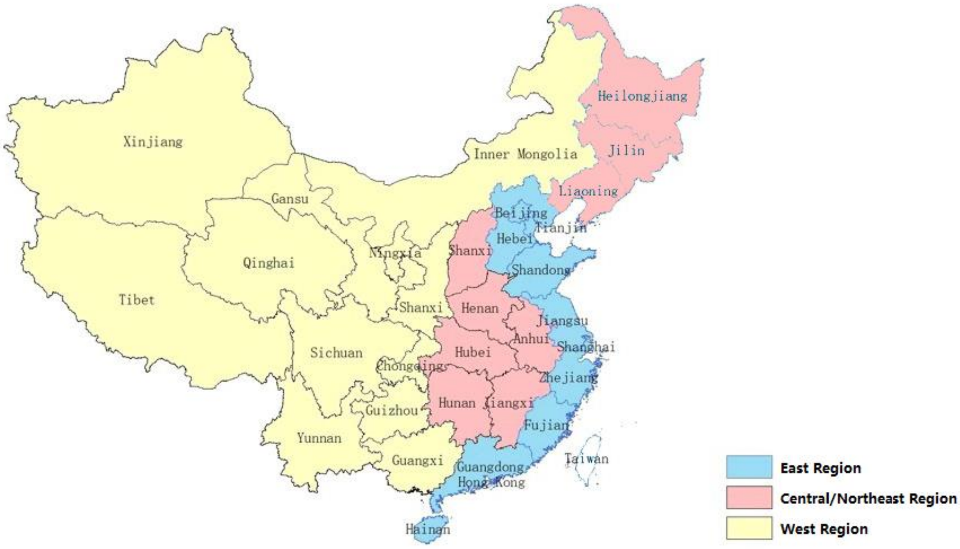

Figure 5.1 Layouts of three regions of different levels of economic development in China

5.4.3 Research steps

The efficiency performance of each province is considered as a DMU in the DEA-based models, all provinces will be first assessed and compared from a multi-dimensional perspective in the study period from 2006 to 2015. Then, less inefficient DMUs are identified from each region for further discussion, according to the overall ranking of construction productive efficiency. The causes of inefficiency and the sources of growth are explored using DFM model for the baseline year 2016. Regional comparison and analysis are accordingly conducted based on the typical provinces from each region in terms of output potential and input optimization, respectively.

5.5 Regional performance of construction productive efficiency

China's construction industry achieved an incredible output growth over the past decade from 2006 to 2015, but the performance of construction productive efficiency was overall stagnant at 0.75, notwithstanding the 'Four Trillion Fiscal Stimulus Package' initiated by central government against the Global Subprime Mortgage occurred in 2009. The vast amount of public investment inflowed into the domains of real estate, infrastructure, transportation, and public facilities created huge counter-cyclical demands to revitalize the economy, but regional construction productive efficiency did not improve immediately, however, continued to decrease in the succeeding years, except for some provinces in the underdeveloped western region. The productive efficiency of construction industry was the highest in developed eastern region due to the strong performance of coastal areas including Jiangsu, Zhejiang, Fujian, and Shandong provinces (Chancellor & Lu, 2016; Wang et al., 2013). In contrast, construction development was investment-driven and subjected to fluctuations of external factors in developing central region. As indicated by the CV upturn in **Figure 5.2**, it is noteworthy that the reduced regional gaps of construction productive efficiency bounced back after 2010, displaying an unbalanced pattern of construction industry development across different regions of China.

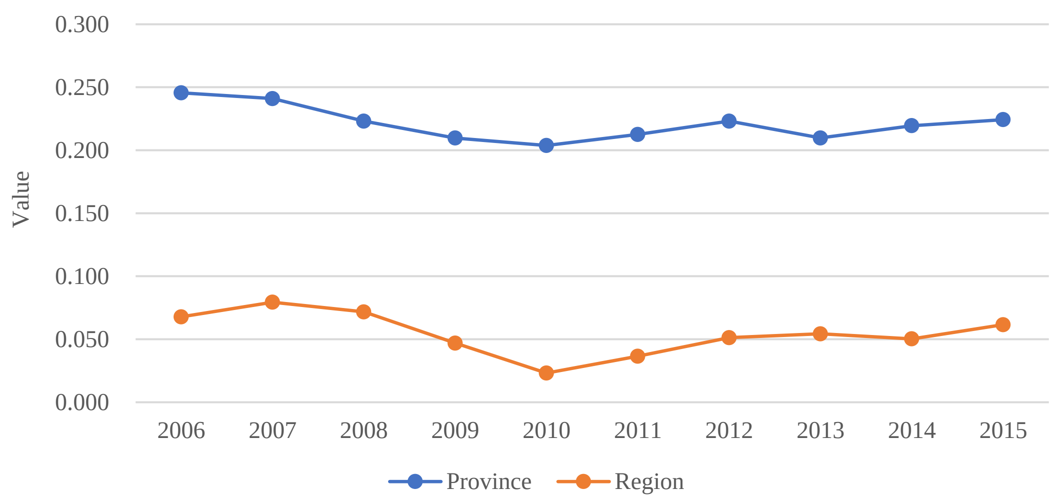

Figure 5.2 CV of construction productive efficiency among provinces and regions (2006 - 2015)

Based on efficiency performance of construction industry shown in **Table 5.1**, three of four efficient provinces are from the developed eastern region. In addition, other high efficiency DMUs are also the leading province in each region. The efficiency gap of construction industry in central region is the minimal. Apart from some remote western provinces, some municipalities in developed eastern region are also found to have low productive efficiency, such as Beijing, Tianjin, and Shanghai, where are the hubs of economic development in subregion. In light of this observation, enhancing the overall performance of construction productive efficiency is a common endeavor in terms of the regional development and economic growth, yet with different characteristics in construction industry performance among three regions with different levels of economic growth.

Table 5.1 Ranking of provincial construction productive efficiency in three regions of China

Province	**Region**	**Score**	**Province**	**Region**	**Score**	**Province**	**Region**	**Score**
Jiangsu	East	1.000	Liaoning	Central	0.780	Shaanxi	West	1.000
Zhejiang	East	1.000	Jiangxi	Central	0.731	Guangxi	West	0.927
Shandong	East	1.000	Anhui	Central	0.711	Sichuan	West	0.918
Fujian	East	0.928	Henan	Central	0.705	Chongqing	West	0.873
Hebei	East	0.783	Hubei	Central	0.672	Yunnan	West	0.791
Guangdong	East	0.730	Hunan	Central	0.654	Inner Mongolia	West	0.747
Hainan	East	0.476	Heilongjiang	Central	0.512	Guizhou	West	0.551
Shanghai	East	0.379	Jilin	Central	0.476	Xinjiang	West	0.501
Beijing	East	0.366	Shanxi	Central	0.408	Gansu	West	0.394
Tianjin	East	0.265				Ningxia	West	0.266
						Qinghai	West	0.185
Average	East	0.693	Average	Central	0.628	Average	West	0.650

5.6 Regional comparison of input optimization and output potential

As is clearly shown in **Figure 3.1**, the projected paths for an inefficient DMU to attain the efficiency frontier are different between CCR-I model and DFM approach, determining the different projection routes for efficiency improvement. The projection results of CCR-I model and DFM model for China's construction industry in 2016 are presented in **Appendix II**. For better comparison of the two sets of modeling results, we take Beijing as an example for detailed illustration. According to the results of CCR-I model, the efficiency score for Beijing is merely 0.366, indicating that two inputs (CE, TER) should be reduced by 63.4%, another input (CLW) is even higher with 73.0%, whilst the industry output remains unchanged. By comparison, the DFM projection results show that Beijing is inefficient because of the inflationary high wages (65.7%), and slightly excessive investment in construction plants and equipment (54.9%) fail to promote the efficient growth of construction output. Overall, the changes of ratios in the DFM model are much smaller than those in the CCR-I model. Besides, construction value added can be increased by 46.4%, if the critical inputs of resources are optimized with a full efficiency based on the projection results of DFM model. In conclusion, DFM model can find the shortcut to the efficiency frontier, providing better solutions than CCR-I model to efficiency improvement (Suzuki et al., 2010).

The concept of slack ratio is thereby introduced to identify the causes of inefficiency and sources of growth by comparing with the optimal system of full efficiency. A slack ratio can be calculated by dividing the value of optimized input or output with the actual value. There are four projection types according to the existence of slacks, i.e. non-slack type, input-slack type, output-slack type, and input-output-slack type (Suzuki et al., 2010). The value of slack ratio can indicate the inefficiency of excessive inputs and the potential of increased outputs (Hu & Liu, 2017). Further, it serves as an important reference for the development of effective strategies to improve construction productive efficiency. **Figure 5.3** summarizes the average slack ratios for the potential increases of construction output and the optimization parts of critical inputs across three regions of China.

5.6.1 Output potential

For the slack ratio of output, it refers to the development potential of construction industry under a full efficiency. All three regions have an enormous potential for expansion. Western region has the greatest development potential with 38.6% for further expansion, followed by 20.3% in developing midland region. In contrast, construction industry in eastern region is relatively mature with limited potential for improvement (4.1%). Faced with the rising labor cost and declining labor supply in construction market, it is imperative for stakeholders to maximize the effective use of inputs for producing desirable industry output. The slack ratio of inputs reveal that critical resources are not fully utilized for producing output with spillover effects in a competitive market. On the other hand, the value of slack ratio can indicate the degree of inverse dependency on which construction industry to achieve the rapid development. The slack ratios of each input, i.e. CE, CLW, and TER, have been examined with regional comparison.

5.6.2 Input optimization

For the value of CE slack ratio, it is the lowest of all three inputs in each region. This reveals that China's construction industry is still labor intensive with heavy reliance on cheap manpower. Due to regional diversities of labor quality, about 8% construction workers were underemployed in both midland and western regions. The underperformance of construction workers was associated with the levels of labor skills and labor wages (Allmon et al., 2000). In comparison, construction workers were more productive with better salaries in eastern region, where regional construction industry was more developed under mature market mechanism (Wang et al., 2013). This can be partly explained by the performance of CLW slack ratios across three regions.

The value of CLW slack ratio is also the least with 7.9% in eastern region, compared with that in western region (8.1%), and midland region (14.7%). To mitigate the effects of labor shortage in the industry, offering higher salaries is a short-term measure to retain and attract construction workers, especially in coastal areas. The wage rate is likely to rise more frequently in the construction boom. Sometimes the high levels of remuneration for unskilled or semi-skilled construction workers may lower the profit margins of contractors, however, does not improve the production efficiency within a short period of time. On the contrary, the upward pressure of construction labor cost restricts the progressive growth of construction output, evidenced from the larger CLW slack ratios in inland regions. Given that construction industry is a labor-intensive sector with low entry requirements, high income is an important driving force that attracts additional migrant workers to stay and serve in the industry. However, most self-employed migrant workers are untrained with lack of competent skills, tend to accumulate the working experience through informal on-the-job training. Normally, it takes at least several years for a new entrant to become a skilled worker through apprenticeship in construction practice. The skill development of construction worker is of immense importance to productivity performance. Skilled construction workers were offered with better salaries particularly for some technically demanding and necessary trades, whereas manual worker whose job can be easily replaced by construction plant and equipment were merely provided with a basic level of renumeration (Nasir et al., 2014). With a rapid growth of labor cost in the entire industry, labor savings by investing more on construction plants and equipment turned out to be more efficient for sustaining the continuous growth of construction industry, which had been proved to be a long-term solution to productivity improvement (Goodrum & Gangwar, 2004).

Similarly, the value of TER slack ratio is merely 0.6% in eastern China, the least of all three regions, in contrast with that over 10% in other two regions. In the past decade, large-scale infrastructure construction became a significant contributor to the rapid development of construction industry (Démurger, 2001). Undoubtedly, the effective utilization of construction plants and equipment played an important role in extending the traditional business to technology-driven field (Azman et al., 2019), further shaping the core competition of construction industry in the east parts. In contrast, regional construction industry is over-reliant on cheap manpower, with a lower level of construction technical equipment owned per capita in inland region, leading to the inefficient utilization of plant and equipment in construction practice. Furthermore, regional construction industry focused more on traditional fields of building construction and municipal engineering. The single market structure refrained the application of advanced equipment and new technology, even hampered the business expansion and productivity growth of construction industry (Liu et al., 2016).

