The Spread Of COVID-19 and Its Impacts on the Economy of Engineering

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AUTHORSHIP STATEMENT

I confirm that the work submitted is my own and that appropriate credit has been given where reference has been made to the work of others.

This thesis has been submitted in an alternative format to provide the flexibility required to incorporate published research. This format enabled the publication of research articles in international journals alongside the completion of the PhD.

Chapter one introduces the research, including its aims, scope, and context. Chapters two to four present three published studies resulting from the research. Chapters five and six discuss the key findings, potential applications, conclusions, and recommendations for future research.

The first article, *"Risk Mitigation: Numerical Analysis of COVID-19's Impact on Major Global Construction Economies,"* by V.E.G. Vilchis, S.J. Antony, and S. Munjal, was published in the *International Journal of Disaster Risk Reduction* in 2025. V.E.G. Vilchis conducted the numerical simulations and validation and prepared the manuscript. S.J. Antony supported manuscript preparation, while S.J. Antony and S. Munjal contributed to the conceptualisation and development of the study.

The second article, *"Dynamic Structural Modelling of Systemic Interactions Under Crisis: A Generalised Moment Framework with Application to Pandemic–Economic Dynamics,"* by V.E.G. Vilchis, S.J. Antony, and S. Munjal, was published in *Economics of Disasters and Climate Change* in 2026. V.E.G. Vilchis derived the equations, developed the initial modelling framework, and prepared the first version of the manuscript. S.J. Antony supported manuscript development and validation of the systems of equations, while S. Munjal contributed to the conceptualisation of the study.

The third article, *"Full Causal Effect Modelling for Construction Sector Stability Under Global Events: Pandemics – A Review,"* by V.E.G. Vilchis, S.J. Antony, and Eric Danso-Boateng, was published in the *Journal of the Indian Institute of Science* in 2026. V.E.G. Vilchis conducted the literature review,

prepared the manuscript, and addressed the reviewers' comments during revision. S.J. Antony and Eric Danso-Boateng supported the development and refinement of the manuscript.

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ABSTRACT

The forces defining the dynamics of a system expose systemic interconnections between the involved variables, often creating multiple interactions that cannot be adequately represented by isolated models. This research develops an integrated statistical framework based on Full Causal Effect (FCE) modelling and systems of simultaneous linear equations (SLE) to investigate how explanatory variables interact during linked events. The technique presented here can be applied to several different systems; the only condition is that the system to be analysed involves interaction between its variables.

This analysis focuses on the influence of the COVID-19 pandemic across fourteen major economies—the United States, China, Japan, Germany, India, the United Kingdom, France, Italy, Canada, Brazil, Australia, Spain, Mexico and the Netherlands—collectively representing approximately 75% of global GDP in the first quarter of 2020.

The research was developed through three complementary stages. First, epidemiological dynamics were obtained using compartmental pandemic models, including SIRDi formulations incorporating transmission, recovery, mortality, quarantines and immunisation effects. Analytical solutions and Particle Swarm Optimisation were used to solve the model. The pandemic analysis permitted the estimation and examination of spreading parameters and the evaluation of how changes in transmission and containment conditions influenced the timing and magnitude of the infection spread. Second, the resulting epidemiological indicators were integrated with macroeconomic and industrial variables. Combinations of instruments and predictors were evaluated using the Generalised Method of Moments, with statistically admissible equations identified through Hansen's J tests. Valid equations were subsequently assembled into simultaneous linear systems and evaluated through least squares optimisation.

The framework was verified through Seemingly Unrelated Regression (SUR), allowing equations with correlated residual structures to be identified and combined into compatible systems of equations. Benchmark comparisons with reduced form dynamic panel models, conventional SUR and lagged specifications were used to examine the consistency of the statistical relationships. Finally, the industrial sector evidence was synthesised through a structured literature review, screening records, assessing full text studies and retaining those studies for relevant analysis of construction disruption, supply chains, labour, project performance, digital transformation and resilience.

The first level of analysis established causal relationships between pandemic and economic variables affecting construction productivity at global and continental levels. Recovery rate, share

prices, foreign direct investment (FDI) and total spending generally supported industrial productivity, whereas inflation, mortality and pandemic related variables frequently increased disruption. The relative risk index (RRI) and relative productivity of the industry displayed a clear inverse pattern: risk increased while productivity declined during the first quarters of 2020, followed by a progressive reduction in risk and recovery in productivity. Polynomial models relating RRI to productivity provided close agreement between observed and forecast productivity, with coefficients of determination of 0.960 globally, 0.978 in America, 0.980 in Asia, 0.969 in Europe and 0.968 in Oceania.

The second level of analysis extended the framework from individual causal relationships and industrial productivity to contemporaneous systems of equations describing multiple variables simultaneously. The results demonstrated that epidemiological shocks propagated through employment, consumption, investment, trade, prices and financial markets, producing interconnected feedback mechanisms. Recovery, transmission and mortality rates generated effects on employment, inflation and private spending, while mobility, liquidity, government spending and financial market variables modified the transmission of the shock through the wider economy. The analysis also identified country level differences in causal structures. For example, employment in the United States was strongly associated with liquidity and recovery conditions; FDI formed an important pathway to exports in China; fiscal expenditure was associated with exports and private spending in Italy; and pandemic and financial variables played different roles across European, Asian and American economies. The relationships also changed over time: transmission and pandemic growth were particularly influential during the initial outbreak, recovery and mobility became more important during vaccination and reopening, while inflation, liquidity and private spending became increasingly influential during the later recovery period.

The third level of analysis consisted of a literature review which further demonstrated that industrial sector events resulted from interacting health, labour, financial, supply chain, regulatory and technological mechanisms rather than from isolated events. The evidence indicates that the mechanisms change between onset, adaptation and recovery phases and vary across countries and industrial subsectors. Supply chain flexibility, workforce adaptation, digitalisation, health and safety measures, public investment and emergency preparedness were consistently identified as mechanisms supporting continuity. The review provides a theoretical and empirical basis for applying FCE modelling for resilience and for developing adaptive strategies under future pandemics, geopolitical disruptions and other systemic events.

The findings demonstrate that pandemic resilience depends on the coordinated behaviour of health and economic systems rather than on isolated interventions. The proposed FCE–GMM–SUR–SLE framework provides a means of identifying multiple statistically admissible causal pathways, examining how their configurations change across time and space, and translating these relationships into risk and productivity measures. The research provides a mathematical foundation for dynamic risk assessment, causal optimisation and adaptive decision making under systemic shocks, with potential applications beyond COVID-19 to future pandemics, geopolitical disruptions, supply-chain failures, climate related events and other complex social and natural processes.

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LIST OF ABBREVIATIONS

Abbreviation	**Meaning**
ACE2	Angiotensin-Converting Enzyme 2
AI	Artificial Intelligence
CSoE	Contemporaneous Systems of Equations
COVID-19	Coronavirus Disease 2019
CSSE	Center for Systems Science and Engineering
DR	Death Rate
FCE	Full Causal Effect
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GDyn	Global Dynamic Model
GFSR	Global Financial Stability Report
GMM	Generalised Method of Moments
I	Infected Population
IHR	International Health Regulations
IMF	International Monetary Fund
IPP	Industrial Production Prices
IRD	Infected–Recovered–Dead Model
IV	Instrumental Variable
JHU	Johns Hopkins University
LS	Least Squares
M3	Broad Money Supply Aggregate M3
MERS-CoV	Middle East Respiratory Syndrome Coronavirus
N	Total Population
NPM	Non-Pharmaceutical Measures
OECD	Organisation for Economic Co-operation and Development

Abbreviation	Meaning
OLS	Ordinary Least Squares
ONS	Office for National Statistics
PHEIC	Public Health Emergency of International Concern
PLS-SEM	Partial Least Squares Structural Equation Modelling
PSO	Particle Swarm Optimisation
Q1	Quarter 1
Q3	Quarter 3
R	Removed/Recovered Population
R_0	Basic Reproductive Number
R_e	Effective Reproductive Number
RI	Risk Index
RR	Recovery Rate
RRI	Relative Risk Index
RPCI	Risk and Productivity of the Construction Industry
SARS-CoV	Severe Acute Respiratory Syndrome Coronavirus
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SC	Supply Chain
SIR	Susceptible–Infected–Removed Model
SIRDi	Susceptible–Infected–Recovered–Dead–Insulated Model
SIRD	Susceptible–Infected–Recovered–Dead Model
SLE	Systems of Simultaneous Linear Equations
SUR	Seemingly Unrelated Regression / Seemingly Unrelated Regressions
SUR–GMM	Seemingly Unrelated Regression–Generalised Method of Moments Framework
TR	Transmission Rate
UK	United Kingdom

Abbreviation	**Meaning**
USA	United States of America
VAR	Vector Autoregression
WHO	World Health Organization

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1. INTRODUCTION

1.1. General Introduction

1.1.1. Preamble

It has long been recognised that the mediators of the evolution of a system are often unobserved rather than observed by the effect they produce (Jiang et al., 2023). This pattern appears across both natural and social sciences. When data from past events are collected, the mediating mechanisms that shape dynamic system states are implicitly embedded within those observations. Building on this assumption, a range of methods has been developed to infer the underlying forces that operate over time on the industry and the wider macro-economy.

Although these economic forces lack a definitive unit of measurement, some of their properties can nevertheless be detected. Their magnitude can be approximated by examining how information behaves when grouped or reorganised. Because this approach does not yield a single, perfectly specified regression model, it instead extracts multiple data configurations that generate statistically significant and internally coherent signals.

A multi-equation explanatory system—characterised by stable regressions and high residual correlations across equations—indicates that the system is responding to a common underlying signal. In this context, the "signal" or initiating spark is the observed data itself, captured in historical registers. The structure of the residual correlations suggests that each equation meaningfully explains its target variable, while the system as a whole is represented by a set of equations that maintain a consistent reading from the empirical behaviour of the economy.

Only a limited subset of equation systems remains valid under these dual criteria. This reduced set implies that the economy alternates the influence of its internal forces across different components. Whether driven by seasonal patterns or non-conventional shocks, these forces become detectable when they act upon an oscillating supply-chain structure. The temporal nature of the data—combined with spatial variation across regions—suggests the presence of a spatio-temporal mediator operating across events. These events unfold within the multidimensional Cartesian space constructed by economic and social interactions. Studies in statistical modelling include the use of neural networks, where simulated models represent real-world phenomena through mathematical equations (Creel, 2017). Neural networks categorise input combinations of variables before regression, which aligns conceptually with this work exploring sets of causal effects. But here, we evaluate model equations. In neural networks, layers

of cause-and-effect links are identified. Such layers correspond to snapshots of occurring events, contained in the registers. Bayesian inference is applied to the network's links, which correspond to multiple sets of causal equations.

The statistical inference using causal models finds links for many events when analysing multidimensional spaces. In this model, we constructed a system of simultaneous linear equations, composed of the equations obtained with the generalised method of moments (GMM). The systems of equations were solved using least squares to predict the observed data utilised to obtain the equations.

The SLE was able to predict the actual information of multiple variables, which were considered valid systems. This happened only at specific points of the panel data. Let's say, when an SLE predicted specific information, it only did so at that point in the registers. In other words, if an SLE predicted the economy of Mexico in the quarter of 2020, that SLE only predicted that country in that specific period. However, multiple SLE were found predicting the economy within the threshold. Increased computational power, able to include more extensive equations, can potentially provide an SLE with validity extended over a period or several regions.

Using the verified SLE, we then optimised the system and identified a convergence limit determined by the implicit acting forces in the system. In other words, the optimised system predicted extreme maximum and minimum values, and it converged to specific levels for each variable. We interpret this optimised state as the extreme condition of the system. In the context of econometrics, this implies that a given policy, production state or social condition determines the optimal functioning within the limits imposed by the supply chain, politics and socio-economic development. All this information is contained in the registers and extracted by the full causal effect.

Another approach to causal inference, proposed by Li et al. (2017), is marginal integration. This method models variables represented as nodes connected by functions, where groups of variables and their lagged and interconnected values explain the current state of the system. The work presented by Li et al. exemplifies what we call a *scenario*: a fixed set of equations defining causation within a system by predicting all the variables in the SLE. Such a system state of certainty is valid only for specific points in time. What Li et al. describe as a property of the marginal integration is one slice of the full causal effect over time.

1.1.2.The Momentum of Causal Effects During Pandemics

The complexity of causal inference and its relevance increased during periods of rapid change. Like the COVID-19 pandemic, historical events like social movements and natural disasters can alter the expected course of events in society. We briefly analyse the effects of COVID-19 on the economic system.

COVID-19 has been a coronavirus pandemic. For decades before the outbreak, there existed scepticism about the emergence of pandemics and that a new virus could reach humankind. However, no large-scale official work, unlike the current amount of COVID-19-related work, has been carried out since 2005, when the International Health Regulations (IHR) were established.

In this work, research has been conducted to understand the spread kinetics of COVID-19 in the population and to develop fundamental understandings of how it affects the economy globally, with relevance to the construction industry from the point of view of minimising such impacts in future disasters. This work aims to link the epidemiological variables and their influences on the economy of the construction industry and macroeconomy during the COVID-19 pandemic. By developing mathematical modelling of the spread of the pandemic and its consequences, the research would help to define fundamental practices to protect the economy under the consideration of different and more realistic epidemiological factors characterising the pandemic in future.

Global health emergencies have revealed the importance of effective measures to control the spread during outbreaks. The combination of spread control measures and advancements in assessing specific containment levels within the population played a crucial role in mitigating monetary losses, preventing a more severe recession attributed to COVID-19 when compared with previous pandemics (Oliu, 2021).

COVID-19 immunisation campaigns and non-pharmaceutical measures (NPM) such as lockdowns and personal health practices positively contributed to the effective reopening of the economy during the coronavirus outbreak (Moore, 2020). In contrast, in earlier pandemics, vaccines were only available after the outbreaks had occurred. Also, less efficient NPMs were implemented due to constrained media circulation and limited ways to communicate risks with the population. The lessons learned from COVID-19 can serve as insights to safeguard industries from future extreme events.

Despite the unknown origin of SARS-CoV-2, and similar to other viruses, this can bring uncertainties surrounding future events (Adnan, 2020; Burki, 2020; Oxford, 2004); this study

analyses pandemic and economic variables to explain the downturn of the construction industry between 2020 and 2023. This statistical approach reveals the pandemic and macroeconomic variables influencing the construction industry and other relevant variables during the COVID-19 pandemic. This model can be employed to design emergency alert systems for industry during pandemics, mitigating the economic losses caused by outbreaks.

1.1.3.Motivation

The emergence of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in December 2019 and the subsequent spread of coronavirus disease 2019 (COVID-19) generated an unprecedented global health and economic disruption. By December 2021, COVID-19 had resulted in more than 293 million infections and more than 5.4 million deaths globally (JHU, 2022). Beyond illness, mortality, and social disruption, the pandemic generated immediate and long term economic consequences affecting trade, transportation, and social activities, including within comparatively stable industries (Kiana, 2021). The rapid transmission of the virus resulted in international mobility restrictions, lockdowns, and the implementation of non pharmaceutical measures (NPMs), including the use of face masks, social distancing and enhanced hygiene practices. Although these interventions were necessary to limit transmission and protect public health, their effects extended beyond the health system and progressively affected economic activity, production, employment, trade, mobility, and supply chains.

The scale of the disruption became evident as the pandemic contributed to increasing poverty rates and a contraction of approximately 3% in the global economy between 2020 and 2022. The interconnectedness of households, businesses, financial institutions, governments, and international markets demonstrated that the consequences of a health emergency can propagate across multiple economic and industrial systems. This interdependence highlights the need for integrated strategies capable of identifying and mitigating risks before localised epidemics develop into global pandemics, while also reducing the potential for severe economic imbalances during future emergencies. The model must reproduce the reality of many variables simultaneously.

The economic consequences of COVID-19 were particularly significant for vulnerable populations and labour markets. By 2020, global working hours had decreased by 8.8%, equivalent to approximately 255 million full-time jobs (Raimo et al., 2021). At the firm level, enterprises also experienced difficulties in receiving payments from customers, further increasing financial pressures during the crisis (Twahirwa et al., 2021). The implementation of NPMs resulted in the

temporary closure or restriction of manufacturing facilities, offices, construction activities and other workplaces, generating direct and indirect economic repercussions (Trabucco et al., 2021). Disruptions in supply, demand, logistics and production delayed activities and caused interruptions across interconnected supply chains. This rapid change exposed the vulnerability of the systems of the studied period and demonstrated how localised disruptions could propagate through the global economy.

The pandemic also occurred during a period in which governments and industries were pursuing sustainability objectives and investing in emerging technologies for long-term economic and environmental preservation (Khan et al., 2021). At the macroeconomic level, governments introduced financial and monetary measures to support households, firms, and economic activity. However, these interventions occurred within existing fiscal constraints, including high levels of public debt and relatively low tax revenues, which limited the capacity of governments to sustain economic support (Buckley, 2016). The disruption created an additional challenge: resources and investment that had been intended to support technological and sustainability transitions were required to address an immediate global crisis. This situation reinforced the importance of understanding how economic systems respond to major disruptions and how available resources can be managed under conditions of uncertainty.

The combination of health, economic, and industrial disruption demonstrates the need for approaches capable of examining complex relationships between multiple elements of a system. Rather than treating the pandemic solely as a health event or an isolated economic shock, this research considers COVID-19 as a systemic disruption capable of influencing interconnected economic and industrial variables over time. The availability of data generated throughout the COVID-19 crisis provides an opportunity to examine these relationships empirically, from the initial spread of the coronavirus through successive periods of restrictions, economic disruption, policy intervention, and the eventual lifting of lockdown measures.

This study is motivated by the need to improve the identification, assessment and management of systemic risks arising from major disruptions. Attention is given to the industry and its relationship with the wider economy, where changes in demand, supply, mobility, employment, investment, trade and financial conditions can interact and propagate through interconnected systems. The objective is therefore not only to describe the economic consequences of COVID-19, but to establish a systematic numerical approach for representing the relationships through which disruptions develop and propagate.

1.1.4.Economy and industry

This work consists of analysing the economic consequences of COVID-19 in the global chain to determine the updates in future events. The motivation for this work was to find gaps between pandemic intensity and its economic impacts in the construction industry.

The methodology consists of computational approaches consisting of two coherent parts: (i) predicting the spread of COVID-19 more realistically in a population and (ii) modelling the links between spread and industrial measures so that the combined understanding would help to manage pandemics in future. Initially, the SIR model (susceptible, infected, and removed) is used to compute the transmission rate (TR), recovery rate (RR) and death rate (DR) for SARS-CoV-2 in the UK. The analysis includes possible scenarios for the construction industry related to the potential future propagation of COVID-19.

There have been many attempts to model the spread process of a virus and, separately, analyses of the pandemic implications on the industry. However, this is the first trial using a combination of epidemic and economic parameters and the validation can only be made when multiple works are compiled and reviewed.

1.1.5.COVID-19 and the supply chain

COVID-19 resulted in more than 293 million infections and more than 5.4 million deaths globally (JHU, 2022). The repercussions of the coronavirus pandemic on society affected most areas of society, including health and the economy. The onset of the pandemic and the outbreak control measures influenced international trade, employment, and local businesses that heavily depend on in-person activities, such as restaurants and accommodation services. The immediate repercussions lasted until the reopening of public spaces. COVID-19 disrupted both primary and secondary production systems, causing supply chain disruptions due to illnesses and furloughs. Key economic sectors like the construction industry, while operational during the pandemic, encountered economic downturns, shortages in labour, restricted access to construction materials, and challenges in securing financial resources during the COVID-19 pandemic. Furthermore, COVID-19 brought uncertainties in finances, with serious consequences for revenues and changes in the strategic plans of companies (Kiana, 2021).

Throughout the history of humankind, numerous pandemics have appeared, reducing the population due to their severity and affecting mental health due to the risk of contracting the illness. Furthermore, pandemics have usually been a crucial factor in conflicts between countries

(Huremović, 2019, Decameron Web, 2010; Papagrigorakis, 2006). Table 1 briefly describes some of the pandemics that have affected humans.

Table 1 Resume of pandemics and afflictions.

Name	*Period*	*Region*	*Infections*	*Deaths*
The Egyptian Plague	1715 BC	Egypt	-	-
The Athenian Plague	430 – 426 AD	Athens	-	100,000
The Black Death	1346 – 1353 AD	Europe and Asia	-	150 million
Spanish Flu	1918 AD	Worldwide	500 million	50 million
SARS-CoV	2002 AD	Worldwide	8,422	919
MERS-CoV	2009 AD	Worldwide	2494	858
COVID-19	2019 AD	Worldwide	200 million	5 million

1.1.6.The Plague of Egypt

In 1715 BC, a plague spread through Egypt with an unknown origin. Studies (Trevisanato, 2004) point out that the plague reached Egypt through Avaris harbour, the main merchandise exchange Egyptian port at that time. Biological identification of the plague occurred in 2004. Based on some manuscripts describing the immunity to the disease of the Hebrew population in Egypt (Trevisanato, 2004). The study concludes that the bacterium Francisella tularentis caused the plague. The pandemic produced tremors, a skin infection and a death rate of 15% without treatment. Additionally, the emergence of the plague in ancient Egypt emphasised pre-existing socio-political difficulties. Due to the Francisella tularentis bacteria epidemic, the central government failed, and the armed forces increased their jurisdiction; as a result, the country was more susceptible to external influences (Huremović, 2019). There is a scarcity of information about the extent of propagation and the number of diseases associated with the Egyptian plague.

1.1.7.The Plague of Europe

Another disease in the ancient world, the Plague, also known as Black Death (Green, 2020), occurred in the period between 1346 and 1353 AD, with recurrent outbreaks during the next six centuries (Kacki et al., 2019). The disease was named the Black Death because of the dark blotches caused by subcutaneous haemorrhages that appeared on the skin of victims (Duncan et al., 2005). Recent studies conclude that the Yersinia pestis bacterium caused the outbreaks and originated in Asia Minor. Due to an already developed commercial system, the illness transferred to Crimea and then to Europe through the path of the Mediterranean Sea (Frith, 2011). The plague

of Yersinia pestis doomed 150 million individuals in Europe, China, Russia, and the Middle East (Huremović, 2019), with a mortality of 60% (Kacki et al., 2019). Entire families were eradicated, bringing a deficit in trade and manufactured products. The social and economic systems were disrupted by the lack of workers in agriculture. As a result, prices of the products had drastically risen, including food and basic products, affecting the economy of the population. Imported products became more expensive because of the risk involved in transportation during the plague; probably, the ancient supply chains were affected by the plague.

1.1.8.The H1N1 Pandemic

Several outbreaks of the Plague continued until the late nineteenth century, when another disease pounded humankind. The H1N1 pandemic occurred in 1918-1919, also known as the Spanish flu. The pathogen that caused the pandemic was the H1N1 strain of influenza, which was detected years after the outbreaks ceased (Huremović, 2019). H1N1 spread was facilitated by the intense connectivity between countries, making it the first pandemic to affect the entire world. The H1N1 pandemic resulted in around 500 million infections and 50 million deaths among mainly young adults and healthy individuals. Due to the H1N1 pandemic, many enlistees from the army died, weakening the troops and influencing the military operations during the First World War. The 1918 outbreak of influenza declined rapidly, within 9 months of its start (Huremović, 2019), but in 1928 and 1934, two mutations of the first H1N1 generated more deadly outbreaks (Telenti et al., 2020), with repercussions in the ongoing World War II at that time.

1.1.9.The SARS-CoV Outbreak

The first spike virus, or coronavirus, largely transmitted was the severe acute respiratory syndrome coronavirus 1 (SARS-CoV), which first appeared in Guangdong Province, China, in November 2002. Due to the efficient transmission of SARS-CoV in three months, the disease spread globally. Genetic sequencing of SARS-CoV was available after three months, bringing the opportunity to better understand the disease and to bring more effective diagnosis of infected patients (APSF, 2020). The SARS-CoV epidemic caused 8,422 infections and 919 deaths (11% mortality) in 32 countries (Yang et al., 2003).

1.1.10. The MERS-CoV Outbreak

In 2012, another coronavirus appeared; it was in a patient who died of acute pneumonia and renal failure in Saudi Arabia (Yang et al., 2003). The Middle East respiratory syndrome coronavirus (MERS-CoV) affects the lower respiratory tract, causing severe respiratory syndrome in humans. Its first outbreak resulted in 2,494 infections and 858 deaths in 27 countries (Yang et al., 2003),

reaching a fatality rate of 34.4%, but probably many cases were asymptomatic. The King Abdullah International Medical Research Centre developed a vaccine that is not commercially available (Chang, 2017).

1.1.11. The COVID-19 Pandemic

In 2019, COVID-19 emerged due to the spread of SARS-CoV-2. It first appeared in Wuhan, China and caused more infections than the previous coronavirus in less time (Marty et al., 2020). Due to the virus's fast spread, the World Health Organization (WHO) declared a public health emergency of international concern (PHEIC) on 30 January 2020, and a pandemic was announced on 11 March 2020 by the same organisation. In the first nineteen months of its detection, the new coronavirus produced more than 293 million cases and 5.4 million deaths in the world (Johns Hopkins University, 2022). Only in the United Kingdom (UK), COVID-19 caused more than 15 million confirmed cases and 150,000 deaths until January 2022. The percentage of infected people developing severe illness, hospitalisation and fatal cases was estimated at 13.8%, 6.1% and 3.6% in the UK (coronavirus.gov.uk, 2021). People over 60 years and with previous health conditions, including hypertension, diabetes, cardiovascular disease, chronic respiratory disease and cancer, are the most affected by the virus, developing severe illness (Verity et al., 2020). Furthermore, COVID-19 deeply altered the world by pressuring the health, political, social, and economic systems. The next section describes in detail the COVID-19 particularities affecting its spread and severity.

1.1.12. Social Effects of Covid-19

The COVID-19 pandemic has been the most severe pandemic caused by a coronavirus. Its first detection was in December 2019. This new virus quickly turned into a pandemic with unforeseeable socioeconomic repercussions, causing hardship. The virus was isolated and genetically classified in record time compared with previous historical events (Dal-Ré, 2020). Despite the achievement in classifying the new coronavirus, its propagation continued and led to a major pandemic in recent times (Kaina, 2021). Initially, the outbreaks grew exponentially because of the lack of precision in the implementation of the IHR and different reactions in countries (Singh et al., 2021).

1.1.12.1. Overview of the Impacts of COVID-19

Mainly, the elderly with pre-existing illnesses have a high risk of mortality. People with cardiovascular diseases, high blood pressure, diabetes, chronic respiratory diseases, and cancer face a 30- 50% risk of fatal outcomes in critical cases. In contrast, only 2.4% of young people

develop symptoms after contracting the virus (Kaina, 2021). However, fatal cases of young, healthy infected people have been recorded. According to a survey made by the Office of National Statistics (ONS) in March 2020, among the 5,432 pupils in the same stages of education, 11.7% tested positive in the same period, and among the 3,467 school staff in primary and secondary schools, 15.4% of them tested positive for COVID-19. Within the nine hundred construction businesses responding to a questionnaire to the ONS, 39.6% experienced difficulties getting materials, goods or services during October 2020, and they had to change suppliers or find another solution to continue their activities. Furthermore, in the same sample of companies, 55.0% required temporary closure due to lockdown regulations (ONS, 2020). COVID-19 caused turnover reductions of between 20% and 50% in 118 of the construction businesses surveyed. Also, 90 of them perceived a reduction in their profits by more than 50% in October 2020, compared with pre-pandemic levels.

1.1.12.2. Propagation Mechanism

The spread of SARS-CoV-2 can occur when droplets reach a new host via droplet and aerosol inhalation (Yang et al., 2020). Droplets and aerosols are expelled when infected individuals speak, cough, sneeze, etc., and the droplets and aerosols reach an uninfected individual. The principal route of transmission occurs from person to person. The transmission mechanism can happen when new potential hosts touch their hands to their mouth, nose and eyes after being in contact with settled droplets from infected people. The infection related to the new coronavirus occurs after the virus reaches a new host and then enters the cell. The virus uses a docking mechanism to attach to the host cell and begin genomic replication. For SARS-CoV-2, the anchor mechanism is mainly done by the angiotensin-converting enzyme 2 (ACE2), which is present in lung cells, kidneys, intestinal epithelium, heart, nose and mucus-forming goblet cells (Kaina, 2021).

The primary infection takes place in the nose, then the virus replicates in other parts of the body (Kaina, 2021). The concentration of ACE2 in the bronchi and nose can explain the early symptoms of the illness, but the presence of receptors of the virus in other organs and blood can lead to necrosis and thus vascular damage resulting in thrombosis and embolism. The ACE2 receptors are also found in the corneal cells located in the eye, so the infection can occur when the eyes are in contact with the virus (Kaina, 2021).

The docking process is assisted by the protease furin, which improves the cleavage of the S-protein, producing effective transmission of SARS-CoV-2. The infection is assumed to be more intense when the amount of virus entering a host is considerable, while a small amount of inhaled virus may result in a symptom-free infection.

The COVID-19 incubation period and recovery period vary according to the severity of the symptoms, but an average of 23.5 days has been reported (Alene, 2021; Mizrahi et al., 2020; Cheng, 2021) in cases without hospitalisation. Previous studies consider a maximum of 32 days of hospitalisation, indicating that most of the patients recover or die in that period (Wang et al., 2021). The shedding period is the time when infected individuals can transmit the virus; the mean shedding period is 8 days after the onset of symptoms (Kampen et al., 2021) and drops below 5% in the following 15.2 days post-infection.

1.1.12.3. The SIRDi Pandemic Model

Numerous mathematical models have been developed for the study of pandemic propagation dynamics (Gounane et al., 2021). Numerical analysis of pandemics gives information about the current state of a pandemic and future intensity for an evolutionary time-based propagation. Mathematical approaches assist the evaluation of risk level, forecasting the spread intensity and aid administrations in decisions for implementing containment policies. Numerical approaches for epidemiological events can give insight into the best practices to protect workers' health and the economy.

The SIR model was first proposed by Ronald Ross and William Hamer in the early twentieth century and describes the evolution of the susceptible (S), infected (I) and removed (R) individuals in a pandemic caused by a virus, bacteria or fungi (Weiss, 2013). This compartmental model consists of three joined non-linear ordinary differential equations. The system of equations is solved using calculus methods since an explicit formulation for the solution does not exist (Weiss, 2013). However, the solution of the differential equations of the SIR model uses the exponential integration presented in (Amanbaev et al., 2021).

In the SIR framework, susceptible corresponds to individuals at risk of getting infected by SARS-CoV-2 for the first time (Gounane et al., 2021). The infected category involves individuals contracting the virus and shifting from susceptible to infected. The removed group includes previously infected individuals who recovered or died because of the infection. The system of coupled equations combines the dynamics between susceptible, infected, and removed individuals with the rates between each category (Amanbaev et al., 2021). Main assumptions in this model include a large and closed population, a fast outbreak, natural births or deaths are null, the incubation period is equal to zero, recovered individuals obtain permanent immunity and a large uniform population mix (Weiss, 2013).

