# A Macroeconomic Analysis of Insolvency in the UK Construction Industry

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## Abstract

### Purpose

This paper examines macroeconomic factors affecting insolvency level in the UK construction industry.

### Design/methodology/approach

A Lagged Dependent Variable (LDV) model is proposed which adequately addressed the serial correlation and endogeneity problems commonly existed in time series data. Objective macroeconomic data from Q3 1997 to Q4 2023 are used to evaluate seven refutable hypotheses.

### Findings

It is found that higher unemployment rate or annual interest burden leads to higher the number of insolvencies, while higher construction output value, or interest rate leads to lower insolvencies. Domino effect in construction insolvency is also confirmed.

### Research limitations/implications

The proposed solutions to the missing data on 3 quarters and the changes in the industry breakdown methods during the study period might have affected the accuracy and consistency of data.

### Practical implications

The paper provides objective insights to factors affecting construction insolvency, offering tools for future policy formulation.

### Social implications

Knowing factors affecting insolvencies helps formulating solutions.

### Originality/value

Previous studies on insolvency in construction industry have largely focused on prediction of insolvency of individual companies using firm level financial data, which are symptoms of failure rather than root causes. Studies using questionnaires could be subjective and the limited studies using macroeconomic factors often have methodological issues. This paper bridges the gap by analysing objective macroeconomic data with a sound methodology.

**Keyword**: Insolvency, Construction, Macroeconomic, LDV model, time series data, UK

## Introduction

Construction industry is one of the major employment providers in the UK. According to online statistics on employment released by Office for National Statistics, the average number of employed people in construction is 7.3% of all employed in the UK from Q1 2010 to Q4 2019, however, after Brexit, the average percentage dropped to 6.6% from Q1 2020 to Q4 2023.

An insolvent construction company may lead to many workers being unemployed. Given the significance of the industry in providing job opportunities, company insolvency is an important issue worth studying. Figure 1 shows the number of construction companies compulsorily wound up in England and Wales. One can find clearly two obvious peaks in the graph. One peak happened during 2008-2009 when there was a global financial crisis started from the collapse of sub-prime housing mortgage market in the USA. Another peak happened after the UK's Coronavirus Job Retention Scheme ended in September 2021.

Although construction insolvencies have attracted scholarly attention, there are several methodological issues in each type of study. A sizeable number of studies on construction insolvencies relied on financial ratios to predict the probability of default of individual companies. The methodological issues of this type of studies are twofold. Firstly, most financial ratios are symptoms of failure rather than factors leading to failure (Argenti, 1976). Secondly, as demonstrated in the literature review below, the study samples favour larger companies or those with complete data, and contain far higher proportion of failed companies (usually 50%) than the actual percentage in the economy, leading to sampling biases.

A second type of studies on construction insolvencies used qualitative factors based on subjective opinions collected from questionnaire. Some authors used broad "catch-all" factors, which are not specific enough, to explain reasons of insolvencies, e.g. "management decision making", "internal strategy", etc. used in Alaka, Oyedele, Owolabi, Oyedele, et al. (2017), "poor management skill" used in Patel, Trivedi, Pandit, and Patel (2022). Some others used options that were not mutually exclusive.

There have been limited studies on effects of macroeconomic factors on number of construction insolvencies. Most such studies had methodologies issues as well. Some ignored the serial correlation or endogeneity problems of using time series data, e.g. Lowe (1997), Lowe and Moroke (2010). Others didn't to present model diagnostics or goodness of fit to demonstrate that such problems had been addressed, e.g. Kim, Lee, and Kim (2011) and Sang, Ham, Kim, and Kim (2014).

This study attempted to make a contribution by evaluating macroeconomic factors affecting number of construction insolvencies in the UK. The next section includes an overview of the insolvency process in the UK, a review of factors affecting insolvencies and a critical review of methodological issues in previous studies. Section 3 proposes a methodology to choose a suitable model to deal with problems of analysing time series data, it also makes hypotheses and explains the variables involved. Section 4 presents and discusses the result and the final section concludes.

## Literature Review

### *A Brief Overview of Modern Insolvency Process in the UK*

Typically, when a company is unable to pay its debts, it is considered to be insolvent. Since the middle of nineteenth century, the English corporate insolvency law has introduce a compulsory liquidation procedure which involves appointment of a liquidator following an order from a court to wind up a company unable to pay its debts (Armour, Cheffins, & Skeel, 2002). This procedure realizes and distributes assets of the company to its creditors, the company involved will be dissolved afterwards.

Following the seminal Cork Report in 1982, which led to the enactment of *The Insolvency Act 1986,* the main philosophy of English corporate insolvency law has shifted from dissolving towards rescue, recovery and renewal of the struggling companies. Therefore, in addition to the traditional compulsory liquidation, *The Insolvency Act 1986* introduced the concepts of Receivership, Administration and Company Voluntary Arrangements (CVA) (Armour et al., 2002). Receivership, initiated by creditors who believes the company cannot pay its debts, involves appointment of a receiver to sell company's business or assets. Administration involves appointment of an administrator to run the business as a going concern. It protects the company from creditors' legal actions, giving the company the opportunities to restructure or better realize value of the company or its assets. A CVA is an agreement between a company and its shareholders and creditors to allow a proportion of its debts to be paid back over time, the company will trade as usual with their directors remain in control (Marsh, 2023).

There are two voluntary procedures for companies registered under *the Companies Act 2006*, namely, Members Voluntary liquidation (MVL) and Creditors Voluntary Liquidation (CVL). MVL happens when the majority of the directors of a solvent company pass a resolution to wind up the company voluntarily. In contrast, CVL happens when the directors, believing the company will become insolvent, resolve to convene meeting of its shareholders and creditors to consider, and if fit, to pass a resolution that the company will be wound up (Marsh, 2023).

A recent reform to the *Insolvency Act 1986* was the moratorium process introduced by the *Corporate Insolvency and Governance Act 2020*, whereby the directors of an eligible insolvent or nearly insolvent company may obtain a moratorium which protects the struggling business from creditor enforcement action and grants a payment holiday in respect of certain liabilities for a "initial period" of 20 business days (Cl. A9).

The number of administrations, receiverships, and Company Voluntary Arrangements have been much fewer than compulsory liquidation and Creditors Voluntary Arrangements, on average from 2011 to 2021 the number of the former 3 types of cases were 10.2% of all insolvency cases in England and Wales. Moreover, the data range for those three cases were much shorter, therefore they are not considered in this paper. Members Voluntary liquidation refers to solvent companies only, therefore it is not considered either.

## ***Prediction of Insolvency of Individual Companies***

Prediction of business failure based on statistical methodologies has been a major research area in corporate finance. The most commonly used statistical method was Multiple Discriminant Analysis (MDA) followed by logit analysis (an approach of conditional probability analysis) (Altman & Saunders, 1998; Balcaen & Ooghe, 2006; Jackson & Wood, 2013). Alaka, Oyedele, Owolabi, Oyedele, et al. (2017) reviewed 28 primary studies on the application of quantitative variables for prediction of insolvencies in construction industry. Their focus has been identification of critical factors, our review below will focus on methodology and their potential issues though. Key information in relevant literature is summarized in Table 1.

*Multiple Discriminant Analysis*

MDA was firstly applied to predict corporate insolvency by Altman (1968). It is a statistical technique used to classify an observation into one of several qualitative groupings, e.g. solvent and insolvent, dependant on the observation's individual characteristics (variables), e.g. financial ratios. MDA compares alternative functions and determines the best set of variables and their coefficients and produce an index, known as Z score after Altman (1968), with an optimal cut-off point to distinguish the groupings.

Possibly due to the popularity of using MDA for prediction of business insolvency, as reviewed by Balcaen and Ooghe (2006) and Ciampi, Giannozzi, and Altman (2021), applications of the MDA model onto construction industry have also been popular. Some authors attempted to identify the best discrimination function to predict construction company insolvencies, examples include Mason and Harris (1979)'s early study based on 20 failed and 20 solvent construction companies in the UK to evaluate 28 discriminating variables, Abidali and Harris (1995)'s study based on 11 failed and 20 non-failed firms in the UK to evaluate 31 variables. Ng, Wong, and Zhang (2011)'s study based on 22 financial indices of 35 contractors in China in 2006. Bal, Cheung, and Wu (2013)'s study based on 15 failed and 30 non-failed companies from 1997 to 2022 in Taiwan; Jaki and Ćwięk (2021)'s study based on 11 failed and 132 non-failed companies from 2010 to 2015 in Poland. The above examples show that to arrive at a best Z score, the number of failed companies as a percentage of total samples included in the study is normally far higher than those actual percentage in the economy.

Alternatively, earlier established models might be used, examples include Langford, Iyagba, and Komba (1993)'s study on 3 contractors based on Mason and Harris (1979)'s model; Chan, Tam, and Cheung (2005)'s study on 8 Hong Kong contractors based on Altman (1993)'s model. Since different studies in different countries would normally arrive at different Z-scores, it is doubtful whether these scores could be used in other countries.

*Conditional Probability Analysis*

There are three approaches of conditional probability analysis, namely, the Linear Probability Analysis (LPA), the Logit Analysis (LA) and the Probit Analysis (PA), with LA being the most popular conditional probability method in business failure prediction (Balcaen & Ooghe, 2006). A notable example of using LA was Filipe, Grammatikos, and Michala (2016) who studied 2.7 million samples. There have been only a few applications of conditional probability analysis on construction industry though, a recent example is Dushuashvili (2024)'s study on Georgian construction companies.