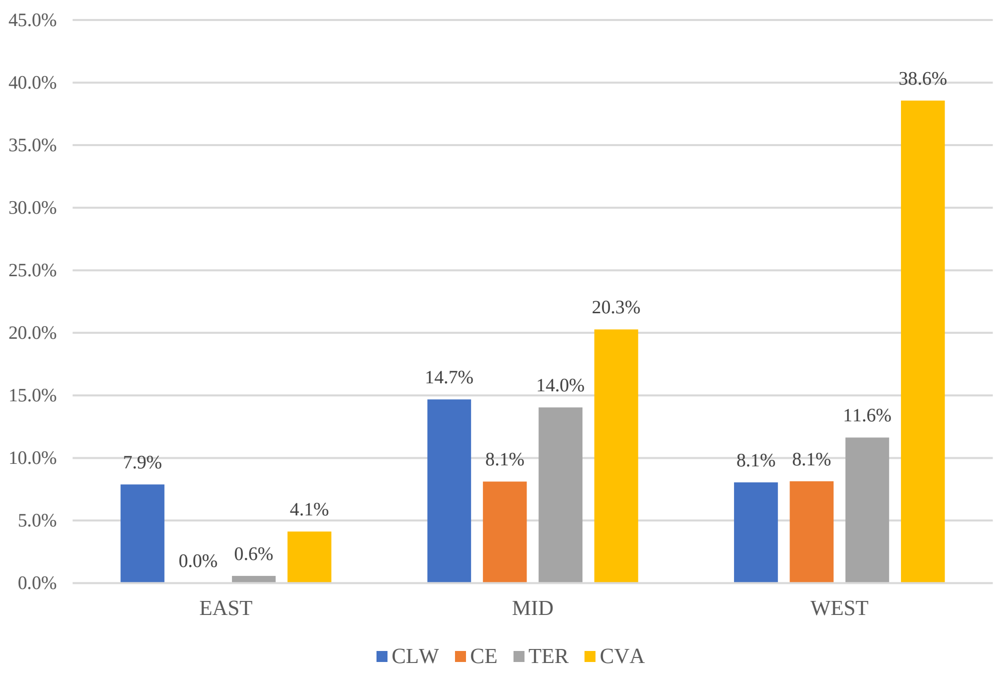

Figure 5.3 Average slack ratios of potential changes in China's regional construction industry

(Source: Luo et al., 2019)

5.7 Summary of the chapter

This chapter develops an overall measurement of construction productivity based on the neoclassical economic theory, single factor productivity and total factor productivity are the two major types of productivity measurement. Based on a review of related literature and principal findings of previous chapter, construction productive efficiency is conceptualized with three inputs and output by using DEA-based model. DEA model is first employed to estimate the regional construction productive efficiency based the performance of selected provinces. It is evident that construction productive efficiency in coastal regions is better than that of inland regions, i.e. western region and midland region. For further investigation of regional gaps, DFM approach is applied to identify the causes of inefficiency and the sources of growth across different regions of China. Based on the results of

DFM model, the development potential of construction industry in western region is the largest, in contrast with that of midland region and eastern region. On the other hand, the inefficiency of inputs involving construction worker, construction labor wage, construction plant and machinery, leads to the diverse performance of construction productive efficiency among different regions of China.

Chapter 6: Stepwise Improvement of Regional Construction Productive Efficiency

6.1 Introduction

This chapter discusses the feasibility and practicability of stepwise efficiency improvement for those inefficient places, particularly low efficiency provinces that cannot make significant improvement within a short period of time across three regions of China. Based on DFM model results in previous chapter, three typical provinces with relatively low efficiency are selected from each region for further discussion. Annual targets for stepwise efficiency improvement are defined by TO approach based on the DFM model, according to the efficiency gap and study period. Further, the optimal improvement pathways for construction productive efficiency are identified across different regions for strategic planning and policy making in the coming period.

6.2 Regional analysis of construction productive efficiency

Based on the regional performance of construction productive efficiency, it could be concluded that the causes of inefficiency and sources of productivity growth are quite different across three regions, according to the results of DFM model in previous chapter. Regional divergences in construction productive efficiency were attributed to a number of factors including economic growth, investment environment, industry structure (Chen et al., 2018; Liu et al., 2014), and technological level (Li & Liu, 2010). The persistent occurrence and excessive increase of regional differences would not only undermine the overall competitiveness of construction industry, but also lead to the undesirable performance of construction productive efficiency due to the inefficient resource allocation and inappropriate target settings. Given that the lagged effects of capital investment on construction activities, it is difficult also unreasonable to make significant productivity improvement within a short period of time, especially for low efficiency provinces. In contrast to the one-step enhancement pathway, a progressive efficiency improvement for regional construction industry is more practical and feasible under the guidance of stage-wise targets, which facilitates the forward-looking policy making and strategic planning for regional development of construction industry in coming periods. The less inefficient provinces, whose efficiency score is lower than 0.4, are summarized by region in **Table 6.1**. To narrow regional gaps for a sustainable growth, three typical low efficiency province or municipality are accordingly selected as representatives from each region for further discussion and comparison, i.e. Shanghai municipality from developed eastern region, Shanxi province from developing midland region, and Qinghai province from underdeveloped western region.

Table 6.1 Less inefficient provinces / municipalities based on DFM model results (2016)

Region	**Province / Municipality**	**Score**
Eastern	Shanghai	0.379
	Beijing	0.366
	Tianjin	0.265
Midland	Shanxi	0.476
	Jilin	0.408
Western	Gansu	0.394
	Ningxia	0.266
	Qinghai	0.185

6.3 Stepwise improvement of construction productive efficiency

DFM approach can explore regional differences of productivity performance in China's construction industry, meanwhile quantify the potential of output growth and the inefficiency of input utilization (Luo et al., 2019). The optimal pathway of output growth and input usage can be further identified for DMUs with inefficient performance according to the projection results of DFM model. However, for a DMU with very low efficiency shown in **Figure 3.1**, the distance from inefficient point to full efficiency frontier is too far to reach in the short run, which indicates that the resources of input need to be optimized step by step, low efficiency DMU could become efficient with the progressive improvement.

In this regard, target setting and strategic planning for stepwise efficiency improvement need to give the considerations to regional growth and construction development. Target Efficiency Score (TES) herein serves as a milestone for the guidance of resource allocation and future planning, also assist low efficiency DMU to make practical and stepwise adjustments for further efficiency improvement. Under this circumstance, Target-Oriented (TO) approach is applied to define an appropriate TES on the basis of DFM modeling results (Suzuki et al., 2015). In previous chapter, 2016 is selected as the baseline year, and the projection period for stepwise improvement is defined as the following period from 2017 to 2020. As such, TES is accordingly determined for each DMU based on the values of Magnification Parameter (MP) using the **Formula 3.4**, with 0.25 in 2017, 0.50 in 2018, 0.75 in 2019, and 1.0 in 2020. TO-DFM model is then employed to identify the efficient improvement path for low efficiency DMUs with the stage-wise targets, the projection results of TO-DFM model for three selected representatives from each region, i.e. Shanghai municipality, Shanxi province, Qinghai province, are shown in **Tables 5.2 ~ 5.4**.

6.3.1 Developed eastern region

Shanghai municipality represents the developed economic area, which is undergoing the transition process of industry upgrade and transformation. Construction sector achieved a slower growth rate with less than 4% contributions in the domestic GDP (Shanghai Provincial Bureau of Statistics, 2017). Nearly half of the total industry output came from external market contributed by the large international construction firms. These construction enterprises kept expanding the market through technical efficiency instead of scale efficiency (MacKenzie et al., 2000), particularly in competitive market with a consecutive fall in labor supply over the past five years. The overall percentage of skilled worker was only 21% (Shanghai Provincial Bureau of Statistics, 2017), it can be anticipated that skill shortages of construction workers would significantly affect the efficiency performance in the succeeding several years, with an annual gap of about 4% as suggested by the TO-DFM model results. To mitigate labor shortage, contractors are encouraged to apply advanced equipment, tools and technologies in construction works, with about 8% increase expected in the coming period. For example, they have established some connections and cooperation with precast companies, and resorted to Modular integrated Construction (MiC) technologies and prefabrication components with strong support from local government and industrial associations (Shanghai Municipal People's Government, 2017). The goal for the application and promotion of technical equipment and new technologies in local construction works is set to be higher than that of national level. All these forward-looking measures were implemented to address the inefficient utilization problems of construction plant and equipment, embrace new technologies for labor savings in some construction activities. The productive efficiency of regional construction industry can be improved with a steady growth and become high level after the completion of industry transition and upgrade in the future.

Table 6.2 Stepwise improvement results of TO-DFM model for Shanghai City (2017 - 2020)

Low efficiency DMU	2016 DEA	DFM	2017 TO-DFM	2018 TO-DFM	2019 TO-DFM	2020 TO-DFM
Shanghai	0.379	1.000	0.475	0.599	0.766	1.000
(I)CLW	-80.6%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)CE	-62.1%	-17.4%	-4.4%	-8.7%	-13.1%	-17.4%
(I)TER	-62.1%	-58.8%	-14.7%	-29.4%	-44.1%	-58.8%
(O)CVA	0.0%	45.0%	11.3%	22.5%	33.8%	45.0%

6.3.2 Developing central region

Shanxi province is located in central part of China with a level of developing economy. The total capacity of construction industry in Shanxi is similar with Shanghai, but the causes of inefficiency are totally different. Shanxi represents developing province seeking a rapid growth of construction output with more contributions to local economy. However, in central region, construction industry relied heavily on cheap resources of inputs and mainly focused on domestic market, especially in some central cities. With an increasing number of competitive enterprises entering local market over recent years, more remuneration was provided for the retention and attraction of construction site workers to meet construction demand. On the other hand, most of the site-workers were unskilled or semi-skilled migrant laborers without much working experience and skill training. Only 15% workers were skilled and no significant growth of labor productivity was observed in the past many years (Shanxi Provincial Bureau of Statistics, 2017). Vocational education and training of skilled labors was lagged behind in the construction market (Ye et al., 2019). Meanwhile, rising labor wage exerted great pressure on cost management and control for the subcontractors, which construction enterprises were usually operated with a high debt ratio (Shanxi Provincial Bureau of Statistics,

2017) . Based on the TO-DFM modeling results, although there is still some potential for wage growth in coming period, an excessive increase of construction labor wage would become a heavy burden for further efficiency improvement of regional construction industry.

Table 6.3 Stepwise improvement results of TO-DFM model for Shanxi Province (2017-2020)

	2016		**2017**	**2018**	**2019**	**2020**
Low efficiency DMU	**DEA**	**DFM**	**TO-DFM**	**TO-DFM**	**TO-DFM**	**TO-DFM**
Shanxi	0.408	1.000	0.503	0.625	0.784	1.000
(I)CLW	-59.3%	-54.0%	-13.5%	-27.0%	-40.5%	-54.0%
(I)CE	-59.3%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)TER	-74.7%	0.0%	0.0%	0.0%	0.0%	0.0%
(O)CVA	0.0%	42.1%	10.5%	21.1%	31.6%	42.1%

6.3.3 Underdeveloped western region

Qinghai province is situated in the underdeveloped western region of China, with the lowest construction productive efficiency of 0.185 in 2016. Other neighboring provinces in this remote area, including Ningxia, Gansu, and Xinjiang provinces have similar issues of low productivity. Regional construction industry was investment-driven with an annual growth of over 8% (Qinghai Provincial Bureau of Statistics, 2017). The total volume of construction works was relatively small, compared with other regions in China. Most migrant workers moved to work in central region or eastern region, where more competitive salaries were offered in construction. Local workers were most unskilled and aged, taking up less than 4% of total employment in local economy (Qinghai Provincial Bureau of Statistics, 2017). The ageing workforces and skill shortages can hardly satisfy the construction demand, thus exerting the significant challenges to productivity improvement of the construction industry (Pan et al., 2020). Even local contractors preferred to recruit skilled labors from other provinces due to shortages of labor in local market. It is imperative to increase the wage level and enhance the vocational education and training program especially for those new entrants without sufficient working experience (Ye et al., 2019). Compared with the informal on-the-job training, vocational education and training program is significant to establish the regional competitiveness to the increasing demands of construction industry (Pan et al., 2020). As revealed from the results of TO-DFM model, the marginal gains of vocational education and training program for labor supply and skill development will grow incrementally over time, and become more critical for productivity improvement of regional construction industry in the long term (McGrath-Champ et al., 2010).

Table 6.4 Stepwise improvement results of TO-DFM model for Qinghai Province (2017-2020)

	2016		**2017**	**2018**	**2019**	**2020**
Low efficiency DMU	**DEA**	**DFM**	**TO-DFM**	**TO-DFM**	**TO-DFM**	**TO-DFM**
Qinghai	0.185	1.000	0.262	0.379	0.580	1.000
(I)CLW	-81.9%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)CE	-81.5%	-68.7%	-17.2%	-34.4%	-51.5%	-68.7%
(I)TER	-87.4%	0.0%	0.0%	0.0%	0.0%	0.0%
(O)CVA	0.0%	68.7%	17.2%	34.4%	51.5%	68.7%

6.4 Recommendations for regional construction development

As shown in **Figure 6.1**, construction industry of the representative low efficiency provinces in three different regions can achieve the stepwise efficiency improvement if resources of input are properly allocated and efficiently utilized with reasonable planning and appropriate targets. According to the results of TO-DFM model, the simulated incremental efficiency growth varies by region primarily due to differences in the causes of inefficiency and sources of growth. The underlying information concerning stepwise efficiency improvement has considerable implications on the strategic planning and policy making for regional development of construction industry in the coming period.