The sum of susceptible, infected and removed is equal to the total population (N=S+I+R) in the modelled period (Gounane et al., 2021). The SIR model coupled differential equations are shown

in Eqs. (1.1-1.3). The coefficients γ and α are the transmission rate and recovery rate, respectively. For a unit period, each infected person will have κ number of contacts in the population. The transmissibility η is determined as the portion of contacts resulting in transmission and becoming infected. The effective transmission δ is defined as the number of contacts being infected by a primary case per unit of time (δ=κη). Moreover, the transmission rate is the effective transmission divided by the total population (γ= k η/N). The effective reproductive number (R_e) is defined as the average number of secondary infections caused by a primary case (The Royal Society, 2020) and is expressed in Eqn. (1.4).

$$\frac{dS}{dt} = -\gamma SI \tag{1.1}$$

$$\frac{dI}{dt} = -\alpha I + \gamma SI \tag{1.2}$$

$$\frac{dR}{dt} = \alpha I \tag{1.3}$$

$$R_e = S_0 \cdot \frac{\gamma}{\alpha} \tag{1.4}$$

As described in Eqn. (1.4), the effective reproductive number must be constant when δ and α are constants. The death rate β is included to distinguish between those infected who recover or die. This modification defines the SIRD model. Considering the situation when S ≈ N and N>>R, then the right side of Eqn. (1.1) is equal to – kηI=-δI, and changes in S are small compared to N. Then the formulation becomes the IRD model contained in Eqs. (1.5-1.7) (Amanbaev et al., 2021).

$$\frac{dI}{dt} = -\alpha I - \beta I + \delta I \tag{1.5}$$

$$\frac{dR}{dt} = \alpha I \tag{1.6}$$

$$\frac{dD}{dt} = \beta I \tag{1.7}$$

The solution of the system of differential equations uses the exponential integrator (Ke et al., 2020). First, the Jacobian matrix of the IRD model is created using coefficients in the mathematical expressions. The matrix is solved to obtain the dominant eigenvalue, which determines the model evolution over time. Eqs. (1.8-1.10) are the IRD model integration where I(0), R(0), and D(0) refer to infected, recovered and dead individuals at the initial time t=0. The exponential growth rate (λ) of the pandemic is expressed in Eqn. (1.11).

$$I(t) = I(0)e^{\lambda t} \tag{1.8}$$

$$R(t) = R(0) + \frac{\alpha I(0)}{\lambda}\left(e^{\lambda t} - 1\right) \tag{1.9}$$

$$D(t) = D(0) + \frac{\beta I(0)}{\lambda}\left(e^{\lambda t} - 1\right) \tag{1.10}$$

(1.11)

$$\lambda = \delta - (\alpha + \beta)$$

The SIRD modified version includes the insulated and vaccinated segments of the population. The insulation coefficient consists of the insulation coefficients for susceptible and infected individuals, σ_S and σ_I, respectively. When the coefficients $\sigma_S=\sigma_I=0$, the insulation between susceptible and infected is null (Amanbaev et al., 2021). The immunisation coefficient σv comprises the portion of the vaccinated population, as well as their effectiveness in reducing symptoms (Ghosh, 2021). The range of values for isolation and immunisation coefficients is $0\leq\sigma_S$, σ_I, $\sigma_v\leq1$. The portion of susceptible non-isolated individuals $(1-\sigma_S)S$ and infected non-isolated individuals $(1-\sigma_I)I$ still contribute to the contagion. The part of the unvaccinated population is expressed by $(1-\sigma_v)S$. Eqs. (1.12-1.14) resulted in the substitution of the generalised insulation coefficient in Eqs. (1.8-1.10).

$$\frac{dI}{dt} = -(\alpha + \beta)I + (1 - \sigma)\delta I \quad (1.12)$$

$$\frac{dR}{dt} = \alpha I \quad (1.13)$$

$$\frac{dD}{dt} = \beta I \quad (1.14)$$

The generalised insulation coefficient σ is obtained from Eqn. (1.12) in the form $\sigma = 1-(1-\sigma_S)\cdot(1-\sigma_I)\cdot(1-\sigma_v)$. With this expression is clear that $\sigma=0$ if $\sigma_S=\sigma_v=\sigma_I=0$, $\sigma=\sigma_S$ if $\sigma_I=\sigma_v=0$, $\sigma=\sigma_I$ if $\sigma_S=\sigma_v=0$, $\sigma=\sigma_v$ if $\sigma_S=\sigma_I=0$ and $\sigma=1$ if $\sigma_S=\sigma_v=\sigma_I=1$. In the IRD model, the generalised insulation coefficient linearly increases as the infection linearly decreases (Amanbaev et al., 2021).

The IRD model integration, considering σ, results in a similar solution as presented in Eqs. (1.8-1.10) with a different λ. The new exponential growth rate with the inclusion of the insulation coefficient is shown in Eqn. (1.15). When the insulation coefficient increases, the exponential growth rate decreases and when (α+β) increases, the exponential growth rate decreases. Moreover, if α or β increases, then the propagation decreases, and if the parameters decrease, then the propagation increases.

$$\lambda = (1 - \sigma)\delta - (\alpha + \beta) \quad (1.15)$$

The isolation coefficients can delimit the boundaries in a pandemic for increasing or decreasing conditions regarding the portion of the isolated population. With this framework, the pandemic spread mainly depends on the generalised isolation coefficient (Amanbaev et al., 2021). However, in pandemic analysis, it is usual to include the reproductive number of the pandemic to determine if the pandemic is growing, decreasing or in an equilibrium condition. The reproductive number of a pandemic using the SIRD model is expressed in Eqn. (1.16). The reproductive number

formulation is valid when the isolation and death coefficients are null, σ=0, β=0; when the disease is σ=0, β=0; when a portion of the population is isolated, σ≠0, β=0; and in the general case for σ=0, β≠0.

$$R_e = \frac{S_0(1-\sigma)\gamma}{(\alpha+\beta)} \tag{1.16}$$

If the Eqn. (1.16) is substituted into Eqn. (1.15), then the exponential growth rate results in λ=(α+β)·(Re-1). Integrating the Eqs. (1.12-1.14) and considering the value of λ in Eqn. (1.15) gives the Eqs. (1.17-1.19), which includes the generalised insulation coefficient (Amanbaev et al., 2021).

$$I = I(0)e^{\lambda t} \tag{1.17}$$

$$R = R(0) + \frac{\alpha I(0)}{\lambda}\left(e^{\lambda t} - 1\right) \tag{1.18}$$

$$D = D(0) + \frac{\beta I(0)}{\lambda}\left(e^{\lambda t} - 1\right) \tag{1.19}$$

To compute the maximum number of infected individuals per unit of time, one can apply the method described in (Amanbaev et al., 2021). First, Eqn. (1.20) is divided by Eqn. (1.12), then the resulting expression is solved according to the variables. On the left side of Eqn. (1.22), the susceptible individuals, and on the right side, the infected. Integrating and separating the variables results in Eqn. (1.23).

$$dS = -(1-\sigma)\gamma SI \tag{1.20}$$

$$\frac{dS}{dI} = \frac{-(1-\sigma)\gamma SI}{(1-\sigma)\gamma SI-(\alpha+\beta)I} \tag{1.21}$$

$$\int_0^t \frac{(1-\sigma)\gamma S-(\alpha+\beta)}{(1-\sigma)\gamma S} dS = -\int_0^t dI \tag{1.22}$$

$$S(t) - S(0) - \frac{\alpha+\beta}{(1-\sigma)\gamma}\{\ln[S(t)] - \ln[S(0)]\} = I(0) - I(t) \tag{1.23}$$

In Eqn. (1.23) the value of removed and deaths at t=0 is assumed R(0)+D(0)=0 and Imax occurs when S(t)=S_c and t=t(I_{max}) (Amanbaev et al., 2021). The number of susceptible individuals when maximum infections occur is Sc. Then Eqn. (1.24) is obtained when the right side of Eqn. (1.2) is equal to zero. Substituting into Eqn. (1.23) results in the value of I_{max}.

$$S_c = \frac{\alpha+\beta}{(1-\sigma)\gamma} \tag{1.24}$$

$$\frac{I_{max}}{N} = 1 - \frac{\alpha+\beta}{(1-\sigma)\delta}\left[1 + \ln\frac{\alpha+\beta}{(1+\sigma)\delta} - \ln N\right] \tag{1.25}$$

In Eqn. (1.24), it is noticeable that I_{max} depends on the insulation coefficient and epidemiological parameters (Amanbaev et al., 2021). A simplified form of Eqn. (1.25) is expressed in Eqn. (1.26)

when Eqn. (1.16) is considered in the integration to calculate the maximum number of infections in the pandemic.

$$\frac{I_{max}}{N} = 1 - \frac{1}{R_e}\left[1 + \ln\frac{1}{R_e}\right] \quad (1.26)$$

Besides the presented mathematical solution for the IRD model, Particle Swarm Optimisation (PSO) is applied to approach the value of the epidemiological parameters based on the real data. Particle swarm optimisation is a stochastic algorithm based on the collective intelligent behaviour of groups of animals like a flock of birds (Wang et al., 2017). This mathematical approach is more accurate in estimating the pandemic parameters but requires more computational resources compared with analytical solutions. The present research has been developed using analytical solutions and PSO algorithms to generate the epidemiological parameters of COVID-19 in the UK.

1.1.12.4. The Spread of COVID-19

During the early pandemic, epidemiological parameters were known with little precision. Understanding the initial outbreaks was possible due to the available information from previous coronaviruses like SARS-CoV and MERS-CoV (Weiss, 2013). The epidemic information for SARS-CoV, MERS-CoV and SARS-CoV-2 is enclosed in Table 2. MERS-CoV has a low reproductive number and relatively high lethality, resulting in low transmission. SARS-CoV has high transmissibility and lethality, intensifying the risk of massive contagion, similar to SARS-CoV-2, which contributed to its massive propagation (Weiss, 2013; Du, 2020).

Table 2 Epidemiological characterisation of coronaviruses causing a respiratory viral infection. (Jha et al., 2021).

Parameter	MERS-CoV	SARS-CoV	SARS-CoV-2
Basic reproductive number (R_0)	0.3 – 0.8	3.0	2.0 – 2.5
Fatality	34.4%	9.6 – 11.0 %	3.4 %
Incubation period	6 days	2 – 7 days	4 – 14 days

As a first approach, Fig. 1 displays the computation of the solution using the SIR model when the reproductive number (R_e), transmission (δ), recovery (α) and death (β) rates are equal to 3.0, 0.24, 0.05 and 0.03, respectively; a 100% detection is assumed. In this study, the population N is 66,796,800 and is comparable to the UK population (Office of National Statistics, 2021).

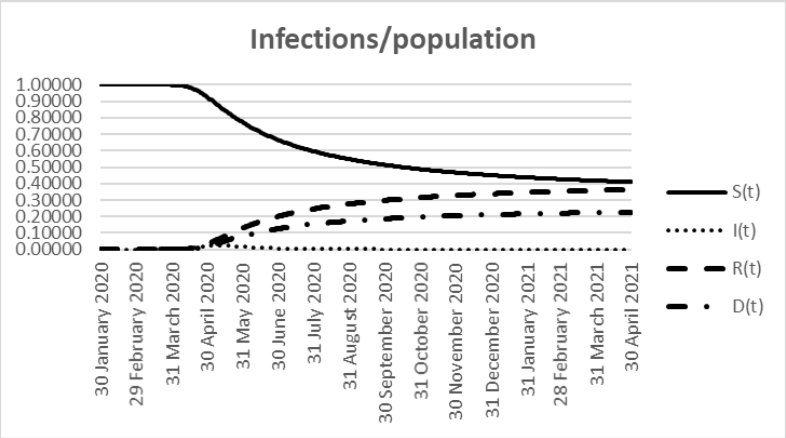


Figure 1 Susceptible, infected, removed, and deceased using Eqs. (8-11).

Using the UK official data (coronavirus.gov.uk, 2021), 2 initial cases were considered for the first day of the pandemic (t=0), on 30 January 2020. Possible infections occurred before the start date of the records, although in this study, only official data accounts for the epidemiological model. The basic reproductive number (R0) is 2.7 during the early spread of COVID-19 (The Royal Society, 2020). The pandemic peak would have occurred on 17 May 2020 without NPM. That situation must have produced more than 30% of the total population getting infected in one day, as presented in Fig. 2. The pandemic gradually decreased until 31 December 2020, when the variations are small compared with other pandemic stages.

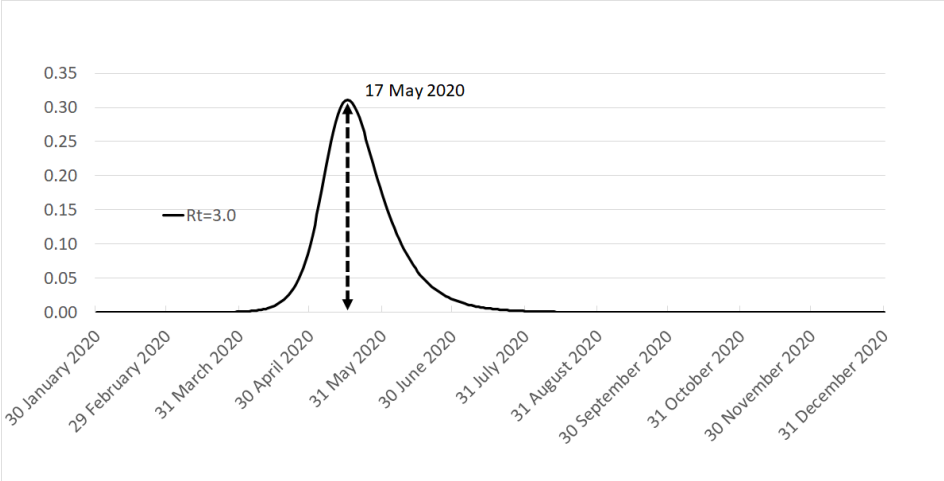


Figure 2 Active cases computed with the SIR model with R0=3.0 and 2 initial cases.

Analysing R0 (constant) in the first stages of the spread of the pandemic helps to forecast the potential consequences of novel viruses, and the study of R (variable) of a pandemic contributes to the decision to ease or intensify the control measures in subsequent stages (The Royal Society, 2020). In Fig. 3, the pandemic peaks for MERS-CoV, SARS-CoV and SARS-CoV-2 are plotted for comparison purposes. The reproductive numbers for the three different viruses are 1.7, 3 and 2.7,

respectively. The peak of a pandemic happens first if the basic reproductive number is high, which means that a higher reproductive number can delay the occurrence of the pandemic peak.

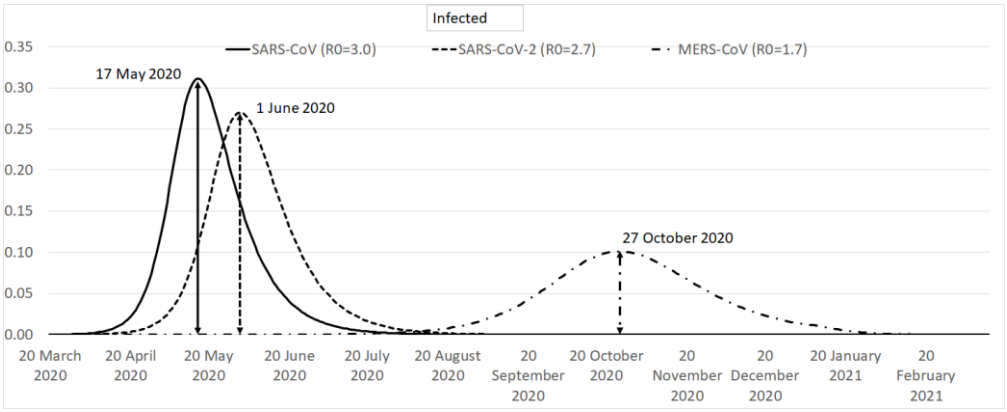


Figure 3 SIR computed active cases for MERS-CoV, SARS-CoV and SARS-CoV-2.

The SIR model computes the total number of susceptible, infected, and removed individuals in a population (Weiss, 2013). In this study, the initial conditions are I(0)=2, R(0)=D(0)=0 and susceptible population is computed with S(0)=N-I(0)-R(0)-D(0). For the COVID-19 pandemic, the reproductive number values range from 2.0 to 2.5 in steps of 0.1. α and DR (α and β) were set constant at 0.05 and 0.03, respectively. The γ was computed using Eqn. (1.4), giving the values of 0.162, 0.171, 0.178, 0.186, 0.195 and 0.203, respectively. The maximum number of daily infections reaches 0.005, 0.007, 0.008, 0.009, 0.012 and 0.013 as a function of N, as shown in Fig. 4. Pandemic spread is considered to begin on 30 January 2020. The crest of the infection wave arrives sooner when R_e increases. The maximum infections vary by up to 45 days with different Re. Total infections of the spread until 31 January 2021 are 0.60, 0.71, 0.82, 0.93, 0.39 and 0.43 for each reproductive number regarding the population N.

The mathematical modelling of a pandemic in the presence of insulation (σ>0) is presented in Fig. 5 (Amanbaev et al., 2021). The variations in transmissibility when σ takes the values 0.00, 0.036, 0.080, 0.121, 0.16 and 0.200 are used in the computation. The estimation is made using Eqs. (1.17-1.19) with the exponential growth rate defined by Eqn. (1.15). Like reducing the R in an early forecast of a pandemic, implementing NPM delay the peak in time and reduces the infections.

Considering the immunisation coefficient σ_v equal to zero during the first months of the contagion until day 314 of the pandemic, vaccination begins on 8 December 2020. The immunisation coefficient monotonically increases by 0.002 per day until it reaches 0.47 N vaccinations. Regarding the vaccination period, reaching 0.47N vaccinations takes 235 days with the mentioned vaccination rate per day. Once the maximum vaccination of 0.47N is reached, its value is constant for the rest of the period. Fig. 6 compares the number of deaths calculated with Eqn.

(1.19) when the immunisation coefficient increases from zero to 0.47N and the insulation coefficients $\sigma_S = \sigma_I = 0$. A vaccination effect is that the number of deaths decreases as the number of vaccinated individuals increases.

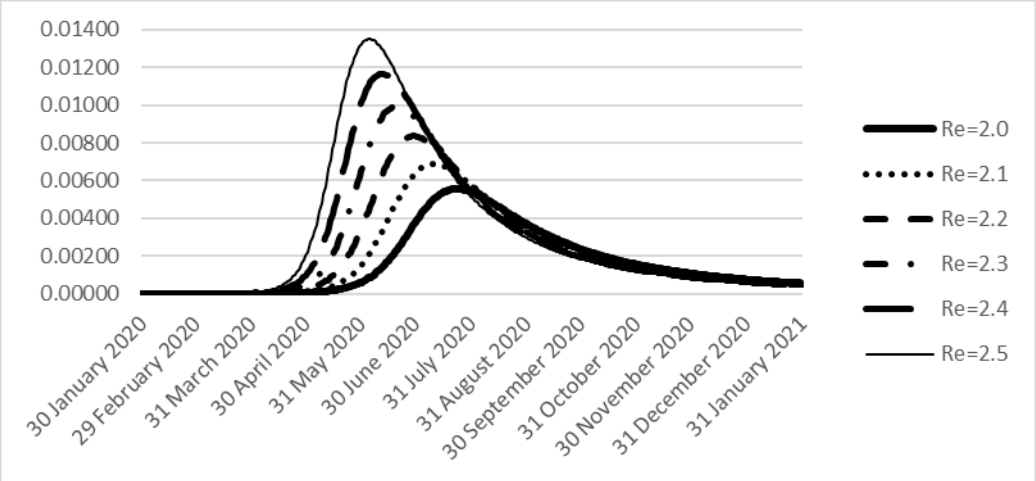


Figure 4 Number of infected individuals per unit of time (I(t)/N) with reproductive number Re=2.0, 2.1, 2.2, 2.3, 2.4 and 2.5 in thick continuous, dot, dash, dot-dash, long dash, and fine continuous lines. Recovery and death rates were set equal to 0.05 and 0.03

Variations in the generalised insulation coefficient σ affect the course of a pandemic (Amanbaev et al., 2021). If σ increases, then the epidemiological intensity decreases, and when σ decreases, the pandemic intensity increases. The pandemic intensity defines the maximum number of infections or the peak infection waves. According to Eqn. (1.26), the maximum number of infections is a function of the reproductive number. If the epidemiological parameters α, β and δ are constant for a pandemic, and if σ varies from 0.1 to 0.6, then the maximum number of infections can be computed. (Fig. 7) displays the maximum number of infections when the generalised insulation coefficient varies from 0.1 to 0.6 for different reproductive number values. As the reproductive number increases, the maximum number of infections increases.

The transmissibility of COVID-19 changed with the non-pharmaceutical measures applied by national administrations. In this direction, the pandemic presented more than one wave, and this behaviour originates from NPM. Despite the several waves caused by health regulations, each wave has been less severe than the wave expected without policies to prevent the saturation of medical centres. (Fig. 6) contains the number of new infections per day registered in the UK (coronavirus.gov.uk, 2021) as a thin line and the number of new cases per day generated with the model as a dotted line.

In Fig. 6, it is noticeable that the modelled data varies in comparison with the real data, especially in peak periods when the number of new cases drastically changes. The accuracy of this approach is 60.0%, and hence, further development of the model is required.

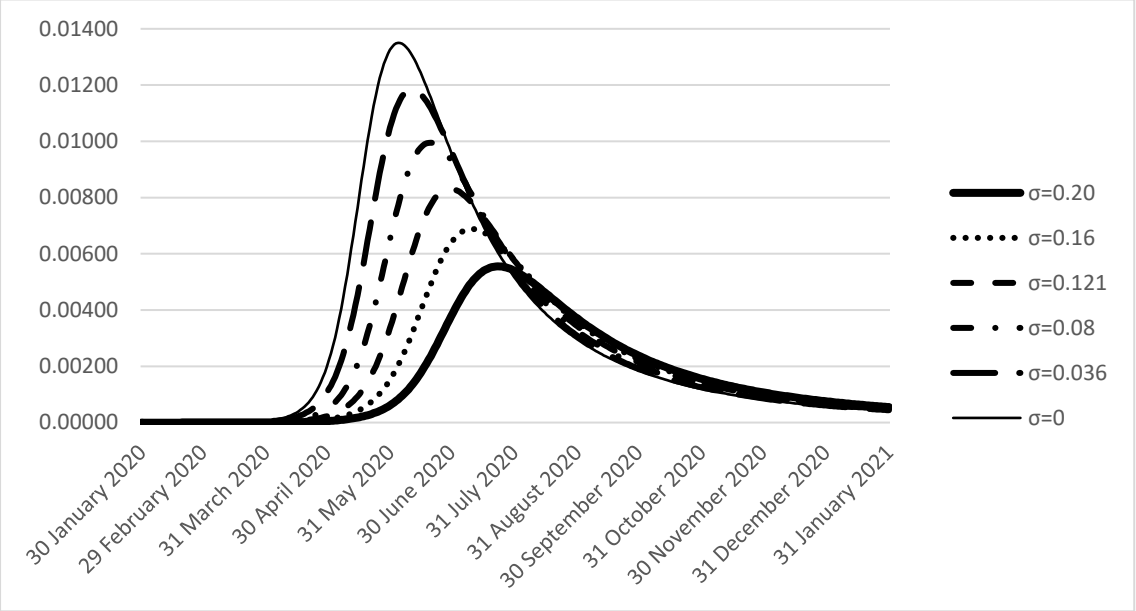


Figure 5 Number of infections (I(t)/N) when the generalised insulation coefficient varies from 0.0 to 0.2 for a pandemic starting on 30 January 2020.

According to Eqn. (1.1), the new cases per day can be computed as δI. Fig. 9 contains the officially detected and modelled new cases per day. With this perspective, it is possible to increase the accuracy of the computation, which can be productive for the study. Using arithmetical approximations, the modelling reaches an accuracy of 96.2%.

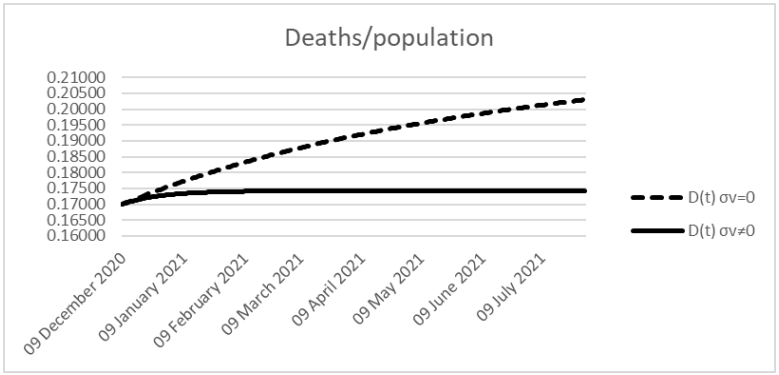


Figure 6 Pandemic deaths considering the absence of vaccination (dashed line) and when the immunisation coefficient varies (continuous line) in the absence of NPM.

COVID-19 and the containment policies impacted the economic system in several ways (Chetty, et al., 2020). Changes in consumption patterns, income reduction and closure of commercial places resulted in reduced wages and job losses (Chetty, et al., 2020). Previous studies attempted to analyse the economic repercussions of COVID-19 during the first stages. Nevertheless, there is a lack of research related to the epidemiological parameters and their impacts on the construction

industry during the whole pandemic. The objective of this work is to construct an integral model for an integral study of COVID-19's impact on the construction industry.

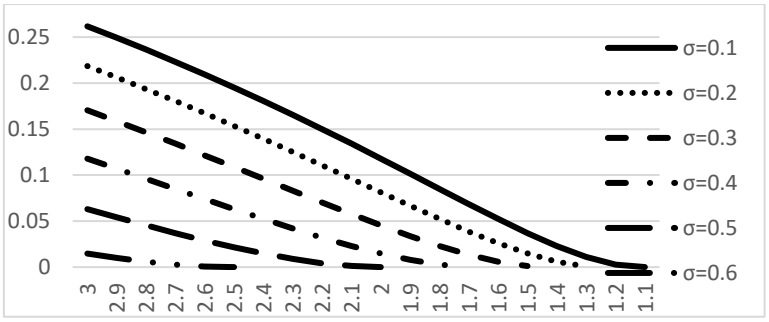


Figure 7 Maximum number of infections for the generalised insulation coefficient equal to 0.1, 0.2, 0.3, 0.4, 0.5 and 0.6 in solid, dotted, dashed, dash-dotted, long-dashed, and long-dash-double-dot curves.

The gaps between health emergencies and the economic system are multidimensional and vary between economic regions. To accomplish an accurate analysis, one must consider the immediate and long-term pandemic repercussions on the economic system. A time delay between pandemic intensity and its impacts adds complexity to the analysis. This section consists of a mathematical study of the implications of COVID-19 in the construction industry. The integral mathematical approach contributes to minimising the economic losses during the pandemic in the construction industry.

For multiple reasons, the COVID-19 pandemic delayed the growth in the construction industry and may have consequences in the future. First, the demand for new construction projects changed due to COVID-19 (ONS, 2021). This analysis searches for the links between the number of new construction projects during the COVID-19 period. Second, the growth index in the construction industry is linked to the pandemic intensity and its variations over time, with an exponential spread during the early pandemic; the construction industry index contracted. The interconnection between the pandemic intensity and the construction industry index is studied with the development of a mathematical model fed with COVID-19 transmissibility, recovery and death data.

The COVID-19 epidemiological parameters in the UK are extracted from the official data (coronavirus.gov.uk, 2021). Using exponential integration of the SIR model, the transmission, recovery, and death rates were obtained. To verify the mathematical process, the pandemic rates computed in this work must be equivalent to the official weekly reproduction numbers of COVID-19. The computation begins on 21 March 2020 and finishes in April 2023.

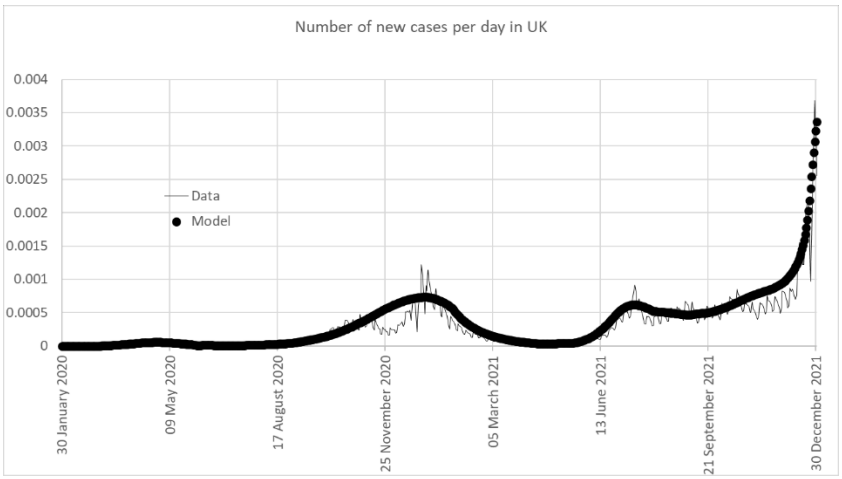


Figure 8 New infections per day in the UK. The official data is shown as a thin line, and the modelled data is shown as a dotted line.

Considering the COVID-19 new cases and deaths in the official data, the transmission, recovery and death rates can be estimated for each day of the pandemic. The recovery rate is equivalent to the subtraction of infections and deaths in a period. The calculation of the reproduction number links Eqn. 1.16 and the pandemic rates of COVID-19 in the UK. Fig. 10 displays the histogram of the calculated reproductive number for the COVID-19 pandemic in the UK. The reproductive number varies between 0.7 and 5.9 during the period of study and 95% of the reproductive values are between 0.7 and 2.5.

The comparative analysis of COVID-19 economic impacts on the construction industry considers the epidemiological parameters in combination with the industry data for the UK to find the interconnections between epidemiological parameters and construction industry indices. Initially, the monthly average values of the epidemiological parameters are compared with the industry monthly index. Fig. 11 shows a graphical comparison between epidemiological parameters and construction industry indexes. From the chart, it is noticeable that the construction index varies strongly, especially during the early stage of the pandemic. For the period between April and September 2020, data show intense dynamics between epidemiological parameters and industry indexes. This situation elucidates the fact that during the first wave of COVID-19, the construction industry personnel learned about the health measures in the workplace. Besides, managers were able to acquire new projects in the subsequent stages of the pandemic when the economy started to recover.

At this stage, the work continues to be developed by searching for and obtaining data from official sources related to the construction industry and epidemic rates concisely. With the comparative analysis, one can notice the influence of the epidemiological parameters on the growth index for the construction industry. To go further in this analysis, the model will be adopted to estimate the

dynamic impact of the COVID-19 pandemic on the construction industry. With the modelling, more detailed analysis can be determined with the incorporation of changes in policies, technology, consumer demand and investment.