Vieira, Pinho, and Correia (2013) used all three approaches of conditional probability analysis to evaluate 8 financial variables as predictors of insolvency in Portuguese construction industry, based on data of 150 failed and 150 operating construction firms from 2009 to 2011. Makeeva and Neretina (2013) compared both LA and PA with Canonical Discriminant Analysis to evaluate 23 variables, based on 60 insolvent construction firms and 60 sound analogues in Russia. Tserng, Chen, Huang, Lei, and Tran (2014) used LA to evaluate 21 ratios, based on 1,560 firm-year observations from 29 defaulted and 58 non-defaulted construction companies. Karminsky and Burekhin (2019) compared LA, PA methods with three machine learning models, namely, classification trees, random forests and artificial neural networks. They have used data on 3,981 companies from 2011-2017 and considered 16 factors include 14 financial ratios, 2 for size and age of companies. Balina, Idasz-Balina, and Achsani (2021) applied LA in addition to MDA, based on data of 40 insolvent and 40 solvent companies in Poland from 2014-2018 to evaluate 42 financial indicators. The above examples show that in conditional probability analysis, the number of failed companies as a percentage of total samples included in the study is also far higher than those actual percentage in the economy.

*Main issues with Statistical Methods*

Statistical methods require financial data on both solvent and insolvent companies. One important issue is sampling bias. Firstly, samples normally focused on large companies, as it is easier to obtain their financial information. However, the majority of companies falling into insolvency are smaller one and the factors affecting larger and smaller companies are often quite different and sometimes even opposite (Alaka, Oyedele, Owolabi, Bilal, et al., 2017). Secondly, many studies choose only companies with complete data which may lead to sample selection bias, as failing companies are more likely to have incomplete data because they tend to be younger and smaller (Balcaen & Ooghe, 2006). Finally, as shown in earlier sections, many studies used status based samples, e.g. an equal number of failed and solvent companies, resulting in over-sampling of failed companies, as in reality failed companies represent only a small proportion in the economy (Balcaen & Ooghe, 2006).

Different studies will normally generate different set of variables with different coefficients. This could be expected. However, it could be an issue if the signs of the variables are contrary to the economic theory or intuition. For instance, higher return on asset (ROA) supposedly means higher profitability, but it leads to higher probability of insolvency in Vieira et al. (2013); In addition, the signs of the same variables in different models based on the same set of companies could be different, e.g. Bal et al. (2013). Furthermore, the predictive power of the ratio based models is usually poor when applied to data relating to the years before failure is apparent (Edum-Fotwe, Price, & Thorpe, 1996). Balcaen and Ooghe (2006) further identified some other issues, e.g. the arbitrary definition of failure, invalid assumption of stationarity of financial variables and stability of relationships among variables over time in the model, and the choice of optimization criteria.

*Attempts to Improve*

Some attempts to improve the performance of balance sheet based information (financial ratios) included the addition of qualitative factors. Alaka, Oyedele, Owolabi, Oyedele, et al. (2017) reviewed of qualitative factors considered in 15 studies. These factors included macroeconomic and industry factors, management / owner / firm characteristics, internal / external strategy, management decision making and even sustainability. A notable early example was Abidali and Harris (1995)'s attempt to supplement Z score obtained through MDA with "A score". A score is an index measuring managerial performance based on various managerial factors, the weighting of which was identified via a questionnaire survey. More recently, Alaka, Oyedele, Owolabi, Bilal, et al. (2017) used an interesting qualitative method of listening to the owner/manager's accounts of the life of their companies from establishment to insolvency.

Since financial values are symptoms rather than causes of failure (Argenti, 1976), it is adverse managerial actions, poor company strategy, etc. that normally lead to poor financial standing and even insolvency of construction business (Alaka, Oyedele, Owolabi, Oyedele, et al., 2017), the following sections will review both external and internal factors (causes) affecting insolvencies.

## *External Factors Affecting Insolvencies*

External Factors are those factors that are beyond the control of individual companies, they could be Macroeconomic factors or institutional / industry factors. Macroeconomic and industry factors identified in previous studies include (fierce) competition, economic recession, unemployment rate, excess credit, interest rate, etc. Institutional factors in the industry include procurement methods used in construction industry characterized as a system of pyramidal contracting chains with extensive sub-contracting (Coggins, Teng, & Rameezdeen, 2016), as well as poor payment practice in the industry leading to cashflow problems.

*Competition and Underbidding*

Construction industry in the UK has long been recognized as highly competitive. One reason is that there are few entry requirements, especially for small and medium contractors and labour based contractors (De Valence, 2007). The survey of owners/managers of insolvent companies by Alaka, Oyedele, Owolabi, Bilal, et al. (2017)'s identified two market competition factors contributing to insolvency, namely, too many firms springing up and immigration from EU (before Brexit) offering unrealistically low prices. In fact, the economic recession factor suggested by the authors impacted on insolvency through higher competition as well.

An early study based on actual failures during 1989-1994 in US construction industry also found that insufficient profit, primarily the result of harsh competitive environment, is the most important reason for insolvency, accounting for 26.71% of failure (Arditi, Koksal, & Kale, 2000).

A study on reasons for contractor insolvency in Indian construction industry by Patel et al. (2022) considered 16 factors. The factor "absence of barrier to entry" was only ranked No. 14, however, another factor "underbidding" was ranked No. 2. Underbidding could be the result of poor tendering skill, but usually it is the result of severe competition. Similarly, Underbidding was found to the No. 2 ranked reason for contractor insolvency in South Australia (Coggins et al., 2016).

*Economic Recession & Unemployment Rate*

Economic recession was found to be the top ranked factors affecting insolvencies of small civil engineering firms according to Alaka, Oyedele, Owolabi, Bilal, et al. (2017)'s questionnaire survey. The authors suggested economic recession would lead to much higher contractor/project ratio, but no actual data on the ratio were collected. In Arditi et al. (2000)'s study on US construction industry, this factor is termed as "industry weakness", which accounts for 22.73% of failure, being the second most important reason for insolvency.

Unemployment was suggested by Kelly, Brien, and Stuart (2015) as a good proxy for economic performance as it reflected poor economic performance in preceding periods. Furthermore, its effect on company insolvency would be non-linear as the longer a firm survives in a recession period, the less likely it will become insolvent.

*Excess Credit in Economy*

Excess credit, i.e. amount of credit deviated from trend level, is considered as one important factor affecting probability of loan default in the study of Irish SMEs by Lawless and McCann (2013). Similarly, Kelly et al. (2015) opined that credit affects company survival from two channels. The first channel was "point in time credit availability" in periods of sudden credit reduction, which could be measured by quarterly changes in credit at sector level. The second channel was "credit standards" which might be lower in periods of credit expansion, and could be measured by percentage deviation of credit from the trend credit level.

*Domino Effect*

The insolvency of a company in the industry would normally affect the solvency of other companies in the supply chain as they cannot receive money for the work done or goods supplied. This is known as Domino effect, as most contractors and suppliers who are involved in a construction project are unsecured creditors (Coggins et al., 2016). In case of insolvency of a debtor, they may not get payment due to the low order of preference of unsecured creditors, thereby leading to their own insolvency.

The inclusion of a lagged value of dependent variable (number of insolvencies) in various regression studies is a good way of measuring domino effect, examples include Lowe (1997) and Lowe and

Moroke (2010). This factor can capture the effects other than those independent variables. Other studies based on opinion surveys have also found some evidence of this factor, e.g. Patel et al. (2022) where this factor was ranked No. 6 based Relative Importance Index.

### *Other Variables*

Kim et al. (2011) and Sang et al. (2014) considered the effect of macroeconomic indicators on the financial ratios (current ratio & debt ratio) and expected default frequency of some top ranked listed construction companies in Korea using a vector error correction model. The common factors they both considered included consumer price index, certificate of deposit interest rate, currency exchange rate. In addition Kim et al. (2011) further considered index of liquidity for the country, Real Gross National Income, while Sang et al. (2014) considered the Korea composite stock price index, corporate bond yield, gross domestic product, lagged values of the dependant variables, & error correction term. The effects of those variables in both studies were tested by variance decomposition and impulse response analysis, though none of them (effect of error correction term not reported) has higher than 0.05% effect on the dependant variables. In addition, the coefficients and goodness of fit as well as diagnostics for the model were not reported.

## ***Internal Factors Affecting Insolvencies***

### *Attraction to and Retention of Quality Staff*

Retention of quality staff was identified as the second most important internal factors affecting insolvency in the survey by to Alaka, Oyedele, Owolabi, Bilal, et al. (2017). Small firms may find themselves difficult to retain quality staff if the strategic positions are low wage payers with little benefit. Interestingly, a similar factor “low attractiveness to quality staff” was also included in the study but categorized as external factor. If these two factors could be combined, the overall importance could be even higher.

### *Management/Owner Characteristics*

One characterises leading to insolvency was found in a survey to be over-optimism as it encourages establishment of under-capitalized firms entrepreneurs (Ucbasaran, Westhead, Wright, & Flores, 2010) or it tends to deprive their ventures of resources and resourcefulness (Hayward, Shepherd, & Griffin, 2006), e.g. buying unnecessary equipment (Alaka, Oyedele, Owolabi, Bilal, et al., 2017). Entrepreneurs have a greater tendency to be over-optimistic than non-entrepreneurs, and amongst entrepreneurs, those repeat entrepreneurs who had not experienced business failure were significantly more likely to report over-optimism (Ucbasaran et al., 2010). Though this study was not limited to construction industry, the importance of over-optimism towards insolvency has been confirmed to be No. 3 ranked internal issues in a later study focused in construction industry (Alaka, Oyedele, Owolabi, Bilal, et al., 2017).