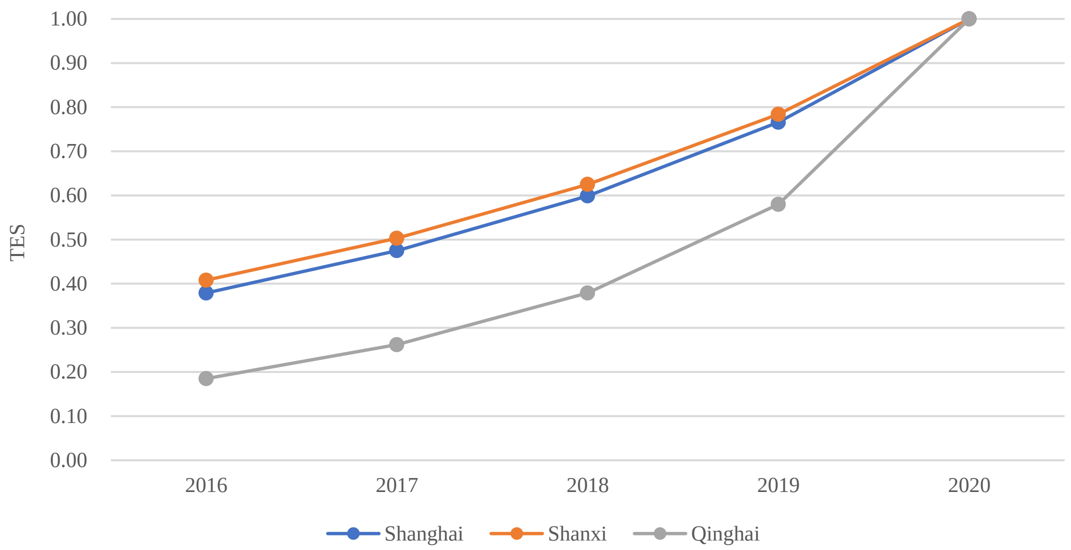

Figure 6.1 Stepwise improvement of construction productive efficiency in three typical provinces / municipalities from different regions of China (2017-2020)

In eastern region, represented by the case of Shanghai municipality, construction industry has been experiencing the process of industry transformation and upgrade with decreasing contributions to local economy. Faced with the declining supply of skilled labors in the coming years, high levels of labor wage becomes an important driving force attracting skilled workers from other regions of China (Chancellor, 2015). However, vocational education and training program cannot meet the increasing demand of construction workforce and offset the impact of labor shortages in the short term. With the ageing construction migrant workers and fewer new blood joining the industry, labor shortage became a main barrier to further growth of construction industry, thus pushed up real wage to a higher level. To resolve the issue of labor shortage, some contractors resort to aggressive recruitment strategies with the provision of better remuneration (Dainty et al., 2004). Meanwhile, contractors tend to employ more construction equipment and advanced technologies for labor savings or substitution in construction activities. Maximizing the use of construction plant and equipment can effectively reduce the demand for manual workers in some works (MacKenzie et al., 2000), and meanwhile improve the performance of construction productive efficiency that is critical to the competition and sustainable development of regional construction industry in the long term, with the fastest annual growth in the coming period.

In contrast, the annual growth of construction productive efficiency is slightly slower in central region, as in the case of Shanxi province. With an increasing amount of public investment over the recent years, the buoyant construction market has attracted many large developers into the central market. Local contractors have to provide disproportionally higher levels of salaries to satisfy the increasing demand of labor in a competitive market. Regional construction industry was labor-intensive with persistent reliance on cheap manual workers. However, most of construction migrant workers were unskilled or untrained without adequate working experience (Shanxi Provincial Bureau of Statistics, 2017). Contractors are reluctant to train casual workers, as they would leave shortly upon the completion of project. The slow-paced skill development and rapid growth of labor wage hinder the productivity improvement of construction industry. Increasing the compensation level can alleviate the pressure of labor shortage, but it might not improve the labor quality within a short period of time. To address this critical issue, vocational education and training program is an alternative response to enhance the skill development of construction workers particularly for new entrants in the medium term (Pan et al., 2020). The marginal gains of vocational education and training program will help to achieve a rapid annual growth of the productive efficiency in regional construction industry as shown in **Figure 6.1**. The incentives mechanism and implementation plan of training program should be put forward to upgrade their knowledge and skills of construction workers before the outbreak of labor shortage, also responsive to changing demands of technology and external impacts. In this way, the scale effect of construction workforce can be maximized with effective growth of industry output and stepwise improvement of construction productive efficiency.

For western region, represented by the case of Qinghai province, economic development and technology adoption levels are lower than the other two regions. Regional construction industry depends more on cheap but unskilled workforce to meet the limited demand, although the potential of industry output is the largest among three regions, according to the TO-DFM model results. Although labor resources are rich in some provinces of western region, skilled construction workers tend to move and work in developing or developed regions, because of more competitive salaries. With the ageing workforce and insufficient new blood in local construction, regional construction industry also suffers from labor shortage, which partly explains the slow growth of construction productive efficiency. Given the wage differentials in construction industry across different regions, raising real wage may not be able to effectively retain local workers in next few years. With more construction projects in coming period, increasing demands of skilled workforce can be expected in construction market. It is quite difficult for construction industry to rely on casual workforce with high levels of self-employment and low levels of skill training, for meeting the needs of continuous growth. Hence, regional construction industry cannot simply rely on public investment to augment the production efficiency, strategic planning and workforce training are also essential to the stable development of regional construction industry. Under this circumstance, a reasonable growth of real wage can attract more available workforce to the industry for satisfying the construction demand, also gradually improving the level of productive efficiency in regional construction industry.

6.5 Summary of the chapter

This chapter applies TO approach to identify the optimal pathways for stepwise improvement based on the results of DFM model, particularly for low efficiency provinces across three regions. Three low efficiency provinces are observed from each region, then selected as case studies for regional analysis and comparison in the coming several years. The annual targets are defined for each region according to the efficiency gap and projection period. The empirical results of TO-DFM models have significant implications on strategic planning and policy making for the stepwise efficiency improvement in regional construction industry. For developed eastern region, investing more on construction plants and equipment for labor savings is more efficient to promote the long-term productivity growth of construction industry. For developing midland region, heavy reliance on cheap manpower can be gradually relieved by allocating more budgets to vocational training and education program boost quality labor force. For underdeveloped western region, raising the real wage of construction workers is required to retain and recruit more workforce to meet the demands of local construction, and further achieve an optimal growth of construction productive efficiency.

Chapter 7: Regional Construction Labor Cost Forecasting

7.1 Introduction

This chapter develops a regional construction labor cost forecasting model based on the critical determinants identified in Chapter 4. Panel vector error correction model consider both time-series and cross-sectional labor cost variations in regional construction industry over the past two decades. To predict future trend of regional construction labor cost, P-VEC models are constructed for each region after passing a series of statistics tests. The reliability and predictability of the P-VEC model is confirmed by conducting in-sample forecasting analysis in comparison with that of P-OLS model. Further, scenario variables are selected based on the modeling results of long-term equilibrium and short-run causal relationship between regional construction labor cost and its explanatory variables. Scenario analysis are then conducted based on P-VEC model to simulate out-of-sample forecasting results of regional construction labor cost.

7.2 Forecasting techniques of construction labor cost

Labor cost estimation and management is vital to the regional development of construction industry, with an increasing share of total cost of construction projects. Meanwhile, it becomes more difficult for contractors to recruit skilled construction workers without offering respectable remuneration. Based on the principal findings of previous chapters, construction productivity level is associated with labor and related inputs, e.g. the level of labor compensation, the scale of labor, and the effect of labor saving by construction plant and equipment. The imbalanced allocation and inefficient utilization of critical resources of inputs leads to unproductive performance in regional construction industry, given the development potential. Consequently, managing the dynamics and development of labor cost in construction market is not only critical to sharpen the core competition of contractors, but also a prerequisite to maintain the sustainable construction industry development under different circumstances.

Previous studies investigated the construction labor cost performance mainly from the supply and demand of labor. Few efforts were directed to examine the labor cost changes over time, mainly restricted by the issue of data availability. Liu et al. (2015) applied an econometric technique, i.e. VAR model, to explore the interactions among construction labor cost, construction output, and CPI and further adopted another extrapolated ARIMA model to predict the labor cost performance in China's construction industry. VAR model and multiple regression model had been used to illustrate the interactions between labor productivity and real wage in construction industry (Liu & Xiang, 2009). It can be anticipated that labor cost would continue to achieve a rapid growth in China's construction industry based on a reliable and robust forecasting method. As one of the most popular univariate models, Box-Jenkins approach, also known as ARIMA model, is widely used to evaluate and predict the temporal performance due to its simplicity of modeling, purely on historic data. The forecasting accuracy of the time series model is largely dependent on time series data particularly in recent periods, which largely limits the medium and long-term forecasting accuracy. Meanwhile, multivariate methods including multiple regression model, VAR model and VEC model can provide insights into the dynamic relationship among variables by considering lag effects. Time series model is proven to outperform the multiple regression model in terms of predictability, but subject to variations caused by external impacts.

In addition to time series models, e.g. Box-Jenkins approach, multiple regression model, and VEC model, cross-sectional techniques have also been employed for the investigations of labor cost performance in construction industry. Given that impact of labor mobility, a series of questionnaire surveys have been carried out to collect the first-hand information concerning construction migrant workers in different provinces and cities. The level of real wage is always the foremost concern for construction migrant workers, even draws public attention because of wage arrears, regardless of other critical problems. Although the empirical results of questionnaire surveys can help better understand the situation of construction migrant workers, recommendations made based on random observations can hardly serve as effective references for strategic planning and policy formulation across regions. Due to the availability and accessibility of labor cost data in construction practices, limited research has been conducted to reveal the dynamics and future trend of construction labor cost across different regions of China.

Based on the major findings of panel data model, critical determinants of construction labor cost are different across three regions of China over time. Also, the relationship between construction labor cost and explanatory variables differs by region, as an overall result of economic growth, investment environment, population size, market structure, and so forth. Construction labor cost performance not only changes with time, but also varies from region to region in China. The differentials in real wage originate from the variations in terms of regional labor supply and demand, also the existing gaps of construction productive efficiency. In this case, the adaptive capability of time series models is readily limited, especially when dealing with the turning points due to the occurrence of great events (Wong et al., 2012). More importantly, time series models cannot provide insightful information into dynamics between construction labor cost and critical determinants among different regions. On the other hand, cross-sectional techniques are incapable of revealing the causal relationships between regional construction labor cost and key factors over time. To overcome the challenges, panel data model is thereby introduced to incorporate time-series and cross-sectional variations of construction labor cost that can facilitate the control of unobserved heterogeneity and hence generate reliable forecasting estimates across different regions. Both regional interactions and temporal fluctuations are considered in modeling the construction labor cost performance. However, the dynamics of regional construction labor cost industry is ignored due to the model limitations. Consequently, panel data modeling provides a reasonable and robust framework for generating more accurate forecasts than either time series or cross-sectional modeling technique. The combination of panel data model and time series method produce a couple of commonly used models that provide the possibility of multidimensional analysis and meanwhile improve the forecasting accuracy, e.g. Panel Vector Autoregressive (P-VAR) model, and Panel Vector Error Correction (P-VEC) model. These panel methods have also been applied to estimate the construction demand and housing prices in regional market with desirable performance (Jiang & Liu, 2014).

7.3 P-VEC model establishment

7.3.1 Research design

Regional construction labor cost forecasting model is built on the preliminary assumptions of panel data model that are described in Chapter 4. The regional performance of construction labor cost is examined with a group of five critical variables, i.e. construction value added, employed persons in construction industry, construction technical equipment ratio, the total amount of fixed assets investment, and floor spare under construction. Further, regional analysis and forecasting are conducted based on the performance of selected provinces from 1997 to 2017 shown in **Figure 6.1**. The annual data of these indicators are sourced from the National Statistics Yearbooks (1998 – 2018) (National Bureau of Statistics of China, 2020a), covering 18 provinces with different levels of economic growth and social development, i.e. underdeveloped western region, developing central region, and developed eastern region.

In this study, an advanced regional forecasting model is first developed to predict the performance of construction labor cost across three regions of China, based on critical determinants identified in Chapter 4. Similar with the requirements of VEC model techniques, several statistics tests including panel unit root test, panel cointegration test, and panel causality test are required to conduct before the establishment of P-VEC models for regional construction labor cost forecasting. Further, the optimal lag length and number of cointegration equations should be defined within the framework of P-VAR model. Three P-VEC models are therefore built for construction labor cost performance in each region. Both the short-run causality and long-term equilibrium relationship between regional construction labor cost and its explanatory variables are elaborated based on the results of P-VEC model, then factored into the P-VEC model for regional construction labor cost forecasting. The in-sample forecasting results of P-VEC model are compared with that of P-OLS model from 1997 to 2017. Final, the optimal panel method with smaller forecasting error is adopted to conduct scenario analysis for out-of-sample forecasting in the coming periods from 2018 to 2022. The details for regional construction labor cost forecasting analysis are presented in **Figure 7.1**.