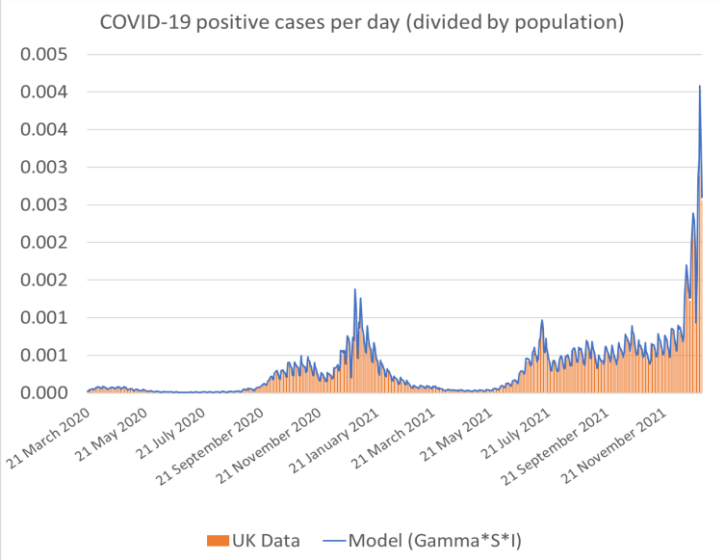


Figure 9 COVID-19 new cases per day. The orange bars are the official data from coronavirus.data.gov.uk and the blue line is the modelled data.

1.2. Pandemic Risks for the Industry

COVID-19 has strongly affected the health of the population and has brought several consequences for society, including economic impacts and effects on the industry and commerce. In the next section, some consequences for relevant economies and their industry are described with the Full Causal Effect.

1.2.1. Economic impacts of COVID-19 and the industry

Reducing the impact of the pandemic on the economy of the construction industry involves a proactive strategy rooted in the application of data science and pertinent information. The inherently dynamic characteristics of macroeconomics make it challenging to develop a universal theory for the construction of GDP. In the absence of a comprehensive framework, this statistical approach assesses the causal connection of individual explanatory variables with the GDP of the construction industry during COVID-19.

The COVID-19 pandemic affected the most vulnerable sectors in society, increasing the difficulties for the working class. Only in 2020 did working hours reduce by 8.8% in the world; this is comparable to 255 million full-time jobs (Raimo et al., 2021). Besides, some enterprises suffered a lack of new projects, delays and cancellations (Twahirwa et al., 2021). The non-

pharmaceutical measures brought the closure of manufacturing industries, offices and other work fields with inevitable economic repercussions. COVID-19 produced economic losses that were not possible to prevent because of the imperative priority of safeguarding the health and life of the population, which weighed more than economic effects during the pandemic. Intermittences in supply, demand, and logistics prevailed with COVID-19, showing the degree of vulnerability of the supply chain affecting the global economy (Trabucco et al., 2021).

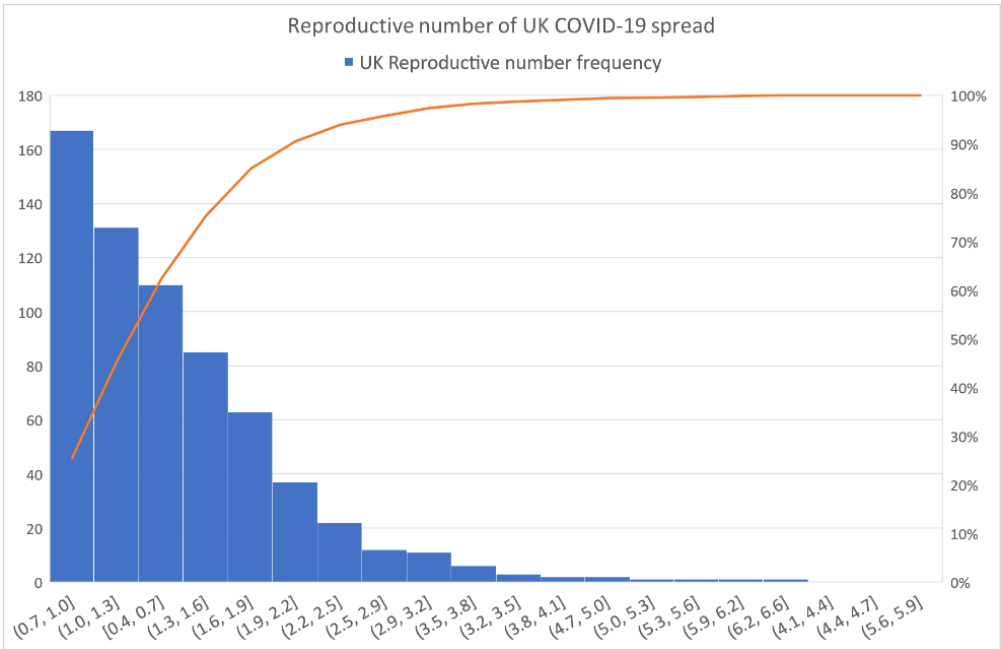


Figure 10 Reproductive number for COVID-19 using UK data. The Re was computed using exponential integration and corroborated with PSO methodology.

Most governments and administrations adopted mitigation rules, including mandatory stay home restraints for people to gather in non-ventilated spaces, closure of schools and workplaces, limited non-essential activities, isolation of people with flu-like symptoms, etc. The measures to contain the spread included restricted opening hours, closed parts of the economy and travel restrictions (Chetty, et al., 2020). The measures affected the population, who experienced a reduction in their incomes, and many others perceived economic uncertainty due to the pandemic; some individuals lost their jobs, and others had to close their businesses (Chetty, et al., 2020).

According to the International Monetary Fund (IMF), governments implemented economic packages to minimise the repercussions of the pandemic on the economy and to help the most affected people during the pandemic. Besides efforts made to minimise economic effects, a technical and economic effort was made to develop and apply COVID-19 vaccines. Table 3 includes the first case detection, economic contraction, vaccination levels and economic packages

for the major economies in the world. The data contains the spending made by national organisations to develop and provide vaccines (IMF and JHU, 2022).

Table 3 COVID-19 first confirmed case, economic contraction, vaccine doses and recovery economic policies for the major economies (source: International Monetary Fund and Johns Hopkins University)

Country	*1st Case*	*Economic contraction 2020 (%)*	*Economic packages (% GDP)*	*Vaccine doses (millions) until January 2021*
United States	*January 2020*	*31.4*	*4.1-2020 8.8-2021*	*505.4*
China	*January 2020*	*6.8*	*7.1*	*2,847.9*
Japan	*January 2020*	*3.6*	*20.9-2020 13.1-2021*	*199.6*
Germany	*January 2020*	*5.0*	*10.3*	*149.7*
United Kingdom	*January 2020*	*9.8*	*2.6-2020 19.5-2021*	*134.1*
India	*January 2020*	*7.3*	*10.0*	*1,466.9*
France	*January 2020*	*8.0*	*23.0*	*123.6*
Italy	*February 2020*	*8.9*	*32.0*	*111.6*
Canada	*January 2020*	*1.4*	*19.7*	*68.7*
Russia	*January 2020*	*3.0*	*4.5-2020 1.5-2021*	*146.7*
Australia	*January 2020*	*10.0*	*15.7-2020 2.5-2021*	*42.8*
Brazil	*February 2020*	*7.2*	*12.0-2020*	*331.3*
Spain	*February 2020*	*3.6*	*7.4-2020*	*86.2*
Mexico	*February 2020*	*8.2*	*6.4*	*148.9*

The results of lockdowns in the economy were reflected during the second quarter of 2020, with consequences after restrictions eased. In the UK, a reduction in spending registered significant effects on the industry at different levels, with more intense effects during the 17 months of the roadmap out of lockdown, from March 2020 to July 2021.

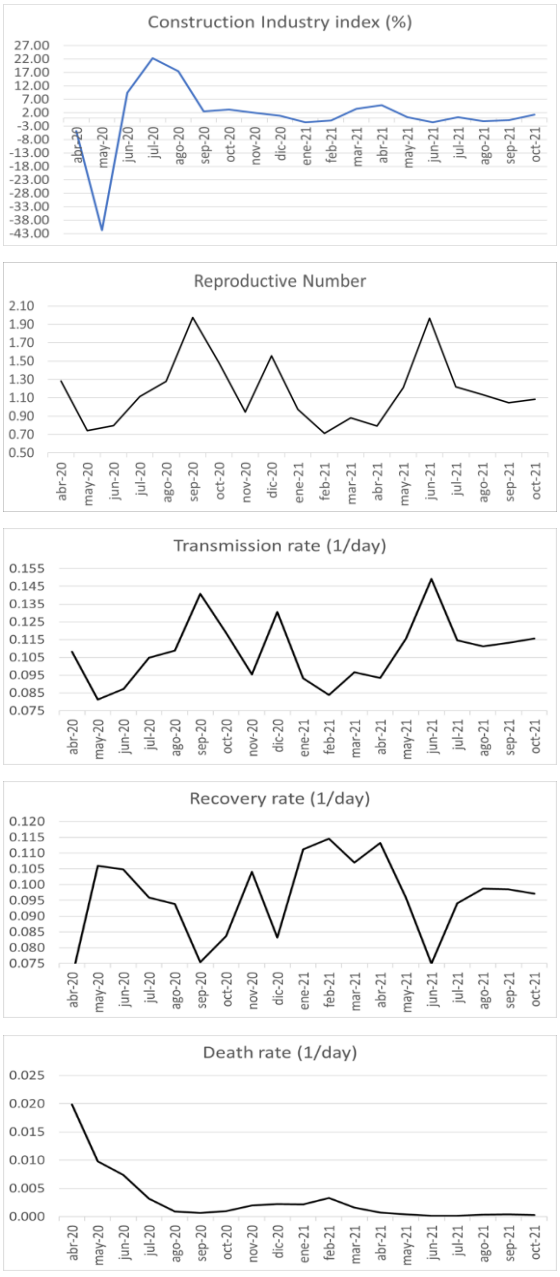


Figure 11 Epidemiological parameter comparison with construction industry growth rate in the UK.

According to the ONS, during the first quarter of 2020, the gross domestic product (GDP) growth average was 1%, a modest decline compared to the previous quarter. In this period, the COVID-19 consequences were not noticeable yet (Harari et al., 2021). In 2020, after the official beginning of COVID-19, the UK GDP fell 9.8%, reaching its lowest level since 1921 (Harari et al., 2021).

The first wave of COVID-19 motivated the implementation of a lockdown in the UK in early 2020. Due to this situation, the GDP of the UK fell 19.4% during the second quarter of 2020 (ONS, 2021). The easing of the restrictions after the first lockdown partially recovered the economy, and this tendency continued until the last quarter of 2020, when infections increased and restrictions were tightened.

The essential economic activities remained open since the beginning of COVID-19, including the construction industry (Harari et al., 2021). The continuity of construction activities held during the fall of the early pandemic. Nevertheless, harm in construction happened. Outbreaks in the job field reduced staff numbers, and companies perceived profit reductions because of increases in the prices of materials and low demand for services (ONS, 2021). Between April and May 2020, the construction industry decreased by 41.7% (ONS, 2021).

The UK economy declined in 2020, and the construction industry registered economic reductions. Disrupted activities on construction job sites negatively affected the health of workers, caused outbreaks and reduced the number of active employees due to quarantines. Further analysis of COVID-19 spread will give insights for tuning the non pharmaceutical measures aiming to minimise the risk in workplaces. Simultaneously, the study of COVID-19 and the construction industry kinetics supports the decision-making to prevent economic losses.

1.3. Research gaps

Various attempts have been made to model the spread of a virus and, separately, to analyse the implications of the pandemic on the economy of the construction industry. However, this is the first effort to combine epidemic and economic parameters in a semi-parametric model, aiming to find the causal connections between pandemic rates, the macroeconomy and the construction industry productivity during an outbreak.

The motivation for this work arose from the intention to find gaps between pandemic intensity and its impacts on the construction industry in a modern economy. This work analyses the effects of COVID-19 on the economy of the construction industry and determines the variables associated with the performance of the construction industry during COVID-19.

1.4. Aim and scope

This work analyses the influence of a pandemic on industrial activity, with particular emphasis on the movement and interaction of supply chains. The central aim and contribution of the study is to develop a numerical representation of these dynamics using a system of interconnected equations. The study was motivated by a period of rapid economic and industrial change, during

which a set of interconnected systems of equations was developed to describe the relatively faster-changing relationships between key economic and industrial variables. Each system consists of linear equations describing relationships between at least two elements, such as private spending and international investment. For each dependent variable, multivariate regression equations are estimated using a set of explanatory variables. Statistically significant relationships are then combined to construct a network of interconnected equations representing the structure of the system.

The resulting model produces a multidimensional distribution of estimated coefficients that describes how relationships between variables evolve. The existence of a group of systems of equations that complete the numerical tests may correspond to the occurrence of each system at a specific location across time and space. This provides a four-dimensional representation in which the interactions between variables constitute the underlying structure, while time and spatial dimensions capture their evolution. The approach therefore provides a numerical framework for representing industrial and supply-chain interactions over the period and countries considered in the study.

The simulation considers the condition of the industry and its dynamics using epidemic, economic, and technical datasets. The analysis of the industry during COVID-19 adopts a global statistical approach based on 14 countries, representing approximately 75% of global GDP. The results are subsequently considered by continent to capture variations across geographical regions and periods.

Industrial productivity is specified as the dependent variable and is related to relevant information from the economic and health sectors during the COVID-19 pandemic. A dataset comprising 25 variables was collected for the analysis, including macroeconomic and pandemic-related information. Auxiliary regressions were used to determine the exogenous variables within the dataset. A collinearity analysis was then conducted to assess the relevance of the predictors for industrial productivity. The resulting statistical relationships provide the basis for identifying the causal links governing industrial activity during the COVID-19 pandemic. The present thesis contains six main objectives:

A) To characterise the influence of the COVID-19 pandemic on industrial productivity using economic, health, and technical indicators.
B) To identify the statistically significant relationships between industrial productivity and relevant macroeconomic and pandemic variables.

C) To determine the causal structure of the interactions between economic, health, and industrial variables using interconnected systems of equations.
D) To develop a multidimensional numerical representation of these interactions across time and space.
E) To compare the resulting relationships across countries and geographical regions, identifying variations and changes between periods of the pandemic.
F) To evaluate the applicability of the proposed modelling framework for representing industrial and supply-chain responses to large-scale disruptions.

The methodology consists of two computational approaches consisting of two parts: (i) predicting the spread of COVID-19 more realistically in a population and (ii) modelling the links between virus spread and datasets in the economy so that the combined understanding would help to manage pandemics in future. The SIRDi model (susceptible, infected, recovered, and deaths) is used to compute the transmission rate (TR), recovery rate (RR) and death rate (DR) for SARS-CoV-2 in the 14 studied countries. The Full Causal Effect (FCE) was applied to the econometric models.

1.5. The origin of the simultaneous equations system

It has been observed that the mediator between cause and effect is often unobserved (Jiang et al., 2023). However, when observations are collected following the occurrence of an event, the resulting data may contain information about the processes that contributed to the observed state of a system. This provides an opportunity to identify and quantify the relationships that influence system behaviour. In this thesis, this concept is developed through the identification of statistically supported relationships between variables and their organisation into interconnected systems of equations. The resulting framework represents system behaviour through relationships whose configurations may vary across space and time. At the current stage of development, these relationships are represented through successive statistical configurations, analogous to snapshots of the system. Further development could extend these configurations towards a more complete representation of how an event propagates through a space–time network and produces subsequent changes within the system.

Several established statistical and causal approaches provide foundations for this development. Neural networks, for example, represent signal–response relationships through interconnected mathematical structures that approximate aspects of real-world systems (Creel, 2017). Their layered architecture can identify combinations of relationships that may not be directly observable in the original data. This is conceptually related to the approach developed in this

thesis; however, an important distinction is that the relationships identified here are explicitly formulated as statistically supported equations and subsequently evaluated as interconnected systems.

Marginal integration provides another relevant approach to causal inference (Li et al., 2017). It represents variables as interconnected nodes through coefficients estimated from regression relationships, including lagged and interdependent variables. This is related to the concept of a *scenario* developed in this thesis, in which a defined configuration of equations represents the relationships within a system under specific conditions. The present research extends this concept by examining how such configurations may vary across multiple locations and periods rather than treating them as fixed representations of a system.

Granger causality has similarly been used to incorporate spatial and temporal information into causal analysis. Skripnikova and Michailidis (2019), for example, demonstrated how observations across multiple countries can be combined with temporal information and lagged cross-country relationships to improve prediction. However, Granger causality primarily establishes predictive precedence and does not, by itself, provide a complete representation of the interconnected structure of a system.

The present research therefore employs moment conditions within a defined regression framework. Combinations of variables are evaluated according to whether they provide statistically valid explanations of the objective function. The resulting statistically supported relationships are then combined into systems of equations rather than being treated as isolated effects. Simultaneous linear equation (SLE) systems are constructed and estimated using least-squares methods to reproduce the observed relationships within the data. The resulting systems can subsequently be evaluated under progressively changing or extreme conditions to identify convergence limits. These convergent states represent alternative configurations of the system and may, in an econometric context, correspond to different combinations of policy, production, economic, or social conditions. The approach therefore extends statistical estimation towards the numerical exploration of alternative system states.

The development and application of this framework are supported by the three manuscripts that constitute the core of this thesis. The first manuscript establishes the empirical foundation by examining the effects of COVID-19 on major global construction economies. Using economic, health, and industrial indicators across 14 countries, it demonstrates how a large-scale disruption can be represented through measurable relationships between industrial productivity and wider

economic conditions. It therefore addresses the initial objective of identifying relevant variables and establishing statistically supported relationships associated with industrial activity during a major disruption.

Taken together, the three manuscripts form a progressive research sequence from empirical observation, through structural modelling, to broader conceptual and evidential validation**.** The first establishes that relationships between industrial and economic variables can be identified during a major disruption. The second formalises these relationships within a structural econometric framework and provides a method for organising and evaluating them as interconnected systems. The third situates the empirical and methodological findings within the wider literature on disruption, construction, supply chains, and resilience.

Collectively, the three manuscripts provide complementary empirical, methodological, and conceptual foundations for the central aim of the thesis: to develop a numerical framework capable of representing interconnected industrial and economic relationships and examining how their configurations change across space and time. In doing so, the research progresses from the identification of individual statistical effects towards a numerical representation of interconnected system dynamics.

1.6. Contributions of the PGR to this work

Across the three publications, V.E.G. Vilchis was responsible for the primary development and execution of the research. For the first article, he conducted the numerical simulations and validation and prepared the manuscript for publication. For the second article, he derived the equations, developed the initial modelling framework, and prepared the manuscript. For the third article, he conducted the literature review, developed and prepared the manuscript, and addressed the reviewers' comments throughout the revision process. In all three cases, he led the preparation and progression of the research towards publication.

2. RISK MITIGATION: NUMERICAL ANALYSIS OF COVID-19'S IMPACT ON MAJOR GLOBAL CONSTRUCTION ECONOMIES

2.1. Abstract

Learning from the past is a key risk mitigation strategy, as it involves analysing previous experiences to identify mistakes or successes. By understanding these lessons, organisations can take proactive measures to address potential risks in the future, minimising both their likelihood and impact. By using high-performance computing, this study mixes economic and pandemic predictors to enhance the understanding, modelling and quantification of disaster risks within the major global construction industries during COVID-19. By systematically identifying key variables and developing a robust risk index through predictive modelling and empirical validations, the research presents the relative risk index for managing crisis responses and resilience strategies at global and continental levels. The framework used here aligns with the globally recognised disaster risk management initiatives, such as the Sendai Framework, and leverages real-time data and automation to facilitate proactive, data-driven decision-making in the face of global crises. Using the Arellano test specification, the study identified 10 significant explanatory variables pertaining to the productivity of the construction industry. FDI, share prices and total spending had positive regression coefficients. An increase in such explanatory variables is beneficial for the productivity of the construction industry. The analysis of the causal effect found that the employment rate, inflation, pandemic growth, reproduction number R and the transmission rate had a negative link with the construction industry productivity. This study remarks that when excluding statistically independent pandemic variables, the model did not obtain valid regressors, emphasising the importance of accounting for both the economic and pandemic data for causal effect detection.

2.2. Keywords

Construction economy, COVID-19, Generalised Method of Moments (GMM), causal link, risk mitigation, pandemics

2.3. Introduction

The construction industry, a basis of global economic growth, is susceptible to disruptions from pandemics and economic downturns [1]. Traditional disaster risk management frameworks often fail to capture the interconnected nature of these crises, necessitating a more integrated and predictive approach [2]. This study seeks to bridge this gap by systematically incorporating

economic and COVID-19 pandemic-driven predictors. By identifying key economic variables—such as foreign direct investment (FDI), employment rates, share prices and total spending—and pandemic-specific indicators, this research develops a robust cross-linked model of the industry. This approach aligns with global disaster risk guidelines, including the Sendai Framework [3], recognising that pandemics are not isolated events but systemic risks with profound economic implications. The study introduces a risk index and exploits advanced numerical modelling to quantify vulnerabilities and enhance crisis preparedness.

Throughout human history, pandemics have risked society by negatively affecting public health and disrupting economic activities [4, 5]. Historical examples of the pandemic include the Egyptian plague of 1715 BC, which is believed to have entered Egypt through Avaris Port, the main merchandise exchange port at that ancient time. The biological classification of the Egyptian plague was estimated around three centuries later, using archaeological records from that period [6]. Another historical pandemic, the Athenian plague (430–426 BC), reduced the population by 25%, with severe repercussions for the health and the economy of Athens [7]. Similarly, the Plague of 1346–1353 AD had a profound and long-lasting impact, causing recurrent outbreaks over six centuries [8]. This pandemic disrupted the socio-economic system, leading to a shortage of workers, increased prices and widespread economic turmoil. The most experienced workers were more severely infected by the virus, leaving the supply chain without experienced labour faster, which can exponentially increase the risk of the pandemic [9]. The historical perspective on pandemics demonstrates that they are not isolated events and can have severe repercussions on society.

More recently, in December 2019, a new pandemic emerged. Originated by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and first detected in Wuhan, China, the coronavirus disease 2019 (COVID-19) caused more infections than previous coronaviruses on a global scale [10]. COVID-19 caused over 293 million infections and more than 5.4 million deaths globally by December 2021 [11], with repercussions for the health and economic systems. COVID-19 containment policies reduced virus spread but simultaneously disrupted the economy, altering consumption patterns, reducing income and causing widespread business closures, which led to wage reductions and job losses [12]. On December 8, 2020, the COVID-19 vaccine became available under emergency approval and was used to immunise the population under emergency approval to reopen public spaces and protect the economy from further damage [13, 14, 15].

During the initial 11 months after the first detected outbreak, an economic crisis occurred, affecting the economy since 2020 [16]. During that period, governments spent considerable

portions of their gross domestic product (GDP) to mitigate the economic repercussions and support the most affected businesses and individuals. According to the International Monetary Fund (IMF) [17], the United Kingdom (UK), United States of America (USA), India, United States of Mexico, Italy, France, Japan and Canada spent 8.8%, 20.9%, 19.5%, 10.0%, 23.0%, 32.0%, 19.7% and 6.4% of their GDP to mitigate and contain the health and economic effects of COVID-19 in 2020, respectively. Besides the expenses induced by the pandemic, according to the IMF, in 2020, their GDP contracted by 31.4%, 3.6%, 9.8%, 7.3%, 8.0%, 8.9%, 1.4% and 8.2%, respectively. In some countries, the loss is nearly 50.0% of the total GDP. The severity of the pandemic not only affected public health, but it also constrained the economy at the global and continental levels [16].

The economic impact of COVID-19 has been studied previously by [18, 19] in terms of the dual demand-supply chain, where shifts in consumer behaviour increased the demand for essential goods like medical supplies, household necessities and electronics. The closure of borders to control the spread reduced international trade, and the supply of goods was limited by the coronavirus outbreaks. Simultaneously, the demand for certain sectors like travel, hospitality and luxury goods dropped, reducing the GDP due to low demand and contributing to production shortages when the demand rebounded [19, 2]. Besides the relevance of the impacts of the pandemic on the economy, there is a lack of integrated research on the numerical analysis of epidemiological parameters and their impact on the construction industry during the COVID-19 outbreak and their detailed relevance for macroeconomic parameters.

The studies on the economic impacts of pandemics emphasise the complex scenario that challenges traditional economic theories and methods for minimising the risks posed by such health emergencies [20]. Economic crises are often turning points [21], and classical economic methods appear insufficient to fully explain and prevent the repercussions of global natural disasters. Preventable but not evitable (yet), there is a need for novel approaches to prevent the stress caused by economic losses due to pandemics [12]. Using causal models [22], we analysed the economic environment around the productivity of the construction industry (PCI), identified its most statistically influential variables during the pandemic of COVID-19 and suitably quantified their interlink in terms of the risk index. In this work, the productivity of the construction industry refers to the efficiency of labour, materials and equipment in completing projects. Productivity of the construction industry provided the basis for evaluating the performance of the firms, their resource allocation and the creation of new companies related to the construction industry [31, 34].

Causal detection research has traditionally focused on two distinct forms of analysis: direct causality and complex causality [22]. Direct causality is primarily concerned with policy design problems [23, 24], often involving a subjective selection of variables to identify causal mechanisms within the studied context. In contrast, complex causality involves developing advanced methodologies to detect causal relationships between dependent and independent variables, usually including extra formulations and assumptions to detect valid models [25, 26, 27, 28, 29]. Our work shifts the paradigm by uncovering the full causal effect, which extracts all the direct causal links in a given dataset [30]. Whether all the scenarios happen at once or if they fluctuate over time with varying influence, this analysis provides a broad understanding of causal relationships within the macroeconomy. The model outcomes consisted of a group of valid multivariate regressions when the instruments, independent data, were kept constant. This perspective offers new insights for designing policies and workflows for the construction industry in future pandemics by using records of COVID-19, as described later here. The analysis included the productivity of the construction industry, measured as the added value created by building works and services related to them [31]

By testing numerous combinations of regressors, our approach aims to demonstrate that causal effects can be thoroughly understood using standard formulations [32]. This work emphasises that the detection of valid models is conditioned on the configuration of data entries and the relevance of statistically independent information [33]. Moreover, this work states that the current state of the theory obtains statistical links properly, and the new theoretical boundary will be seen from the replication of the full-causal effect to the macroeconomy, initially applied in the next pages of this work.

Building on previous research in causal analysis [35, 36, 37, 38] and utilising high-performance computing (HPC), the study uses an integrated approach, combining verified methods and tools to process, interpret and derive insights for the construction industry during pandemics [39].

This study provides insights for the economic development community by bridging theory and practice and examining the macroeconomic impact of infrastructure. The authors employ a rigorous methodology, utilising a comprehensive dataset and numerical techniques to compute the full causal effect. While simple causality identifies individual interconnections [35, 36, 37, 38], full causality offers a holistic perspective, updating the concept of complex causality [22]. This causal framework enhances econometric analysis, providing relevant statistical data on the economic phenomena. The causal effect will help in the prevention of future economic risks associated with health crises. Furthermore, through empirical analysis and statistical modelling, this research provides insights for policymakers and industry leaders, equipping them with

information to optimise crisis response strategies when such an event occurs in future. By enhancing risk understanding and fostering long-term resilience, the study contributes to the development of adaptive frameworks that mitigate both direct and indirect disruptions in the construction industry.

The work is structured as follows: it begins with a materials and methods section that outlines the dataset and analytical techniques, applying standard versions of the models. The results section presents key findings, including relevant regression analyses, statistical models with valid p-values, and the distribution of predictor coefficients for the variable of interest. This work is finalised with a discussion and conclusions about the importance of our findings for disaster risk reduction during pandemics on infrastructure projects.

2.4. Materials and Methods

To understand the problem of causal detection, one should consider the concept of heteroskedasticity. In the area of causal analysis using regressions, heteroskedasticity assumes that the variance of the error is not constant across the observations [39]. Heteroskedasticity causes the error term to increase with the number of predicted observations [40]. The heteroscedastic model shifts the variance of the error terms over a period [41]. The presence of heteroskedasticity requires an integrated approach to effectively detect and prevent it in the regressions. From a statistical perspective, the selection of a set of information and analysis methods is accurate when minimising heteroskedasticity [42]. Including or excluding specific information affects the validity of a model. Depending on the characteristics of the information, multiple valid models may explain the same variable using different sets of predictors. To detect every causal link with the productivity of the construction industry, this study tested all possible combinations of predictors using the variables presented in Table 2.

This study integrates pandemic and macroeconomic perspectives to find valid datasets with the generalised method of moments (GMM). One of the strengths of the GMM is that it searches for conditions across the data and prevents bias due to collinearity [43]. Economic indicators were sourced from the Organisation for Economic Co-operation and Development [31] and the World Bank [44]. Data for computing COVID-19 pandemic rates were obtained from the Johns Hopkins University [45] repository and averaged quarterly. The variables considered in this study are presented in Table 4. The corresponding data are available for the different countries presented, which contribute to 75% of the GDP of the world. The matrix of correlations displayed in Table 1 includes the correlation between the variables obtained using the software Stata [32].

The dependent variable, the productivity of the construction industry, represents the added value generated by infrastructure-related activities. This includes the extraction, processing and transportation of raw materials [46]. The pandemic analysis follows the epidemic model presented by Amanbaev and Antony [47].

2.4.1.Model Description

The full causal analysis is briefly described below. The full causal study is achieved through a series of combinatorial processes to detect exogeneity and predictors between data over an initial group of variables whose effects on the studied variable are initially unknown. This method enables a deep understanding of causal relationships by testing and selecting variables using different candidate for regressors, combining them and testing their relevance within a defined level of exogeneity. This work focuses on the validated combinations of variables explaining the construction industry within a determined range of statistical tests [32]. The innovation of this method arises from the elevated configurations of information, maximising data utilisation to extract useful information with intensive exploratory techniques developed here.

Besides the complex interplay in detecting statistically independent information, the contributions of this study include the evaluation of the causal effect across the group of available information, utilising the canonical formulations of causal analysis. This framework demonstrates that the accuracy of the causal effect corresponds to the quality of the data.

The GMM, introduced by Hamilton [48], is an alternative to maximum likelihood estimation (MLE). When variables are correlated, MLE can produce biased coefficients. While the MLE focuses on statistical associations, GMM emphasises the moment conditions (statistical expectations) that capture better the causal relationships. GMM is particularly useful when dealing with endogeneity and instrumental variables.