A second characterises leading to insolvency was autocracy which means a person possessing sole authority or holding multiple executive positions. The total weighting of this factor found in a survey in the UK study (Abidali & Harris, 1995) was 16% (14% for sole authority and 2% for chief executive and chairman being the same person). In a later study by Alaka, Oyedele, Owolabi, Bilal, et al. (2017), the weighted occurrence of this factor was also found to be a total of 16% among 13 factors.

#### *Weak Financial Director*

An early study based on 28 questionnaires on UK construction industry found that weak financial director, with only shared responsibilities for financial decisions, was the No. 1 ranked management related reason (weighted 17%) (Abidali & Harris, 1995). It is likely that this could be one of the root management causes for cashflow problems discussed below.

*Cashflow & its root causes*

Construction companies require “heavy operating expenses”, which was found to be the reason accounting for 17.80% occurrence of insolvency in the US from 1989-93 (Arditi et al., 2000). This issue may sometimes be solved by relying on trade credits (Coggins et al., 2016), but timely payment to meet cashflow requirement is the most important, otherwise “burdensome institutional debt” may happen, which accounts for another 5.93% occurrence of insolvency in the US (Arditi et al., 2000). Indeed, cashflow problems, caused by poor management of debt or funding associated companies, was found to be the second most important reason for company failure in UK construction industry from 1973-1983, according to either company director’s perception (58 + 12 = 70 out of 300 cases, 23.3%) or official receiver’s perception (18 + 18 = 36 out of 319 cases, 11.3%) (Young and Hall 1991).

Poor payment practice was identified as one of the major problems in the UK construction industry decades ago (Latham, 1994), The *Housing Grant, Construction and Regeneration Act in 1996* and its amendment in 2009 seeks to address this issue through prohibition of “pay when paid” or “pay when certified” clauses, mandatory inclusion of stage/interim payment provisions in construction contracts, and introduction of a rapid statutory adjudication procedure. Nonetheless, collecting receivable was still identified as the most important internal failure factor in Alaka, Oyedele, Owolabi, Bilal, et al. (2017)’s study, However, it was found to be only a valid factor, but not very important in an earlier study, as the weighted occurrence was only 1.46% (Arditi et al., 2000).

Poor payment practices have also been identified as the most important factor leading to construction insolvency in Australia (Coggins et al., 2016). This was the case despite the introduction of “proof of payment” clauses into several standard forms of contracts in the 1990s and the introduction of building and construction industry security of payment legislations in all states in Australia between 1999 and 2011 (Coggins & Donohoe, 2012; Ndekugri, Silverio, & Mason, 2024; Yung & Rafferty, 2015).

A study on India construction industry also suggested that cash flow problem was the most important reason for contractor insolvency (Patel et al., 2022). The authors further found that poor financial control, overtrading, onerous conditions of contract, were three other reasons leading to contractor insolvency (ranked No. 3, 5 & 15 respectively). Poor financial control included lack of proper accounting process, failure to collect debts, etc. The mechanism how overtrading leads to insolvency was suggested to be tying up of funding, and the onerous contract conditions examples given were “pay when paid” clauses and high retention percentage. It seems these three factors should be some of the root causes for cashflow problems though. This methodology was largely followed in a similar study on Nigerian construction industry, however, only overtrading was found significant, but not cash flow problem, not poor financial control, nor onerous conditions of contract (Okereke, Ejekwu, & Ohamma, 2021).

*Imprudent Diversification*

Another poor management practice leading to contractor insolvency was imprudent diversification. This factor was ranked as No. 7 in a study on Indian construction industry (Patel et al., 2022), but ranked No. 1 (highest mean score) in a study on Nigerian construction industry[1] (Okereke et al., 2021).

[1] There was a technical error in Okereke et al. (2021)’s paper, they wrongly thought the factors with t-values smaller than critical value were significant in the one-sample t-test, it should be the opposite, and in this paper we have interpreted their results based on factors with higher t-values are significant. In addition, they have

*Managerial Incompetence or Poor Management Skills*
Alaka, Oyedele, Owolabi, Oyedele, et al. (2017)'s review on earlier 18 studies has ranked (poor) "management decision making" as the top qualitative factor affecting insolvency. Since construction industry consists of many small businesses started by skilled workers, poor management skills or managerial incompetence is often an issue (Young & Hall, 1991). Managerial incompetence may include inexperience in bidding or poor response to market change, together weighted 15% in an early study on UK construction insolvencies (Abidali & Harris, 1995). Poor business management skills was also ranked to be No. 3 reason in Patel et al. (2022)'s study on Indian construction industry. Examples of poor management skills include technical skills of business such as persistent underbidding, failure to understand risks; as well as soft skills such as negotiation and decision making (Patel et al., 2022). In addition, successive generation of family business, if associated with disinterest, lack of skills, often lead to insolvency. This factor was ranked to be No. 12 reason (Patel et al., 2022).

*Undercapitalization*
The construction industry is characterized more by skilled labour than capital-intensive production. Many skilled workers start up their small scale business with limited amounts of capital, relying on bank finance and trade credits for funding (Young & Hall, 1991). Undercapitalization, defined as a firm having insufficient funds to carry out day-to-day business, was found to be the single most important reason for company failure in UK construction industry from 1973-1983, according to either company director's perception (89 out of 300 cases, 29.7%) or official receiver's perception (204 out of 319 cases, 63.9%) (Young & Hall, 1991). It was also a commonly cited reason for construction insolvency in Australia (Coggins et al., 2016). Similarly, insufficient capital was also identified as the reason accounting for 8.29% occurrence of insolvency in the US from 1989-93 (Arditi et al., 2000).

*Size & Age of Company*
An early analysis of 375 failed companies during the period from 1973 to 1983 in the UK construction industry revealed that failure was almost confined to relatively small firms (Young & Hall, 1991). This is not surprising as smaller firms are normally undercapitalized, and therefore easily affected by cashflow problems.

The UK study above further revealed that the average life span of the 375 insolvencies in construction industry was 6.75 years (Young & Hall, 1991). This was consist with another study on UK small firms (not limited to construction industry), which confirmed that dissolution rates decrease with increasing firm age, until a firm reached about 10 years of age, among young firms of less than 5 years of age, dissolution rates were highest amongst firms of less than 50 employees (Stewart & Gallagher, 1985). Another early study on US construction industry over two 11-year periods (1973-83 & 1984-94) revealed that the percentage of failed construction companies increased over the first few years after their establishment, reached a peak, and decreased afterwards (Kale & Arditi, 1999).

Age of company of course might not be the root reason why a company fail, it might simply be a proxy to measure the relative impacts from declining of initial stock of assets, goodwill, etc. and those from the building up of business skills through organizational learning as time passes. In

included this factor twice in the study, as "diversification" and "imprudent diversification" respectively, and both were significant.

addition, long-established companies have a better chance of being supported by financial institutions (Arditi et al., 2000).

*Illegal Phoenix Activity*

Illegal Phoenix Activity refers to deliberate liquidation of a company to avoid paying creditors or tax, after transferring the company's assets elsewhere (Coggins et al., 2016). This factor was not found to be the top 5 reasons for in their study on Australia, and similarly was only ranked No. 8 in Patel et al. (2022)'s study on India.

### *Methodological Issues with Studies on Macroeconomic Factors*

There have not been plenty of studies that focused macroeconomic factors affecting construction insolvencies, even fewer focused on UK. The methods used can be broadly categorized into quantitative and qualitative studies. Quantitative models mainly include multiple regression models, logit models, and VAR models. Examples of multiple regression models included Lowe (1997) and Lowe and Moroke (2010)'s studies on determinants of number of insolvencies in the UK; A notable example of using logit model to study UK construction insolvency is Filipe et al. (2016). Examples of using VAR models include Kim et al. (2011) and Sang et al. (2014)'s studies on Korean construction industries. Qualitative studies mainly used questionnaire surveys and reported frequencies of responses. There are some methodological issues with previous studies which will be reviewed below.

#### *Treatment of Time Series Data*

An early example of using multiple regression model was the study by Lowe (1997) covering the period from 1969 to 1994. The dependent variable was quarterly number of insolvent companies in UK construction industry, significant explanatory variables included Annual Profitability (profit / value of capital assets), Annual Working capital as % of construction output; Quarterly Bank borrowing as % of construction output; Domino effect measured as Dependent variable lagged 4 quarters; while insignificant variables included Quarterly Credit Availability measured as velocity of circulation of money; Interest Rate; Quarterly Fluctuating Demand measured as absolute values of changes in construction output as % of construction output.

The major problem in Lowe (1997) was that all variables are time series data, which will almost certainly be correlated over time (Hill, Griffiths, & Lim, 2018), i.e., data observed in one quarter will be correlated with those observed in a few previous and subsequent quarters, violating the basic assumptions of regression models of no serial correlation and exogeneity. Although the inclusion of a lagged value of the dependent variable as explanatory variable (this is known as autoregression) alleviated the problem, the use of only a 4-period lag rather than 1-period lag seemed arbitrary without a demonstration on existence of seasonality.

A second problem in Lowe (1997) lies in the definition of the variable "Fluctuating Demand" measured as absolute values of changes in construction output as % of construction output. The problem is that taking absolute values eliminated the difference between an expanding market (higher output than previous quarter) and a diminishing market. Indeed, not only this variable was not found significant, but also the sign was opposite to the expectation.