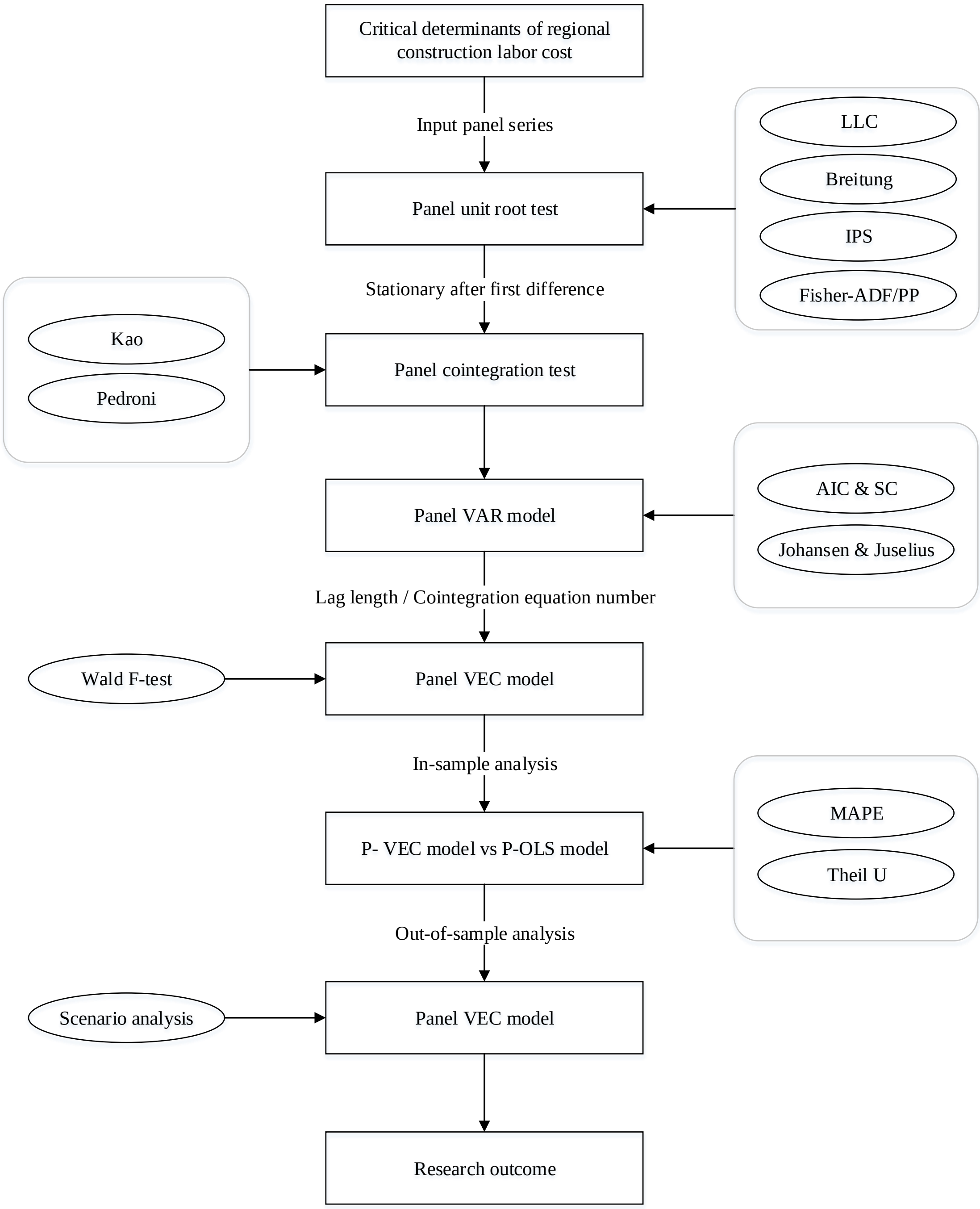

Figure 7.1 Flowchart for regional construction labor cost forecasting analysis

7.3.2 Panel unit root test

The first step in constructing P-VEC model is to test for the stationary of all variables listed in panel.

Inclusion of non-stationary panels might lead to spurious estimation in the modeling. The variables are tested for unit root to examine the order of integration to attain stationary. Results of panel unit root tests for each variable across three regions are summarized in **Tables 7.1 ~ 7.3**. All panel unit root tests including the LLC, Breitung, IPS, Fisher-ADF, and Fisher-PP, were conducted under the individual trends and intercepts for each series. The results of the panel unit root tests indicate that most of the level values are non-stationary, and nearly all tests reject the null hypothesis at the significance level of 5% in the level of first difference. Thus, six panel series can be considered as stationary in the first difference level, which is the precondition for conducting panel cointegration tests to determine the existence of long-run equilibrium between construction labor cost and its explanatory variables across three regions.

Table 7.1 Results of panel unit root tests (eastern region)

Unit root test	**Variable**	**LLC**	**Breitung**	**IPS**	**Fisher-ADF**	**Fisher-PP**
Level	ULC	-2.81445[a]	-2.51522[a]	-2.16637[b]	26.1807[b]	31.2163[a]
	CVA	-2.04084[b]	4.33062	0.52859	10.0696	13.4769
	CE	-2.53458[a]	-0.09507	-0.88876	15.6660	10.6779
	CW	-1.49192	3.46637	-0.39444	12.6367	7.62886
	TI	-1.82477[b]	5.59195	-0.25750	12.8186	8.69052
	TER	-1.72734[b]	-1.50724[c]	-2.83363[a]	28.7167[a]	24.8824[b]
First difference	ULC	-3.65304[a]	-4.30427[a]	-4.46635[a]	40.6575[a]	70.2233[a]
	CVA	-2.93823[b]	2.51504	-1.76443[b]	25.6296[b]	25.6442[b]
	CE	-5.40153[a]	-3.74629[a]	-6.8294[a]	59.7011[a]	66.0819[a]
	CW	-2.81315[a]	0.96447	-2.01922[b]	23.4558[b]	17.5060
	TI	-2.35687[a]	1.42274	-1.47944[c]	24.6463[b]	24.6633[b]
	TER	-10.2235[a]	-8.97424[a]	-10.0218[a]	84.2099[a]	97.2768[a]

Note: a, b and c mean that rejection of null hypothesis of unit root based on their P-value at the 0.01, 0.05, and 0.1 significance levels, respectively.

Table 7.2 Results of panel unit root tests (midland region)

Unit root test	Variable	LLC	Breitung	IPS	Fisher-ADF	Fisher-PP
Level	ULC	-3.28593 [a]	2.10365	-3.35403 [a]	40.7579 [a]	45.2531 [a]
	CVA	0.56047	6.89676	4.27247	1.01515	0.97736
	CE	0.90953	3.07371	2.15313	9.26278	8.78636
	CW	-0.29603	5.16216	2.69787	5.07797	5.27915
	TI	0.66936	7.5342	3.28459	8.13409	0.8199
	TER	-4.00575 [a]	0.07408	-2.60243 [a]	26.7224 [a]	27.1882 [a]
First difference	ULC	-5.97707 [a]	-0.98732	-7.35222 [a]	64.044 [a]	108.674 [a]
	CVA	-4.53383 [a]	0.06432	-3.04176 [a]	28.0089 [a]	23.809 [b]
	CE	-5.53482 [a]	-1.5449 [c]	-5.99024 [a]	52.877 [a]	88.4669 [a]
	CW	-0.97585	1.81288	-2.09793 [b]	30.2276 [a]	23.4940 [b]
	TI	-1.25213	2.26209	-0.62333	28.5138 [a]	44.2835 [a]
	TER	-13.5847 [a]	-6.68838 [a]	-12.1321 [a]	100.712 [a]	117.174 [a]

Note: a, b and c mean that rejection of null hypothesis of unit root based on their P-value at the 0.01, 0.05, and 0.1 significance levels, respectively.

Table 7.3 Results of panel unit root tests (western region)

Unit root test	Variable	LLC	Breitung	IPS	Fisher-ADF	Fisher-PP
Level	ULC	-0.62387	-0.13708	-1.37901 [c]	17.8292	27.3778 [a]
	CVA	5.54466	10.3308	9.93047	0.22172	0.10374
	CE	4.18956	6.67247	5.561909	6.53041	5.48575
	CW	-1.58765 [c]	0.81667	-0.16368	12.5072	2.94208
	TI	4.22047	6.43546	7.80144	0.63793	0.21415
	TER	-4.66503 [a]	-0.31492	-3.37373 [a]	30.9796 [a]	22.0849 [b]
First difference	ULC	-6.54778 [a]	-4.48091 [a]	-7.99494 [a]	70.3617 [a]	110.957 [a]
	CVA	-2.04491	1.97562	-0.62448	13.9403	11.2595
	CE	-4.15412 [a]	2.37654	-2.82947 [a]	42.9558 [a]	82.7557 [a]
	CW	-2.02764 [b]	2.81047	-3.34192 [a]	31.7917 [a]	24.1434 [b]
	TI	-2.92082 [a]	0.78670	-3.21065 [a]	35.5789 [a]	49.4937 [a]
	TER	-11.1054 [a]	-6.06484 [a]	-9.58123 [a]	83.1264 [a]	99.8841 [a]

Note: a, b and c mean that rejection of null hypothesis of unit root based on their P-value at the 0.01, 0.05, and 0.1 significance levels, respectively.

7.3.3 Panel cointegration tests

Since six variables are all stationary in the level of first difference, panel cointegration test is then conducted to test the presence of long-run equilibrium relationship between construction labor cost and five explanatory variables. As described before, there are two major types of panel cointegration tests, i.e. Kao's test and Pedroni's test, with the null hypothesis of no cointegration. Both tests were conducted as group cointegration to see whether there was a bivariate cointegration relationship between labor cost and variables in regional construction industry. The results of panel cointegration test or construction labor cost and critical determinants are reported in **Tables 7.4 ~ 7.6**. The first four test statistics are based on the "within-dimension", and the last three ones are based on the "between-dimension". In this case, panel cointegration tests results show that four out of seven Pedroni's panel tests reject the null hypothesis of no cointegration at the significance level of 1% in both eastern region and midland region. For panel results in western region, only three out of seven Pedroni's panel tests can reject the null hypothesis. To ensure the validity of panel cointegration results, Kao's test is also conducted for panel series in western region. The results clearly reject the hull hypothesis at 0.01 significance level, and finally confirm the existences of long-run equilibrium relationship between construction labor cost and selected variables in regional construction industry of China.

Table 7.4 Results of panel cointegration tests (eastern region)

Test statistics	Panel tests	Statistic	P-value
Common AR coefficients	Panel v-statistics	-1.695407	0.9550
	Panel rho-statistics	2.09937	0.9821
	Panel PP-statistics	-5.813026	0.0000
	Panel ADF-statistics	-5.04662	0.0000
Individual AR coefficients	Group rho-statistics	3.032336	0.9988
	Group PP-statistics	-11.44941	0.0000
	Group ADF-statistics	-5.784662	0.0000

Table 7.5 Results of panel cointegration tests (midland region)

Test statistics	Panel tests	Statistic	P-value
Common AR coefficients	Panel v-statistics	-1.135152	0.8718
	Panel rho-statistics	1.500585	0.9333
	Panel PP-statistics	-6.64076	0.0000
	Panel ADF-statistics	-5.230444	0.0000
Individual AR coefficients	Group rho-statistics	2.319448	0.9898
	Group PP-statistics	-8.931283	0.0000
	Group ADF-statistics	-7.342086	0.0000

Table 7.6 Results of panel cointegration tests (western region)

Test statistics	Panel tests	Statistic	P-value
Common AR coefficients	Panel v-statistics	-2.430979	0.9925
	Panel rho-statistics	1.919807	0.9726
	Panel PP-statistics	-1.524369	0.0637
	Panel ADF-statistics	-2.165056	0.0000
Individual AR coefficients	Group rho-statistics	3.273443	0.9995
	Group PP-statistics	-0.828587	0.2037
	Group ADF-statistics	-1.889986	0.0294
ADF (Kao)	Residual cointegration test	-3.112680	0.0009

To select the optimal lag length for P-VEC model, unrestricted Panel VAR model is first established. The optimal lag length is determined based on the smallest values of several criteria including the likelihood ratio (LR) test statistic, final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan Quinn information criterion (HQ) tests. Based on the results of panel VAR lag length, the optimal lag length for each region is derived with both four for western and eastern regions, and three for midland region in P-VEC models. Then, the Johansen and Juslius panel cointegration tests need to be carried out to determine the number of cointegration equations within each P-VEC model. The results of Johansen and Juselius's panel cointegration tests are summarized in **Tables 7.7 ~ 7.9** and the number of cointegration equations (CEs) is one for both western and midland regions, two for eastern region according to the results of Trace statistics test. Thus, the P-VEC model for regional construction labor cost can be established based on the statistic results of lag length and cointegration number for further discussion.

Table 7.7 Results of Johansen and Juselius's panel cointegration tests (eastern region)

Hypothesized no. of CE(s)	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**	**P-value**
None *	0.289329	107.8509	95.75366	0.0057
At most 1 *	0.266466	73.01321	69.81889	0.0272
At most 2	0.198443	41.40533	47.85613	0.1761
At most 3	0.102108	18.84303	29.79707	0.5042
At most 4	0.043762	7.857125	15.49471	0.4808
At most 5	0.031767	3.292793	3.841466	0.0696

Note: Trace test indicates two cointegrating equations with the rejection of the null hypothesis at the 0.05 level.

Table 7.8 Results of Johansen and Juselius's panel cointegration tests (midland region)

Hypothesized no. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	P-value
None *	0.29825	95.75646	95.75366	0.0500
At most 1	0.189986	57.50527	69.81889	0.3199
At most 2	0.151751	34.74932	47.85613	0.4613
At most 3	0.114384	16.97451	29.79707	0.6419
At most 4	0.030612	3.855495	15.49471	0.9148
At most 5	0.004598	0.497719	3.841466	0.4805

Note: Trace test indicates one cointegrating equations with the rejection of the null hypothesis at the 0.05 level.

Table 7.9 Results of Johansen and Juselius's panel cointegration tests (western region)

Hypothesized no. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	P-value
None *	0.436926	119.6188	95.75366	0.0004
At most 1	0.257305	61.03575	69.81889	0.2049
At most 2	0.180131	30.69385	47.85613	0.6829
At most 3	0.062393	10.43558	29.79707	0.9731
At most 4	0.03591	3.864292	15.49471	0.9142
At most 5	0.001314	0.134069	3.841466	0.7142

Note: Trace test indicates one cointegrating equations with the rejection of the null hypothesis at the 0.05 level.