2.4.2.Identification of Instruments

Considering a n number of observations and W, which is a symmetric positive-definite matrix known as a weight matrix, the optimal weight matrix $W = ((1/n)\sum_i z_i z'_i)^{-1}$ [49] attains a non-increasing series of ε_t when the prediction time increases. The estimator of the regression coefficients, presented in Eq. 2.1, is the argument $\hat{\theta} = arg\,min_\beta\, Q(\theta)$ where Q is the quadratic function that determines an ideally fixed value [32].

$$\hat{\theta} = \{[(1/n)\sum_i x_i z'_i][(1/n)\sum_i z_i z'_i]^{-1}[(1/n)\sum_i z_i x'_i]\}^{-1} \cdot \{[(1/n)\sum_i x_i z'_i][(1/n)\sum_i z_i z'_i]^{-1}[(1/n)\sum_i z_i y_i]\} \quad (2.1)$$

Let $\mathfrak{B} = \sum_{a=1}^{m} \binom{a}{1}$ be the sum of the number of combinatory elements containing from 1 to m variables selected from a given dynamic panel data and $Y = PCI$, the studied variable. The coefficient $\hat{\theta} = \frac{\sum_{t=1}^{n} X_t Y}{\sum_{t=1}^{n} X_t^2}$ in the ordinary least squares (OLS) [43] becomes

$$\hat{\theta}_k = \sum_{t=1}^{n} \frac{X_{t,k} Y}{X_{t,k}^2}\Big|_{k=1}^{\mathfrak{B}} = \theta_k + \varepsilon_k|_{k=1}^{\mathfrak{B}}, \text{ where } \varepsilon_k = \sum_{t=1}^{n} \frac{\varphi_t X_t}{X_t^2}$$

where φ_t is an i.i.d. noise with mean zero, non-seasonal stationary process [33].

Let $\hat{X}$ be a group of explanatory variables which can have a link with the dependent variable w, and let us consider the elements of $\hat{X}$ identical and able to hold every subgroup $\hat{X}_{i,k}$ of $\hat{X}$. The group of explanatory elements accounts for a regression model of the type [50]

$$w_{t,i} = X_{i,k}\theta_{i,k,m}^{0} + Z_j\theta_{i,k,m}^{0} + \varepsilon_{i,k}\Big|_{k=1}^{\mathfrak{B}} \tag{2.2}$$

where

$w_{t,i}$ is an array of dependent variable observations,

$X_{i,k}$ is an array of independent variables,

$\theta_{i,k,m}^{0}$ characterises a series of unspecified parameters with dimension $m = 1, 2$

$\varepsilon_{i,k}$ is a sequence of unobserved error variables.

Because of the error term $\varepsilon_{i,k}$ have a mean of zero and a finite variance in one or more of the elements of k. Then $X_{i,k}$ and $\varepsilon_{i,k}$ are considered orthogonal, the element in Eq. 2.3 follows the orthogonality property in a high-dimensional space of information

$$\frac{1}{T} X_{i,k}' \varepsilon_{i,k} \to 0. \tag{2.3}$$

The explanatory X and instrumental Z variables included pandemic rates using the SIRDi pandemic model [47] and applying it to the data from the COVID-19 pandemic. It is worth saying that the COVID-19 pandemic had varying patterns due to spreading control measures, virus mutations and vaccines. One model was created for a period of 32 months from January 2020 until September 2023. This work extracted pandemic rates from new infection and death records and used the novel SIRDi model, which includes susceptible (S), infected (I), recovered (R), deceased (D) and quarantined (i) populations to extract relevant information for the statistical causal model. We anticipated that COVID-19 was an independent event from the economic system. Another example of a stochastic event having random effects on the economy is meteorological variables, like environmental temperature and humidity, which are relevant to

the creation of wealth [51]. Even if such events slightly affect the economy, they occur independently of social behaviours, at least initially in the early outbreaks. This approach depends upon the quality of the information and emphasises the frequency of the collection of data. While the pandemic was monitored daily, the economy usually includes quarterly reports. The pandemic data was employed with econometric parameters to obtain enhanced statistical models across the world.

The spread of the pandemic varied with international and local regulations and led to fewer infections compared to a free-spread scenario. The SIRDi model [47] allowed advanced data collection across multiple countries by extracting the outbreak rates from the registers of daily new infections and fatalities in every studied country. Details on pandemic rates and a comprehensive explanation are provided in Appendix A. The pandemic rates were averaged quarterly.

This work tested the assumption of instrumental variables to prevent perfect correlation between variables. The first assumption ensured that each instrument appeared only once in the GMM model, preventing duplication of rows in Z_i.

Using the 84 significant auxiliary regressions with $R^2 \geq 0.990$ and their residuals, this work tested a second assumption of instruments, where no collinearity of instruments Z with the residual term $\varepsilon_{i,k}$ is considered if $\left\{\text{corr}\left(z_j, \varepsilon_{i,k}\right)\Big|_{j=1}^{\pi}\Big|_{i=1}^{\omega}\right\} \leq 0.100$, where π is the number of elements in the panel data where the valid instruments are going to be found. We selected 7 instruments ($\mathfrak{f} = 7$) with correlations with the error term below the threshold. Those 7 instrumental variables helped to perform the study of the causal effects.

2.4.3.Identification of the predictors

The research on instruments requires the correlation effects between the groups of instruments $\hat{X}$ and predictors $\hat{\mathrm{Z}}$. The parametric boundary of $\left\{\text{corr}\left(z_j, x_i\right)\Big|_{j=1}^{\mathfrak{f}}\Big|_{i=1}^{\tau}\right\} \geq 0.700$ to detect the explanatory variables $\hat{X}$. A total of 10 predictors were identified based on their correlation coefficient with one or more of the instruments. The groups of explanatory variables were detected in a combinatory process between the predictors, starting from one variable up to six variables. The maximum number of predictors completed the rank condition [32].

Table 4 Statistical description and correlation matrix of the information used in this research.

Variable	Mean	SD	Min	Max											
PCI (2015=100)	109.640	22.980	65.790	168.200	1.000										
Recovery rate (1/day)	0.010	0.010	0.000	0.020	-0.072	1.000									
Mortality rate (1/day)	0.010	0.020	0.000	0.120	-0.111	0.675	1.000								
Pandemic growth rate (1/day)	0.100	0.220	-0.050	1.210	-0.045	0.478	0.496	1.000							
Transmission rate (1/day)	0.090	0.020	0.000	0.160	0.093	-0.340	-0.467	0.033	1.000						
Pandemic reproduction number	1.620	0.780	0.430	4.050	-0.093	0.426	0.495	0.645	0.177	1.000					
Inflation (2015=100)	115.610	11.440	101.560	147.760	0.142	-0.165	-0.114	-0.068	0.056	-0.208	1.000				
Share prices (2015=100)	125.750	38.250	64.130	247.990	0.321	-0.108	-0.149	-0.054	0.051	-0.137	0.665	1.000			
Employment rate (%)	66.680	10.580	40.850	82.070	0.015	0.079	-0.112	-0.068	-0.047	-0.088	-0.519	-0.395	1.000		
FDI (US$M)	1.920	2.960	0.020	13.650	0.517	-0.063	-0.009	0.003	0.047	0.010	-0.050	-0.034	0.185	1.000	
Total spending (US$T)	4.079	4.514	0.582	17.808	0.470	-0.126	0.008	0.062	0.120	0.062	0.084	0.073	-0.156	0.823	1.000

2.4.4.Combinatory causal model

Various combinations of the 10 predictors were tested using the GMM. The seven instruments remained constant during the combinatory process. A Hansen's *J* statistic *p-value* ≥ 0.1 [42, 52] was applied during the selection of valid combinations to ensure conditions were fulfilled by preventing weak instrumental power [31].

This research tested the instrumental variables using the Wald statistic test [53]. We utilised the expression $r_j = \boldsymbol{W}_{jj}^{1/2}\{\sum_{i=1}^{n}(1/n)z_{ij}u_i\}$ for every model and determined a threshold value for r_j. This work selected the explanatory variables producing the lowest variability across the r_j when the instruments remained constant across the simulations.

The statistical methods were applied to the countries detailed in Table 3, selected based on data availability to ensure a comparative analysis. Through a detailed analysis, the major countries (contributing to 75.0% of the global GDP) were grouped into their continents as well as at a global level. The amount of statistical information to extract depends on the properties of the data and the level of certainty required. The different configurations of variables find valid models by including specific information and excluding others until all the combinations of variables are tested with the two described methods. This exploratory approach confirms the abilities of classical statistical approaches to extract causal effects when applied recursively across the configurations of the information.

The analysis identified variables that were exogenous to the construction industry productivity, meaning they were independent and not influenced by it. The exogenous condition relies on the following assumptions. The model utilised auxiliary OLS with linear regression to obtain a group of $\varepsilon_{t,k}$ by comparing actual and forecasted values of the construction industry productivity. The matrix W_k, a symmetric and positive-definite matrix, is also known as the weight matrix [49]. The matrix W varied with the combinatory process, which varied when $z_{i,k}$ remained constant. The product $z_{i,k}\varepsilon_{i,k}(\theta_k)$ varied with every iteration in the loop. A regression is considered statistically significant when it holds a model fit of 0.9. A total of 1,023 auxiliary regressions were performed. Between the auxiliary regressions, a total number of $\omega = 6$ resulted in statistical significance. Such regressions were retained for the exogeneity analysis. Table 5 shows the countries where the full-causal effect was observed.

Table 5 The 14 countries included in the analysis, presented by their GDP, starting with the highest GDP first.

Country	Continent
United States of America	America
China	Asia
Germany	Europe
Japan	Asia
India	Asia
United Kingdom	Europe
France	Europe
Italy	Europe
Canada	America
Brazil	America
Australia	Oceania
Spain	Europe
United States of Mexico	America
Netherlands	Europe

Fig. 12 illustrates the general process of extracting the full causal effect from panel data. This workflow facilitates the computational automation of causal detection, incorporating variables of X and Z within the GMM.

2.5. Results

2.5.1.Hypotheses of the Study

This study examines the effects of macroeconomic factors and COVID-19 on the productivity of the construction industry. It highlights key drivers influencing the construction sector at both global and continental scales. While the impact of these predictors on the economy has been studied before, this research specifically focuses on their effects on construction industry

productivity. In subsection 3.1.1, we hypothesise the effects of the selected regressors and analyse how they influence the productivity of the construction industry.

2.5.1.1. Positive linked pandemic rate

The recovery rate of the pandemic represents the proportion of active cases recovering from infection. This rate is often linked to a country's level of development and serves as an indicator of healthcare system quality [54]. While a higher recovery rate reflects an improved health response, it may also necessitate stricter containment policies, which can reduce overall economic productivity, including within the construction industry. Given the need for developed medical installations and the infrastructure to care for patients, we hypothesise:

Hypothesis 1. An increase in the recovery rate of the pandemic was positively associated with the productivity of the construction industry.

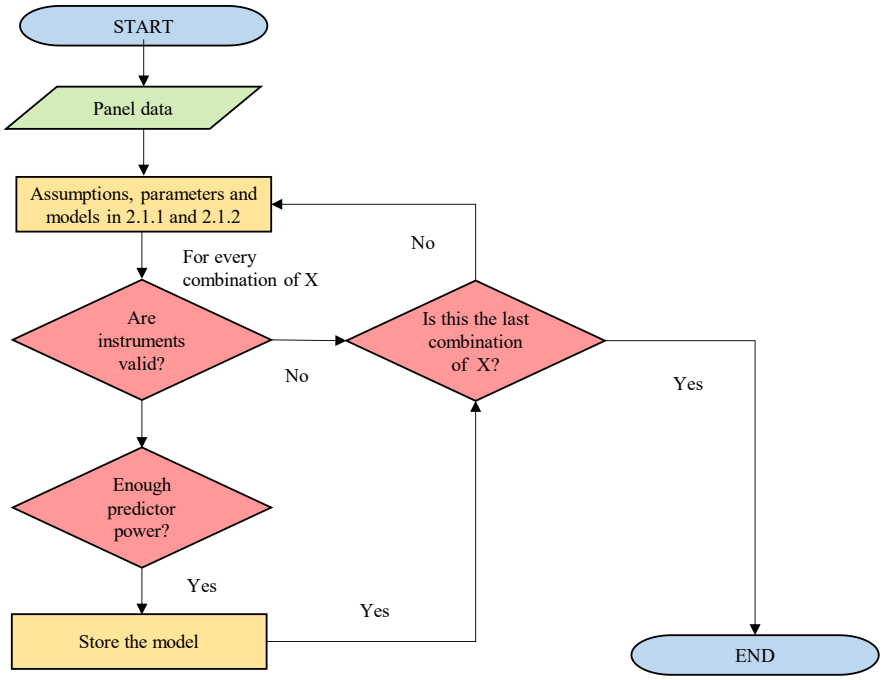


Figure 12 Details of the process used in this work to detect predictors and instruments from a given panel data set. This method was consistently applied to obtain robust configurations of variables and to detect higher validity among the population of models in t.

2.5.1.2. Negative-linked pandemic rates

The mortality rate, pandemic growth rate, transmission rate and pandemic reproductive (R) number define the rate at which infections and their severity change over time. When $R > 1 \rightarrow$ the outbreak is growing, when $R = 1 \rightarrow$ the outbreak is stable and when $R < 1 \rightarrow$ the outbreak is reducing.

These four pandemic parameters relate to the portions of new fatalities, the percentage and number of increases in active infections, and the secondary cases that an infected person can cause, respectively [47]. An increase in pandemic rates in this hypothesis suggests that stricter anti-spread policies may be implemented, potentially slowing economic activity and negatively impacting industrial productivity. These measures can lead to material and labour shortages while affecting safe distancing practices on construction sites. As a result, we hypothesise the following:

Hypothesis 2. An increase in the mortality rate, pandemic growth rate, transmission rate and/or pandemic reproductive number was not positively associated with the productivity of the construction industry.

2.5.1.3. Global economy and the construction industry

Inflation arises from economic conflicts between social groups demanding larger shares of resources, often outpacing overall economic growth [55]. Its impact on various sectors, including construction, differs across countries [56]. Due to the complexity of the construction industry, inflation can negatively affect projects by increasing material, labour and energy costs. Musarat [57] established a direct link between inflation and building material prices, demonstrating how inflation contributes to cost overruns in construction projects. Therefore, we analyse the following:

Hypothesis 3. Inflation had a negative effect on the productivity of the construction industry.

Share prices in this study encompass multiple economic sectors, including construction. The valuation of construction industry shares depends on a company's financial performance and its ability to generate capital from infrastructure projects [58]. Economic factors influencing construction productivity ultimately impact share prices—positively when company performance improves, or negatively when external factors cause a decline in productivity.

Maintaining high standards during disruptive events can boost share prices, as investors are more likely to support well-backed initiatives. However, upholding high construction standards requires significant resources from construction companies. Based on this, we hypothesise:

Hypothesis 4. Share prices have a positive link with the productivity of the construction industry.

The employment rate plays a crucial role in the construction industry's ability to complete projects. Employment levels impact productivity in various ways, particularly during economic downturns. The COVID-19 pandemic led to widespread furloughs and layoffs in the construction sector [59]. A volatile economy—due to pandemic containment measures and financial

uncertainty—increased furloughs [60]. The decline in employment rates can serve as an indicator of pandemic-induced economic disruptions. Therefore, we hypothesise:

Hypothesis 5. The employment rate had a negative link with the productivity of the construction industry.

During the COVID-19 pandemic, the construction industry faced significant challenges, which increased risks in foreign investments due to border closures and economic uncertainty [61]. FDI became crucial for economic stability during this period. Previous studies have demonstrated the positive impact of FDI on industries such as agro-industrial production. FDI has been linked to poverty reduction in high-GDP countries. Besides its relevance, its impact on construction industries in low-GDP nations remains underexplored [62]. Therefore, we hypothesise:

Hypothesis 6. FDI has a positive link with the productivity of the construction industry.

Infrastructure spending—both from public and private spending—has been shown to drive economic growth [63]. Public and private investment, the two primary sources of construction financing, are strongly linked to industry productivity [64, 65, 66]. The economic benefits of such spending depend on regulatory policies and external factors affecting the industry [64]. Given these considerations, we hypothesise that:

Hypothesis 7. Total spending had a positive link with the productivity of the construction industry.

2.5.2. Global Causal Models

Through the combinatory process, a total of 967 combinations of explanatory variables were tested to identify the validity of the computations. Among the scenarios, six passed the validity tests described before. We applied a probabilistic summary of the coefficients to assess the magnitude of the space of the causal coefficients.

Table 3 provides the causal coefficients for the most significant regressions at a global level and replicated to the continents to explain the productivity of the construction industry. This approach, spanning diverse continents and nations, offers an understanding of the factors influencing construction industry productivity worldwide using Stata [32]. Even though the most significant regression at a global scale may not be the best at a continental level, this exercise helps to determine the necessity of a full causal effect performed across different regions.

Hypothesis 1 could not be verified using Table 6. For hypothesis 2, which suggests that increases in the mortality rate, pandemic growth rate, transmission rate and pandemic reproductive

number were not positively associated with construction industry productivity, the table only provides data on the pandemic R number. The global coefficient of the pandemic R number is significantly negative ($\theta = -1.556$, $p < 0.01$), supporting the hypothesis by indicating that higher transmission rates reduce productivity. In America and Oceania, the coefficients remain negative and significant ($\theta = -0.170$, $p < 0.10$; $\theta = -0.104$, $p < 0.01$), reinforcing this trend. In Europe, the pandemic R number is significantly positive ($\theta = 2.098$, $p < 0.05$), suggesting a counterintuitive relationship where higher transmission rates are linked to increased construction productivity. Given these regional inconsistencies, the hypothesis holds in some areas but not universally.

Hypothesis 3, which posits that inflation negatively affects construction productivity, is strongly supported by the global results ($\theta = -0.713$, $p < 0.01$). In America, inflation remains significantly negative ($\theta = -0.175$, $p < 0.01$), reinforcing the argument that rising costs hinder productivity. In Oceania, the relationship is negative but not statistically significant. In Europe, inflation has a significantly positive effect ($\theta = 2.862$, $p < 0.05$), suggesting that inflation coincided with increased construction productivity in that region. Asia shows no significant relationship. These results indicate that while inflation generally harms productivity, regional economic conditions and policy responses may alter its impact.

The results support hypothesis 4, which suggests that share prices are positively linked to construction productivity. The global coefficient for share prices is significantly positive ($\theta = 0.473$, $p < 0.01$), indicating that stronger financial markets contribute to higher construction productivity. The relationship remains positive and significant in America and Oceania ($\theta = 0.193$, $p < 0.01$; $\theta = 0.330$, $p < 0.01$, respectively). In Asia and Europe, the coefficients are not statistically significant, suggesting that other economic factors may have a more dominant influence in those regions [58].

Hypothesis 5, which states that the employment rate negatively affects construction productivity, is supported globally ($\theta = -0.391$, $p < 0.05$), confirming that employment fluctuations can disrupt productivity. In Asia and Europe, the relationship is not statistically significant, indicating that employment levels had no measurable effect on productivity in those regions. Interestingly, in America, the relationship is positive ($\theta = 0.194$, $p < 0.01$), implying that higher employment rates contributed to increased productivity, contradicting the hypothesis. These results suggest that the impact of employment rates on productivity is context-dependent, and potentially influenced by labour market structures and economic policies [59].

For hypothesis 6, which posits that FDI positively affects construction productivity, the global coefficient is significantly positive ($\theta = 0.637$, $p < 0.01$), supporting the hypothesis. In America,

the relationship remains positive and highly significant ($\theta = 0.553$, $p < 0.01$), reinforcing the role of foreign investment in boosting productivity. In Oceania, the effect is exceptionally large and highly significant ($\theta = 8.375$, $p < 0.01$), suggesting a strong dependence on FDI. In Asia and Europe, the relationship is not statistically significant, indicating that FDI did not have a measurable impact on construction productivity in those regions with the provided dataset.

Table 6 Significant regression with the highest Hansen's J statistic p-value for construction industry productivity.

	Region				
Predictor	**Global**	**America**	**Asia**	**Europe**	**Oceania**
Pandemic R number	-1.556*** (0.474)	-0.170* (0.101)	0.064 (0.204)	2.098** (0.962)	-0.104*** (0.015)
Inflation	-0.713*** (0.201)	-0.175*** (0.064)	0.628 (0.623)	2.862** (1.207)	-0.105 (0.077)
Share prices	0.473*** (0.157)	0.193*** (0.041)	0.163 (0.481)	0.642 (0.467)	0.330*** (0.049)
Employment rate	-0.391** (0.161)	0.194*** (0.050)	-0.129 (0.248)	-0.489 (0.748)	0.071 (0.081)
FDI	0.637*** (0.146)	0.553*** (0.039)	-0.147 (0.561)	0.215 (1.691)	8.375*** (2.554)
b0	1.189*** (0.303)	0.182*** (0.069)	0.286 (0.227)	-0.672* (0.384)	0.190*** (0.050)
Observations	182	52	39	78	13
Lag	t-1	t-1	t-1	t-1	t-1

In this table, the GMM model is displayed. Standard errors are presented in parentheses. The p-values are indicated by *** (significant at 1%), ** (significant at 5%) and * (significant at 10%).

In addition to the described regressions in Table 6, five more cases of globally valid regressions were detected, all with predictors significant at 10%, though not presented here; these six valid regressions are used to determine the risk index described later. The six valid regression models contained different configurations of the ten predictors. Fig. 13 shows the distribution of the coefficients of each explanatory variable across these six regressions at a global scale. This information gives a range of variations of the causal link across scenarios. We are interested in

how they influenced construction industry productivity. In Fig. 2 & in Figures 4-7 presented later, all the coefficients were significant at the 10% level (i.e., 90% confidence) or less. Each box plot shows the distribution of these coefficients: the bottom of the box represents the 25th percentile, and the top represents the 75th percentile. The interquartile range (IQR) is the difference between these percentiles. The whiskers extend to the adjacent values, with the bottom whisker (lower adjacent value) being the 25th percentile minus 1.5 times the IQR [32], and the top whisker (upper adjacent value) being the 75th percentile plus 1.5 times the IQR. The line inside the box denotes the average coefficient value.

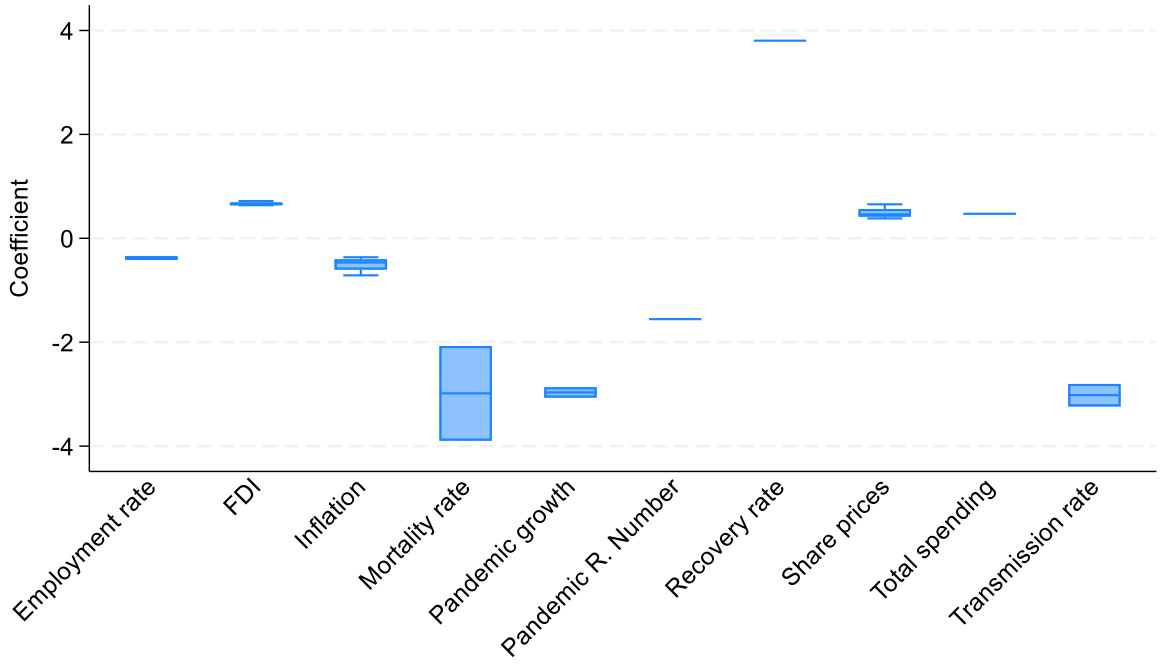


Figure 13 Distributions of the coefficients of the valid regressions, including all the countries considered here (global measure)

Fig. 14 presents a graphical representation of how the predictors interact with construction industry productivity, based on regressions with valid p-values. Although each regression only included a subset of the total regressors at a time, by analysing the six regressions collectively, we can assess the impact of the regressors within the valid regressions. When the model included all countries and produced valid solutions, the sign of the coefficients is either positive (direct link) or negative (inverse link). The consistent sign of the coefficients for the individual variables here suggests that, on the global level, causal models can identify consistent causal effects across the economy and pandemic, helping to explain and predict construction industry productivity. The following subsections explore the influence of every regressor at a continental level.

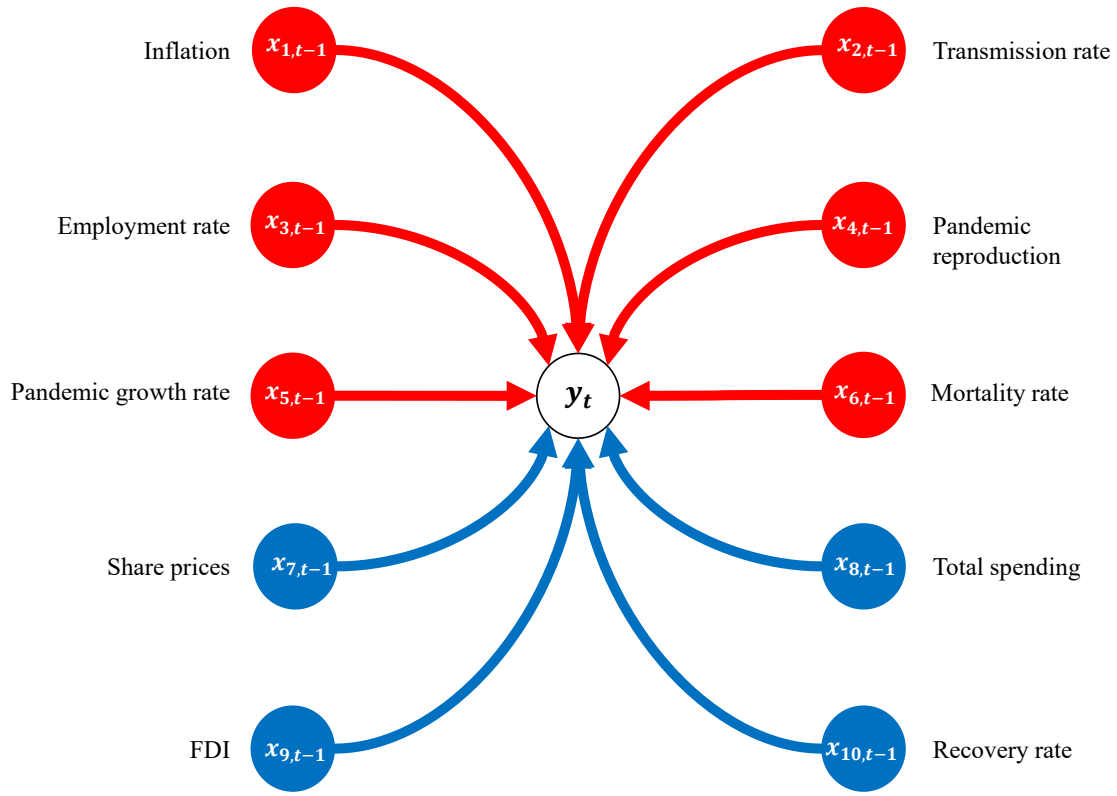


Figure 14Network of the causal effects of the explanatory variables on the productivity of the construction industry. The variables presented in the diagram exist in the range of time 1…t, and are ordered by the absolute value of the coefficient in descending order. Variables are shown in red, $x_{1\cdots6,t-1}$ indicate a negative relationship with productivity, while variables are shown in blue $x_{7\cdots10,t-1}$ indicate a positive relationship.

We extracted coefficient values from boxplots to construct linear equations for a risk index, quantifying industry vulnerability to pandemics and economic downturns. The index approximates average predictor coefficients from the boxplots, using their sign to formulate corresponding linear equations. The risk index serves as a dynamic tool for monitoring risk variations over time. By comparing risk levels relative to a baseline, the magnitude and sign of the index help assess whether industry vulnerability is increasing or decreasing as predictors change.

2.5.2.1. Global risk index

We define the risk index (RI) of the construction industry as a composite measure of various factors that influence the industry's relationship with the economy and the effects of the pandemic. This index is calculated as the inverse of the sum of the average value of the coefficients of all valid regressors in the statistical models. The study includes regressions in which all regressors were valid at a significance level of at least 10%.

The global risk index of the construction industry (RI_{Global}) is calculated using Eq. 2.4 in terms of the employment rate, inflation, mortality rate, pandemic growth, R number and transmission rate, which negatively affect the risk index, while FDI, recovery rate, share prices and total spending contribute positively. The recovery rate has the strongest positive influence, while the mortality rate and transmission rate have the strongest negative impact.

$$\begin{aligned} RI_{Global} = {} & -0.8 \times \text{Employment rate} + 1.2 \times \text{FDI} - 0.5 \times \text{Inflation} \\ & - 3.0 \times \text{Mortality rate} - 2.5 \times \text{Pandemic growth} \\ & - 1.7 \times \text{Pandemic R number} + 3.6 \times \text{Recovery rate} \\ & + 0.9 \times \text{Share prices} + 0.8 \times \text{Total spending} - 3.0 \times \text{Transmission rate} \end{aligned} \quad (2.4)$$

This section includes the significant regressions per continent.

2.5.2.2. America

Fig. 15 shows the distributions of coefficients of the valid models considering America. One can note the slightly positive coefficient of inflation, which challenges hypothesis 3. This hypothesis anticipated a negative effect of inflation on construction industry productivity, but the data suggest a weak positive association instead. Regarding share prices, the coefficient is positive, which supports hypothesis 4. This hypothesis shows that there is a positive relationship between share prices and construction industry productivity, and the data confirm this expectation.

The coefficient for the employment rate is positive, which contradicts hypothesis 5. This hypothesis proposed a negative association between employment rates and productivity, but the data suggest the opposite, indicating a positive relationship [60]. For FDI, the coefficient is positive, aligning with hypothesis 6, which suggests a positive link between FDI and construction industry productivity. The coefficient for total spending is also positive, supporting hypothesis 7, which predicts a positive relationship between total spending and productivity in the construction industry.

The results for America show a negative coefficient distribution for mortality rate and pandemic indicators. This suggests a stronger negative association between these factors and productivity compared to the global average. The positive macroeconomic factors, including inflation and share prices, appear more moderate than in other regions. The heavy economic disruptions and policy responses, including lockdowns and fiscal interventions, may have played a role in exacerbating these negative impacts [67].