A later updated study by Lowe and Moroke (2010) covered the period from 1969 to 2008. Apparently, the problem of using absolute values of change in construction output has been addressed, as actual values of change in output were used this time. However, the variable used was annual change rather than quarterly change. Interestingly, the significant variable found in previous study, i.e. bank borrowing as % of construction output, was not included. And two other previous found significant variables, namely, Annual Return on capital (industry level), and Annual Working capital as % of construction output, were now found insignificant, though the variables used this time were the 1 year lagged values. Nonetheless, other than the lagged value of the dependent variables, all variables are annual data rather than quarterly data.

*VAR models*

Vector Autoregressive (VAR) models including Vector Error Correction Models (VAR models with error correction term) are models that can properly treat serial correlation problems commonly appeared in time series data. Since Moody's acquisition of KMV in 2002 (Jackson & Wood, 2013), there have been a number of studies on macroeconomic factors affecting firms' Expected Default Frequency (EDF), many of them were studies by central banks. These studies normally use Vector Autoregressive (VAR) models with EDF being the dependent variable, and macroeconomic factors being the explanatory variables. The EDF calculated with Moody's KMV model, which measures a firm's distance (measured as number of standard deviations) to default (defined as market value of assets lowering than debts) within a given time horizon. Examples include Åsberg and Shahnazarian (2008)'s study on Sweden, Castrén, Dées, and Zaher (2008)'s study on Euro area.

One issue with such macroeconomic studies is the choice of variables. Since it is difficult to know *a priori* what effect each of the macroeconomic variables may have on a firm's insolvency, the choice of variables may have to be trialled and tested using empirical data (Åsberg & Shahnazarian, 2008).

There have been few studies using VAR models on construction industry, with two notable exceptions on Korean construction industry (Kim et al., 2011; Sang et al., 2014). The studies did considered issues of time series data and used the Vector Error Correction model to address the issues. However, the goodness of fit and diagnostics for the model and the coefficients were not reported, indeed, the effects of the variables included in the studies on the dependent variable seemed very minimal (Kim et al., 2011; Sang et al., 2014).

### *Questionnaire Survey Studies*

One issue with previous studies using qualitative factors is that generic labelling of poor management may be suggested as reasons for contractor insolvency. e.g. "management decision making", "internal strategy", "external strategy", etc. used in Alaka, Oyedele, Owolabi, Oyedele, et al. (2017), and "poor business management skill" and "poor financial control" used in Patel et al. (2022). The main problem with this kind of generic labelling is that without knowing specifically which part of practices are poor, it is quite impossible to improve.

Another issue is that factors chosen were not mutually exclusive. One example was both generic catch-all factors of poor management skill and poor financial control were used, in addition to some specific management practices such as over trading and imprudent diversification (Patel et al., 2022). Another example was both the resultant problem, e.g. cash flow problem, and some of their root causes, e.g. excessive trading, poor financial control, imprudent diversification, onerous conditions of contract, etc. were used as parallel choices (Okereke et al., 2021; Patel et al., 2022). Since the factors are not fully distinguishable, the differences between the factors could be too small, e.g. the mean score for all the 10 factors ranged from 3.23 to 3.63 only in Okereke et al. (2021)'s study. A further problem is that the results could be quite different in different surveys.

A third issue is that many studies do not distinguish between factors and symptoms. This is one of the main problems identified earlier for statistical studies based on financial ratios, but it is also a problem even in qualitative studies. Factors such as low profit levels or cashflow problems should merely be symptoms rather than root causes. The last issue is that questionnaires are based on subjective information provided by respondents, which might not be an accurate reflection of the truth, as often factors found in one study could be quite different from those found in other studies.

### *Summary*

Insolvency prediction models frequently used financial ratios which are symptoms rather than factors. There is some evidence that macro-economic factors may be more important than micromanagement factors. For example, Alaka, Oyedele, Owolabi, Bilal, et al. (2017)'s study found that the top 4 factors affecting insolvency of small firms were all "external issues", namely, economic recession, fluctuation of material cost, immigration and too many new firms. Nonetheless, there have been few studies on macroeconomic factors affecting insolvencies in construction industry (Wang, Li, Skitmore, & Chen, 2024), many of them are not without methodological issues. This paper attempts to bridge this research gap.

## Methodology, Hypotheses and Data

This section shows the methodology to choose the best econometric model, the definition of dependent variable and method to estimate its 3 missing values. It further explains the independent variables and makes refutable hypotheses.

### *Time Series Model Selection*

Cross-sectional data uses many observations at a short time period. Typically, the experimental design should aim to collect, for each variable, random samples of many observations that are independent to each other. However, time series data uses values of the same variable at different time points as observations. There is only one observation for each variable at a particular time point and the value is frequently, if not always, correlated to the value at previous time points. This is known as serial correlation and it violates one of the basic assumptions of linear regression model (Hill et al., 2018).

One solution to serial correlation is the use differenced variables, i.e. converting the variable $X_t$ to $\Delta X_t$ ($\Delta X_t = X_t - X_{t-1}$). This method may remove the trend and thereby avoid the problems of spurious regression. However, it also removes the long-run information from the data (Harris & Sollis, 2003), therefore it is not recommended.

Another solution is to add lagged values of variables or errors (ε) to the regression. A time series model without any lagged values is known as a static model. For instance, equation (1) shows a static model with two independent variables:

$$Y_t = \alpha_0 + \alpha_1 X1_t + \alpha_2 X2_t + \varepsilon_t \qquad (1)$$

A lagged dependent variable can be added this model to form a Lagged Dependent Variable (LDV) model, e.g. LDV of order 1 which contains 1 period lag of the dependent variable looks like:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_1 X1_t + \beta_2 X2_t + \varepsilon_t \qquad (2)$$

Autoregressive (AR) model is a special case of LDV model where there are no other independent variables. By setting $\beta_1 = \beta_2 = 0$ in equation (2), equation (3) is obtained which is known as an AR(1) model:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon_t \qquad (3)$$

Lagged independent variables can be added a static model to form a Finite Distributed Lag (FDL) model. For instance, adding 1-period lags of both independent variables to equation (1) gives an FDL model of order 1 below:

$$Y_t = \alpha_0 + \beta_1 X1_t + \beta_2 X1_{t-1} + \theta_1 X2_t + \theta_2 X2_{t-1} + \varepsilon_t \quad (4)$$

If both lagged dependent variable and lagged independent variables are present in the model, they are known as an Autoregressive Distributed Lag (ARDL) model, e.g.

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_1 X1_t + \beta_2 X1_{t-1} + \theta_1 X2_t + \theta_2 X2_{t-1} + \varepsilon_t \quad (5)$$

In equation (3), if the lagged dependant variable is replaced with a lagged error term, the resultant model is known as a Moving Average (MA) model of order 1, denoted as MA(1):

$$Y_t = \alpha_0 + \varepsilon_t + \phi_1 \varepsilon_{t-1} \quad (6)$$

If there are other independent variables in the model, the MA model is also known as autocorrelated error model:

$$Y_t = \alpha_0 + \alpha_1 X1_t + \alpha_2 X2_t + \varepsilon_t + \phi_1 \varepsilon_{t-1} \quad (7)$$

If a further lagged dependant variable is added to equation (7), the resultant model is an Autoregressive Moving Average (ARMA) model.

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_1 X1_t + \beta_2 X2_t + \varepsilon_t + \phi_1 \varepsilon_{t-1} \quad (8)$$

It is now quite clear that the differences of these models lie on the inclusion of lags of different items. The choice of the models depends primarily on the purpose of study. ARDL model is well suited for testing causal theories, as parameters in the estimated model can easily match the parameters of theoretical model. However, ARMA fits better for forecasting (Pickup, 2015), as errors in earlier period is considered in the model directly. The purpose of this study is to evaluate macroeconomic factors affecting construction insolvencies based on economic theories, therefore the ARDL end of spectrum is more suitable.

The ARDL model has several advantages over other models. Firstly, it can estimate both short-run and long-run effects of explanatory variables. Secondly, by including different lags for all variables, ARDL model can correct both serial correlation and endogeneity problems (Pesaran & Shin, 1999). Thirdly, since many macroeconomic variables are endogenous variables which are at least partly changed and determined by other variables in the model, the estimated coefficients of the long-run model using ARDL approach are unbiased with t-statistics (Pesaran & Shin, 1999), making interpretation of the model much easier. The choice of the order of ARDL model is based on the following criteria:

1. the principle of parsimony, i.e. using the simplest model, i.e. starting with static model, then the lags of dependent variable is added to form LDV models, then if necessary, lags of independent variables are further added to form ARDL models.
2. The independent variables are all included in a full model first, but the most insignificant variable will be eliminated until all variables left are significant, this method is known as backward elimination (Cortinhas & Black, 2012).
3. The process stops when the model produces white noise residuals, as a time series model is considered as a good fit to the data when the resulting residuals are a white noise process (Li, 2004).

## *The Variables, Hypothesis and Data Source*

### *The Dependent Variable: Number of Winding-up Orders*

The dependent variable used in this study is the number of winding-up orders, including both compulsory liquidations and creditors voluntary liquidations in England and Wales. Since no comparable figures before 2007 are available for Scotland and Northern Ireland (Lowe, 1997), and Scotland's insolvency number is much lower than England & Wales, being only about 13% of the latter on average from Q3 2007 to Q4 2021. Therefore, only data for England and Wales are used as a proxy for the Great Britain in this study.