7.4 P-VEC modeling results

According to the results of panel unit root test and cointegration test, P-VEC models are established to examine the bidirectional causality relationship between construction labor cost and explanatory variables by pooling the time series data across three regions of China. The optimal lag length and cointegration equation number are defined within the framework of the P-VAR model, and the importance parameters of the P-VEC model for each region are summarized in **Table 7.10**.

Table 7.10 Important parameters of P-VEC models for regional construction labor cost

Region	**Optimal lag length**	**No. of cointegration equations**
Eastern	4	2
Midland	3	1
Western	4	1

Then, the P-VEC model for regional construction labor cost ($ULC_{i,t}$) can be written as follow:

$$\Delta ULC_{i,t} = \alpha_i + \lambda_i ecm_{i,t-1} + \sum_{k=1}^{h} \theta_{1,i,k} \Delta ULC_{i,t-k}$$
$$+ \sum_{k=1}^{h} \theta_{2,i,k} \Delta CVA_{i,t-k} + \sum_{k=1}^{h} \theta_{3,i,k} \Delta CE_{i,t-k} + \sum_{k=1}^{h} \theta_{4,i,k} \Delta CW_{i,t-k}$$
$$+ \sum_{k=1}^{h} \theta_{5,i,k} \Delta TI_{i,t-k} + \sum_{k=1}^{h} \theta_{6,i,k} \Delta TER_{i,t-k} \quad t = 1,2,\ldots,T;\ i = 1,2,\ldots,N \quad (7.1)$$

Where T is the total study period and N is the total number of provinces considered in regional modeling. $ecm_{i,t-1}$ is the serially uncorrelated error correction component, θ is the coefficient of estimated parameters. For explanatory variables, $CVA_{i,t}$ is the value added of construction industry, $CE_{i,t}$ is the total number of employed persons in construction industry, $CW_{i,t}$ is the floor spare under construction, $TI_{i,t}$ is the total amount of fixed assets investment, and $TER_{i,t}$ is construction technical equipment ratio. The long-run equilibrium and short-run causal relationship can be then revealed from the empirical results of P-VEC models.

7.4.1 Panel Granger causality tests results

Table 7.11 shows the results of short-run Granger causality between regional construction labor cost and five explanatory variables. The significance of the causality tests is determined by the Wald F-test. In the short run, an increase in total fixed assets investment will create enormous demands for construction industry due to its close linkages with the rest of economy. The change of construction demands will immediately influence the levels of labor wage, particularly in eastern region with the labor shortage. This can be also evidenced by the bidirectional causalities between labor cost and employment level in construction industry. Regional construction industry is investment-driven with vast amount of fixed assets, but the steady creation of construction demands cannot be satisfied with a declining supply of construction manpower, and hence raise the level of labor cost in construction market. Alternatively, an increase of construction technical equipment ratio is an effective strategy to reduce the demands of construction workers, and further improve the productivity of construction in both eastern and midland regions. The competitiveness of construction labor cost is built mainly through the desirable performance of labor productivity rather than low wage rate in the long term. Thus, a rapid growth of labor cost in Midwest underlies the necessity of applying more construction equipment and new technologies in real practices, even though the prevailing real wage is relatively low. Unlike the developed eastern region, construction industry is more labor intensive but still has enormous potential for further growth in western and midland regions. The excessive reliance on cheap workforce may discourage innovation and investment in construction plants and equipment, thus hindering the productivity growth due to the lack of technology progress and investment in construction plant and machinery. Ultimately, labor cost advantage of regional construction industry would be undermined with the shifts of labor supply and demand.

Table 7.11 Results of short-run causality tests in P-VEC models

Null hypothesis	Eastern region	Midland region	Western region
$\Delta CE \rightarrow \Delta ULC$	0.0107[a]	0.5745	0.0490[b]
$\Delta CW \rightarrow \Delta ULC$	0.5369	0.0026[a]	0.3847
$\Delta CVA \rightarrow \Delta ULC$	0.7416	0.2935	0.7255
$\Delta TI \rightarrow \Delta ULC$	0.0575[c]	0.0052[a]	0.0303[b]
$\Delta TER \rightarrow \Delta ULC$	0.0131[b]	0.0060[a]	0.0000[a]
$\Delta ULC \rightarrow \Delta CE$	0.0416[b]	0.5334	0.6622
$\Delta ULC \rightarrow \Delta CW$	0.1098	0.0742[b]	0.0207[b]
$\Delta ULC \rightarrow \Delta CVA$	0.6570	0.5635	0.3411
$\Delta ULC \rightarrow \Delta TI$	0.0527[b]	0.7373	0.5891
$\Delta ULC \rightarrow \Delta TER$	0.4905	0.0479[b]	0.0816[b]

Note: The null hypothesis means that the variable x does not Granger cause variable y, with the rejection of different significance levels at 1% (a), 5% (b) and 10% (c), respectively.

7.4.2 Dynamic panel estimation of P-VEC model

In addition to short-run causal relationship, long-run equilibrium of the P-VEC model for regional construction labor cost is determined by the presence of error correction term ($CointEq$), shown in **Table 7.12**. The value of error correction term delivers important information in relation to near-term forecasting, which indicates the speed of adjustments from short-term disequilibrium back to the long-run equilibrium state (Jiang & Liu, 2014). The significance of error correction term is confirmed with different degrees across three regions, with an increase and insignificant trend from east to central region, then west region. The negative and significant coefficient of error correction term implies that labor cost tends to converge to its long-term equilibrium in response to the changes in terms of the explanatory variables. Apart from both midland and western regions, construction labor cost development would not keep pace with that of construction value added in the long term.

This implies that construction industry has been undergoing the process of industry transition with a declining share of regional GDP. Because of economic structure and industry distribution, labor-intensive construction development will become the history with more investment in construction equipment and labor-saving technologies. Further, regional disparities of construction labor cost can be also reflected by the performance of lagged explanatory variables.

The coefficients capturing short-term dynamics of the lagged variables across three regions of China are summarized in **Table 7.12**. The empirical results reveal that development trend of construction labor cost is normally stable based on the historic performance. However, construction labor cost in eastern region is more sensitive to market changes. In contrast, construction industry is more labor intensive in inland regions due to rich labor force. However, labor advantages are neither effectively utilized nor transformed into the labor cost competitiveness in construction market. Contractors are inclined to improve their competitiveness by wage moderation, especially for those low-skilled and unskilled migrant workers. With the steady creation of construction works through increasing public investment, regional advantage of construction labor cost is maintained by adequate labor supplies in construction market of central region. On the other hand, enhancing labor cost competitiveness through more application of construction technical equipment with productivity growth may lead to employment losses within a short period. Emphasis on efficiency improvement would cut the employment base of low-skilled workers, also reduce heavy dependence on unskilled workers in the long term. Meanwhile, it is conducive to gain a larger market share and create more productive job opportunities with high renumeration for skilled craftsmen in a diversified labor market. The sources of labor cost growth have considerable implications for quality and renumeration of jobs.

This implies that regional construction industry can apply different strategies to improve labor cost competitiveness by wage moderation or productivity gains. The divergences of labor strategies in construction activities can partly explain the regional differences of construction labor cost, further construction industry development in China.

Table 7.12 P-VEC modeling results for regional construction labor cost

Error correction	**Eastern region**	**Midland region**	**Western region**
$CointEq1$	-0.203161[a]	-0.168302[b]	-0.084501[c]
$CointEq2$	0.000241[b]		
$\Delta ULC(-1)$	-0.045629	-0.198764[c]	-0.181327
$\Delta ULC(-2)$	0.005509	-0.100903	-0.022911
$\Delta ULC(-3)$	0.257177[b]		-0.247671[b]
$\Delta CVA(-1)$	-7.81E-05	0.000105	-0.000266
$\Delta CVA(-2)$	-0.000287	-0.000317	0.000345
$\Delta CVA(-3)$	5.19E-06		0.000206
$\Delta CE(-1)$	1.10E-07	-5.58E-08	-1.91E-07[b]
$\Delta CE(-2)$	-2.06E-07[b]	3.85E-08	-1.97E-07[b]
$\Delta CE(-3)$	9.30E-08		-4.97E-08
$\Delta CW(-1)$	-6.27E-06	-1.39E-05[a]	-1.03E-05
$\Delta CW(-2)$	3.74E-06	-1.13E-05[b]	-8.68E-06
$\Delta CW(-3)$	-6.45E-06		-2.68E-06
$\Delta TI(-1)$	2.45E-05	-5.56E-06	-2.76E-06
$\Delta TI(-2)$	1.45E-05	3.89E-05[a]	6.54E-05[a]
$\Delta TI(-3)$	4.44E-05[b]		-3.63E-05
$\Delta TER(-1)$	-6.91E-06[a]	-1.24E-05[a]	-1.22E-06
$\Delta TER(-2)$	-3.70E-06	-1.24E-06	-1.44E-05[a]
$\Delta TER(-3)$	-4.51E-06		-4.10E-06
C	0.006937	0.060549[a]	0.045025[a]

Note: a, b, and c mean that rejection of null hypothesis of unit root based on their P-value at the 0.01, 0.05, and 0.1 significance levels, respectively.

7.5 Predictability of the P-VEC model

The predictive capability of P-VEC model is tested to conduct an in-sample forecasting analysis of regional construction labor cost, in comparison with the performance of a conventional forecasting model. Panel ordinary least squares regression model is a commonly used panel multiple regression model, which has been widely applied for forecasting construction activities and markets across different regions or sections. P-OLS model for regional construction labor cost $ULC_{i,t}$ is presented as follow:

$$ULC_{i,t} = \gamma_i + \beta_1 \mathrm{CVA}_{\mathrm{i,t}} + \beta_2 \mathrm{CE}_{\mathrm{i,t}} + \beta_3 \mathrm{CW}_{\mathrm{i,t}} + \beta_4 \mathrm{TI}_{\mathrm{i,t}} + \beta_5 \mathrm{TER}_{\mathrm{i,t}} + \varepsilon_{i,t} \qquad (7.2)$$

$$t = 1, 2, \dots, T;\ i = 1, 2, \dots, N$$

Where T is the number of study periods and N is the number of provinces considered in regional modeling. γ_i is the heterogeneity of unobserved variables and β_i is the coefficient of the regressor. All explanatory variables are transformed into the natural logarithms in the P-OLS model. $CVA_{i,t}$ is the value added of construction industry, $CE_{i,t}$ is the total number of employed persons in construction industry, $CW_{i,t}$ is the floor spare under construction, $TI_{i,t}$ is the total amount of fixed assets investment, and $TER_{i,t}$ is construction technical equipment ratio. The adaptive capability of P-OLS model for regional performance of construction labor cost is good with a desirable R-squared value.

The P-VEC models need to be validated by conducting several diagnostics tests before forecasting construction labor cost across three regions of China. The results of model validation including LM and non-normality tests are reported in **Table 7.13**, demonstrating no significant departure from the standard assumptions for the established P-VEC models.

Table 7.13 Results of P-VEC model validation tests

Diagnostics tests	**Eastern region**	**Midland region**	**Western region**
$LM(5)$	46.51600	43.70809	36.79658
$LM(8)$	42.32393	44.99664	38.79256
$Skewness$	-0.119798	-0.000148	-0.301096
$Kurtosis$	3.178097	3.316444	3.906018
$Jarque-Bera$	0.533419	0.712883	6.207098

The forecasting accuracy and reliability of these two models can be measured by the following two indicators, i.e. Mean Absolute Percentage Error (MAPE) and Theil's inequality coefficient *U* (Theil *U*), according to **Equations 7.3 and 7.4**, respectively. The forecasting error is acceptable if result is smaller than 10% of MAPE test, while a value of Theil *U* closer to zero is considered as a good fit. The MAPE can be computed by

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|e_t|}{Y_t} \times 100 \tag{7.3}$$

The Theil's inequality coefficient *U* can be calculated as follows:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t' - Y_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t')^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t)^2}} \tag{7.4}$$

Where $e_t = Y_t' - Y_t$, e_t is the forecasting error at time t, Y_t' and Y_t are the forecasted value and actual value at period t, respectively. T is the number of study period.

In this research, the entire datasets are divided into training datasets for model establishment, and testing datasets for model validation. The optimal regional forecasting model is preferred with a smaller prediction error within the in-sample forecasting period. The predictive capability of the P-VEC model and P-OLS model is evaluated by comparing the predicted values with the actual construction unit labor cost in each province across three regions of China. Details of the P-VEC model and P-OLS model forecasting results are attached in **Appendix III**. The statistics values of MAPE test and Theil *U* coefficient for each province and region are herein summarized in **Tables 7.14 - 7.15**, respectively.