2.5.2.2.1. Risk index for America

The model for America indicates that employment rate, FDI, inflation, recovery rate, share prices and total spending reduce the risk index, with the recovery rate having the highest positive effect. Mortality rate and pandemic growth increase the risk index, while the pandemic R number has a small positive coefficient.

$$\begin{aligned} \mathrm{RI}_{\mathrm{America}} = {} & 1.0 \times \text{Employment rate} + 1.3 \times \text{FDI} + 0.6 \times \text{Inflation} \\ & - 2.5 \times \text{Mortality rate} - 0.4 \times \text{Pandemic growth} \\ & + 0.9 \times \text{Pandemic R number} + 4.6 \times \text{Recovery rate} \\ & + 0.6 \times \text{Share prices} + 0.5 \times \text{Total spending} \end{aligned} \tag{2.5}$$

2.5.2.3. Asia

Fig. 16 shows the distributions of the coefficients of the regressions with data from the studied countries in Asia. Hypothesis 1 suggests that an increase in the pandemic recovery rate is positively associated with construction industry productivity. The model lacks data on the recovery rate, making it impossible to validate or contradict this hypothesis at a continental level in Asia. Hypothesis 2 posits that an increase in the mortality rate, pandemic growth rate, transmission rate or reproductive number is not positively associated with construction industry productivity. The chart shows that the average of the coefficients of the pandemic reproductive number and mortality rate is slightly positive, contradicting this hypothesis, which predicted a negative or neutral association. This situation may be due to the relatively reduced transmission of COVID-19 in China due to stricter policies to prevent the pandemic since an early stage of the outbreak [47].

Hypothesis 3 claims that inflation negatively affects construction industry productivity. The chart shows a positive average coefficient for inflation, contradicting this hypothesis and suggesting a positive relationship between inflation and productivity. Hypothesis 4 asserts that share prices have a positive link with construction industry productivity. The chart confirms this hypothesis, as the average coefficient for share prices is positive, validating the hypothesis.

Hypothesis 5 suggests that the employment rate negatively affects construction industry productivity. The chart shows a negative average coefficient for the employment rate, which aligns with this hypothesis, supporting its validity. Hypothesis 6 posits that FDI has a positive link with construction industry productivity. The chart reveals a positive average coefficient for FDI, validating this hypothesis [60].

Hypothesis 7 claims that total spending has a positive link with construction industry productivity. The chart shows a slightly positive average coefficient for total spending, supporting this hypothesis, although the result is weak, making it inconclusive when considering China, Japan and India simultaneously.

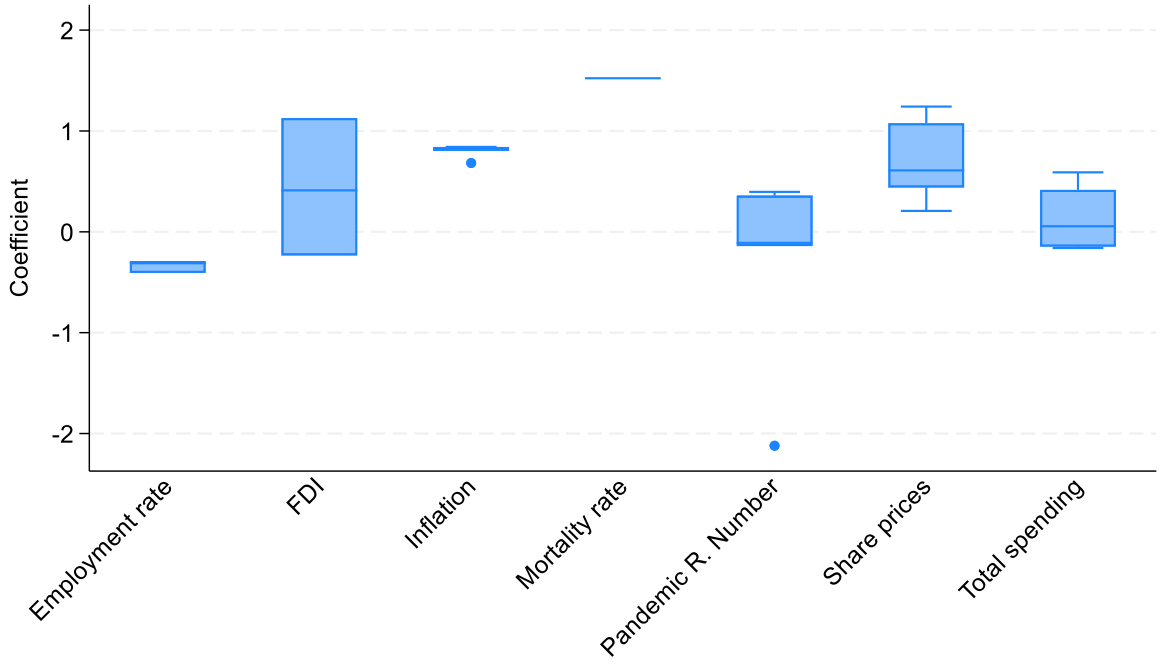


Figure 15 Distributions of the coefficients of the valid regressions, including the studied countries in Asia.

The models for Asia show wider variability, with larger box-and-whisker spreads for FDI and recovery rate. This suggests a more heterogeneous relationship with productivity. Pandemic-related coefficients remain mostly negative but with a broader range than in the Americas. The variation may stem from differing pandemic responses across Asian economies, where some nations imposed strict containment measures while others maintained more open policies [68].

2.5.2.3.1. Risk index for Asia

The model for Asia suggests that the employment rate increases the risk index, whereas FDI, inflation and mortality rate reduce it. Pandemic R number slightly increases risk, while share prices and total spending contribute positively, showing a relatively moderate overall effect.

$$\begin{aligned} \mathrm{RI}_{\mathrm{Asia}} = {} & -0.7 \times \text{Employment rate} + 1.5 \times \text{FDI} + 0.8 \times \text{Inflation} \\ & + 1.5 \times \text{Mortality rate} - 0.4 \times \text{Pandemic R number} \\ & + 0.7 \times \text{Share prices} + 0.3 \times \text{Total spending} \end{aligned} \tag{2.6}$$

2.5.2.4. Europe

Fig. 17 shows the distributions of the coefficients of the regressions with data from the studied countries in Europe. Hypothesis 1, which suggests that an increase in the pandemic recovery rate is positively associated with construction industry productivity, is supported by the chart. The recovery rate shows a positive median, aligning with the hypothesis. However, hypothesis 2, which posits that higher rates of mortality, pandemic growth and transmission are not positively associated with productivity, is partially validated. While the mortality rate has negative average coefficients, which support the hypothesis, the transmission rate and pandemic reproductive number unexpectedly show a positive median, contradicting the hypothesis [47].

Hypothesis 3, stating that inflation negatively affects construction industry productivity, is contradicted by the chart. The median coefficient for inflation is positive, which goes against the predicted negative relationship [55]. Hypothesis 4, which claims a positive link between share prices and construction productivity, is validated by the chart, as share prices show a slight positive median. On the other hand, hypothesis 5, which expected a negative relationship between employment rate and productivity, is contradicted by the data. The median coefficient for the employment rate is positive, showing an unexpected positive link with productivity [59].

Hypothesis 6, which posits that FDI positively impacts construction productivity, is supported by the chart, as FDI has a positive median coefficient with considerable dispersion. Hypothesis 7, suggesting that total spending has a positive link with productivity, is contradicted by the chart, which shows a negative median for total spending, indicating a negative relationship [64].

The results for Europe showed a relatively strong positive influence of share prices and strong negative effects for specific pandemic factors, especially the R number. This combination suggests that financial market performance may have been particularly influential in European construction productivity, while pandemic severity had a more strongly negative impact. The strong role of financial markets in European economies may explain why share prices showed a more pronounced effect compared to other regions [72].

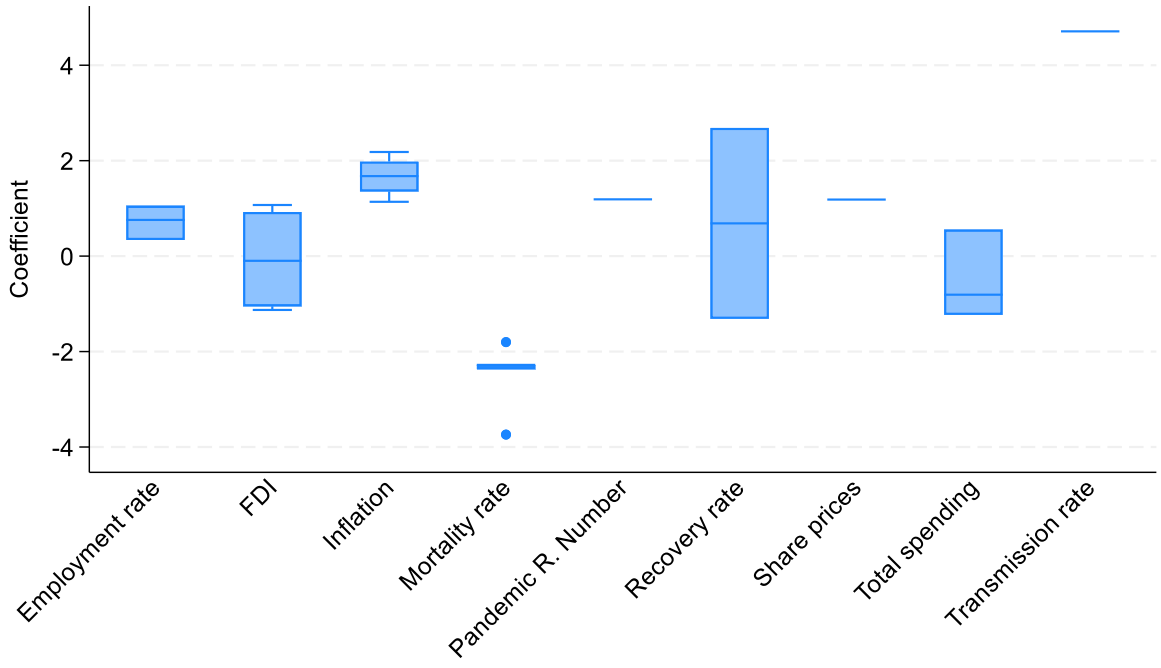


Figure 16 Distributions of the coefficients of the valid regressions, including the studied countries in Europe.

2.5.2.4.1. Risk index for Europe

The model for Europe demonstrates that employment rate, inflation, pandemic R number, recovery rate and share prices all reduce the index, with the transmission rate playing a significant role. Mortality rate and total spending increase the risk index, indicating a complex balance between financial conditions and pandemic effects.

$$\begin{aligned} \mathrm{RI}_{\mathrm{Europe}} = {} & 0.9 \times \text{Employment rate} + 0.1 \times \text{FDI} + 1.8 \times \text{Inflation} \\ & - 2.2 \times \text{Mortality rate} + 1.2 \times \text{Pandemic R number} \\ & + 1.2 \times \text{Recovery rate} + 1.7 \times \text{Share prices} - 0.6 \times \text{Total spending} \\ & + 4.1 \times \text{Transmission rate} \end{aligned} \tag{2.7}$$

2.5.2.5. Oceania

The Australian data shown in Fig. 18 confirms that a higher recovery rate positively correlates with construction productivity, supporting Hypothesis 1. The chart reveals a moderately positive coefficient for recovery rates, suggesting that improved healthcare outcomes and increased workforce availability contribute to a stable construction industry. This aligns with the expectation that as recovery rates rise, disruptions decrease, leading to higher productivity levels [54].

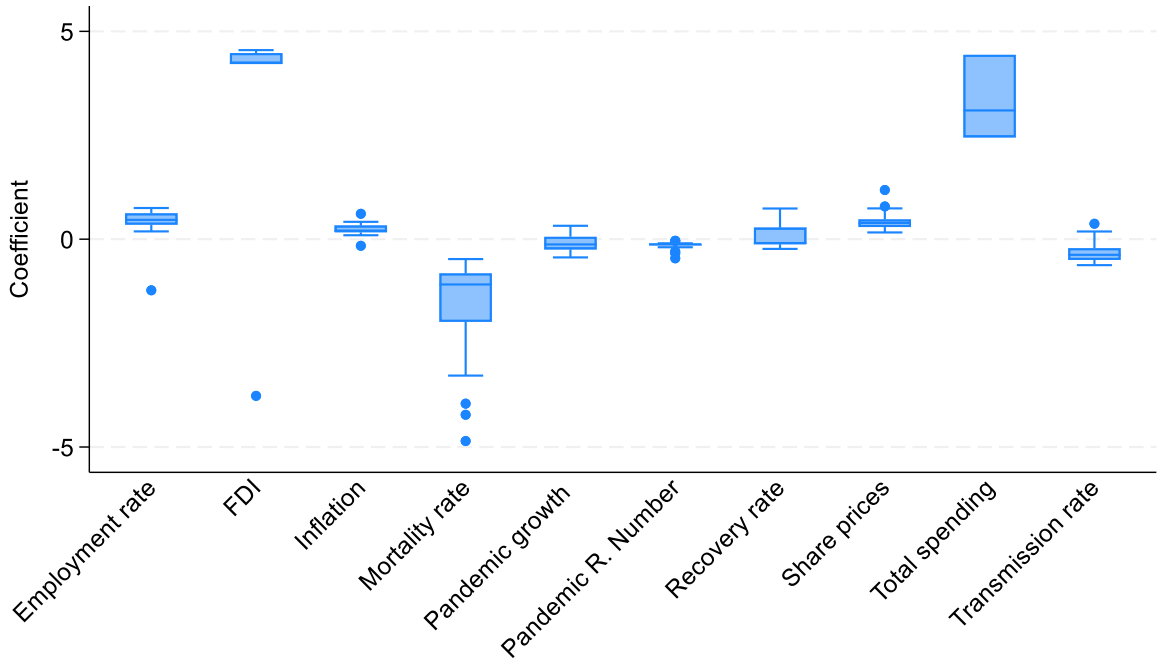


Figure 17 Distributions of the coefficients of the valid regressions, including the studied countries in Oceania.

Hypothesis 2 is validated, as higher mortality rates, pandemic growth, transmission and reproductive numbers exhibit negative associations with construction productivity. The data suggest that worsening pandemic conditions impose stricter containment measures and increased uncertainty, which negatively impact the industry. These findings confirm that heightened pandemic severity is not positively linked to construction productivity, reinforcing the hypothesis.

The negative coefficient of inflation supports hypothesis 3, as rising costs for materials and labour reduce profitability and increase the financial strain on construction projects. This aligns with the prediction that inflation negatively affects productivity by making projects more expensive and reducing investment incentives. Conversely, share prices demonstrate a positive correlation, supporting hypothesis 4. A rising stock market fosters investor confidence and increases funding opportunities, which can enhance construction sector performance to cover infrastructure demands during and after the disaster.

Confirming hypothesis 5, a decline in employment likely reflects workforce shortages or economic downturns that disrupt productivity [60]. FDI shows a small but positive link to construction productivity, validating hypothesis 6. External capital inflows help stabilise financial conditions, providing necessary resources for infrastructure projects.

Finally, total spending exhibits a strong positive effect on construction productivity, supporting hypothesis 7. Increased investment in infrastructure, whether from public or private sources, fuels industry growth and ensures a steady pipeline of projects. This finding reinforces the idea that government and private sector spending play a crucial role in sustaining construction activity.

Oceania displays a positive transmission rate coefficient relative to other regions. This suggests that rising transmission had a more complex or less negatively perceived effect on construction productivity compared to other parts of the world. Other macroeconomic variables, such as inflation and total spending, appear more tightly clustered around moderate positive values relative to the global baseline. This may reflect the region's relatively successful pandemic management and the resilience of its construction sector [69].

2.5.2.5.1. Risk index for Oceania

The model for Oceania highlights that employment rate, FDI, inflation, recovery rate, share prices and total spending reduce the RI in Oceania, with FDI and total spending being strong drivers. Mortality rate, pandemic growth, R number and transmission rate increase the risk index, though their influence varies in magnitude.

$$\begin{aligned} \mathrm{RI}_{\mathrm{Oceania}} = {} & 1.1 \times \text{Employment rate} + 4.6 \times \text{FDI} + 0.7 \times \text{Inflation} \\ & - 1.8 \times \text{Mortality rate} - 0.2 \times \text{Pandemic growth} \\ & - 0.2 \times \text{Pandemic R number} + 0.5 \times \text{Recovery rate} \\ & + 1.2 \times \text{Share prices} + 3.2 \times \text{Total spending} - 0.7 \times \text{Transmission rate} \end{aligned} \tag{2.8}$$

2.5.3.Evolution of the RI and Productivity of the Construction Industry During COVID-19

Using the results of this study described above, here we develop the relative risk index and productivity of the construction industry, normalised as follows:

$$Relative\ index\ of\ x = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2.9}$$

in which x represents the value of the variable (risk index or productivity of the construction industry) at a given time, and x_{max} and x_{min} denote the maximum and minimum values of x over the whole duration of the pandemic considered here. In the following, RRI refers to the relative risk index and RPCI to the relative productivity of the construction industry.

Fig. 19 presents the relative risk index of the construction industry and the productivity of the construction industry per continent. This figure shows a negative correlation between the RRI and RPCI during COVID-19. In Q1-Q2 2020, the RRI spiked while the RPCI dropped sharply across all regions. As RRI levels are relatively more stabilised post-2020, RPCI gradually recovered. This inverse relationship highlights the pandemic's disruptive impact on global activities related to the construction industry, such as shipping operations, especially during the early pandemic [71].

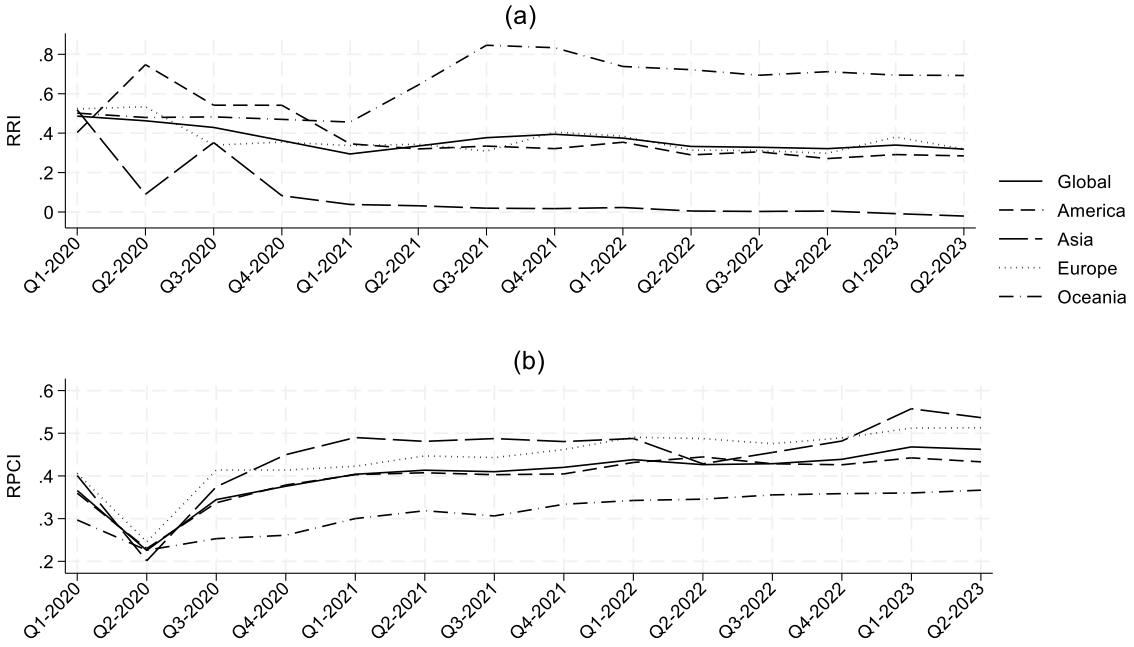


Figure 18 Risk analysis during COVID-19: (a) and (b) represent the relative risk index and relative productivity of the construction industry, respectively.

Furthermore, using the above data, we develop a polynomial regression model to forecast the relative productivity of the construction industry using the relative risk index. Equations 2.10–2.14 present this for the global and continental levels (America, Asia, Europe, and Oceania). Fig. 20 displays the forecasted and actual measures of the relative productivity of the construction industry using the polynomial [79] as a function of the relative risk index, which shows a good level of agreement between them in this complex problem.

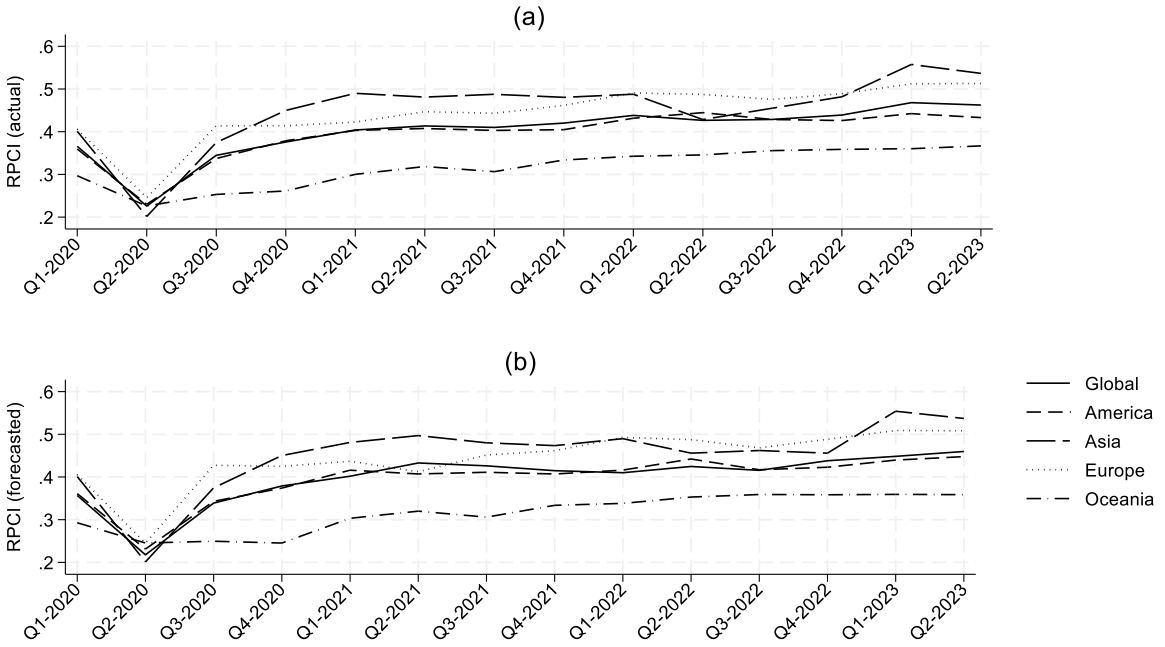


Figure 19 Comparison of the actual and forecasted relative productivity of the construction industry using the relative risk index: (a) and (b) represent the actual and forecasted relative productivity of the construction industry, respectively. The R^2 of the polynomial regressions are 0.960, 0.978, 0.980, 0.969 and 0.968 for the models at the global scale and in America, Asia, Europe and Oceania, respectively.

2.6. Discussion

From the analysis and results presented above, here we discuss the impacts of the research under different themes as follows:

2.6.1.Economic And Pandemic-Driven Risks in the Construction Industry

The construction industry is an important contributor to economic growth. After COVID-19, the economy, including infrastructure activities, remains vulnerable to disruptions from pandemics and economic risks [2]. A limited number of previous studies have also explored the construction industry during the COVID-19 pandemic. For example, Shibani et al. [70] examined the UK construction sector, revealing that residential and commercial projects faced the most significant challenges, including financial losses from project cancellations and decreased consumer spending. However, these findings lack information on a global perspective for mitigating pandemic-related challenges. Ogunnusi et al. [71] conducted a global survey across 16 countries, highlighting how social distancing, quarantines and furloughs disrupted built asset procurement and facility management. The study described the difficulties of transitioning to remote work in a labour-intensive industry and called for improved public resource allocation to support emergency responses. However, it did not fully explore the macroeconomic implications of

pandemics on construction projects, necessitating further research into data-driven approaches. Existing traditional management frameworks often fail to account for the integrated effects of pandemic parameters and productivity measures of the construction industry. The research presented here provides an integrated computational framework to quantify the level of RRI to RPCI due to an unexpected pandemic, here COVID-19, at the global and continental levels, accounting for the major contributors to the world construction economy.

$$RPCI_{Global} = 3970559154.927 - 76146252296.580 * RRI_{Global} + 656128642636.901 * RRI_{Global}^{2} - 3345117353394.890 * RRI_{Global}^{3} + 11174378537916.322 * RRI_{Global}^{4} - 25556047415072.504 * RRI_{Global}^{5} + 40523917628289.492 * RRI_{Global}^{6} - 43992356602286.531 * RRI_{Global}^{7} + 31290483618835.941 * RRI_{Global}^{8} - 13167358745727.469 * RRI_{Global}^{9} + 2489361958615.297 * RRI_{Global}^{10} \quad (2.10)$$

$$RPCI_{America} = -25366.119 + 323864.741 * RRI_{America} - 1757803.230 * RRI_{America}^{2} + 5254658.791 * RRI_{America}^{3} - 9337587.340 * RRI_{America}^{4} + 9856543.675 * RRI_{America}^{5} - 5717779.731 * RRI_{America}^{6} + 1404819.227 * RRI_{America}^{7} \quad (2.11)$$

$$RPCI_{Asia} = -4693.925 + 174733.137 * RRI_{Asia} - 2772747.933 * RRI_{Asia}^{2} + 24421040.039 * RRI_{Asia}^{3} - 130026205.540 * RRI_{Asia}^{4} + 426231531.310 * RRI_{Asia}^{5} - 834270288.215 * RRI_{Asia}^{6} + 884325613.914 * RRI_{Asia}^{7} - 386283923.024 * RRI_{Asia}^{8} \quad (2.12)$$

$$RPCI_{Europe} = 12737765.324 + -189859698.441 * RRI_{Europe} + 1234470489.684 * RRI_{Europe}^{2} - 4572854693.998 * RRI_{Europe}^{3} + 10554475390.185 * RRI_{Europe}^{4} - 15541523441.241 * RRI_{Europe}^{5} + 14256836898.329 * RRRI_{Europe}^{6} - 7448563614.145 * RRI_{Europe}^{7} + 1696773372.435 * RRI_{Europe}^{8} \quad (2.13)$$

$$RPCI_{Oceania} = 32506.970 - 289014.969 * RRI_{Oceania} + 1095524.597 * RRI_{Oceania}^{2} - 2295108.850 * RRI_{Oceania}^{3} + 2870208.404 * RRI_{Oceania}^{4} - 2142806.607 * RRI_{Oceania}^{5} + 884347.796 * RRI_{Oceania}^{6} - 155657.035 * RRI_{Oceania}^{7} \quad (2.14)$$

2.6.2.Advancing Risk Assessment Through Statistical Analysis

Despite extensive research on the impacts of sudden disruptions in construction, no prior studies have employed statistical regression methods using the relative productivity of the construction industry to manage pandemic-related risks. This study introduces a system based on statistical analysis, demonstrating how time-series analysis can establish causal relationships between economic and pandemic-specific variables. The integration of economic indicators such as FDI, employment rate, share prices and total spending offers a robust approach to quantifying industry-wide vulnerabilities [1, 36]. Aligned with global disaster risk guidelines, including the Sendai Framework [72], this research reinforces that pandemics are not isolated events but systemic risks with significant economic consequences. The computational framework (risk assessment) used here, and the related findings, could equip policymakers and industry leaders to assess and improve preparedness, optimise resource allocation and enhance resilience against a future COVID-19-like pandemic crisis.

2.6.2.1. Causal Effect Analysis and Model Validation

This study advances causal effect analysis by integrating the full causal effect, which consists of a combinatorial process to assess pandemic and economic data interactions. A validation framework ensures statistical instrument reliability across the space of possible regressions. The application of the full causal effect can be further enhanced by code optimisation and improved computational power. Such improvements could enable performing the analysis of larger datasets and for the whole world in future. In this research, the generalised method of moments used offers advantages that enable the detection of the full causal effect. Compared to other methods, GMM is efficient in the presence of heteroskedasticity [30] and demonstrates superiority over OLS by allowing the use of instrumental variables to address endogeneity problems [32]. Although GMM could suffer from weak instrumentation (exogenous variables) in some cases, it can be limited, for example, by taking advantage of Hansen's J-statistic test in GMM to assess the validity of the model—a test that is difficult to apply using methods like OLS [43]. It is preferred to OLS because it allows the potential to utilise dynamic panel data models in future, which could help to mitigate bias caused by endogenous regressors even better [50].

According to our methodology, including an external event is crucial for the model's convergence when computing the causal effect. During the spread of COVID-19, economic data was limited to quarterly reports, while pandemic data was recorded daily. This limitation in economic records prevented accurate prediction of when the industry would return to its normal trajectory.

2.6.2.2. Regional Variations in The RPCI Of the Construction Industry

The research here examined the relative productivity of the construction industry across global and continental levels during the COVID-19 pandemic. The employment rate had negative links with RPCI in the global models and across Asia. This may be due to labour shortages and supply chain disruptions during the COVID-19 pandemic, which particularly affected construction projects in Asian economies [59]. In America and Europe, the employment rate had positive links with the RPCI, potentially reflecting government stimulus programs and labour market resilience. In Australia, the effects were mixed but mainly positive, possibly due to localised policy measures and infrastructure investments [60].

FDI had positive coefficients on a global scale and in America, likely due to strong capital flows and investment in infrastructure projects [61]. However, FDI had mixed effects in Asia, Europe, and Oceania, possibly reflecting differing regulatory environments and pandemic-related uncertainties affecting investor confidence [62].

Inflation showed negative coefficients globally, which may be linked to rising material costs and supply chain disruptions [55]. However, in America, Asia, and Europe, inflation exhibited a positive relationship with construction, suggesting that in some cases, price increases were accompanied by higher project valuations and investment activity [56]. In Oceania, the effects were mixed, reflecting variations in monetary policies and construction sector responses [57].

The mortality rate had negative coefficients in global models as well as in America, Europe, and Oceania, likely due to workforce losses and project delays caused by health crises. In one regression for Asia, however, a positive coefficient was observed, which may indicate that despite health challenges, economic recovery efforts in certain countries offset the impact.

The pandemic growth rate had negative coefficients in global regressions and in America, reflecting the direct economic disruptions caused by COVID-19 lockdowns. In Oceania, the effects were mixed, possibly due to varying degrees of containment success and economic policies. This variable was not significant in Asia and Europe, suggesting that other economic factors played a more dominant role in construction sector performance.

The pandemic reproductive number had negative coefficients in global regressions and Oceania, indicating that higher transmission rates led to more severe disruptions [47]. However, in America and Europe, positive coefficients were observed, possibly because construction activities continued despite rising case numbers, aided by adaptive measures such as remote project

management and government interventions. In Australia, the effects were mixed, likely due to shifting lockdown policies and stimulus efforts [69].