The lagged dependent variable can be used as a measure of domino effect in construction insolvency. Earlier studies provided evidence on the existence of domino effect, as explained in the literature review. The following hypothesis is made:

*H1: The higher the number of insolvencies in a quarter, the higher the number of insolvencies in the following quarter.*

The insolvency data for all industries were derived from administrative records of the Business, Innovation and Skills (BIS) Insolvency Service and Companies House Executive Agencies, which can be downloaded from the government's website. The industry breakdown method used up to Q3 2006 was Insolvency Trade Classification (ITC). Standard Industrial Classification (SIC) 2003 was used as a replacement industry breakdown method from Q3 2007 to Q3 2014. However, ITC and SIC 2003 were not consistent and there was not industry breakdown data between Q4 2006 and Q2 2007 in either classification.

There are two issues with the data. First, there are 3 missing data for construction industry insolvencies, as there was no breakdown by industry in the following 3 quarters: Q4 2006, Q1 & Q2 2007. It is impossible to perform many tests on time series data with missing entries. Therefore, there is a need to estimate the missing values with multiple regression.

The second issue is the existence of two sets of data in certain period. Standard Industrial Classification (SIC) 2007 version was used as the industry breakdown method from Q1 2009, to gradually replace SIC 2003. There are two sets of data from Q1 2011 to Q3 2014, based on SIC 2003 and SIC 2007 respectively. Since the differences between the two set of data from 2009 to 2012 is only around 3%, the effect of choosing either set of data before should be minimum. The difference between the two sets of data in 2014 were higher (15%) and as SIC 2003 method was discontinued in Q4 2014, therefore SIC 2007 based data was used since Q1 2014.

### *The Explanatory Variables & Hypothesis*

The most important root cause for insolvency would be fierce competition which often leads to underbidding, as shown in previous studies reviewed in earlier section. The macroeconomic measures for extent of competition in this study are the amount of work available and the number of participants in the industry.

The amount of work available would be measured by non-seasonally adjusted (nominal) quarterly construction output value of all works in Great Britain, published by Office for National Statistics. The output values were adjusted to constant price level, using the Output Price Index published by Building Cost Information Service (BCIS). The resulting variable, denoted as "OPV", is calculated by dividing the nominal OPV in a quarter with the OPI in the same quarter, and multiply by OPI at Q4 2023 (index = 410). It is obvious that more work will alleviate the extent of competition, given the same number of competitors in the market, therefore the following hypothesis is made:

*H2: The higher the construction output, the lower the number of construction insolvencies.*

The total number of participants in the industry can be measured by either the number for firms in the industry or the number of people in the industry. Unfortunately, only annual figures on number of firms are available in the UK. Use of interpolation method to create quarterly data is not recommended as it means 75% of data are estimated with no guarantee on the accuracy. In addition, it is a common practice in construction industry that a special project company is set up with the sole purpose of carrying out the project. The number of companies at a given time is always inflated by unknown number of project-based companies. Therefore, the number of firms is not considered in this study. Instead, the total number of people in industry in a quarter (variable symbol: PPL), published by Office for National Statistics, including both employed and unemployed, is used in this study. It is expected that more people in the industry leads to higher competition, therefore the following hypothesis is made:

*H3: The higher the number of people in industry, the higher the number of construction insolvencies.*

A second important macroeconomic reason for construction insolvency is the sudden economic recession, e.g. the global financial crisis in 2008-2009, and the Covid-19 and Brexit in 2020-2021, as shown in Figure 1. Kelly et al. (2015)'s suggestion of using unemployment rate as a proxy for economic performance is followed in this paper. The unemployment rate (variable symbol: "UnEmR") is obtained by dividing the number of unemployed people by the total number of employed and unemployed people in the industry, both published by Office for National Statistics. It is expected that the higher the unemployment rate, the poorer the economic performance, therefore the following hypothesis is made:

*H4: The higher the unemployment rate, the higher the number of construction insolvencies.*

Cashflow has been identified as one of the most important factors affecting construction insolvency, as discussed extensively in the literature review section. The quarterly net amounts of lending to construction companies by UK financial institutions in all currencies, published by the Bank of England, are used as a measure of aggregate amount of cash in the industry. It is expected that the more the money loaned to the industry, the few the problems caused by broken cashflow, therefore the following hypothesis is made:

*H5: The higher the mount of lending to the industry, the lower the number of construction insolvencies.*

Another factor affecting the cashflow is the interest rate. The Bank of England Monetary Policy Committee sets Bank Rate, also known as Bank of England Basic Rate, as a part of actions to keep the inflation low and stable. The interest rate charged by financial institutions are normally depending on the Basic Rate and the risks of the borrowers. The frequency of changes in basic rate is not regular, therefore the quarterly average basic rate is calculated by the basic rate weighted by the number of days it lasts for.

It is commonly expected that the higher the interest rate (variable symbol: "BR"), the higher the burden of the contractors. However, interest rate has increasingly been used by central banks to regulate the inflation and the economy as a whole, the higher interest rate might simply mean the economy is booming or inflation is beyond the long-term "healthy" target. Therefore, the resulting effect of interest rate on construction insolvencies is not certain and should be verified based on empirical findings, the following null hypothesis is made:

*H6: Bank basic rate has no effect on number of construction insolvencies.*

The interaction effect of amount of net Lending and interest rate, which could be interpreted as a measure for (annual) interest burden due to the loan, though the actual interest rate would be higher than the Basic Rate, and the period of loan may vary. Contractors cannot obtain loans from the banks if the latter are not satisfied with the former's ability to repay. It is expected that the higher the interest burden (variable symbol: L*BR), the tighter the cashflow, therefore the following hypothesis is made:

*H7: The higher the interest burden, the higher the number of construction insolvencies.*

There is no point to perform extensive data mining by trying as many macroeconomic factors as possible. Where there are no accepted theories on how the factors may affect construction insolvency, the factors will not be considered in this study. Examples include consumer price indices and stock market indices. Table 2 shows a description of the data for all variables used in this study; all data are ranged from Q3 1997 to Q4 2023.

## Results and Discussion

IBM SPSS program with R extensions on time series analysis were used to perform the analyses. The results are presented below.

### *OLS Estimates of Missing Values in Dependent Variable*

The following static multiple linear regression model is used to estimate the values of 3 missing quarterly data:

$$Y_t = \alpha_0 + \alpha_1 OPV_t + \alpha_2 PPL_t + \alpha_3 UnEmR_t + \alpha_4 Lending_t + \alpha_5 BR_t + \alpha_6 L{*}BR_t \ldots + \varepsilon_t$$

The results of the regression model are shown in Table 3. It can be found that the model has a reasonable explanatory power (Adjusted $R^2 = 0.661$). The variable "Lending" is only marginally significant, but all other variables are very significant. It is therefore considered that this model is good enough to estimate the value of the missing data in dependent variable. The respective values of the variables for Q4 2006 to Q2 2007 are shown in Table 4, the windup numbers for the 3 quarters are estimated to be 479, 535 and 554 respectively.

With the missing values of dependent variable now estimated, time series analysis can now be performed. Figure 2 shows the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the errors of the above static model. There are spikes in both ACF and PACF that are beyond the confidence limits, indicating that there is serial correlation problem. Therefore, we proceed to next step: LDV model.

### *Lagged Dependent Variable Models*

Figure 3 shows the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the dependent variable "Windup". By visual inspection, although the ACF shows many significant spikes, but they are declining, and at the same time the PACF shows only 1 significant spike, therefore Limited Dependent Variable of order 1, denoted as LDV(1), is recommended over the MA model, which fits better where ACF has only 1 spike, but PACF has many significant but declining spikes. This reinforces our choice of model in earlier section based on purpose of study.

The results of the LDV models are shown in Table 5. The most insignificant variable in the initial full LDV model (1) is "Lending", it was removed to obtain model (2). The most insignificant variable in model (2) is "PPL", which is removed to obtain the model (3). Note that "Lending" marginally significant and PPL was very significant in the earlier static model, it is possible that most information has now been included with the addition of a lagged dependent variable. Note further that in full model (1), the variables “BR” and “L*BR” were not significant, but with the removal of the above two variables, they become marginally significant and significant at 5% level respectively.

Nonthesis, since the normalized Bayesian Information Criteria (BIC) improved as we delete these two variables (BIC value becomes smaller), and changes in $R^2$ (coefficient of determination) is trivial. The low Mean Absolute Percentage Error (8.98%) indicated any prediction based on this model is highly accurate. It is believed that this model (3) is the best LDV model. The next step is to examine the residuals of this model and see if lagged independent variables are required.

Figure 4 shows the ACF and PACF of the residuals from the above LDV model (3). No spike in either ACF and PACF extends beyond the upper and lower confidence limits. Further examination on the Box-Ljung statistics up to 16 lags doesn’t reject the null hypothesis that the process is white noise.

The simple rule of thumb provided by Huang (1970) is used for testing of multicollinearity. If the absolute values of the simple correlation coefficient between each two of the explanatory variables is less than the Coefficient of Determination ($R^2$), then there is no multicollinearity problem. Table 6 shows Pearson correlation among the variables. In this study, the highest correlation between independent variables is between “OPV” and “BR”, being 0.765, which is still smaller than the $R^2$ (0.872). Therefore, it is very likely that there is no multicollinearity problem.

Finally, linear regression of the residual against the independent variables is further conducted, both t-tests and F test showed that the residual is not correlated to any of the independent variables, confirming the assumption of exogeneity. Therefore, This LDV model (3) is considered the optimal model, and there is no need to add further lagged independent variables to create ARDL models.