Table 7.14 P-VEC and P-OLS models in-sample forecasting results of regional construction labor cost

Region	**Province**	**P - VEC model**		**P - OLS model**	
		MAPE	**Theil *U***	**MAPE**	**Theil *U***
Eastern	Beijing	16.1%	0.09	25.3%	0.17
	Tianjin	9.4%	0.07	16.8%	0.13
	Shanghai	11.9%	0.06	29.3%	0.17
	Jiangsu	6.9%	0.07	10.3%	0.09
	Zhejiang	7.9%	0.08	11.1%	0.09
	Shandong	7.0%	0.07	8.1%	0.07
Midland	Shanxi	7.1%	0.06	11.2%	0.02
	Anhui	3.5%	0.04	3.4%	0.04
	Jiangxi	7.7%	0.07	9.0%	0.10
	Henan	5.5%	0.05	8.1%	0.07
	Hubei	4.6%	0.05	4.6%	0.05
	Hunan	3.7%	0.04	5.5%	0.06
Western	Guangxi	7.3%	0.07	6.0%	0.06
	Chongqing	5.4%	0.05	5.1%	0.05
	Sichuan	5.8%	0.05	8.9%	0.08
	Guizhou	4.8%	0.05	8.6%	0.10
	Yunnan	6.9%	0.06	8.6%	0.07
	Shaanxi	5.9%	0.06	7.6%	0.09

Table 7.15 Predictability comparison between P-VEC model and P-OLS model

Region	**P-VEC model**		**P-OLS model**	
	MAPE	**Theil *U***	**MAPE**	**Theil *U***
Eastern	9.86%	0.071	10.41%	0.090
Midland	5.36%	0.051	6.97%	0.074
Western	6.01%	0.055	7.45%	0.074
All	7.08%	0.059	8.28%	0.079

The values of MAPE test in the P-VEC model for each region are less than 10%, except for two municipalities (Beijing and Shanghai) in eastern region. The overall forecasting accuracy of P-VEC model is about 7%, with a closer value of Theil *U* coefficient (0.059). In contrast, the average forecasting deviations of P-OLS model is around 8%, due to the unfavorable performance of eastern region, with an over 10% forecasting error and higher Theil *U* coefficient (0.079). Therefore, it can be concluded that the P-VEC model outperforms the P-OLS model in forecasting construction labor cost across different regions of China. The P-VEC model is thereby proven to be a more reliable and robust method for regional forecasting in construction market, if multi-dimensional interactions and links are well recognized and modeled between target variable and explanatory variables.

7.6 Scenario analysis

Based on the empirical results of P-VEC causality tests in **Table 7.12**, the bidirectional relationships are found between construction labor cost and total amount of fixed assets investment, construction technical equipment ratio in the short-term and long-term among regions. The changes of these two critical factors would significantly cause the variations of construction labor cost in regional market over time. However, the further trends of regional construction labor cost cannot be foresighted due to the limitations of data availability. Scenario analysis is a projection technique of future trend by providing alternative possible outcome underlying certain assumptions (Huss, 1988).

In light of the desirable forecasting performance, scenario analysis is thereby incorporated based on established P-VEC models to generate the forecasting results in next five years from 2018 to 2022. Given that the extrapolation of construction labor cost is based on historic trend, the change rate of scenario variables needs to be reasonably defined with overall considerations of economic growth and regional development over the past years. In terms of Granger causality tests in P-VEC model results across three regions, the total amount of fixed assets investment, and construction technical equipment ratio are identified as scenario variables for construction labor cost simulation across three regions of China. The annual change rate of two control variables for each region are defined according to historic trends in **Table 7.16**, ceteris paribus.

Table 7.16 Scenarios of regional construction labor cost forecasting (2018 - 2022)

Region	**Scenario 1** **TI**	**Scenario 2** **TER**
Eastern	+5%	+1%
Midland	+10%	+1%
Western	+10%	+1%

Historically, construction labor cost is the highest in developed eastern region, due to huge volume of construction demands and high level of living cost. Compared with inland regions, construction labor cost in eastern region is more sensitive to external change. Fluctuations can be clearly observed around 2009 and 2013, with the occurrences of economic crisis or great event. The regional gaps of construction labor cost tend to narrow considerably during construction boom, and gradually widen in a period of economic prosperity. **Figures 7.2 – 7.3** present the out-of-sample forecasting outcomes of regional construction labor cost for two scenarios, i.e. Scenario TI (eastern region: +5%, Midwest: +10%), and Scenario TER (all: +1%). The regional performance of construction labor cost exhibits a totally different trend in the subsequent periods.

7.6.1 Scenario 1

Construction demands are created with substantial public investment by government to offset the pressure of economic downturn, particularly in underdeveloped western region where infrastructure construction needs further improvement. Construction industry development relies more on capital investment without the challenge of labor shortage in the underdeveloped area. Consequently, construction unit labor cost would rise markedly with a steady growth of fixed assets investment in western region. In stark contrast, labor cost competitiveness will be further improved with only a half growth rate of total fixed assets investment in eastern region, particularly for coastal provinces such as Jiangsu and Zhejiang provinces. New technologies and construction equipment have been widely adopted in construction activities, and wage rate of skilled workers moves closely with the improvement of labor productivity on site. Nevertheless, differentials in real wage determine the regional differences of construction unit labor cost between eastern and midland region in the short term. The comparative advantage of construction labor cost would be undermined with persistent reliance on cheap workforce in central region.

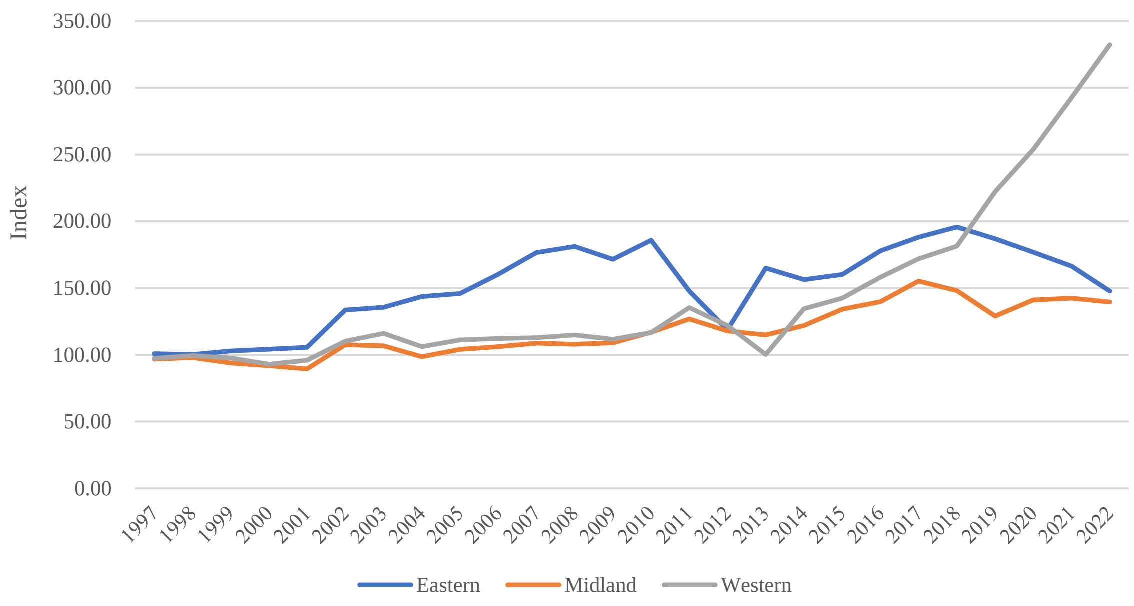

Figure 7.2 Scenario 1 (TI)

7.6.2 Scenario 2

Investment in construction plant and equipment can reflect the application of technical equipment in construction activity, also the overall level of technological progress in the whole industry. Using construction equipment is regarded as an effective alternative for labor savings with the support of new technologies in real practice. Undoubtedly, the level of construction technical equipment ratio is the highest in developed eastern region, presenting a diminishing trend from developing midland region to western region. Statistically, the value of construction technical equipment ratio is not only determined by capital formation, but also the total number of construction workers. That can explain the unstable performance of technical equipment ratio in regional construction industry. Compared with eastern and midland regions, construction plant and equipment have limited impact towards the enhancement of labor cost competitiveness in western region, where regional construction industry is more labor intensive underpinned by abundant available workers. However, construction development often suffers from an acute labor shortage in eastern region. Faced with the short supply of construction workers, labor saved by construction equipment and technology will become an effective strategy with significant improvement of labor productivity, further sharpen the long-term competitiveness in a shrinking construction market.

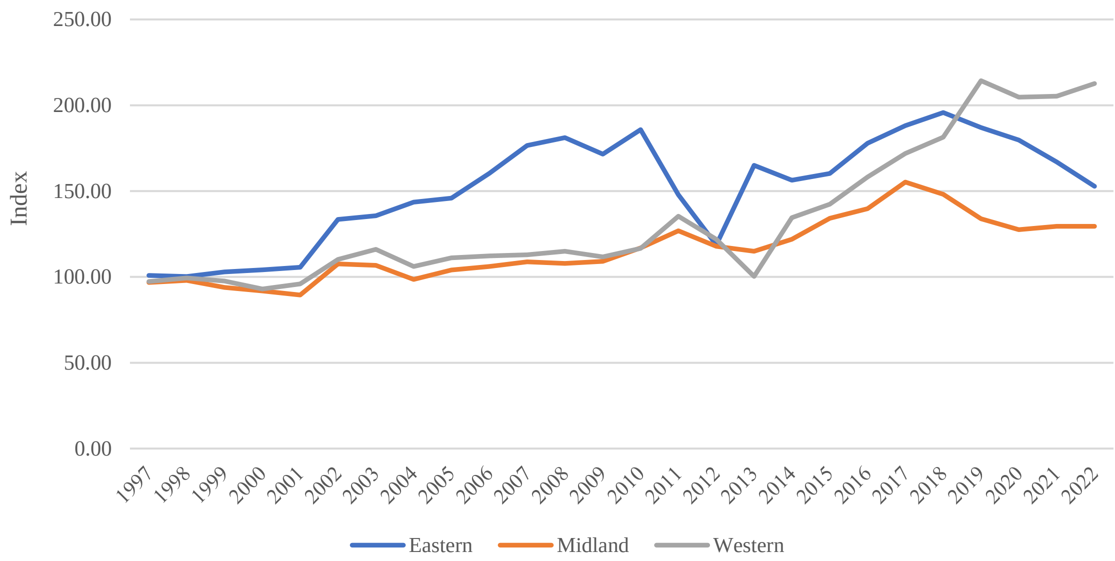

Figure 7.3 Scenario 2 (TER)

7.7 Summary of the chapter

This chapter first reviews several econometric techniques and methods for labor cost forecasting in construction industry. Compared with time series methods and cross-sectional modeling techniques, P-VEC model provides the possibility of multi-dimensional analysis and meanwhile improves the predictability in a changing regional market. Based on the empirical results of panel data model in Chapter 4, P-VEC model is constructed to predict the regional construction labor cost after defining the optimal lag length and number of cointegration equations within the framework of P-VAR model.

The predictive capability of the P-VEC model is then validated through the in-sample forecasting analysis in contrast with that of the P-OLS model. According to the forecasting error quantified by two indicators of MAPE and Theil U coefficients, P-VEC model outperforms the P-OLS model in predicting the regional construction labor cost performance in China. To predict further trend of construction labor cost, two critical factors including total amount of fixed assets investment and construction technical equipment ratio are identified as scenario variables, based on the empirical results of long-term equilibrium and short-run causal relationship in the P-VEC model. The change rates of two control variables are defined with an overall consideration of regional development and economic growth. Scenario analysis are then conducted based on P-VEC model to simulate the results of construction labor cost across three regions of China. The simulation results indicate that regional construction labor cost exhibits a different trend in subsequent periods, due to the inherent divergences of local resources and regional development. Construction labor cost competitiveness can be enhanced via various ways in different regions. However, contractors focus more on short-term returns and prefer the labor-intensive development, which is not conducive to establish the long-term competitiveness in a tight construction market. With an increasing real wage over recent years, labor cost advantage would be undermined with a slow growth of labor productivity in construction practice. In response to the labor shortage in the industry, corresponding measures and effective strategies should be put forward to maintain the sustainable development of regional construction industry in China.

Chapter 8: Conclusions

8.1 Introduction

This chapter summarizes the primary research findings and suggests the future research directions based on the limitations in this study. The research aim and objectives are reviewed through the study. The principal research findings are summarized from each chapter, and the contributions to the existing body of knowledge are concluded. Final, research limitations and future directions are discussed.

8.2 Review of research objectives

Labor cost estimation, control, and regulations are of great importance to achieve the final success of construction project. The affordability and availability of construction workforce, underpinned by rich labor force in China, has become the history and exerted widespread effects on construction manpower recruitment, and construction cost management, even construction industry development. Previous studies mainly focus on the qualitative evaluation and analysis of construction labor cost. However, little attention has been given to the in-depth investigation of labor cost performance in China's regional construction industry. A comprehensive understanding of construction labor cost is essential to better management of construction workforce, and effective strategies of construction enterprise, further healthy development of construction industry.

As clarified in Chapter 1, the primary aim of this research is to investigate the performance of labor cost in China's construction industry through a multi-dimensional analysis. To realize the research aim, four specific objectives were addressed.

To achieve objective 1, Chapter 4 selects the potential factors affecting construction labor cost based on the empirical analysis of literature review and questionnaire survey. Panel data model was then applied to investigate the associations between construction labor cost and its critical determinants across three regions of China with different levels of economic growth and social development over past two decades.

To realize objective 2, construction productive efficiency is conceptualized based on the neoclassical economic theory, measured by three common inputs and one output under the framework of DEA model. Regional differences of construction productive efficiency were explored by using the DFM model. The causes of inefficiency, and the sources of growth for regional construction industry were compared in terms of input optimization and output potential, respectively.

To attain objective 3, three less inefficient provinces were selected from each region to illustrate the feasibility and validity of stepwise efficiency improvement using the TO-DFM model. The optimal pathways for stepwise efficiency improvement were accordingly identified with stage-wise targets for three typical provinces or municipalities across regions of China.