Total spending had positive coefficients in global models as well as in America and Oceania, suggesting that government and private sector spending played a crucial role in sustaining the industry during the crisis [63]. However, in Asia and Europe, the effects were mixed, potentially due to differences in stimulus policies and economic recovery speeds [66].

The COVID-19 transmission rate had negative coefficients in global models, reflecting its adverse impact on labour availability and project timelines [62]. In Australia, the effects were mixed, likely due to localised containment measures and varying state policies [72]. In Europe, a positive coefficient was observed, possibly due to the adaptation of the construction sector to pandemic conditions, including improved safety measures and continued operations. This variable was not significant in America and Asia, suggesting that other factors had a more prominent role in construction sector performance.

2.6.2.3. Enhancing Economic Stability and Resilience

A key contribution of this research is the introduction of a full-causal framework for economic analysis, surpassing previous studies that identified single causal relationships [35, 37, 38]. This dynamic approach captures interdependencies between economic variables, improving predictive accuracy and informing adaptable economic strategies. The collection of coefficients provides insights for policymakers to implement economic controls that foster a resilient and responsive economy during crises.

2.6.2.4. Practical Implications of the RRI

A contribution of this research is the creation of a relative risk index tailored specifically for the construction industry in the studied regions. By integrating economic and epidemiological predictors, the relative risk index quantifies vulnerabilities and potential disruptions caused by pandemics. This index allows decision-makers to assess the likelihood and severity of future crises, enabling proactive mitigation strategies. The model incorporates real-time data to enhance predictive accuracy, helping industry leaders implement timely interventions to minimise economic and operational disruptions.

Private and public managers can leverage the study findings to assess how economic variables impact RPCI. Private stakeholders can periodically review explanatory variables to forecast economic conditions and adjust operations accordingly. During extreme events, the RRI framework can help mitigate uncertainty and volatility (Baek, 2020).

Project managers and stakeholders can optimise workflows by using predictive coefficients to anticipate disruptions and recovery trajectories. For instance, construction companies could have used this method during COVID-19 to measure its impact on their projects, enabling proactive labour adjustments and workflow modifications. Furthermore, project managers can apply the full causal effect to detect key variables of their industry and to manage the risk of disaster with more certainty during pandemics. The relative risk index of the relative productivity of the construction industry aligns with the aims of the IMF by enhancing economic stability, financial resilience and sustainable growth by preventing future extreme events [78]. Since construction is a key driver of GDP, monitoring its risks helps prevent economic disruptions linked to pandemics [67]. The IMF is supported here by relative risk indices that provide early warning signals for banking and investment vulnerabilities related to construction financing. Additionally, by assessing debt levels and fiscal risks associated with large infrastructure projects, the index can be applied to optimise key sectors in the economy. It also promotes investor confidence by offering transparency and stability, aligning with the IMF goal of fostering stable environments for foreign direct investment in the construction industry as required by regions [62].

2.7. Conclusions

This study advances disaster risk management in the construction industry by integrating economic and pandemic-driven predictors into a systematic framework. Previous causal effect studies typically considered only one regression at a time [73, 74, 75, 76, 77]. While some exceptional research incorporated multiple models, they did not integrate multiple regressions into a comprehensive index. Our study explored the full range of valid solutions and, for the first time, integrated them to analyse the interactions between the pandemic and the economy on the relative productivity of the construction industry. The relative risk index and predictive models could empower decision-makers with COVID-19 data-driven insights for crisis preparedness and mitigation. By leveraging automation and real-time data, this research enhances proactive risk assessment and quantifies the links between the risk indicators and the leading construction economies of the world, fostering industry resilience.

Future efforts should refine computational models, incorporate additional predictors, and promote cross-sector collaboration to strengthen global disaster risk reduction efforts. For long-term resilience, this research suggests future analysis of the full causal effect on the macroeconomy. Further work could focus on replicating this study across the entire economy to optimise decision-making by policymakers and to develop a theoretical framework compatible with the macroeconomy in future. By applying this methodology, industries beyond construction can improve safety and disaster preparedness. Linear programming could be utilised to find

optimum configurations of the dynamics of the economic system once more variables are explored with the full causal effect. The proposed approach for future work can inform disaster risk reduction strategies across economic sectors, ensuring greater stability in the face of future global challenges. The integration of automated technologies capable of real-time data analysis and autonomous decision-making will further strengthen the ability of the construction industry to navigate crises using the full causal effect.

2.8. References

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3. DYNAMIC STRUCTURAL MODELLING OF SYSTEMIC INTERACTIONS UNDER CRISIS: A GENERALISED MOMENT FRAMEWORK WITH APPLICATION TO PANDEMIC–ECONOMIC DYNAMICS

3.1. Abstract

This study models the behaviour of economic systems during pandemic events by extending Zellner's Seemingly Unrelated Regressions (SUR) within a Generalised Method of Moments (GMM) framework. The proposed approach identifies systems of equations that remain stable when explaining one or more variables simultaneously. Applied to pandemic–economic dynamics across major economies (2020–2023), the results show interactions between epidemiological indicators (transmission, recovery, mortality) and macroeconomic variables (employment, trade, investment, inflation). The findings suggest that the pandemic negatively affected employment and trade, while higher recovery rates acted as stabilising forces, reducing inflationary pressures and supporting economic resilience. The framework captures how structural relationships evolve across risk phases, including initial shock, early recovery and post-vaccination, identifying systemic vulnerabilities and resilience pathways during global disruptions.

3.2. Introduction

The COVID-19 pandemic triggered unprecedented disruptions in both public health systems and global economic activity. Governments implemented large-scale fiscal and monetary interventions to stabilise labour markets, sustain firms and support healthcare responses. While these measures mitigated short-term economic collapse, they also revealed structural vulnerabilities in interconnected economic systems (Baldwin & di Mauro 2020).

The COVID-19 pandemic did not simply disrupt isolated economic variables; it triggered a cascade of interconnected reactions across health systems, labour markets and financial structures. Understanding this crisis, therefore, requires not a single equation, but a narrative of interacting and evolving forces (Nicola et al. 2020).

Pandemics and their mitigations required support to control economic vulnerability during extreme events (Eichenbaum et al. 2021). To model COVID-19 risk, we analyse the economic system and identify the forces shaping key macroeconomic variables within contemporaneous systems of equations (CSoE). This approach can detect regime change and modified significance. The methodology of this work is inspired by previous research, which attempted a multidimensional system.

Unlike the natural sciences, econometric analysis relies on forces that can only be observed indirectly through system behaviour (Jiang et al. 2023). Although data implicitly capture observable interactions, they do not reveal the underlying mechanisms linking economic variables. Analysing economic dynamics over time requires methods capable of capturing both the strength of interactions and the system's response to external shocks (Hoover 2015).

The cause and effect in the economy, studied by previous authors, is briefly mentioned next. Even though limited to one, two or three explained variables with one equation each, the previous researchers implicitly aimed for what our work proposes: a method to identify the spectrum of governing equations in the economy.

Mao Takongmo & Lebihan (2021) studied the associations between public spending and national productivity. Their work found that variations in the information used to compute regressions can cause balanced coefficients to fluctuate. Their study of the government spending influence on GDP showed how it only impacted when the exchange rate of currencies was excluded from their model. Once the exchange rate was included and varied strongly, the coefficient of government spending diminished and even reversed, suggesting that fiscal policies and monetary conditions present multiple associations. The intensity of these associations depends on economic conditions, and their influence can vary over time.

Under stable regimes, coefficient signs are often expected to remain consistent; however, previous empirical evidence suggests that they may change under structural shifts. For instance, a smooth transition process from positive to negative coefficients between inflation and uncertainty perception was reported by Hajamini (2019). In this research, the authors explained alternating coefficients due to uncertainties among the public about the next policy controlling inflation. If a policy implements controlled inflation, then uncertainty can be controlled, but if volatile inflation comes into effect, the uncertainty will increase. The work of Hajamini raises questions about the intrinsic origin of these transitions and whether their existence represents actual regime changes or mere numerical imbalances.

One can infer this about the expectation of balanced coefficients in econometrics: if a change of sign occurs, a breakpoint in the models must occur. Such inflexion points must be brought about by changes in the actual interactions. Another option is that the change of sign occurred from region to region when studying international panel data. Although regime changes can be modelled explicitly, the number of possible configurations quickly becomes computationally intractable.

Another study on multiple statistical inference, conducted by Raunig (2023), examined the direction and magnitude of coefficients between policy uncertainty and stock market volatility. Using explanatory diagrams with lagged effects, they showed that stock market volatility does not always produce economic uncertainty, especially when the variations in the market can be anticipated by the investors. One can interpret the interaction of the stock market and volatility in terms of the frequency of occurrence of normal and extreme events. The stronger the variations, the less can be anticipated, causing more volatility in the markets. Later in this work, we show that the concept of oscillating perturbances can expand beyond a single equation to CSoE, where specific variables gain relevance at periods, turning multiple equations into a distribution of structural coefficients under specific regimes. This aligns with system-based approaches to macroeconomics (Sims 1980), where overidentified models must be elaborated further to fully explain the economy and the risks induced by stochastic events.

Besides the studies of interlinked systems with varying coefficients, only a few studies have attempted to map the full network of relationships across key economic variables. Advances in the field of multiple equation analysis by Vilchis et al. (2025) simplify previous similar approaches. They employed Arellano–Bond estimators to identify stable coefficients across samples of equations for the construction industry. Their methodology introduced the concept of causal manifolds detected with a method called full causal effect (FCE). Their method captures robust groups of equations resulting from stochastic combinatorial selection and a consistent test of validity. Besides the explanatory power of the FCE, it was applied only to explain one variable at a time. In practice, systems involve multiple variables, requiring extra dimensions to better represent reality.

Building on the described works, the present study applies an algebraic framework that captures the seemingly unrelated regression proposed by Bias and Zellner (1962), extended to the root cause and effect. In his classic work, Zellner described a generalisation of the linear model regression with multiple equations. He found a method to verify if a group of regressions preserved its validity when considered as a system of equations.

This study contributes to the literature in three ways. First, it extends the SUR framework using GMM to identify systems of equations that are jointly and individually consistent. Second, it introduces a methodology to detect structural configurations across multiple economic contemporaneous variables. Third, it applies this framework to pandemic–economic dynamics, revealing how relationships evolve across different crisis phases. This study follows the economic

system through three distinct phases—shock, adaptation, and restructuring—revealing how relationships between variables emerge, invert and stabilise under extreme conditions.

This work aims to reduce uncertainty reduction from multiple specifications by identifying patterns and distributions of plausible mathematical systems (Leamer 1983). Even though identification of structural relationships remains inherently challenging in observational systems (Heckman 2005), this work presents the arrangement of economic structures, such as systems of simultaneous equations.

The next chapters of this research are structured as follows: Section. "Materials and Methods" presents the methodology for designing and selecting models across samples of macroeconomic variables. The methodology includes a construction based on mathematical conditions for the identification of CSoE. Sect. "Results" details the equations for the economy during the first and second outbreaks, and includes a post- vaccination period. The conclusions and discussions note the dynamic patterns of statistical interaction, which are validated with two numerical approaches and previous literature.

3.3. Materials and Methods

To identify the statistical interactions, we require a framework capable of tracking isolated effects in detail. At the same time, the model must capture coordinated movements across the system. Using the FCE for multiple relevant economic indicators, we constructed systems of equations composed of individually valid regressions looking for the most likely systems to coexist as an ensemble (Diebold et al. 2012).

3.3.1.Explanatory Mechanisms on Structural Systems

Let $y_{i,j}$ denote the explained variables in a set of GMM estimated equations, where i indexes equations and j indexes explanatory variables. Eq. 3.1 represents the general form of a sample of k CSoE.

$$Y_k = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_i \end{bmatrix}_k = \begin{bmatrix} \theta_{1,1}x_2 + \theta_{1,2}x_3 + \cdots + \theta_{1,j}x_j \\ \theta_{2,1}x_1 + \theta_{2,2}x_3 + \cdots + \theta_{2,j}x_j \\ \vdots \\ \theta_{i1}x_1 + \theta_{i,2}x_2 + \cdots + \theta_{i,j}x_j \end{bmatrix}_k \tag{3.1}$$

3.3.2.The Cause-Effect SLE

The application of the GMM and FCE implies that the weighting matrix of the CSoE adds an extra dimension when considering the number of k valid equations $\partial Q_k(\hat{\theta}_{i,j})/\partial\theta_{i,j} = 0$ within a level of certainty. Using $\hat{\theta}_{i,j}(Z_i) = \hat{\theta}_{i,j}(Z_i^0) + [\hat{\theta}_{mi,j}(Z_i) - \hat{\theta}_{i,j}(Z_i^0)]$ as a sample of valid coefficients, it follows that the optimal stacked estimator of instruments is given by Eq. 3.2, where $n_{i,j}(Z_i^0) = -\{E[Z_i^0 u_{i,j}(\theta_{i,0})/\partial\theta'_{i,j}]\}^{-1} Z_i^0 u_{i,j}(\theta_{i,0})$. Using the asymptotic covariance matrices of the CSoE, one can generalise the validity of a single independent model to the case of many valid equations.

$$\begin{aligned} T^{1/2}[\hat{\theta}_{i,j}(Z_i^0) - \theta_{i,0}] &= T^{1/2} \sum_{t=1}^{T} n_{i,j}(Z_i^0) \\ &= T^{1/2}[\hat{\theta}_{i,j}(Z_i^0) - \theta_{i,0}] + T^{1/2}[\hat{\theta}_{i,j}(Z_i) - \hat{\theta}_{i,j}(Z_i^0)] \end{aligned} \tag{3.2}$$

The standard GMM framework follows the large sample property established by Hansen (1982); an equation initially tested alone must remain valid when considered as a system of equations. The contemporaneous validity requires the asymptotic variance $D(Z)$ =Avar$[\hat{\theta}_{i,j,T}(Z_{i,j}) - \hat{\theta}_{i,j,T}(Z_{i,j}^0)]$ to be positive semi definite to be valid in the system of GMM models explaining multiple contemporary elements for every value of T.

3.3.3.Implementation of SUR

The SUR estimation finds linear coefficients of the form $\hat{B}_i = ({X_{i,j}}'{\Omega_{i,j}}^{-1}X_{i,j})_i{}^{-1}{X_{i,j}}'{\Omega_{i,j}}^{-1}y_i$. A system is considered contemporaneous if each of its elements, variable by variable, neglects the null hypothesis in Hansen's J statistics alone. If the system is valid when considering equation by equation, then the system can be verified with the SUR method, if it meets the following three conditions (Zellner 1962):

Condition 1 ensures that each equation is individually significant. In the SUR context, the rejection of the null hypothesis is tested on the stacked form using $H_{0,i}: \beta_{i,1} = \beta_{i,2} = \cdots = \beta_{i,n_{sq}}$ where the Wald statistic is $W_k = (R_{i,j}\widehat{\beta}_i)'(R_{i,j}Var(\widehat{\beta}_{i,j})R_{i,j}')^{-1}(R_{i,j}\widehat{\beta}_{i,j})$ corresponding to the $W_{i,j} \sim \chi^2_{i,j}$ satisfying $p_{i,j} = P(\chi^2_{i,j-1} \geq W_{i,j}) = 0$. This condition implies individual significance, considering equation by equation.

Condition 2 ensures that predictors are significant within the system. The rejection of the null hypothesis per regressor includes the elements of X_k and their coefficients for Y performing better than $H_{i,j,0}: \beta_{i,j,1} = \beta_{i,j,2} = \cdots = \beta_{i,j,k} = 0$. The sample of coefficients in the system k has a

weighting matrix $W_{i,j,k} = (U_{i,j,k}\widehat{\beta}_{i,j,k})'(U_{i,j,k}Var(\widehat{\beta}_{i,j,k})U_{i,j,k}')^{-1}(u_{i,j,k}\widehat{\beta}_{i,j,k})$ corresponding to the chi-squared $W_{i,j,k} \sim \chi^2_{i,j,k}$ for their p-values. An equation is valid when $p_{i,j,k} = P(\chi^2_{i,j-1,k} \geq W_{i,j.k}) = 0$ and replicated to find k systems of contemporaneous equations. This condition implies statistical relevance for the distributions of elements of X_k corresponding to the explanatory information of the dynamic panel data.

Condition 3 ensures that residuals are correlated across equations, validating the SUR structure. The third condition of contemporaneous systems is the correlation of the residuals. Using the standard formulation of residuals in linear models, $\left(\hat{\varepsilon}_{i,j,T}\right)_k = \left(y_{i,j,T} - X_{i,j,T}\hat{\beta}_{i,j}\right)_k$ for each observation T, the simultaneous correlation can be found using Eq. 3.3, where the SUR model disturbs the multidimensional correlation matrix $\sigma_{q,n_{sq}} \neq 0$ for every $i \neq j$ in scenario k.

$$\sigma_{i,j,k} = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{i,k,T}\hat{\varepsilon}_{j,k,T}}{\sqrt{\sum_{t=1}^{T} \hat{\varepsilon}_{i,k,T}{}^2}\sqrt{\sum_{t=1}^{T} \hat{\varepsilon}_{j,k,T}{}^2}} \tag{3.3}$$

Let the system Y_k in Eq.1 be investigated for validity at a contemporaneous level where $\mathrm{E}(\varepsilon_k) = 0$ and $\mathrm{E}\{corr(\varepsilon_i\varepsilon_j')\} = \{\sigma_{i,j,t}I_t\}$ for every $t = 1, \dots, T$. The residuals in Eq. 3.3 are governed by the covariance matrix $\Omega = \Sigma \otimes I_T$ with $\Sigma = (\sigma_{i,j})$ capturing contemporaneous cross equation error correlation between a distribution of elements of explained variables per system.

Heterogeneity across economies may lead to varying structural relationships (Pesaran & Smith 1995). To derive results from CSoE, each system satisfies the condition. $|\bar{\sigma}_{i,j,k}| \geq 0.5$ for every $i \neq j$. The threshold of correlation between residuals was defined with the postulates of Zellner (1962): "The gain in efficiency is an increasing function of the absolute value of the correlation between disturbances". We applied the SUR approach to find the systems of equations with the most correlations. Even though 0.5 is a conservative value for contemporaneous correlation, previous researchers indicate a correlation of residuals of 0.1, 0.3 and 0.5 as small, medium and large correlations, respectively (Cohen 1988).

3.3.4. Integration of GMM and SUR

This approach provides a mathematical framework to integrate sectors of the economy in subgroups of equations with balanced coefficients, joint significance and correlated residuals. Fig. 21 describes the process of identification of contemporaneous equations in the context of the FCE.

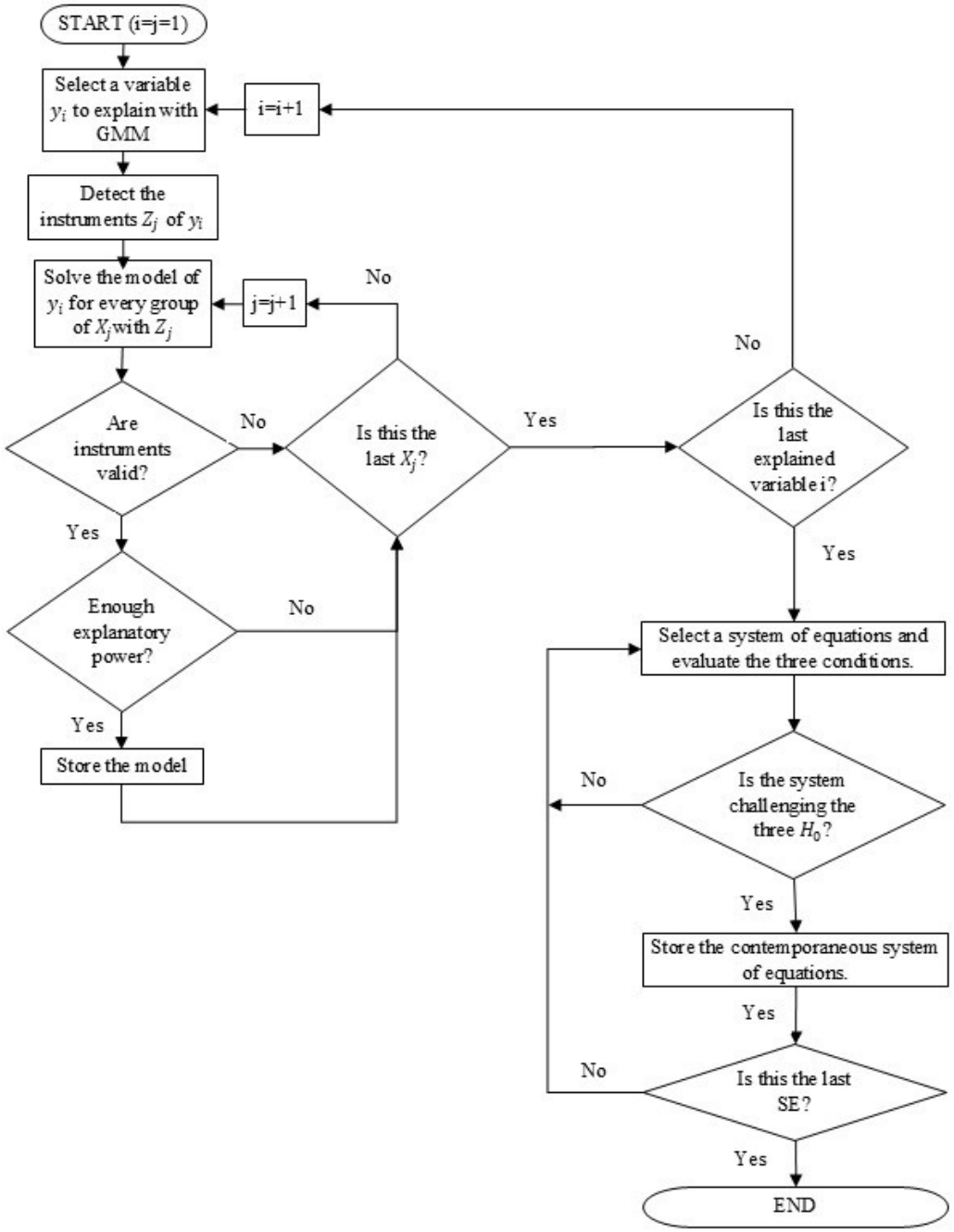


Figure 20 Flow chart to detect the FCE and CSoE.

3.3.5.Methodology Justification

This study identifies systems of balanced equations that explain multiple economic variables. When a system of equations satisfies the conditions outlined above, then the system of equations is classified as a CSoE. This implies that the equations simultaneously explain *i* number of variables, with coefficients that are valid in a contemporaneous context. The initial selection of GMMs provides the first dimensions of the cause and effect. The linear multivariate formulations are arranged in a system of *i* equations explaining *i* different variables. The first and second

conditions were applied to the SUR models, and the third Condition was applied to both SUR and GMM, yielding comparable results.

This method finds multiple equations within the admissible parametric levels. Each system of equations suggests a plausible pathway of interactions reflected in the observed data. By identifying the full range of statistical effects, it captures a broader spectrum of explanatory coefficients across variables. In this sense, CSoEs are not isolated; rather, they coexist one next to another, sharing the supply chain, acting with variable intensity.

3.3.6.Benchmark Models and Comparison with Established Approaches

To assess whether the systems of equations of GMM provide insights beyond those obtainable with more conventional econometric methods, we benchmark our results against an established modelling approach, the Seemingly Unrelated Regressions. These benchmarks are not intended to replicate the full system level identification strategy proposed in this study, but rather to provide reference points against which the behaviour and coherence of the detected structural systems can be evaluated.

3.3.7.Reduced Form Dynamic Panel Models

As a first benchmark, we estimate reduced form dynamic panel regressions for selected key economic variables. These models take the general form:

$$y_{i,t} = \alpha y_{i,t-1} + X'_{i,t}\beta + \varepsilon_{i,t} \tag{44}$$

where $y_{i,t}$ denotes the dependent macroeconomic variable, $X_{i,t}$ includes a limited set of epidemiological and economic covariates. Estimation is conducted using fixed effects and dynamic panel GMM techniques commonly employed in the applied macroeconomic literature.

These reduced form models provide a baseline for understanding average directional relationships between health and economic variables. Consistent with prior studies, they recover stable sign patterns for core pandemic economic interactions, including positive associations between recovery rates and employment, and inflationary pressures linked to mobility and supply constraints. However, by construction, these models treat equations independently and do not account for contemporaneous cross equation dependencies or coordination across multiple economic outcomes.

3.3.8.Classical SUR Systems without Instruments

As a second benchmark, we estimate standard Seemingly Unrelated Regression systems using the same sets of dependent variables and regressors considered in the systems of the GMM framework, but without instrumental variables or combinatorial equation selection. In this setting, system estimation exploits cross equation residual correlations to improve efficiency but does not impose moment based identification or equation level validity constraints.

The classical SUR benchmark confirms the presence of statistically significant contemporaneous correlations across selected macroeconomic equations, particularly during the peak crisis phase of the pandemic. However, unlike the proposed framework, standard SUR estimation yields a single fixed system and does not distinguish between multiple admissible structural configurations. As a result, it cannot capture the regime dependent emergence, inversion, or reorganisation of relationships documented in the SUR–GMM systems.

3.3.8.1. Implications of the Benchmark Comparison

Taken together, the benchmark models confirm that the main directional relationships uncovered by the SUR–GMM framework are broadly consistent with those obtained using more established econometric approaches. At the same time, they highlight the limitations of single equation, lag dominant, or fixed system methods in capturing the contemporaneous and systemic nature of pandemic induced economic dynamics.

The contribution of the proposed SUR–GMM framework does not lie in outperforming conventional models in point estimation or predictive accuracy, but in identifying ensembles of contemporaneous systems that are jointly and individually statistically valid. By revealing how economic variables coordinate into alternative structural configurations under different crisis phases, the framework complements existing econometric approaches and provides a system-level perspective that is difficult to obtain using standard benchmarks alone. For a reference of the correspondence between the systems of GMM and the benchmarks, refer to Appendix B.

3.4. Results

3.4.1. Case study period: the COVID-19 pandemic

Table 7 contains the statistical description of the information utilised in this research. The information was obtained from the Organisation for Economic Co-operation and Development

(2024), St. Louis Federal Reserve Economic Data (2024), World Bank (2024) and Johns Hopkins University of Medicine (2024).

The methodology employed in this study adopts a variation of the conventional approach for Z. The matrix Z is established through groups of vectors that are collinear, uncorrelated with the error term and sufficiently correlated with the vectors of X (Hall 2009). This construction mitigates weak-instrument concerns by ensuring sufficient correlation with X and orthogonality with the error term."

3.4.2. The Modes of the Economy During the Pandemic

Table 8 shows whether each economic relationship is positive or negative across four econometric models. It highlights where the models agree, with most relationships remaining consistently positive. The following subsections present the results by dividing the period of COVID-19 into three. The first corresponds to the initial crisis in the first quarter of 2020. The second includes the early recovery during the remaining three quarters of 2020, and the third period corresponds to the post treatment and vaccination period with established trends between 2021 and 2023. The formulations of the statistical scenarios for the three periods of study are presented in Appendix C.

3.4.2.1. The First Quarter of 2020

3.4.2.1.1. M3 and Employment Rate

At the onset of the pandemic, labour markets did not gradually weaken—they collapsed. As employment fell sharply, monetary expansion emerged not as a driver of growth, but as a reactive stabilisation mechanism attempting to contain systemic decline (Coibion et al. 2020). The negative link between monetary variables and employment (β=-0.402, 90% CI) reflects a reactive policy environment: central banks expanded liquidity (higher M3) as employment declines often signalled deteriorating business conditions that led firms to cut jobs (Brunnermeier et al. 2019).

The perspective about employment during the pandemic resonates with previous research that proposed that unemployment could not be controlled by broadening access to temporary financial supports, including the use of payroll subsidies for companies. Both access support broadening and supporting wages were not available to large, profitable companies, leaving a few workers without support during the pandemic Carranza et al., (2020). The monetary regulations in the United States of America determined that companies with strong financial positions were

Table 7 Descriptive statistics and correlation matrix.

| Variable | Mean | SD | Min | Max | | |

circulation and deposits, institutional and market funds and purchase agreements. During the use of the GMM, correlations of over 0.7 were observed between inflation, industrial production prices, FDI, exports, imports and government and private spending. The pairs of predictors with a correlation above 0.7 were omitted in the GMM. Those variables were included only in separate equations, one by one, to ensure low correlated information.

3.4.2.1.2. Transmission and Private Spending (β=0.921, 90% CI)

Although counterintuitive, higher transmission and mobility were associated with increased private spending during early Q1 2020 due to behavioural and structural responses. The literature on the health–economy trade-off highlights that fear-induced changes in purchase patterns occur simultaneously with economic disruption, especially during the early outbreaks. Once a pandemic or other extreme event has been officially declared, economic demand reallocates across sectors. Previous research revealed that the consumer's income, age and occupation are important in the context of adaptive shopping patterns (Valaskova et al. 2021). During the early pandemic, private spending shifted toward essential goods and personal protective equipment. This reflects a rapid reallocation of demand in response to lockdown conditions (Addo et al. 2020).

Table 8 Cross-Model Sign Concordance

ECONOMIC RELATIONSHIP	SUR–GMM Systems	Panel GMM with lags	SUR	SUR (with lags)
Government Spending → Employment Rate	Positive	Negative	Positive	Positive
Production Prices → Employment Rate	Positive	Positive	Positive	Positive
Mobility Rate → Exports	Positive	Negative	Positive	Positive
M3 → Inflation	Positive	Positive	Positive	Positive
Mortality Rate → Inflation	Positive	Positive	Positive	Positive
Recovery Rate → Inflation	Positive	Negative	Positive	Positive
Transmission Rate → Private Spending	Positive	Positive	Positive	Positive

ECONOMIC RELATIONSHIP	SUR–GMM Systems	Panel GMM with lags	SUR	SUR (with lags)
Mobility Rate → Private Spending	Positive	Positive	Positive	Positive
Employment Rate → Production Prices	Positive	Positive	Positive	Positive
Government Spending → Share Prices	Positive	Positive	Positive	Positive

Positive and Negative show whether the effect stays consistently positive or negative across the valid models.

3.4.2.1.3. Recovery Rate and Inflation (β=–0.840, 90% CI)

A negative relationship between the COVID-19 recovery rate and inflation suggests that faster recovery alleviated price pressures during the initial outbreak. The negative coefficient to explain inflation using the recovery rate of COVID-19 is consistent with macroeconomic theory, which suggests that when the infection period shrinks, by natural or induced mechanisms like new treatments, the economic system will get less strained by the pandemic. A faster recovery from infections increases certainty and stabilises both public and private price expectations (Cavallo 2020).

The link between recovery rate and inflation explains why inflation was slightly reduced or kept nearly constant at the beginning of the pandemic. The previous literature on COVID-related economic uncertainty found that inflation increments in the pandemic era were associated with supply chain disruptions. Lockdowns reduced spending on travel, dining and entertainment, while remote work and fiscal stimulus increased demand for goods such as technology (Pamidimukkala, 2021). This shifted consumption away from services toward durable goods, and the surge in global demand exposed weaknesses in highly fragmented production systems that rely heavily on global value chains (Santacreu & Labelle, 2022).