### *Interpretation of Results*

Our optimal model is a Lagged Dependent Variable (LDV) similar to equation (2), but with 4 variables. The coefficients ($\beta_i$) of an independent variable shows the impact propensity, i.e. short-run effect on the dependant variable due to one unit change in the independent variable. However, the changes in dependant variable in this period will cause changes of the dependant variable in the following period. Therefore in the long run, one unit permanent change in the independent variable will cause $\beta_i/(1 - \alpha_1)$ changes in the dependent variable (Pickup, 2015).

The 1-quarter lagged dependent variable is very significant ($p < 0.001$), its positive coefficient (0.842) indicates that the higher the number of insolvencies in the previous quarter, the higher the number of in this quarter. Therefore hypothesis 1 is not refuted.

The Construction Output Value at 2023 Q4 constant price (OPV) is significant at 1% level. It has a negative coefficient of -5.821, indicating that the higher the construction output, the lower the number of construction insolvencies, therefore Hypothesis 2 is not refuted. The unemployment rate (UnEmR) is significant at 5% level. Its positive coefficient (25.367) also indicates that the higher the unemployment rate, the higher the number of construction insolvencies, therefore Hypothesis 4 is not refuted.

The variable Bank basic rate is only marginally significant (p-value = 0.070), it has a negative coefficient (-46.592), indicating that the higher the interest rate, the lower the number of insolvencies. Therefore, the null hypothesis H6 is refuted. Since the interest burden has been captured in the variable “L*BR”, the interest rate variable here might simply become a proxy for economic prosperity, which will supposedly have negative correlation with insolvency.

The variable “L*BR”, obtained by multiplying the amount of Lending with basic rate, is a proxy for the annual interest burden, though the actual interest rate should be much higher than the basic rate. The variable is significant at 5% level, its positive coefficient (1.925) indicates that the higher the interest burden, the higher the number of construction insolvencies, therefore Hypothesis 7 is not refuted.

Both number of people (“PPL”) and amount of lending are not significant in our final optimal model, indicating that they have no effect on number of insolvencies, given the values of all other variables. Therefore, hypothesis 3 and hypothesis 5 are both refuted. The results of hypothesis testing, short run and long run effects are summarized in Table 7. They provide objective insights to factors affecting construction insolvency, offering tools for future policy formulation.

### *Discussion*

There is strong evidence on the existence of domino effects. As the 1-quarter lagged dependent variable is very significant ($p < 0.001$), its positive coefficient (0.842) indicates that the higher the number of insolvencies in a quarter, the higher the number in the following quarter. This is consistent with earlier study by Lowe (1997) and Lowe and Moroke (2010).

The construction output value represents the total amount of work available in the industry for a given quarter, representing demand for construction services. This is what every company is competing for. It is not surprising that other factors being equal, the higher the construction output value, the lower the need to underbid to obtain a job. This is consistent with earlier studies that found underbidding (Coggins et al., 2016; Patel et al., 2022) or insufficient profit (Arditi et al., 2000) to be one of the main reasons for construction insolvencies.

Unfortunately, quarterly data on number of firms are not available. Number of people was used as a measure of the supply of construction services in this study. However, this variable is not significant, which means it has no effect on construction insolvencies given other variables. A possible reason is that the subject of study is insolvencies of companies, not people, so number of people is not a good measurement of competition of firms because, firstly, the number of people in different firms vary a lot, and secondly, many workers work on contract basis as contractors rather than employees.

Other than measures of demand and supply for construction services, unemployment rate is used in this study to measure the extent of competition. Intuitively higher unemployment rate usually come with economic recession. This is consistent with Alaka, Oyedele, Owolabi, Bilal, et al. (2017) and Arditi et al. (2000)’s’s finding that “economic recession” or “industry weakness” are one of the top ranked factors (No. 1 & No. 2 respectively).

The amount of lending represents availability of credits in the industry. In this study the amount of lending appears in the form of itself and in the variable “L*BR” as a measure of interest burden. Amount of credits affect firm survival through its availability and its deviation from trend (Kelly et al., 2015). However, the amount of lending actually is highly correlated with interest rate, therefore with both interest rate and interest burden considered, amount of lending is not found significant in our optimal model.

## Conclusion

This paper is a contribution to the limited existing studies on macroeconomic factors affecting number of construction insolvencies in the UK. The literature review summarizes both micro level and macro level factors affecting construction insolvencies as well as pinpointing some methodological issues. A methodology is proposed to choose suitable econometric models to avoid common problems of using time series data, i.e. serial correlation and endogeneity. A linear regression model is used to estimate the 3 missing values in the dependent variable, these missing values and the changes in the in the industry breakdown methods during the study period might have affected the accuracy and consistency of data. A Limited Development Variable Model is used to verify 7 refutable hypotheses using UK data ranged from Q3 1997 to Q4 2023. The result shows that domino effect exists in the construction insolvencies, factors leading to higher insolvencies include unemployment rate, annual interest burden, while factors leading to lower insolvencies include construction output value, bank basic rate. Number of people in industry and amount of lending to industry were not found significant given the other variables. Further work could be directly towards other factors affecting the insolvency levels, such as the furlough scheme introduced in the UK to relief the impact of coronavirus.

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**Table 1: A Summary of Factors Affecting Insolvency in Construction Industry**

| Author (date) | Method & Dependent Variable | Macroeconomic factors | Firm level factors | Data, Industry & Country |
|---|---|---|---|---|
| Lowe (1997) | **Method:**<br>Multiple regression<br>**Dependent Variable:**<br>Nr. of Insolvent companies in a quarter | **Significant:**<br>Annual Return on capital (industry level);<br>Annual Working capital as % of construction output;<br>Bank borrowing as % of construction output;<br>*4Q lagged value of dependent variable;*<br>**Not significant:**<br>Velocity of circulation of money;<br>Interest rate;<br>Absolute % change in quarterly construction output | Not included in study | Quarterly from 1969 to 1994, construction industry, UK |
| Lowe and Moroke (2010) | **Method:**<br>Multiple regression<br>**Dependent Variable:**<br>Nr. of Insolvent companies in a quarter | **Significant:**<br>Annual % change in construction output;<br>4Q lagged value of dependent variable;<br>**Not significant:**<br>Return on capital (industry level) lagged 1Y;<br>Working capital as % of construction output lagged 1Y; | Not included in study | Quarterly from 1969 to 2008, construction industry, UK |
| Kelly et al. (2015) | **Method:**<br>Discrete time survival analysis (complementary log-log regression model)<br>**Dependent Variable:**<br>Dummy = 1 when a firm becomes insolvent in a quarter | **Significant:**<br>Ln (Unemployment rate);<br>Quarterly change in credit;<br>Quarterly Excess credit at birth of company | **Significant:**<br>Time (Nr. of quarters since establishment);<br>Time squared;<br>Some location dummies<br>Some sector dummies; | Quarterly from 1995Q1 to 2012Q4, all sectors, Ireland |
| Alaka et al. (2017) | **Method:**<br>Interviews of insolvent companies' owner/managers;<br>Questionnaire, ranking of factors; factor analysis<br>**Dependent Variable: N/A** | **Top 3 factors:**<br>Economic recession;<br>Immigration;<br>Too many new firms | **Top 3 factors:**<br>Collecting receivables;<br>Retention of quality staff;<br>Management/owner characteristics | 18 interviews; 81 questionnaire, civil engineering, UK |

| Author (date) | Method & Dependent Variable | Macroeconomic factors | Firm level factors | Data, Industry & Country |
|---|---|---|---|---|
| Patel et al. (2022) | **Method:**<br>Questionnaire, ranking factors, rank correlation<br>**Dependent Variable: N/A** | Few considered, none in top 5 factors | **Top 5 factors:**<br>Cash flow problems;<br>Underbidding;<br>Poor management skill;<br>Poor financial control;<br>Overtrading | 124 questionnaire, Construction industry, India |
| Okereke et al. (2021) | **Method:**<br>Questionnaire,<br>One sample t-test<br>**Dependent Variable: N/A** | Few considered, none in top 5 factors | **Top 5 factors:**<br>(Imprudent) Diversification;<br>Management buy-outs;<br>Family firms;<br>Overtrading;<br>Overwhelming claims | 90 questionnaire, Construction industry, Nigeria |
| Coggins et al. (2016) | **Method:**<br>Questionnaire,<br>Ranking factors<br>**Dependent Variable: N/A** | Not considered in study | **Top 5 factors:**<br>Poor payment practice;<br>Underbidding;<br>Poor financial management skills;<br>Procurement methods;<br>Undercapitalized firms | 42 questionnaire, Construction industry, Australia |
| Kim et al. (2011) | **Method:**<br>Vector Error Correction Model;<br>Impulse response analyse & variance decomposition analysis<br>**Dependent Variable:**<br>Current ratio;<br>Debt ratio | **Factors considered** (coefficient & significance not reported)<br>Dependant variable;<br>Real Gross National Income;<br>Index of overall liquidity in Korea;<br>Exchange Rate<br>Certificate of deposit interest rate;<br>Consumer Price Index; | Dependant variables themselves:<br>Current ratio = current asset/ current liability;<br>Debt ratio = total liability / equity | Quarterly from 2001 to 2008, top 30 companies, construction industry, Korea |
| Sang et al. (2014) | **Method:**<br>Vector Error Correction Model;<br>Impulse response analyse & variance decomposition analysis<br>**Dependent Variable:** | **Factors considered** (coefficient & significance not reported)<br>Dependant variable;<br>Korea Composite Stock Price Index;<br>Consumer Price Index;<br>Corporate bond yield<br>Currency exchange rate; | Dependant variable itself: Value of assets & its volatility, short term & long term debts, leverage ratio are required to calculate the Dependant variable | Quarterly from 2001 to 2010, 25 companies, construction industry, Korea |