To achieve objective 4, P-VEC model was developed based on identified critical determinants for regional construction labor cost forecasting analysis. The predictability of P-VEC model was validated in comparison with that of P-OLS model for the in-sample forecasting. Scenario analysis was further conducted based on two control variables to predict the regional construction labor cost performance in coming periods.

8.3 Summary of research findings

8.3.1 Findings on critical determinants of regional construction labor cost

Regional development of construction industry is overall labor intensive. Regional differences of construction labor cost are the combined results of diverse performance of real wage and labor productivity. Unlike inland regions with heavy reliance on cheap labor and fixed assets investment, construction industry in eastern region is more mechanized with extensive application of plants and equipment in construction activities, offsetting the pressure of rising real wage of skilled workers. Construction labor cost in coastal area is higher than that of hinterland areas, stays at a moderate and reasonable level. The slow productivity growth in regional construction industry weakens labor cost competitiveness. In contrast, the competitive edge of construction industry in western and midland regions is sharpened primarily through a lower level of labor wage. Increasing construction demands supported by public investment promote a stable growth of the real wage of construction workers in Midwest. Compared with central region, construction industry is more investment-driven in western region. Although western region has abundant construction migrant workers, the labor-intensive development of regional construction industry hinders efforts towards productivity growth. The undesirable performance of construction productivity can be also explained by limited adoption of plants and equipment in construction works, which is not conductive to establish the long-term labor cost competitiveness of regional construction industry.

8.3.2 Findings on regional differences of construction productive efficiency

The efficiency performance of construction industry in coastal regions is better than that of inland regions, based on the results of DEA model. The development potential of construction industry in western region is the largest, in contrast with that of midland and eastern regions. On the other hand, the inefficiency of input usages leads to diverse performance of construction productive efficiency among different regions of China, according to DFM model results. Besides, three low efficiency provinces that cannot become high efficiency in the short term are selected as the case studies from each region. The optimal pathways for stepwise efficiency improvement with reasonable stage-wise targets planned are illustrated for regional construction industry in coming periods. For developed eastern region, investing more on construction plants and equipment for labor savings is proven to be more efficient to long-term productivity growth of construction industry. For developing midland region, heavy reliance on cheap manpower can be relieved by allocating more budgets to vocational training and education program boost quality labor force. For underdeveloped western region, raising the wage level of construction workers is required to retain and recruit more workforce to meet the local demands, further achieve an optimal growth of construction productive efficiency.

8.3.3 Findings on regional construction labor cost forecasting

P-VEC models are constructed based on the identified critical determinants for regional construction labor cost forecasting. The predictive capability of the P-VEC model is validated to be better than that of P-OLS model. To predict the further trend of regional construction labor cost, two control factors including the total amount of fixed assets investment and construction technical equipment ratio are identified as scenario variables. Scenario analysis are then conducted based on the P-VEC model to predict the forecasting results of regional construction labor cost. The prediction results indicate that regional construction labor cost exhibits a different trend in the subsequent five years, due to inherent divergences of local resources and regional development. Construction labor cost competitiveness can be enhanced through various ways across different regions of China. However, contractors focus more on short-term returns and prefer the labor-intensive development, which is not conducive to establish the long-term competitiveness in a shrinking construction market. With the rapid growth of real wage over recent years, the advantage of labor cost would be undermined with a slow growth of labor productivity in construction practice. In response to emerging labor shortage in the industry, corresponding measures and effective strategies should be put forward to maintain the sustainable development of regional construction industry.

8.4 Contributions of the research

This study makes contributions to the knowledge and practice of labor cost in construction industry covering following several aspects.

From an academic perspective, this research provides a new perspective for understanding the labor cost performance in the China's construction industry. This study first reviews existing literature on labor cost analysis, labor cost modeling and forecasting in construction domain from the viewpoint of supply and demand, total factor productivity. The research findings and gaps identified based on previous studies could serve as the basis for recommending future research in relevant field. Second, this study provides a holistic analysis of construction labor cost from both temporal and regional dimensions, panel data modeling and forecasting analysis in construction labor cost that enrich the body of knowledge in construction labor cost management and estimation. In addition, this study develops an overall efficiency measurement for the construction industry under the framework of the neoclassic economic theory. The established DEA-based model contributes a novel methodology for benchmarking the overall performance from labor, capital, and equipment inputs in producing construction output. More importantly, the developed model provides the possibilities of quantifying the inefficiency of input usage and the potential of output growth in regional construction industry. Furthermore, the stepwise improvement pathway with considerations of efficiency gaps and study period provides a paradigm of resource optimization and investment planning under the guidance of stage-wise targets.

From a practical perspective, questionnaire survey can provide insights into an overall picture of migrant workers and labor cost management in construction practice. In accordance with literature review, investigating the regional construction labor cost performance through panel data model can help both stakeholders and policymakers better understand labor cost variations in the evolving construction market, provide valuable insights for contractor to formulate forward-looking market strategies and for government to fine tune economic policies. Besides, the development of DEA-based model can identify the causes of inefficiency, the sources of growth in regional construction industry, and map out the optimal pathways for stepwise efficiency improvement under the guidance of target setting, which serves as good references for resource optimization and investment planning across different regions of China. Further, regional construction labor cost forecasting can provide early information concerning labor cost variations in regional market, practical implications for the construction labor cost estimation, construction workforce management, and construction industry development.

8.5 Research limitations and future studies

Despite the contributions to existing research, this study has some limitations that require further improvement in future studies. First, this study mainly used construction labor cost data at industry level in the developed models, whereas labor cost information derived from construction project can be further incorporated into the models for conducting more in-depth analysis. In addition, annual data of construction labor cost might not fully reflect the dynamics of labor cost performance in regional market. Therefore, quarterly data or monthly data are required to optimize the modeling results of regional construction labor cost. Third, questionnaire surveys were mainly conducted in Chongqing municipality from western region of China, perhaps more samples need to be collected in the same period from both midland and eastern regions for the overall consideration of research integrity and comparability. Also, expert interview was conducted with several project managers from each region, more experienced professionals need to be interviewed from different background in the industry across different regions of China. Final, major factors affecting construction labor cost are considered in the established models. Other micro level variables concerning labor cost management skills in construction project, social issue of construction migrant worker, and so forth should be further considered in the regional comparison and analysis of construction labor cost performance.

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Appendix I: Questionnaire Survey on Construction Migrant Workers

尊敬的受訪者：

您好！我們正在對建築業人工成本進行相關調查。問卷采取不記名方式，且您所提供的數據僅用于學術研究，不會作爲商業用途，謝謝您的支持和幫助！

1、年齡：

A、30 歲以下 B、30～40 歲 C、40～50 歲 D、50 歲以上

2、 受教育程度：

A、小學及以下 B、初中 C、高中或中專 D、高中或中專以上

3、 工種（可多選）：

A、砼工 B、木工 C、鋼筋工 D、水泥工 E、架子工 F、水電工 G、漆工 H、其他

4、什麼時候開始從事建築工地的工作__________。

A、1 年前 B、1～2 年前 C、2～5 年前 D、5～10 年前 E、10 年以前

5、目前平均月收入：

A、2000 元/月及以下 B、2000～3000 元/月 C、3000～5000 元/月

D、5000～8000 元/月 E、8000 元/月以上

最高時的水平： 最低時的水平：

一年前平均月收入： 五年前平均月收入： 十年前平均月收入：

6、你對目前條件下的預期工資是多少？ 對當下工作狀況的滿意度如何？（滿分 100）

工資:____________ 滿意度：______________

7、工資結算采取何種方式：

A、打到工資卡 B、由負責人發現金 C、直接放至工人手裏 D、其他

8、你目前所在工地平均每天工作時間約幾小時__________，戶口是否在城市_______。

9、你對目前工作中最不滿意的是________，如果可以選擇是否還願意從事建築業_______。

A、工資少 B、生活條件差（如伙食，住處等） C、工作時間太長 D、其他

10、你的子女或後代（針對年齡在 18-30 歲之間的人群）目前從事的什麼工作：__________，你更願意他們的工作地點是_______（後一個問從 B、C 中二選一）。

A、未參加工作 B、建築工地 C、工廠上班 D、其他

感謝您對此次調查的支持，祝身體健康，工作順利！

Appendix II: Projection Results of CCR-I and DFM Models for Inefficient DMUs (2016)

DMU	TOS	CCR-I	DFM	DMU	TOS	CCR-I	DFM	DMU	TOS	CCR-I	DFM
Beijing	IS	0.3659	1.000	Hainan	NS	0.4762	1.000	Chongqing	IS	0.8725	1.000
(I)CLW	89464	-73.00%	-65.70%	(I)CLW	45557	-76.00%	0.00%	(I)CLW	51537	-54.00%	-29.40%
(I)CE	581441	-63.40%	0.00%	(I)CE	74219	-52.40%	0.00%	(I)CE	2090773	-12.70%	0.00%
(I)TER	17494	-63.40%	-54.90%	(I)TER	6170	-52.40%	-37.80%	(I)TER	5801	-12.70%	-8.50%
(O)CVA	1025.5	0.00%	46.40%	(O)CVA	424.5	0.00%	35.50%	(O)CVA	1715.12	0.00%	6.80%
Tianjin	NS	0.265	1.000	Shanxi	NS	0.4075	1.000	Sichuan	NS	0.9183	1.000
(I)CLW	67943	-73.50%	-69.10%	(I)CLW	46632	-59.20%	-54.00%	(I)CLW	48088	-2.00%	0.00%
(I)CE	736372	-73.50%	0.00%	(I)CE	754344	-59.20%	0.00%	(I)CE	2828652	-8.20%	0.00%
(I)TER	41928	-88.70%	0.00%	(I)TER	19473	-74.70%	0.00%	(I)TER	7972	-8.20%	-5.30%
(O)CVA	786.89	0.00%	58.10%	(O)CVA	895.63	0.00%	42.10%	(O)CVA	2472.96	0.00%	4.30%
Hebei	NS	0.7832	1.000	Anhui	IS	0.7107	1.000	Guizhou	IS	0.5512	1.000
(I)CLW	42662	-21.70%	-18.70%	(I)CLW	51399	-47.20%	-38.00%	(I)CLW	53487	-63.50%	-7.10%
(I)CE	1308848	-21.70%	0.00%	(I)CE	1679962	-28.90%	-17.40%	(I)CE	675305	-44.90%	0.00%
(I)TER	13196	-37.10%	0.00%	(I)TER	9104	-28.90%	-16.50%	(I)TER	9089	-44.90%	-40.70%
(O)CVA	1885.27	0.00%	12.20%	(O)CVA	1763.53	0.00%	16.90%	(O)CVA	955.44	0.00%	28.90%
Liaoning	NS	0.7802	1.000	Jiangxi	IS	0.7305	1.000	Yunnan	NS	0.7911	1.000
(I)CLW	43585	-22.00%	-18.60%	(I)CLW	50108	-51.30%	-42.60%	(I)CLW	41945	-20.90%	-17.30%
(I)CE	1261368	-22.00%	0.00%	(I)CE	1525715	-27.00%	-17.80%	(I)CE	1156319	-20.90%	0.00%
(I)TER	10941	-22.40%	0.00%	(I)TER	7913	-27.00%	-13.20%	(I)TER	11454	-27.40%	0.00%
(O)CVA	1880.85	0.00%	12.30%	(O)CVA	1610.91	0.00%	15.60%	(O)CVA	1806.22	0.00%	11.70%
Jilin	NS	0.476	1.000	Henan	NS	0.7053	1.000	Tibet	IS	0.734	1.000
(I)CLW	44968	-52.40%	-43.30%	(I)CLW	44753	-29.50%	0.00%	(I)CLW	59075	-84.80%	-82.50%
(I)CE	570236	-52.40%	0.00%	(I)CE	2609049	-32.30%	0.00%	(I)CE	28397	-26.60%	-15.30%
(I)TER	22815	-75.40%	0.00%	(I)TER	12640	-32.30%	-35.50%	(I)TER	17526	-86.20%	-84.10%
(O)CVA	960.87	0.00%	35.50%	(O)CVA	2292.04	0.00%	17.70%	(O)CVA	342.73	0.00%	15.30%
Heilongjiang	IS	0.5121	1.000	Hubei	NS	0.6722	1.000	Gansu	NS	0.3944	1.000
(I)CLW	39922	-48.80%	-37.50%	(I)CLW	54636	-44.70%	0.00%	(I)CLW	43683	-60.60%	-53.20%
(I)CE	373570	-48.80%	0.00%	(I)CE	2696423	-32.80%	0.00%	(I)CE	565755	-60.60%	0.00%
(I)TER	20243	-73.30%	-64.00%	(I)TER	10175	-32.80%	-23.30%	(I)TER	12753	-64.70%	0.00%
(O)CVA	874.23	0.00%	32.30%	(O)CVA	2192.97	0.00%	19.60%	(O)CVA	776.35	0.00%	43.40%
Shanghai	NS	0.379	1.000	Hunan	NS	0.6543	1.000	Qinghai	NS	0.1853	1.000
(I)CLW	88034	-80.60%	0.00%	(I)CLW	45492	-34.60%	-27.10%	(I)CLW	50431	-81.90%	0.00%
(I)CE	1040183	-62.10%	-17.40%	(I)CE	2199556	-34.60%	-13.50%	(I)CE	114412	-81.50%	-68.70%
(I)TER	11429	-62.10%	-58.80%	(I)TER	17079	-59.00%	0.00%	(I)TER	19548	-87.40%	0.00%
(O)CVA	879.81	0.00%	45.00%	(O)CVA	2016.59	0.00%	20.90%	(O)CVA	348.67	0.00%	68.70%
Fujian	NS	0.9281	1.000	Mongolia	NS	0.7472	1.000	Ningxia	IS	0.2658	1.000
(I)CLW	53557	-37.40%	0.00%	(I)CLW	42968	-25.30%	-16.20%	(I)CLW	46832	-75.80%	-24.10%
(I)CE	3252705	-7.19%	0.00%	(I)CE	297038	-25.30%	0.00%	(I)CE	99345	-73.40%	-58.00%
(I)TER	7361	-7.19%	-4.90%	(I)TER	17377	-50.80%	0.00%	(I)TER	12577	-75.70%	0.00%

(O)CVA	2421.34	0.00%	3.70%	(O)CVA	1322.5	0.00%	14.50%	(O)CVA	434.2	0.00%	58.00%
Guangdong	NS	0.7298	1.000	Guangxi	IS	0.9271	1.000	Xinjiang	NS	0.5008	1.000
(I)CLW	55263	-27.00%	-26.90%	(I)CLW	47079	-56.90%	-0.30%	(I)CLW	58576	-57.00%	0.00%
(I)CE	2285741	-27.00%	0.00%	(I)CE	1200224	-7.30%	-6.70%	(I)CE	384143	-49.90%	0.00%
(I)TER	14811	-34.60%	0.00%	(I)TER	5031	-7.30%	0.00%	(I)TER	13364	-49.90%	-38.50%
(O)CVA	2551.82	0.00%	15.60%	(O)CVA	1458.41	0.00%	3.80%	(O)CVA	1049.93	0.00%	33.30%

Note: Type of slack (TOS), Non-slack projection type (NS), Input-slack projection type (IS).