The epidemiologic variable for recovery from infections is linked to higher volatility in the economy. Low recovery is also linked with extended closure periods and fears of getting infected (Porcelli, 2020). The relevance of new treatments gained momentum during the pandemic to control price increases. This result highlights how living costs and inflation were associated with broader socioeconomic stress, supporting the postulates that inflation interacts with broader risk contexts of health crises (Goodell, 2020). In the long term, inflation control during pandemics is referred to by some researchers as modifications to the tails of the inflation distribution.

Considering only the statistical facts, inflation control may focus on controlling the extreme values of inflation, especially in the early spread periods where recovery rates are relatively low (López-Salido & Loria 2020).

3.4.2.1.4. Mobility Rate and Inflation (β=0.640, 90% CI)

Positive coefficients of mobility in public spaces explaining inflation indicate that the level of spread control measures, specifically the lockdown intensity, can raise price levels during pandemics. As people move more in public venues and the economy reactivates, consumer demand can outpace supply under pandemic disruptions, driving inflationary pressures and stressing the supply chain. It has been noted that during the lockdown in the United Kingdom, inflation surged sharply, more than ten times higher than in previous years, and affected the most demanded products and services during the isolation period (Jaravel & O'Connell 2020).

3.4.2.1.5. Exports and FDI (β=0.874, 90% CI)

The result of this subsection indicates that countries with strong export infrastructure attracted more investment, even during periods of increased risk due to pandemic conditions. Once the spread of the new coronavirus started in 2020, only countries with adequate international trading infrastructure, such as adequate ports and airports to operate during the outbreak, continued activities during the period of COVID-19. The policy management was identified in our results, where adequate personal protective equipment (PPE) allowed activities. The connections between exports and FDI during the pandemic are consistent with previous studies, which detected that countries with resilient trade relationships weathered shocks robustly. Besides the efforts to keep international trade as in normal periods, the main economic interaction path to attract FDI by preserving exports includes the increase in export prices and the reduction in global trade due to border closures and low productivity. Countries with sustained export systems guaranteed continuation and potentially new investments from international resources (Al-kasasbeh et al. 2022).

3.4.2.1.6. Mobility Rate and FDI (β=0.243, 90% CI)

The positive coefficient between foreign investment and pandemic related mobility restrictions in public venues reflects the financial flows to sectors or countries seen as resilient or safe. The mobility rate reduced less when society adapted to the spread control rules. Sustained mobility helped to attract FDI even during early 2020. Previous research conducted by Doytch et al. 2021 showed that industries with quick adaptation to remote work experienced increased investment.

Investment in manufacturing and industries declined during the pandemic. Figure 22 illustrates a tightly coupled system, where shocks in epidemiological variables propagate into economic outcomes, forming a network of dependencies characteristic of systemic crises.

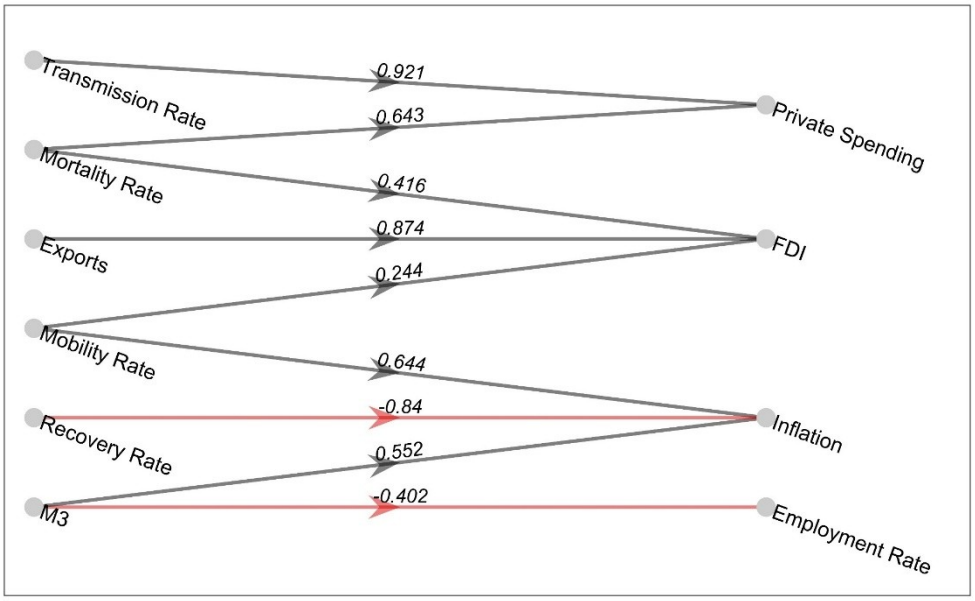


Figure 21 System of equations behaving as interconnected systems during Q1 2020.

3.4.2.2. Second to Fourth Quarter of 2020

Following the initial shock, the system entered a phase of partial adaptation. Economic relationships did not return to normal; instead, they reorganised under persistent uncertainty and evolving pandemic control conditions. This chapter compares the structural equations with previous investigations.

3.4.2.2.1. Recovery Rate and Employment Rate (β=0.810, 90% CI)

The COVID-19 pandemic was related to socioeconomic disruption, economic damage and loss of life. As a result, the government prompted responses worldwide. Beyond overwhelming health systems, it triggered widespread economic shutdowns and mass unemployment across virtually all sectors (Fakhruddin et al. 2020).

The influence of the pandemic on supply is described here in terms of the interactions between pandemic control, spread and the global economy. This result finds the influence of infections

recovered from COVID-19 on the levels in the occupational market. From the perspective of the FCE, the pandemic recovery rate, together with other variables, had a positive impact on the employment rate by keeping existing jobs and reopening initially closed job vacancies during the pandemic (Liu & Mai 2020).

The recovery rate relatively increased during this period when compared to the first quarter of the spread. An increase in the recovery rate from COVID-19 infections was promoted by new treatments (The RECOVERY Collaborative Group 2021). Together with the development of new treatments, society changed its behaviour towards more controlled buying and product availability. As the pandemic evolved after the onset of the spread, infected people got isolated easily, preventing the spread and reducing the saturation of hospitals and health care units (Wu & McGoogan 2020).

This relationship between the pandemic recoveries and employment rate highlights the relevance of epidemiological therapies improvement for labour market normalisation during the pandemic (Handwerker et al. 2020). A coefficient of 0.81 suggests that increased health services translated almost one for one into employment gains, consistent with models where labour supply and labour demand are constrained by health risk. As the COVID-19 recovery rate rose, firms faced fewer disruptions from furlough (Acemoglu 2025).

3.4.2.2.2. Mortality Rate and Employment Rate (β=−0.860, 90% CI)

COVID-19 had economic consequences not only due to its moderate lethality, but primarily because of stringent government containment measures. The significant negative coefficient of the COVID-19 mortality rate on employment compared with how the recovery modified the economy, but with even greater magnitude and opposite sign. However, the magnitude of the recovery rate was higher than the mortality rate, suggesting different levels of influence of the pandemic variables on the economy (Bhapkar et al. 2020). This asymmetry suggests that adverse health shocks had disproportionate labour market effects. Beyond direct labour force reductions, high mortality rates amplified precautionary behaviour, regulatory shutdowns and firm pessimism brought by the recurrent waves of virus spread and their corresponding control rules (Breuer et al. 2023). The link between mortality from the pandemic and employment supports models of disaster risk and hysteresis, which outline social and economic reactions, like the protective attitude towards working and infection risks, persist once the hazard has been removed. Historically, labour market effects documented after pandemics and wars indicate that mortality shocks affect expectations and have consequences long after the immediate shock dissipates(Callegari & Feder 2022).

3.4.2.2.3. Mobility Rate and Exports (β=−0.720, 90% CI)

The negative relationship between mobility rate in public venues and the value of exports has an unexpected sign coefficient. As verified by FCE-GMM and SUR, the result here can be defended using classic theoretical standpoints. Increased domestic mobility during reopening phases likely coincided with a reorientation of production toward domestic demand and services, reducing export intensity. Additionally, global supply chain disruptions meant that increased internal mobility did not translate into export capacity, causing uneven impacts and pushing international firms to nearshoring instead of automated driven reshoring (D'Ambrosio & Lavoratori 2025).

The reopening of public venues increased the transmission rate, keeping international commerce at restricted levels until the pandemic was under control and until the recovery phase of the economy was established in the long run, allowing international trade to materialise with a controlled risk of pandemic spread. To control the reopening of public venues without inducing risk, the work carried out by Wang et al. 2023 determined that the points of interest were classified into risk levels, and the corresponding minimum standard prevention and control measures were proposed to be implemented according to different risk levels. Focusing on the link between national mobility rate and exports supports trade models where domestic reopening does not imply international integration in the short term (Rose et al. 2021).

3.4.2.2.4. Mobility Rate and FDI (β=−0.530, 90% CI)

The negative coefficient of mobility on foreign direct investment suggests that short term reopening dynamics may have increased policy uncertainty for international capital allocations. The early relaxation of the spread control measures signalled unstable national containment strategies, discouraging long term foreign commitments (Foy, 2021). In contrast to portfolio flows, FDI is highly sensitive to institutional credibility and expectations of stability, especially during events posing a risk for the economy (Moosa & Merza, 2022).

The link between mobility rate and FDI aligns with international investment theory, where FDI responds more to medium term risk assessments than to short term cyclical indicators. Structural shifts away from globalisation (Mas-Coma, 2020), alongside digitisation and Industry 4.0, may further weaken FDI by reducing incentives for cross border production and traditional capital commitments. Besides the imminent risk posed by COVID-19 to internal investment, FDI inflows experienced a partial rebound after the first quarter of 2020, reflecting a short-term macroeconomic shock and mild uncertainty affecting long-term international investment decisions (Iqbal 2024).

3.4.2.2.5. M3 and Production Prices (β=0.59, 90% CI)

The interaction of money supply with production prices suggests that liquidity injections raised input costs and upstream prices before feeding into consumer inflation. This sequencing of risk related events supports cost-push interpretations of pandemic era inflation, where monetary expansion interacted with constrained supply rather than overheating demand (Knicker et al. 2025).

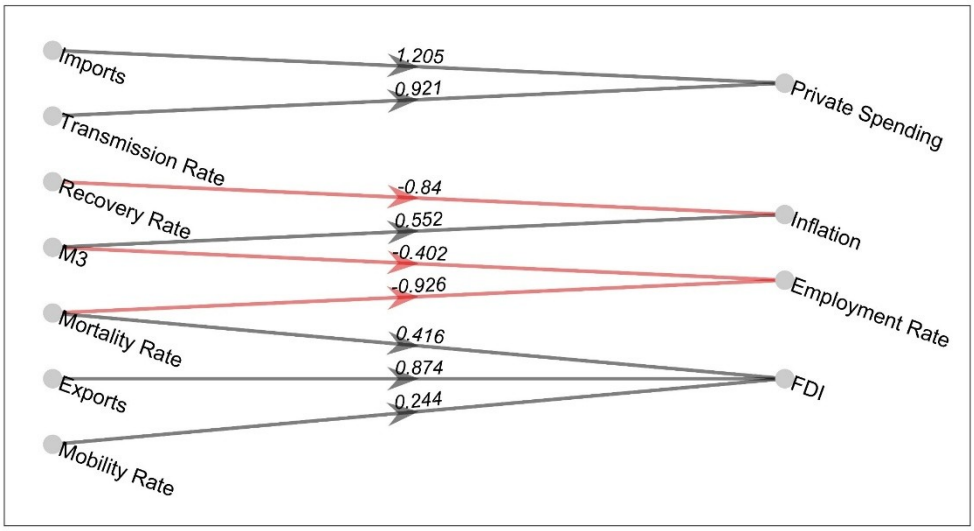


Figure 22 System of equations behaving as interconnected systems during Q2-Q4 2020.

Compared to the initial phase, the network of dependencies becomes less reactive and more structured, reflecting a transition from shock driven behaviour to adaptive dynamics. This effect is shown in Fig. 23 of this chapter.

3.4.2.3. The Recovery Period: 2021-2023

By 2021, the system no longer behaved as a crisis structure, but as a reconfigured economy shaped by the medium- to long-term effects of the pandemic. Associations observed in earlier phases of COVID-19 either stabilised, reversed or gave way to new structural dynamics, all of them detected by the SUR-GMM regressions. Fig. 24 shows the chord diagram of this period of study.

3.4.2.3.1. FDI and Employment Rate (β= −0.421, 90% CI)

For the period 2021–2023, the negative association between FDI and employment reflects a structural rather than cyclical mechanism. Unlike 2020, when FDI was influenced by uncertainty, post pandemic FDI increasingly induced capital labour substitution. Foreign investment during this phase was directed toward support for organisations. The main areas to reactivate the economy were automation, digitalisation, logistics and energy efficient production, rather than labour intensive expansion (Badmus et al. 2022).

3.4.2.3.2. Government Spending and FDI (β=0.532, 90% CI)

Between 2021 and 2023, government spending shifted from emergency stabilisation to investment oriented programs. This transitional period was noticeable in infrastructure with continued activities guiding the reception, increased demand for digital transformation and environmental preservation transition (Taghizadeh-Hesary 2023). The positive coefficient of government spending on FDI in the recovery era reflects strategic complementarity and accuracy of capital allocations rather than short term demand support for recovery.

3.4.2.3.3. Pandemic Growth and Private Spending (β=-0.411, 90% CI)

Even after the acute phase of COVID-19, the pandemic growth effects continued to exert a negative influence on private spending. During 2021–2023, this coefficient reflects a chain reaction rather than new restrictions due to new risks induced by the pandemic. Households internalised health and income risk more persistently, maintaining elevated precautionary savings despite labour market recovery (Dabija et al. 2025).

3.5. Discussion

The results presented here reflect a region of statistical validity within the population of observed events. A total of 23 systems of structural equations were found. The 23 systems of structural equations are presented in Appendix D.

In the context of structural multivariate analysis, this work identifies the likelihood of groups of equations occurring in parallel. The combined verification using the FCE (Vilchis 2025) framework for individual equations, together with their likelihood of occurring contemporaneously, contributes to reducing the uncertainty of the simultaneous validity of each system. By maintaining tightly defined and consistent parameters, the framework further mitigates the risk of unexpected or spurious outcomes corresponding to regions outside the

validity of the parameters. Taken together, the results describe a system that does not simply respond to shocks but reorganises itself in systems of contemporaneous equations. Each phase of the pandemic reveals a different governing logic, adaptation and structural adjustment. Moreover, the systems were coherent with the procedures described by other researchers. When combined, the work ensures consistency across every dimension of the matrix of structural coefficients in the economy during COVID-19. The key insight from this approach is that economic relationships are not stable under stress—they are conditional, evolving and often temporarily inverted.

Time varying dynamics have long been observed in macroeconomic systems (Engle 1982). These findings suggest that policy responses and pandemic–economic dynamics were influenced by interdependent mechanisms that evolved throughout the crisis. The CSoE—validated through Hansen J statistics, cross equation significance and residual correlation thresholds—shows that macroeconomic behaviour during systemic disruptions cannot be holistically explained using single equation models. Instead, the economy operates as a synchronous system in which epidemiological shocks propagate simultaneously through monetary, labour, production and consumption (Forni et al. 2000).

3.5.1. Health Shocks and Economic Instability

During the initial outbreak in the first quarter of 2020, epidemiological variables including transmission, recovery and mortality influenced economic outcomes. The negative relationship between monetary aggregates and employment reflects a reactive policy environment in which liquidity could expand as labour markets deteriorated. This pattern corresponds with the widespread job losses and essential public support during the early stages of the pandemic (Mckibbin et al. 2020).

The negative coefficient of recovery rates on inflation suggests that improvements in public health outcomes stabilised price expectations. Faster recovery shortened expected lockdown durations, moderating precautionary price adjustments. These results mark epidemiological conditions as pattern signals within economic systems during health crises.

3.5.2. Lockdown Adaptation and Consumption Dynamics

One of the most distinctive results of the structural systems is the positive contemporaneous association between transmission rates and private spending. Although counterintuitive from a conventional macroeconomic perspective, this relationship reflects responses characteristic of crisis environments.

In the earliest phase of the crisis, economic behaviour risked optimisation while urgency gained momentum. Households shifted from planned consumption to immediate acquisition. The pandemic transformed private spending into a short term response to uncertainty rather than a previously established spending pattern. Early pandemic consumption was influenced by precautionary purchases, which temporarily increased demand for essential goods and protective equipment (Arafat et al. 2020).

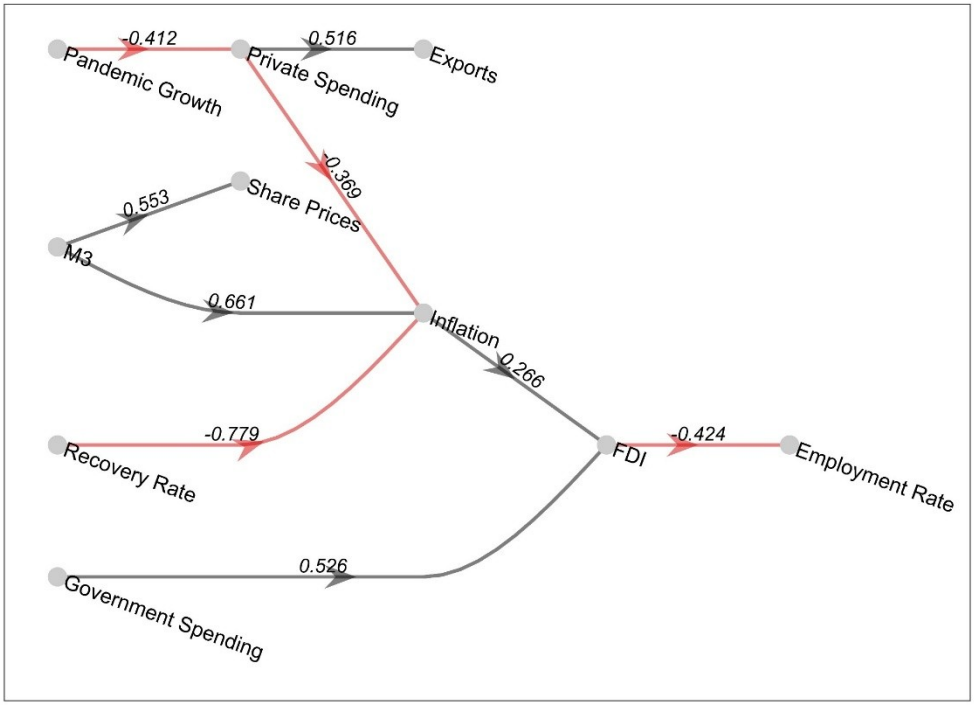


Figure 23 System of equations behaving as interconnected systems during Q1 2021 – Q4 2023.

The recurrence of this relationship across identified systems of equations indicates that these structural responses were systemic rather than incidental. This suggests that early crisis stages may generate short term consumption increases of specific products even if broader economic conditions deteriorate.

3.5.3. Mobility, Inflation and Systemic Frictions

The positive coefficient of mobility on inflation illustrates the interaction between responses to COVID-19 and supply chain disruptions. Increased mobility amplified price pressures through higher transmission risks, unplanned buying and reduced productivity. The faster reopening of public venues prolonged economic uncertainty and constrained production and distribution

processes (Baldwin, Richard & Weder di Mauro, Beatrice, 2020). These mechanisms support the interpretation that inflation dynamics during COVID-19 were influenced by supply chain constraints and shifts in consumption patterns (Guerrieri, Veronica et al., 2022).

3.5.4. Industrial Production Prices and Supply Chain Disruptions

Industrial production prices displayed predominantly negative coefficients across the valid structural systems, reflecting the vulnerability of manufacturing activity during the disruptions caused by COVID-19. Lockdowns, labour shortages and transport restrictions interrupted production processes and weakened the pricing power of producers.

The structural equations indicate that industrial prices acted as a transmission channel linking monetary policy, trade activity and private consumption. During the most severe disruption periods, reduced industrial activity and constrained production altered price tendencies. In some production sectors, the industry increased logistics to cover an increase in demand during lockdowns, while other parts of the industrial sectors experienced low demand and required financial support. As supply chains gradually adapted, these pressures diminished, and price behaviour stabilised (Attinasi 2024).

3.5.5. Dynamic Interactions Across Pandemic Phases

The analysis of the interconnected system shows correspondence in economic–pandemic interactions. The links between epidemiological variables and macroeconomic indicators evolved across three phases: the initial outbreak in early 2020, the intermediate recovery phase during 2020 and the post vaccination recovery between 2021 and 2023.

During the initial phase, behavioural responses and uncertainty dominated economic dynamics, producing relationships such as the positive association between transmission and private spending. In the intermediate phase, structural health indicators, particularly recovery and mortality rates became determinants of the labour market. In the post pandemic period, structural economic mechanisms regained prominence, with foreign direct investment, domestic consumption and government spending emerging as key economic adjustments. The negative association detected between foreign direct investment and employment suggests that the recovery phase involved capital-intensive restructuring rather than labour-intensive growth.

3.5.6. Methodological Implications

This research expands the detection of structural equations to systems of equations. Traditional macroeconomic models frequently rely on single equation regressions or small fixed systems. In

contrast, the framework proposed here identifies ensembles of equations that are both individually and jointly consistent.

By combining Generalised Method of Moments estimation, Hansen–Sargan validation and Zellner's Seemingly Unrelated Regression structure, the methodology detects structural systems whose residuals display significant cross equation correlations. This approach suggests branches of valid models rather than a single preferred specification. The mathematical configurations capture the multidimensional and evolving paths of statistical interactions during systemic disruptions.

3.6. Conclusions

This study develops a dynamic structural framework for identifying statistical systems of equations in the economy. By including economic and epidemiological variables, the investigation of structural coefficients brings a network of interacting elements. The application to large scale disruptions reveals the underlying momentum of each stage of the pandemic. The novelty of this project starts by integrating the GMM with structures derived from Zellner's related regressions. The framework identifies combinations of equations that are statistically valid both individually and as interconnected systems.

The analysis of the COVID-19 pandemic demonstrates that macroeconomic systems under crisis behave as interconnected networks rather than isolated numerical relationships. This characteristic of the financial systems was observed with the intense dynamics caused by the pandemic. Epidemiological shocks propagated through labour markets, monetary aggregates, production systems and consumption behaviour, generating feedback mechanisms throughout the crisis.

Three principal conclusions emerge from the results. First, epidemiological variables played a central role in shaping economic outcomes during the early stages of the pandemic. Transmission, recovery and mortality rates exerted contemporaneous effects on employment, inflation and consumption, confirming that health shocks consistently caused temporal macroeconomic crises.

Second, population responses generated short term economic distortions, with rapid movements increasing cascade effects. Precautionary consumption, mobility driven inflation dynamics and liquidity employment interactions illustrate how economic agents adapt to uncertainty. These mechanisms become visible only when equations are analysed within a contemporaneous structural system, where the GMM systems and SUR detect structural systems of equations. Besides the identification of concurrent coefficients between the pandemic and the economy, the

model remains highly dependent on initial conditions in the economy in the pre-pandemic period and on the levels of policies to contain the spread.

Third, the proposed SUR–GMM framework provides a methodology for identifying structures of linked economic environments. By validating equations jointly through optimal instruments, statistical significance and residual correlation, the method finds coherent systems of relationships even when regimes vary across regions and periods.

Ultimately, this study reframes economic crises not as isolated disruptions, but as dynamic systems undergoing continuous reconfiguration. By capturing these transitions with multidimensional homoscedasticity, the proposed framework provides not only a method for analysis but a lens through which future systemic shocks can be understood and anticipated with more certainty.

The limitations of this research correspond to the data availability and utilisation of the method. The approach can only be applied when the information exists. The second limitation is the interpretation of multidimensional conditions, and whether the existence of compatible equations opens the field for linear algebra in structural modelling. Since the findings are conditional on the model selection framework, results should be interpreted as statistical patterns, not definitive causal laws. Even though the correlation of residuals suggests synchronous varying patterns with high correlation, the model can not identify cascade effects, which can depend on initial conditions and rapidly propagating events during high-risk events.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work, the authors used AI to increase readability and optimise routines. After using AI tools, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

Data availability: Data will be made available upon reasonable request.

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4. FULL CAUSAL EFFECT MODELLING FOR CONSTRUCTION SECTOR STABILITY UNDER GLOBAL EVENTS: PANDEMICS – A REVIEW

4.1. Abstract

The COVID-19 pandemic exposed the interconnections of the global construction and industrial systems, in which labour availability, material supply, mobility, investment, financial conditions and policy interventions interact under rapidly changing conditions. These interactions alter both the magnitude and direction of inter-variable relationships across different disruption stages, limiting the ability of models with limited specification to represent complex systemic responses. This study reviews the mechanisms through which major external disruptions affect construction sector performance and evaluates the Full Causal Effect (FCE) framework as an approach for representing multiple statistically admissible causal configurations of changing conditions. The review synthesises evidence on economic impacts, supply chain disruption, labour market dynamics, policy responses, technological adaptation and construction resilience. The FCE analysis identifies multiple admissible systems of equations and demonstrates that the estimated magnitude and direction of relationships can vary across countries and crisis stages. The results indicate that variables like foreign direct investment, share prices, total spending and inflation can exhibit distinct relationships with construction productivity, while pandemic related variables exert changing influences during different phases of disruption and recovery. The findings support the use of multi equation and configuration approaches for analysing construction sector resilience under major external disruptions. Rather than replacing established econometric methods, FCE provides a framework for systematically examining alternative statistically valid representations of interconnected economic and operational mechanisms.

4.2. Keywords

Construction-sector resilience, COVID-19 pandemic impacts, Supply-chain disruptions, Full Causal Effect (FCE) modelling, Adaptive workforce strategies

4.3. Introduction

Events such as extreme weather, pandemics and geopolitical disruptions exert influence on economic activity and industrial performance. Both extreme and cyclical events alter production

processes, resource availability and supply chain performance[A]. The magnitude and direction of these effects depend on the characteristics of the system through which goods, services and resources are traded.

The relationship between industrial variables and external forces is either positive or negative. A positive relationship indicates that an increase in one variable corresponds to an increase in another, whereas a negative relationship reflects movement in opposite directions, e.g. food and essential goods; whereas a negative relationship occurs when the variables move in opposite directions. In complex socioeconomic systems, however, these relationships do not remain constant over time. Previous research, discussed later in this work, has demonstrated that coefficients can switch signs under changing conditions, indicating either statistical instability or a genuine change in the underlying regime governing the relationship. When supported by robust statistical testing, the sign changes can be interpreted as evidence that the interaction between variables has shifted in response to external pressures.

Recent studies increasingly emphasise the integration of advanced technologies, Industry 5.0 principles, circular economy practices, organisational adaptability and resilient policy frameworks as essential components of post pandemic recovery. The comparison matrix highlights the immediate impacts of COVID-19 and identifies the strategic capabilities needed to enhance the resilience, sustainability and competitiveness of the construction industry in an increasingly uncertain global environment.

4.4. Methodology

The evidence identified in the literature is summarised in Table 9, where a total of 1,100 records were identified through representative database searching. Following the screening and eligibility assessment process, only a portion of the searched studies were retained in the final evidence synthesis. The included studies examined COVID-19 impacts on construction activity, infrastructure development, supply chain resilience, workforce adaptation, and digital transformation. The studies employing statistical Structural Equation Modelling (SEM) were prioritised when publications were produced between 2020 and 2026, reflecting the growth of research on prevention[B] and resilience for construction and infrastructure projects.

A This literature review examined the measures implemented to protect the construction industry during the COVID-19 pandemic and subsequent events.

B Attention is given to the mechanisms through which these events affected labour availability, supply chains, investment patterns and project delivery. The review provides the theoretical foundation for developing a

The review evidence was categorised into ten interrelated themes reflecting the dominant areas of research emerging from the pandemic as a major external event and its implications for the construction sector. These themes include macroeconomic impacts, construction industry disruption, project performance, supply chain challenges and resilience, workforce adaptation, health and safety, digital transformation, infrastructure recovery, resilience frameworks, labour market dynamics, and sustainability. Table 10 provides a comprehensive understanding of how the pandemic affected construction activities and how organisations, governments, and stakeholders responded to substantial uncertainty and disruption.

Table 9 Sample Study Selection

PRISMA Stage	***Number of Articles***	***Percentage of Initial Search (%)***	***Notes***
Records identified through database searching	1,100	100	Initial search results
Records excluded during abstract screening	780	70.9	Duplicated and
Full-text articles assessed for eligibility	320	29.1	Multimodal study
Studies included	99	9.0	Studies listed in bibliography

Percentages are calculated relative to the initial 1,100 records identified through database searching.

The comparison matrix summarises the key studies in terms of their methodological approaches, principal findings and relevance of each theme to construction resilience. The evidence demonstrates that COVID-19 generated significant economic and operational constraints, like reduced investment, supply chain disruptions, labour shortages, project delays and changing

multivariate modelling framework capable of identifying critical relationships within the construction sector and supporting the prediction and mitigation of future disruptions.

work practices[C]. At the same time, the literature highlights relevant adaptive strategies like digitalisation, remote and hybrid working, enhanced health and safety measures, resilient supply chain management and infrastructure initiatives.

4.4.1.Research Questions of the Review

The review is guided by three research questions[1,2]:

RQ1: Which economic, epidemiological, labour, supply chain and policy mechanisms influence construction performance during major external disruptions? RQ2: How do the relative influence and configuration of these mechanisms change from normal to disruption, adaptation and recovery conditions, and across different countries and construction subsectors? RQ3: What analytical capabilities are required to represent these changing configurations, and to what extent can FCE provide those capabilities compared with alternative approaches?

4.5. Construction Industry Responses to COVID-19

The COVID-19 pandemic introduced unprecedented restrictions. The pandemic affected supply chains, employment, investment activity and broader economic performance when compared with normal operating conditions with stable operating conditions[3]. Previous research shows that the construction industry evolved through interconnected factors and multidimensional interactions during the pandemic[4].

Beyond its measurable economic consequences, the pandemic generated major health and safety challenges on construction sites, together with policy, contractual and managerial modifications[D]. Unlike many service sectors, construction activities could not transition to remote working, increasing operational vulnerability during periods of restriction[5].

The initial stages of the pandemic required alternative project management strategies and modified shift arrangements designed to reduce worker density and minimise infection risks. At the same time, firms faced shortages of materials and equipment, project postponements, payment delays, rising costs and financial uncertainty[6]. Although construction activities gradually resumed, recovery rates varied between project types. Residential developments and healthcare

[C] By synthesising findings across these thematic areas, the matrix identified critical resilience factors and informed strategies that can strengthen the construction sector's capacity to withstand future systemic links.

[D] Social distancing requirements, hygiene protocols and mobility restrictions created significant difficulties in an industry that relies heavily on physical presence and on-site coordination.

facilities often received priority, whereas transportation and commercial projects were frequently postponed or cancelled.