| Author (date) | Method & Dependent Variable | Macroeconomic factors | Firm level factors | Data, Industry & Country |
|---|---|---|---|---|
| | Expected default frequency measured by KMV model | **Relatively negligible factors**<br>Gross Domestic Product<br>Certificate of deposit interest rate; | | |
| Arditi et al. (2000) | **Methods:**<br>Ranking factors according to failure rate due to a factor multiplied by annual industry failure rate<br>**Dependent Variable: N/A** | **Top factors & weighting:**<br>Industry weakness (22.73%);<br>All other factors below 3% | **Top 3 factors & weighting:**<br>Insufficient profit (26.71%);<br>Heavy operating expenses (17.80%);<br>Insufficient capital (8.29%);<br>Burdensome institutional debt (5.93%)<br>All other factors below 4%. | Dun & Bradstreet business failure records 1989-93, Construction industry, US |
| Young and Hall (1991) | **Method:**<br>Frequency distribution of factors per company director (D)'s perception & Official Receiver (OR)'s perception<br>**Dependent Variable: N/A** | **Top factors & weighting:**<br>Lack of demand (D: 6%; OR: 0.6%)<br>All factors below 4% | **Top factors & weighting:**<br>Undercapitalization (D: 29.7%; OR: 63.9%);<br>Poor management of debt (D: 19.3%; OR: 5.6%)<br>Inaccurate costing & estimating (D: 9%; OR: 4.4%)<br>Funding associated companies (D: 4%; OR: 5.6%)<br>All other factors below 4%. | Dept of Trade & Industry archive on involuntary insolvency 1973-83, 375 cases, construction industry, UK |
| Filipe et al. (2016) | **Method:**<br>Multi-period logit model<br>**Dependent Variable:**<br>Distress (in the next year) dummy variable | **Top factors:**<br>FX rate (% change)<br>Unemployment<br>Economic sentiment indicator;<br>Loans granted to non-financial sector (% change);<br>Years to resolve insolvency proceedings | **Top Factors:**<br>Earnings before tax to total asset;<br>BITDA to interest expenses;<br>Current liability to total assets;<br>Cash flow to current liabilities;<br>Turnover to total liabilities<br>Time at risk (nr of years a firm stays in the sample);<br>3 country panels;<br>6 industry sectors;<br>location (urban or not) dummy;<br>3 legal form dummies;<br>Shareholder (more than 2 or not) dummy;<br>Size of firm (ln (total assets) | Amadeus and Orbis Databases financial statements of 2.7 million SMEs: 1999-2010;<br>All industry, Europe |

**Table 2: A Description of Variables and Data**

| Symbol | Variable Definition | Unit | N | Mean | Minimum | Maximum | St. Dev |
|---|---|---|---|---|---|---|---|
| Windup | The number of registered company winding-up orders (compulsory liquidations + creditors voluntary liquidations) | Nr | 103 | 594.20 | 310 | 1092 | 200.52 |
| OPV_OPI | Construction Output Value in UK, adjusted to 2023Q4 price level with BCIS OPI (index = 410), all works, not seasonally adjusted | £1,000 million | 106 | 65.78 | 31.16 | 99.38 | 14.73 |
| People | Total number of people employed and unemployed in construction industry | 1,000 person | 106 | 2,349.13 | 2,104.17 | 2,742.47 | 159.31 |
| UnEmR | Number of unemployed people as a % of total number of people | % | 106 | 4.55 | 1.44 | 9.76 | 2.14 |
| Lending | Quarterly amounts outstanding of UK financial institutions in all currencies net lending to construction companies, not seasonally adjusted | £1,000 million | 106 | 28.98 | 8.08 | 56.88 | 13.57 |
| BR | Bank of England official Bank Rate, quarter average weighted by number of days the rate lasted | % | 106 | 2.67 | 0.10 | 7.50 | 2.40 |
| L_BR | Lending x BR | £10 million | 106 | 52.29 | 3.66 | 175.25 | 44.15 |

**Table 3: Results of Linear Regression Model for Estimating Missing Values**

| Variables | Coefficient | Coeff SE | t | Significance |
|---|---|---|---|---|
| Constant | 1797.360 | 264.581 | 6.793 | <0.001 |
| OPV | -7.889 | 2.060 | -3.830 | <0.001 |
| PPL | -0.332 | 0.103 | -3.220 | 0.002 |
| UnEmR | 43.490 | 6.967 | 6.242 | <0.001 |
| Lending | -3.471 | 1.884 | -1.842 | 0.069 |
| BR | -83.228 | 24.950 | -3.336 | 0.001 |
| L*BR | 4.180 | 0.855 | 4.886 | <0.001 |

Notes: Dependant Variable: Windup (with 3 missing values), Adj $R^2$ = 0.661, N=102

**Table 4: Estimates of Missing Values in Dependent Variable**

| Variables | Unit | Coefficient | 2006 Q4 | 2007 Q1 | 2007 Q2 |
|---|---|---|---|---|---|
| **Windup** | number | | **479** | **535** | **554** |
| Constant | | 1797.36 | 1797.36 | 1797.36 | 1797.36 |
| OPV | £ billion | -7.889 | 69.96 | 69.46 | 68.21 |
| PPL | 1,000 persons | -0.332 | 2,643.71 | 2,638.26 | 2,644.97 |
| UnEmR | % | 43.49 | 3.84 | 4.21 | 3.83 |
| Lending | £ billion | -3.471 | 20.67 | 22.50 | 23.85 |
| BR | % | -83.228 | 4.89 | 5.22 | 5.39 |
| L*BR | £ 10 million | 4.18 | 101.16 | 117.47 | 128.61 |

**Table 5 LDV models**

| | LDV model (1) - full | | | LDV model (2) | | | LDV model (3) | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coeff.** | **t** | **Sig.** | **Coeff.** | **t** | **Sig.** | **Coeff.** | **t** | **Sig.** |
| Constant | 332.746 | 0.708 | 0.480 | 474.417 | 1.075 | 0.285 | 902.167 | 6.251 | <0.001 |
| Windup L(1) | 0.888 | 14.175 | <0.001 | 0.876 | 13.944 | <0.001 | 0.842 | 13.282 | <0.001 |
| OPV | -5.490 | -2.434 | 0.017 | -5.779 | -2.595 | 0.011 | -5.821 | -2.629 | 0.010 |
| PPL | 0.217 | 1.167 | 0.246 | 0.186 | 1.018 | 0.311 | deleted | | |
| UnEmR | 25.048 | 2.173 | 0.032 | 25.502 | 2.249 | 0.027 | 25.367 | 2.300 | 0.024 |
| Lending | 1.701 | 0.743 | 0.459 | deleted | | | deleted | | |
| BR | -29.829 | -0.925 | 0.357 | -40.834 | -1.451 | 0.150 | -46.592 | -1.831 | 0.070 |
| L*BR | 1.137 | 0.991 | 0.324 | 1.580 | 1.590 | 0.115 | 1.925 | 2.087 | 0.039 |
| Model Fit | $R^2$ = 0.874; Norm. BIC = 8.927; MAPE: 8.885 | | | $R^2$ = 0.873; Norm. BIC = 8.881; MAPE: 8.947 | | | $R^2$ = 0.872; Norm. BIC = 8.837; MAPE: 8.984 | | |
| Action | Delete “Lending” | | | Delete “PPL” | | | Check residual | | |

Notes: Dependant Variable: Windup, N=105.

**Table 6: Pearson Correlation among Variables**

| | | Windup | OPV | PPL | UnEmR | Lending | BR | L*BR |
|---|---|---|---|---|---|---|---|---|
| Windup | Pearson Correlation | 1 | -0.686 | 0.238 | -0.016 | 0.594 | -0.503 | -0.015 |
| | Sig. (2-tailed) | | <0.001 | 0.016 | 0.872 | <0.001 | <0.001 | 0.880 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | 103 | 103 | 103 | 103 | 103 | 103 | 103 |
| OPV | Pearson Correlation | -0.686 | 1 | -0.227 | 0.424 | -0.739 | 0.765 | 0.255 |
| | Sig. (2-tailed) | <0.001 | | 0.019 | <0.001 | <0.001 | <0.001 | 0.008 |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |
| PPL | Pearson Correlation | 0.238 | -0.227 | 1 | 0.056 | 0.157 | -0.122 | 0.245 |
| | Sig. (2-tailed) | 0.016 | 0.019 | | 0.570 | 0.108 | 0.214 | 0.012 |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |
| UnEmR | Pearson Correlation | -0.016 | 0.424 | 0.056 | 1 | -0.067 | 0.090 | -0.155 |
| | Sig. (2-tailed) | 0.872 | <.001 | 0.570 | | 0.498 | 0.360 | 0.112 |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |
| Lending | Pearson Correlation | 0.594 | -0.739 | 0.157 | -0.067 | 1 | -0.780 | -0.337 |
| | Sig. (2-tailed) | <0.001 | <0.001 | 0.108 | 0.498 | | <0.001 | <0.001 |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |
| BR | Pearson Correlation | -0.503 | 0.765 | -0.122 | 0.090 | -0.780 | 1 | 0.745 |
| | Sig. (2-tailed) | <.001 | <.001 | .214 | .360 | <.001 | | <.001 |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |
| L*BR | Pearson Correlation | -0.015 | 0.255 | 0.245 | -0.155 | -0.337 | 0.745 | 1 |
| | Sig. (2-tailed) | 0.880 | 0.008 | 0.012 | 0.112 | <0.001 | <0.001 | |
| | N | 103 | 106 | 106 | 106 | 106 | 106 | 106 |