Appendix III: In-Sample Forecasting Results of P-VEC model and P-OLS model (1997-2017)

Eastern	Beijing			Tianjin			Shanghai			Jiangsu			Zhejiang			Shandong		
	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS
1997	0.57		0.63	0.50		0.69	0.62		0.69	0.59		0.54	0.60		0.63	0.57		0.50
1998	0.52		0.61	0.55		0.74	0.59		0.72	0.64		0.54	0.59		0.64	0.54		0.51
1999	0.55		0.69	0.54		0.77	0.71		0.78	0.59		0.54	0.57		0.65	0.56		0.51
2000	0.57		0.67	0.58		0.78	0.67		0.74	0.57		0.60	0.57		0.69	0.60		0.55
2001	0.52	0.71	0.68	0.54	0.72	0.79	0.82	0.79	0.72	0.55	0.64	0.57	0.56	0.59	0.69	0.62	0.64	0.51
2002	0.76	0.57	0.70	0.83	0.65	0.84	0.95	0.86	0.75	0.65	0.61	0.61	0.62	0.61	0.73	0.76	0.64	0.56
2003	0.84	0.83	0.73	0.87	0.87	0.90	0.89	0.98	0.79	0.65	0.67	0.65	0.62	0.63	0.72	0.77	0.74	0.57
2004	1.02	0.86	0.86	0.89	0.86	0.98	1.14	1.01	0.86	0.62	0.68	0.73	0.61	0.68	0.82	0.63	0.82	0.67
2005	0.98	1.08	0.87	0.94	1.00	0.96	1.21	1.17	0.89	0.61	0.70	0.76	0.62	0.61	0.80	0.63	0.65	0.69
2006	1.22	1.00	0.85	0.95	0.99	0.97	1.32	1.12	0.90	0.62	0.62	0.78	0.66	0.68	0.80	0.71	0.72	0.69
2007	1.38	1.28	0.86	0.98	1.05	0.97	1.61	1.41	0.92	0.61	0.73	0.79	0.68	0.74	0.80	0.78	0.74	0.71
2008	1.51	1.25	0.88	1.00	1.07	1.00	1.53	1.46	0.92	0.66	0.56	0.79	0.70	0.65	0.79	0.80	0.77	0.71
2009	1.46	1.44	0.88	1.02	1.03	1.01	1.39	1.45	0.88	0.62	0.60	0.78	0.70	0.70	0.78	0.68	0.77	0.72
2010	1.64	1.39	0.88	1.16	1.02	1.02	1.48	1.40	0.88	0.66	0.52	0.77	0.70	0.68	0.77	0.72	0.65	0.70
2011	1.26	1.45	0.94	0.74	1.13	1.12	1.12	1.33	0.88	0.59	0.57	0.81	0.62	0.68	0.81	0.73	0.74	0.76
2012	0.65	1.13	1.10	0.65	0.76	1.26	0.83	1.12	0.93	0.61	0.59	0.89	0.64	0.57	0.81	0.68	0.63	0.78
2013	1.13	0.91	1.17	0.65	0.65	1.10	1.12	0.93	0.93	0.98	0.74	0.81	1.18	0.89	0.82	0.58	0.88	0.81
2014	1.08	1.28	1.04	0.88	0.78	1.06	1.23	1.11	0.95	0.73	0.74	0.81	0.74	0.98	0.80	0.69	0.64	0.83
2015	1.08	1.06	1.01	0.88	0.84	1.01	1.23	1.17	0.88	0.77	0.79	0.82	0.80	0.96	0.79	0.72	0.76	0.82

2016	1.24	1.20	1.01	1.16	1.22	1.07	1.33	1.41	0.91	0.78	0.89	0.82	0.81	0.92	0.80	0.77	0.65	0.83
2017	1.30	1.41	0.99	1.32	1.21	1.01	1.34	1.43	0.94	0.83	0.76	0.81	0.82	0.70	0.79	0.82	0.81	0.81

Midland	**Shanxi**			**Anhui**			**Jiangxi**			**Henan**			**Hubei**			**Hunan**		
	Real	**P-VEC**	**P-OLS**	**Real**	**P-VEC**	**P-OLS**	**Real**	**P-VEC**	**P-OLS**	**Real**	**P-VEC**	**P-OLS**	**Real**	**P-VEC**	**P-OLS**	**Real**	**P-VEC**	**P-OLS**
1997	0.46		0.50	0.54		0.47	0.66		0.52	0.62		0.57	0.48		0.50	0.55		0.49
1998	0.44		0.55	0.57		0.51	0.62		0.54	0.53		0.59	0.57		0.51	0.62		0.51
1999	0.42		0.54	0.55		0.50	0.58		0.55	0.50		0.59	0.54		0.52	0.62		0.53
2000	0.41	0.44	0.55	0.52	0.53	0.54	0.61	0.58	0.56	0.50	0.55	0.62	0.50	0.53	0.53	0.60	0.61	0.56
2001	0.39	0.43	0.56	0.51	0.52	0.53	0.57	0.58	0.58	0.52	0.53	0.62	0.50	0.50	0.54	0.57	0.59	0.55
2002	0.58	0.43	0.56	0.56	0.53	0.55	0.64	0.59	0.61	0.68	0.57	0.63	0.60	0.58	0.55	0.62	0.62	0.56
2003	0.58	0.53	0.59	0.59	0.54	0.58	0.63	0.62	0.64	0.71	0.66	0.66	0.55	0.55	0.56	0.59	0.59	0.55
2004	0.52	0.61	0.61	0.54	0.61	0.62	0.61	0.66	0.68	0.59	0.72	0.70	0.54	0.57	0.57	0.57	0.58	0.57
2005	0.60	0.56	0.60	0.54	0.58	0.59	0.59	0.63	0.65	0.66	0.69	0.67	0.61	0.56	0.55	0.56	0.58	0.55
2006	0.65	0.61	0.61	0.58	0.56	0.59	0.61	0.64	0.65	0.65	0.72	0.65	0.57	0.61	0.56	0.57	0.59	0.56
2007	0.63	0.66	0.62	0.62	0.62	0.60	0.63	0.68	0.66	0.66	0.69	0.64	0.56	0.62	0.58	0.62	0.60	0.57
2008	0.66	0.66	0.64	0.63	0.60	0.62	0.60	0.68	0.67	0.59	0.63	0.66	0.55	0.54	0.60	0.66	0.60	0.59
2009	0.72	0.65	0.69	0.64	0.63	0.66	0.62	0.65	0.68	0.57	0.62	0.69	0.55	0.61	0.65	0.63	0.63	0.64
2010	0.74	0.74	0.71	0.66	0.68	0.67	0.78	0.67	0.70	0.58	0.63	0.70	0.58	0.61	0.66	0.66	0.70	0.65
2011	0.90	0.77	0.72	0.68	0.64	0.68	0.69	0.79	0.71	0.64	0.62	0.71	0.74	0.63	0.68	0.69	0.67	0.66
2012	0.88	0.84	0.70	0.71	0.71	0.68	0.66	0.78	0.71	0.59	0.68	0.71	0.52	0.64	0.67	0.67	0.64	0.67
2013	0.66	0.85	0.69	0.52	0.63	0.69	0.61	0.67	0.71	0.62	0.56	0.72	0.64	0.62	0.67	0.88	0.72	0.67
2014	0.87	0.72	0.70	0.66	0.62	0.70	0.74	0.65	0.71	0.64	0.61	0.73	0.59	0.61	0.67	0.67	0.79	0.69
2015	0.92	0.86	0.71	0.68	0.73	0.70	0.91	0.71	0.72	0.71	0.69	0.72	0.62	0.50	0.68	0.75	0.74	0.70
2016	1.09	0.94	0.71	0.70	0.76	0.71	0.98	0.89	0.74	0.54	0.63	0.73	0.68	0.72	0.68	0.79	0.86	0.71
2017	1.07	1.05	0.72	0.73	0.78	0.72	1.29	1.06	0.77	0.62	0.69	0.77	0.68	0.73	0.69	0.92	0.86	0.73

Western	**Guangxi**			**Chongqing**			**Sichuan**			**Guizhou**			**Yunnan**			**Shaanxi**		

	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS	Real	P-VEC	P-OLS
1997	0.61		0.58	0.54		0.54	0.57		0.64	0.54		0.53	0.61		0.53	0.46		0.46
1998	0.55		0.58	0.62		0.56	0.60		0.65	0.53		0.52	0.60		0.52	0.50		0.45
1999	0.53		0.58	0.62		0.56	0.61		0.67	0.55		0.53	0.55		0.53	0.48		0.45
2000	0.48		0.57	0.56		0.57	0.59		0.66	0.53		0.54	0.53		0.54	0.49		0.46
2001	0.53	0.54	0.59	0.60	0.58	0.59	0.59	0.63	0.68	0.48	0.56	0.56	0.57	0.57	0.56	0.51	0.49	0.47
2002	0.62	0.53	0.60	0.65	0.58	0.61	0.65	0.61	0.72	0.52	0.49	0.58	0.67	0.58	0.58	0.66	0.51	0.49
2003	0.63	0.61	0.61	0.66	0.64	0.61	0.71	0.59	0.74	0.54	0.55	0.59	0.76	0.66	0.59	0.67	0.60	0.49
2004	0.57	0.58	0.60	0.60	0.62	0.60	0.64	0.63	0.69	0.55	0.54	0.59	0.68	0.69	0.59	0.59	0.59	0.48
2005	0.66	0.55	0.64	0.62	0.63	0.60	0.68	0.71	0.70	0.56	0.56	0.59	0.76	0.65	0.59	0.52	0.55	0.50
2006	0.68	0.72	0.63	0.68	0.75	0.62	0.67	0.89	0.71	0.54	0.64	0.59	0.63	0.83	0.59	0.64	0.67	0.51
2007	0.71	0.69	0.65	0.72	0.70	0.63	0.71	0.67	0.72	0.59	0.57	0.59	0.65	0.68	0.59	0.48	0.60	0.50
2008	0.73	0.71	0.66	0.69	0.71	0.68	0.75	0.70	0.75	0.62	0.62	0.60	0.61	0.66	0.60	0.53	0.61	0.61
2009	0.62	0.74	0.67	0.57	0.68	0.67	0.76	0.78	0.76	0.78	0.66	0.62	0.64	0.70	0.62	0.45	0.47	0.61
2010	0.70	0.65	0.70	0.63	0.60	0.71	0.83	0.82	0.79	0.67	0.75	0.62	0.68	0.66	0.62	0.48	0.46	0.64
2011	0.68	0.77	0.71	0.88	0.69	0.77	1.08	1.03	0.87	0.73	0.73	0.69	0.83	0.74	0.69	0.43	0.54	0.63
2012	0.80	0.78	0.73	0.73	0.83	0.72	0.70	0.82	0.78	0.64	0.66	0.63	0.70	0.77	0.63	0.60	0.55	0.63
2013	0.55	0.74	0.75	0.74	0.71	0.73	0.72	0.82	0.84	0.29	0.41	0.66	0.54	0.59	0.66	0.59	0.50	0.67
2014	0.76	0.70	0.71	0.67	0.76	0.76	0.96	0.95	0.88	0.83	0.74	0.72	0.71	0.58	0.72	0.67	0.76	0.71
2015	0.83	0.76	0.82	0.65	0.74	0.79	0.98	0.97	0.85	0.97	0.91	0.74	0.79	0.76	0.74	0.65	0.67	0.69
2016	0.92	1.01	0.85	0.71	0.71	0.80	1.12	1.03	0.86	1.10	1.05	0.81	0.86	0.74	0.81	0.70	0.66	0.69
2017	1.12	0.89	0.89	0.78	0.79	0.82	1.29	1.26	0.91	0.99	0.99	0.83	0.96	0.94	0.83	0.74	0.81	0.71