**Table 7: Hypothesis Testing Results and Factor Effects on Insolvencies**

| | **Hypothesis** | **Results** | **Short Run Effect** | **Long Run effect** |
|---|---|---|---|---|
| H1 | *The higher the number of insolvencies in a quarter, the higher the number of insolvencies in the following quarter* | Not refuted | Evidence of domino effect in construction insolvency | |
| H2 | *The higher the construction output, the lower the number of construction insolvencies.* | Not refuted | £1,000 million increase in Construction Output Value will reduce 5.82 number of insolvencies | £1,000 million increase in Construction Output Value will reduce 36.84 number of insolvencies |
| H3 | *The higher the number of people in industry, the higher the number of construction insolvencies.* | Refuted | No further effect given other variables | No further effect given other variables |

| | | | | |
|---|---|---|---|---|
| H4 | *The higher the unemployment rate, the higher the number of construction insolvencies;* | Not refuted | 1 point increase in unemployment rate (e.g. from 3% to 4%) will increase 25.367 number of insolvencies | 1 point increase in unemployment rate (e.g. from 3% to 4%) will increase 160.55 number of insolvencies |
| H5 | *The higher the mount of lending to the industry, the lower the number of construction insolvencies* | Refuted | No further effect given other variables | No further effect given other variables |
| H6 | *Bank basic rate has no effect on number of construction insolvencies* | Refuted | 1 point increase in basic rate (e.g. from 2% to 3%) will reduce 46.592 number of insolvencies | 1 point increase in basic rate (e.g. from 2% to 3%) will reduce 294.89 number of insolvencies |
| H7 | *The higher the interest burden, the higher the number of construction insolvencies* | Not refuted | £10 million increase in annual interest payment will increase 1.925 number of insolvencies | £10 million increase in annual interest payment will increase 12.18 number of insolvencies |

**Figure 1 – Company Insolvency in England and Wales**

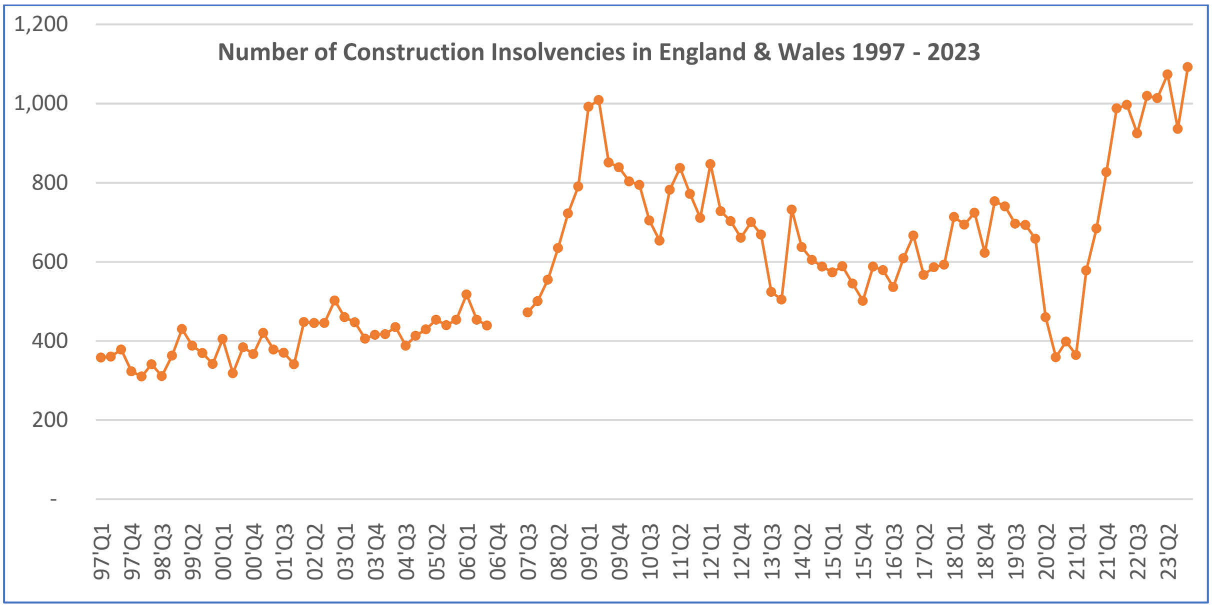



**Figure 2 ACF & PACF of errors in linear regression model**

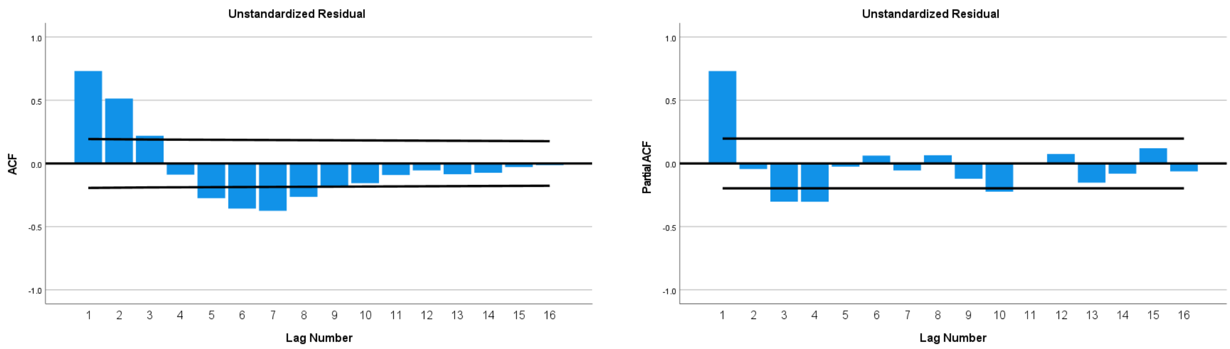



**Figure 3 ACF & PACF of Dependent Variable**

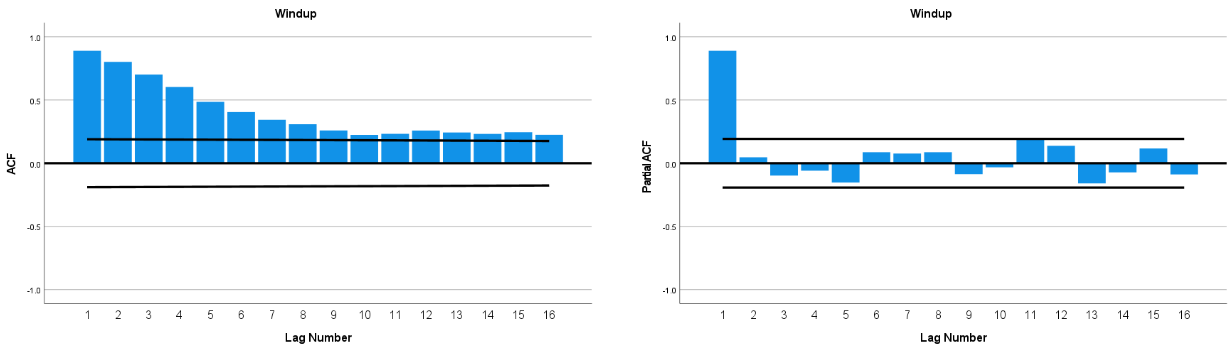
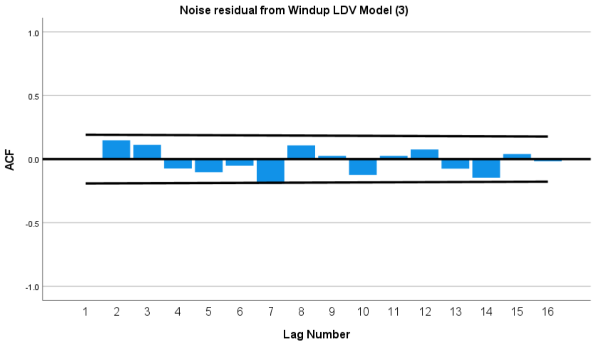
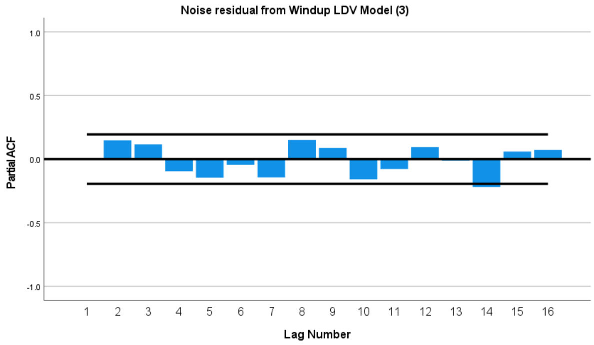



**Figure 4 ACF & PACF of errors in LDV model (3)**


Noise residual from Windup LDV Model (3)
ACF
1.0
0.5
0.0
-0.5
-1.0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Lag Number


Noise residual from Windup LDV Model (3)
Partial ACF
1.0
0.5
0.0
-0.5
-1.0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Lag Number