Table 10 Comparison Matrix of Included Studies (n = 99)

THEME	KEY STUDIES	RESEARCH METHOD	MAIN FINDINGS	RELEVANCE TO CONSTRUCTION RESILIENCE
ECONOMIC IMPACT OF COVID-19	Coibion et al. (2020); Baldwin & di Mauro (2020); Furman et al. (2020); Botha et al. (2021); Fana et al. (2020)	Economic analysis, policy modelling	Lockdowns reduced spending, employment, and investment; stimulus policies	Demonstrates macroeconomic pressures affecting construction demand and project financing
CONSTRUCTION INDUSTRY DISRUPTION	Shibani et al. (2020); Alsharef et al. (2021); Ogunnusi et al. (2020); Salem et al. (2024); Selcuk (2026)	Surveys, empirical studies, reviews	Labour reduction, site closures, project delays, productivity losses	Direct evidence of modifications caused by COVID-19
CONSTRUCTION PROJECT PERFORMANCE	Rhodes et al. (2022); Stiles et al. (2021); Iqbal et al. (2021); Araya	Modelling, SEM, case studies	Enhanced H&S measures, revised shift patterns, crisis-response frameworks	Identifies operational mitigation strategies

THEME	KEY STUDIES	RESEARCH METHOD	MAIN FINDINGS	RELEVANCE TO CONSTRUCTION RESILIENCE
	(2021); Radzi et al. (2022)		improved performance	
SUPPLY CHAIN	Goel et al. (2021); Yu et al. (2022); Hausmann (2020); El Korchi (2022); Qazi (2025)	Econometric analysis, reviews. Conceptual, empirical, digital transformation studies	Global supply chains, digitalisation, integration	Supply and demand on digital platforms.
REMOTE AND HYBRID WORK	Tietze & Nadin (2011); de Lucas Ancillo et al. (2023); Iogansen et al. (2024); Blank et al. (2023); Burdett et al. (2024)	Reviews, surveys	Wide applications, productivity and wellbeing	Construction management and design personnel
WORKFORCE HEALTH AND SAFETY	Olanrewaju et al. (2021); Pan et al. (2022); Kamga & Eickemeyer (2021); Tan et al. (2023)	Reviews and empirical analyses	Spread control protocols reduced transmission risks	Provides foundations for future site safety standards

THEME	KEY STUDIES	RESEARCH METHOD	MAIN FINDINGS	RELEVANCE TO CONSTRUCTION RESILIENCE
DIGITALISATION AND INDUSTRY 5.0	Ghobakhloo et al. (2025); Islam (2020); Allioui et al. (2024); AlRushood et al. (2023)	Framework development, reviews	AI, drones, robotics and scale automation for relevant projects	Major enabler of post pandemic transformation
INFRASTRUCTURE	Vaslavskiy (2021); Kudtarkar (2020); Ruddock & Ruddock (2022); Alcaraz Carrillo de Albornoz et al. (2024)	Policy and investment studies	Investment stimulates economic recovery and employment	Strategic mechanism for initial stability
LABOUR MARKET EFFECTS	Görtz et al. (2023); Fana et al. (2020); Feist (2024); MacEwan et al. (2025)	Economics and qualitative studies	Labour supply and productivity risks	Workforce planning and resource management
SUSTAINABILITY AND RECOVERY	Alaloul et al. (2022); Bertino et al. (2021); Sağlam (2025);	Report assessments	Efforts linked to sustainability, circular economy and life cycle	Resilience and sustainability goals

THEME	KEY STUDIES	RESEARCH METHOD	MAIN FINDINGS	RELEVANCE TO CONSTRUCTION RESILIENCE
	While & Eadson (2022)			

The studies are grouped thematically according to their primary research focus. The synthesis highlights the principal methodological approaches, findings, and their relevance to construction resilience and post-pandemic recovery.

Construction projects are executed within complex environments that require coordination among multiple stakeholders, subcontractors and supply networks. The introduction of health protection measures added constraints to an already complex process, resulting in reduced productivity, project delays and increased costs[7,8]. The modifications were the consequence of limited workforce availability[E].

COVID-19 is treated in this study as an example of a large-scale external event affecting the industry. However, the analytical framework is not restricted to pandemic events and is extended to other disturbances by incorporating contextual variables. The broader managerial challenge remains the absence of a fully integrated framework linking regulation, technology, management practices and economic development together[F].

Evidence from previous studies indicates that the impacts of global disruptions propagate at different levels. These differences highlight the importance of considering technical, economic, health, labour, investment and supply chain variables simultaneously, excluding a universal pattern of response. The preservation of local economic and cultural characteristics therefore requires a high analytical perspective capable of capturing both general and specific context dynamics.

[E] The main goal at that time was to prevent the spread of infection through workforce absences and disruptions to material deliveries by keeping a safe distance of minimum 2 meters.

[F] The model could benefit from analytical systems capable of supporting both prevention and adaptation strategies, reducing future disruptions and maintaining stable performance during both normal and extreme conditions.

4.5.1.Market Indexes During Major External Disruptions

The need for work plans capable of shifting smoothly between normal and emergency conditions became clearer[9]. Updated contingency plans aimed to preserve productivity across multiple disruption scenarios. Updating plans and adapting the industry required additional coordinating activities to secure the continuation of activities during the outbreak[10]. Public organisations like the Organisation for Economic Co-operation and Development (OECD) issued guidance and procedures to enhance workplace safety during pandemics with campaigns promoting physical distancing and the use of personal protective equipment (PPE)[11]. Although these measures enabled construction projects to continue during the outbreak[12], productivity initially declined and posed risks that are addressed here to improve early responses in the future.

4.5.2.Prevention Using Rapid Response

The construction industry applies structured procedures and work patterns designed to optimise resource allocation and ensure project viability. However, the pandemic disrupted established practices. Changes occurred abruptly during the pandemic; for example, physical distancing and mandatory PPE required rapid coordination during an uncertain period. Other examples of sudden imposed change included price increases, outbreaks on site and project delay or cancellation. Nevertheless, other repercussions of the pandemic appeared gradually, e.g. the periodic isolation of infected workers, which was influenced by infection rates and recovery rates[13]. In general, the complexity brought by the pandemic, combined with infection-control policies, altered work patterns, increased project costs and placed added stress on the broader economy[14]. Despite the negative impacts, the industry received help from public programmes and private investment, which helped it respond to the external shock caused by the outbreak of the coronavirus[G].

4.5.3.Construction Activities During Lockdown

Construction was designated as an essential activity in countries during the pandemic, allowing continuity during the later stages of the outbreak[15]. The uninterrupted activities in construction saw materials and machine shortages, while the broader demand and supply chain affected revenues and the stability of construction businesses with modified patterns[16]. The economic downturn reduced services around public infrastructure, with the initial stages of the pandemic

[G] Also, accurate responses by public and private organisations prevented the uncertainty to freely propagate on the economy.

acting on the construction economy[H]. The reduced requirement for infrastructure projects emerged with low productivity in construction activities, which on average fell by half and added complexity to the building systems. In contrast, sectors like infrastructure for telecommunications and automated warehouses increased demand for more projects[17]. Balancing stable and distressed subsectors can be numerically modelled to optimise the supply chain during different scenarios and plan for specific projects during outbreaks[I].

4.5.4.Searching for Resilience and Stability During Pandemics

Flexible and hybrid work primarily concerns office functions, whereas site based construction requires physical presence. Robotics, autonomous equipment and digital supply chain systems reduce this constraint over time. These technologies are considered later in this work as one resilience mechanism; their role here is limited to establishing why operational adaptation requires technological reconfiguration.

4.5.5.Full Causal Effect Modelling for Construction Stability

The COVID-19 pandemic and subsequent international conflicts revealed a fundamental characteristic of relevant events: minor initial conditions can propagate throughout economic systems and alter the configuration of entire industries. Major external disruptions like pandemics generate temporary oscillations that change planning processes, affecting investment, labour markets and supply chains. The numerical sensitivity to initial conditions suggests that early intervention and targeted industrial support can reduce economic losses and improve resilience.

The pandemic demonstrated that the ability to adapt to major external disruptions influences both policy decisions and capital allocation strategies. The experience highlighted the necessity of preparing industries for rapidly changing conditions. Here, traditional practices include expected situations in the economy without major external disruptions. The traditional method also includes the established limitations of the initial analysis when regressions provide multivariate structural equations for the properties of the system determining a specific variable[J].

[H] Productivity losses were partly due to learning curves associated with adaptation to procedures and low personnel on sites.

[I] Construction reacted to the changes in transport, manufacturing and logistics. The result of those modifications is the basis for the

[J] The methodology proposes a system of equations, each equation multivariate and sharing explanatory variables. When validated, the model provides a standard system of linear equations.

While conventional analytical approaches estimate outcomes through a single selected equation within a single specification, the challenge posed by recent global disruptions is the need to understand and control multiple interacting mechanisms simultaneously. This does not imply that existing approaches assume stable conditions, as many methods explicitly incorporate structural change and time varying relationships. The challenge is whether multiple admissible configurations can be analysed together in a manner that reflects the complexity of the economy under both normal and extreme circumstances, improving time response and providing extra flexibility to the response.

Recent geopolitical conflicts and the pandemic have reinforced the view that the construction industry operates within a highly interconnected global system. Construction supply chains are shaped by decision makers, institutions, regulations and market forces whose interactions generate cascading effects across labour markets, material availability, financial flows, transportation networks and public health conditions[18]. Disruptions affecting one component of the system can rapidly propagate through other interconnected sectors.

An example is the transition to remote and hybrid working arrangements during the pandemic. Organisations required a period of adaptation before establishing effective operating procedures for the conditions. Evidence from this period suggests that reducing reaction time can improve organisational stability and resilience during future pandemics[K]. Although organisations subsequently returned to office working arrangements, the experience demonstrated that changes in work patterns influence broader economic and operational systems and should be analysed jointly with other relevant variables. Fig. 25 exemplifies the evolution of working arrangements during and after the pandemic, highlighting the sustained growth of hybrid working models during normal periods[19]. The objective is to minimise the magnitude of initial disruption and strengthen system resilience to subsequent shocks.

The literature reviewed in this study suggests that a multiple explained variables approach provides a more comprehensive representation of complex economic systems. The FCE framework evaluates alternative relationships among variables and identifies statistically admissible configurations across the period represented by the panel data. Within this framework, causal validity requires more than statistical significance alone. Retained pathways must satisfy a combination of criteria, gaining theoretically meaningful direction, valid

[K] This perspective of rapid reaction emerges from the exponential propagation of the pandemic and the relevance of its initial conditions.

instrumental variables, satisfactory Generalised Method of Moments (GMM) diagnostics and stability across model specifications[L].

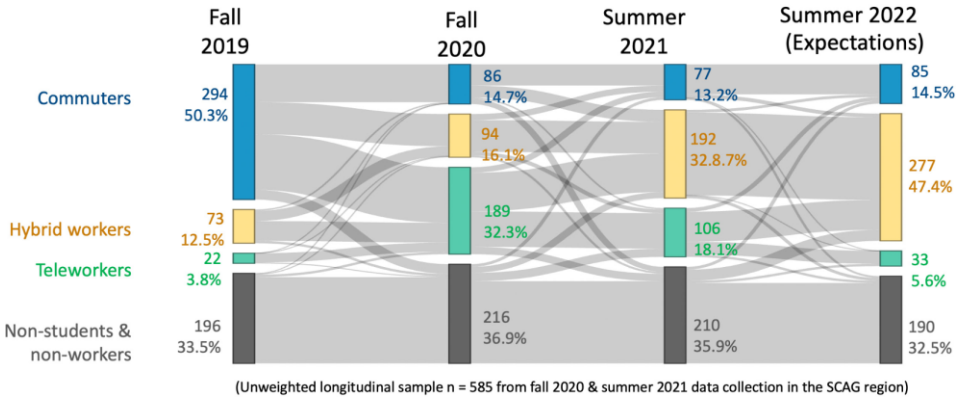


Figure 24 Evolution of work patterns during and after the COVID-19 pandemic. Adapted from[18].

The framework supports the analysis of industry behaviour under diverse conditions, including pandemics, geopolitical conflicts, supply chain disruptions, and other external shocks. Instead of simplifying all dynamics into a single estimated relationship, the method examines the range of statistically valid pathways through which linked outcomes emerge[20].

Operationally, the FCE procedure estimates distributions of coefficients obtained from admissible non-collinear systems of equations. In addition to conventional validity requirements, the framework introduces a further selection on the similarity between observed and generated correlation structures[M], where the preferred configurations minimise the difference between actual and modelled correlation structures. If the system of equations has varying coefficients, the system of equations gives a general picture of a system that can repeat over time in cyclic patterns.

To ensure the reliability of identified causal configurations, endogeneity is addressed through established econometric procedures. Predictor variables are evaluated for correlation with the error term, and instrument validity is evaluated using the Hansen J statistic. Although implemented here within the GMM framework, the FCE procedure is not restricted to a single

[L] The Full Causal Effect framework has properties for analysing these interconnected systems and their evolution. Unlike multivariate equation approaches for one variable, which estimate a variable of interest through one selected specification, FCE is a broader analytical process that evaluates multiple non-collinear configurations of equations, explaining multiple variables simultaneously, and retains those expressions completing a predefined statistical and econometric criteria.

[M] The comparison is therefore not between conventional methods and FCE, nevertheless, between a single selected representation and a framework capable of examining multiple admissible system configurations simultaneously. Then, allocation is dictated by the branch benefiting the most from the variables of interest.

estimation technique and can be applied to alternative regression families, provided that equivalent validity and diagnostic requirements are satisfied.

From a construction management perspective, the rationale is based on economic variables within construction systems influencing one another simultaneously, creating endogeneity and making causal interpretation difficult. GMM addresses this issue through instrumental variables and diagnostic testing. The FCE framework extends this process by systematically exploring multiple admissible equation specifications and retaining only those that meet the criteria together[N].

4.5.6.Productivity and Temporary Projects During COVID-19

In addition to creating a need for innovative financial and technical approaches to sustain infrastructure projects, the COVID-19 pandemic provided an opportunity to examine the resilience of the construction industry. Compared with sectors like hospitality, tourism, entertainment and retail, construction experienced a comparatively lower level of disruption and maintained a greater degree of operational continuity throughout the pandemic[21]. While industries faced prolonged closures, severe reductions in demand and extensive job losses, construction activities were often permitted to continue because of their strategic importance to economic stability and infrastructure provision.

The pandemic nevertheless produced modifications to the industry, including material shortages and workforce market variations. Global unemployment reached levels seen during the 2008 financial crisis. In contrast, during the COVID-19 crisis, workers displaced from other sectors sought employment opportunities in construction[22]. The ability of construction projects to continue operating enabled individuals to strengthen skills and integrate into the workforce despite the adverse economic conditions[23].

The relative continuity of construction operations highlights the importance of maintaining critical productive capacity during major crises. The benefits of continued activity depended on the implementation of adequate health, safety and risk management measures that protected workers and surrounding communities while allowing projects to remain operational. The

[N] A statistical pathway is classified as a causal configuration only when it demonstrates statistical significance, instrument validity and consistency across the specified diagnostic requirements, and significance alone.

pandemic demonstrated both the value and the limitations of construction as a mechanism for economic stabilisation during periods of severe disruption[O].

4.5.7.Limitations of Continued Activity During the Outbreak

Construction projects continued operating in regions. Evaluations indicate that their capacity to generate employment and sustain productivity was constrained by public health restrictions and operational disruptions. Social distancing, occupancy limitations, worker absences caused by illness and restrictions on workforce density reduced site efficiency during the initial stages of the outbreak.

The ability of construction projects to stabilise employment and productivity was constrained by several interacting factors. These included the temporary loss of experienced personnel, the learning period required for the recruited workers, interruptions to material availability and disruptions from domestic and international supply chains. While construction remained active, these conditions reduced productivity and prevented the industry from fully offsetting the broader economic consequences of the pandemic.

4.5.8.Effects of the Pandemic on Office Environments

The pandemic also affected office based functions within construction organisations. The rapid transition to remote working was implemented with little preparation and presented significant challenges for employees[24]. Even when remote working enabled administrative continuity, the adaptation process generated temporary reductions in efficiency and coordination, particularly among workers lacking suitable working environments or prior experience with digital collaboration tools.

Studies at that time reported that remote working outcomes varied according to individual circumstances, digital competencies and organisational support mechanisms. Challenges included reduced engagement, difficulties maintaining collaboration and limitations associated with home based work environments[25]. Organisations adapted over time, and productivity gradually improved as employees became familiar with remote practices and digital communication technologies.

[O] the industry partially absorbed labour market shocks by offering employment and training opportunities during a period of widespread economic uncertainty.

The performance decline observed during the early stages of the pandemic was therefore transitional[P]. The COVID-19 period accelerated organisational learning, digitalisation and supply chain innovation, contributing to a more resilient construction sector[26].

The pandemic highlighted the importance of adaptability, whether achieved through proactive preparation or reactive adjustment. The ability to modify operational practices, workforce arrangements and resource allocation strategies proved essential for maintaining project continuity during periods of uncertainty. As argued by Hynes (2020)[27], adaptation, optimisation and modernisation can enhance resilience and support economic stability when major external disruptions occur.

4.6. Revision of Industrial Patterns During Turmoil

Evidence reported in previous studies demonstrates the mechanisms through which external shocks affect construction performance. During the COVID-19 pandemic, these mechanisms emerged through a sequence of disruptions involving labour availability, demand fluctuations, supply chain constraints, policy interventions and productivity changes[Q].

The construction industry accounted for approximately 13.4% of global GDP during the pandemic period and remained one of the largest productive sectors worldwide[28]. Beyond its direct contribution to economic output, construction maintains extensive linkages with industrial activities, amplifying its influence on the wider economy. These linkages extend from the extraction and processing of raw materials to the manufacture of products ranging from steel structures and specialised machinery to installation components like timber frames, electrical wiring and piping systems[29]. This interconnected character partly explains why the industry's performance became a significant determinant of economic resilience during the COVID-19 event[R].

[P] As health restrictions eased, organisations accumulated experience and workforce adaptation increased; operational performance improved across both site and office activities.

[Q] The present chapter considers the economic role of construction primarily as a contextual framework for interpreting these interconnected effects into the outcomes of the economy.

[R] As a result, disruptions affecting construction can propagate throughout multiple sectors, and cascade effects reaching elsewhere in the economy. Somewhat less relevant is how the continuous propagation is a cycle becomes recursive in loops. can similarly influence construction demand, productivity and project delivery.

4.6.1.Disruption Mechanisms

The literature suggests that the continuous demand for infrastructure and essential services encouraged the construction industry to implement protective measures while maintaining continuity during successive waves of COVID-19[30]. Construction activity during crises has been shown to partially mitigate labour market shocks, sustain economic activity, and reduce the severity of economic contraction in sectors capable of operating under restricted conditions[31].

4.6.2.The Constraints of Sustained Production During COVID-19

Maintaining construction activity during the pandemic required adjustments to planning processes, project delivery methods and operational procedures in response to evolving public health regulations and changing financial conditions between public and private stakeholders[32]. These developments demonstrated that modernisation efforts implemented during normal periods should remain compatible with emergency response requirements.

Fig. 26 illustrates the evolution of government interventions during 2020. The left-hand panel shows the escalation and subsequent relaxation of policy measures for 183 countries, while the right-hand panel presents policy duration indicators measured until the first sustained reduction in restrictions. For example, workplace closures were eased earlier than restrictions on public events, indicating differences in governmental risk management strategies[S].

Performance assessments of construction firms played an important role in ensuring that project bids remained realistic and that technically capable organisations were selected to deliver critical infrastructure projects[33]. The rapid changes in policy and regulatory requirements necessitated the development of updated emergency management procedures, allowing urban and municipal development projects to continue despite reductions in productivity.

To maintain infrastructure development, governments implemented a range of financial support measures directed toward construction firms. Public investment programmes, subsidies, and targeted funding initiatives helped sustain project delivery and supported the implementation of technological and operational adaptations[34]. Additional assistance included tax reductions for companies experiencing financial distress[35] and income support programmes for furloughed employees or workers facing unemployment risks[36].

The evidence highlights a contradiction within the construction sector. On one hand, continued construction activity can stabilise employment, preserve supply chain activity and support

[S] The comparison highlights differences in the adoption and withdrawal of specific interventions.

economic recovery during periods of crisis. On the other hand, the industry's reliance on temporary, subcontracted and vulnerable labour transfers health, financial and contractual risks to workers during uncertain periods. Employment continuity should be viewed as a form of conditional resilience that can become an unconditional benefit when managed adequately to preserve the health of the workers.

The literature indicates that construction functions most effectively as an employment stabiliser when projects remain financially viable, essential activities can be performed safely, and labour resources can be reassigned without generating disproportionate health or contractual risks. The stabilising role of the sector diminishes when workforce shortages, infection risks, training requirements, or precarious employment arrangements reduce productivity and compromise worker security[T]. The following section therefore examines the specific policy responses and managerial interventions adopted to sustain construction operations during periods of severe disruption.

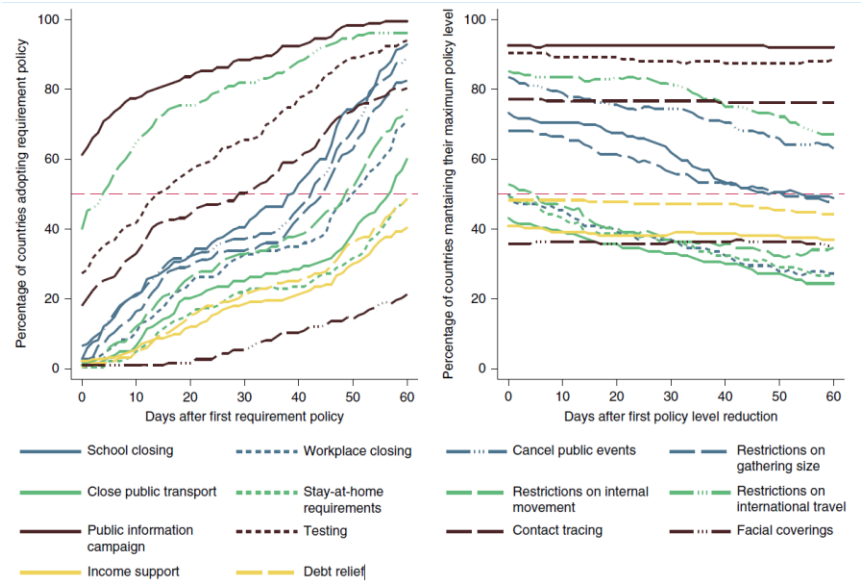


Figure 25 Periods of response and policy duration by country. Adapted from[31].

[T] A central uncertainty emerging from these findings is how governments and firms balanced their influence toward the objective of maintaining economic activity against the need to protect workers, businesses and supply chains.

4.6.3.Response Mechanisms

The effects of COVID-19 on the construction industry were profound and changed standard construction procedures[U]. Even after the introduction of pandemic control measures and financial support programmes, the construction sector experienced substantial economic disruption during the early stages of the pandemic[37]. Although the construction industry contributed to economic recovery, companies depended on income support from public programmes designed to mitigate budget shortfalls caused by the virus's spread[38].

Fig. 3 displays the safety measures and policies applied to the construction industry during COVID-19. One can differentiate between the two branches of safety measures during the pandemic. The first protocol, on the left-hand side of Fig. 3, shows the activities carried out by workers to protect their health, while the second branch of policies, located on the right-hand side of Fig. 27, shows the support and precautionary measures carried out by managers and stakeholders to protect the health and safety of their enterprises.

Investment in infrastructure during emergencies can support workers who lose their jobs by providing temporary employment[V] and monetary assistance[40]. Because construction was appointed a key activity in countries, the sector generated jobs during the outbreak and contributed to economic stability while other industries went through more severe contractions[41]. This is a positive characteristic of construction projects, where funding can be secured due to the strategic relevance of the works during temporary emergencies[42,43].

Previous methodological work described the FCE, which provides the basis for examining systemic statistical roots and alternative equation configurations relevant to supply chain continuity. In this review, that work is used to describe the methodological evidence of complex models[W].

[U] The repercussions included a reduction in stable workplaces and a contraction of long term employment opportunities.

[V] For construction enterprises, job creation during crises often comes with low stability due to the prevalence of temporary labour contracts.

[W] It only repeats previous techniques and derives the valid equations between parametric boundaries.

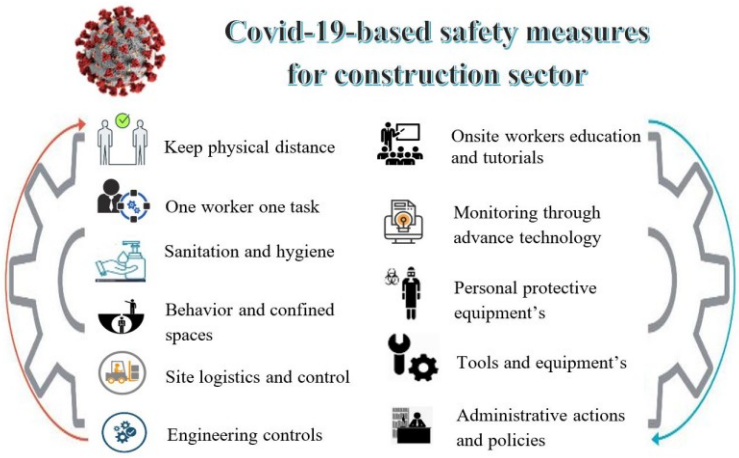


Figure 26 Safety measures during the COVID-19 pandemic. Reproduced from Brazilian Journal of Operations and Production Management[37].

4.6.4.The Economic Scenarios of the Industry

The effects of the pandemic on material and machinery supply, as well as on employment levels, became more complex, especially when considering the interlinked nature of infrastructure projects and their supply of materials and machinery[44]. The variables of interest for construction companies include those related to the supply of materials and equipment, which, if affected, would have a cascade effect on projects[45]. The industrial system was influenced by the degree of interconnectedness within construction activities, as projects depend on specialised materials sourced from distant regions or imported from abroad. Project susceptibility increased when construction required workforce mobility from regions far from the work site, making labour availability vulnerable to travel restrictions and global health events[46].

To reduce the risk of contracting the coronavirus, transit restrictions lowered transportation for construction activities, which, combined with border closures, caused scarcer access to equipment, materials and occupancy throughout the pandemic[47].

The pandemic exposed the stability of globalised supply chains. Even though efforts were made, the early stages of the pandemic exposed the need for more resilient procurement and logistics strategies[48]. Looking toward the post pandemic period, the priority is to minimise negative effects while maximising stability and resistance in future. Fig. 28 illustrates a productivity conceptual model, showing how resilience enablers drive operational configurations that generate sustainability outcomes within a dynamic feedback system[X]. These strategies support supply

[X] The system links key enablers, like digital infrastructure, agile capabilities and collaboration, to operational strategies that enhance adaptability and sustainability.

chain continuity, reduced environmental impact and added value. Preparing the supply chain for pandemics and other major external disruptions requires novel methods of understanding economic interdependencies and developing adaptive mechanisms capable of responding to a range of external shocks[49].

The review identifies no universally optimal sourcing configuration. Localisation is advantageous where distance and border restrictions dominate risk; geographic diversification is advantageous where local concentration creates a single point of failure. Supplier redundancy and substitutability should therefore be selected according to the mechanism of action. The advancement proposed by the FCE is the consideration of valid configurations happening in the industry and their relevance for the control of the supply chain.

4.6.5.The Effects of Lockdowns on Site

The delayed implementation of lockdowns and the differing levels of restrictions between nations produced asymmetric effects on economic activity during COVID-19. In countries where the virus was detected early, governments reacted promptly[Y]. In China and Italy, the construction of health facilities was crucial for expanding healthcare capacity and reducing hospital saturation[49]. In contrast, countries like India and Mexico implemented lockdowns late, resulting in delayed transmission rates, with risks of saturation of services and later quarantines with consequences for both public and private infrastructure assets[50].

In South Africa, road maintenance was exempted from the national lockdown, ensuring continuity of critical infrastructure[51]. In countries where construction sites were initially closed, in Austria, Barbados and Russia, they were among the first sectors to reopen after the first wave, demonstrating that full closure was not necessary once stringent safety conditions were established [Z].

Reopening decisions were based on evidence that construction activities could be performed safely with proper controls, making the sector a priority among other activities. However, the timing and intensity of policy responses varied with the economic and the capacity of the different health systems. While developed countries had sufficient fiscal reserves to sustain prolonged lockdowns, developing countries faced the risk of pushing public finances to critical levels if they

[Y] China, for instance, implemented containment measures that reduced transmission to near-zero levels within a brief period.

[Z] Short-term contracts were widely used to manage uncertainty, but they limited long-term workforce retention and slowed post-pandemic recovery in some regions.

tried economic shutdowns [AA]. These disparities produced uneven impacts on the construction economy and highlighted the importance of specific context policy design.

4.6.6.Industrial Outcomes

The impact of COVID-19 on construction enterprises stemmed from a reduced capacity for spending and production, combined with widespread precautions to avoid infection, including the use of infrastructure and services like restaurants, hotels, schools and highways. Affected companies had elevated liquidity constraints and entered bankruptcy during the initial outbreak as revenues collapsed, and operational costs remained elevated. The imbalances affected the construction industry in conceptually apparent ways, nevertheless extremely difficult to quantify holistically using traditional analytical tools [BB]. As the multidimensional dynamics of the economy reacted to an exogenous shock, firms became increasingly dependent on access to financial resources, including public emergency support packages[52].

In addition to these constraints, countries suspended production of building materials, while experienced workers became unavailable because of infection, reducing the productivity of industrial activities and compromising the economy[53]. Productivity shortages increased prices and delayed projects, pressuring enterprise budgets. Stakeholders often expressed the need for technological solutions, including automation or advanced digital tools, which could have mitigated the effects of the pandemic on the construction industry[54]. The situation worsened when factories closed for extended periods, forcing companies to rely on existing stock or get materials from more distant locations[55], increasing logistical complexity and elevating infection risks among workers involved in transportation and handling [CC]. This cascading supply and demand disruption is a central analytical transition in the review because it links otherwise separate labour, financial, material, transport and demand mechanisms. The difficulty is not simply the number of variables but the fact that their interactions occur simultaneously, with lags, feedback and changing stages. The analytical difficulty includes simultaneous relationships, temporal lags, nonlinear effects, structural breaks, endogeneity, feedback loops, model uncertainty and complex interactions. These features mean that a single observed correlation

[AA] Supply-chain resilience increasingly depends on diversification, digital monitoring, and reduced reliance on single-source suppliers.

[BB] Traditional economic models struggle to capture cascading disruptions across multi-linked supply chains, especially under global events.

[CC] Long-distance procurement increased exposure risks and contributed to further delays due to transport bottlenecks and border restrictions.

changes when another mechanism becomes active or when the system moves into another statistical regime.

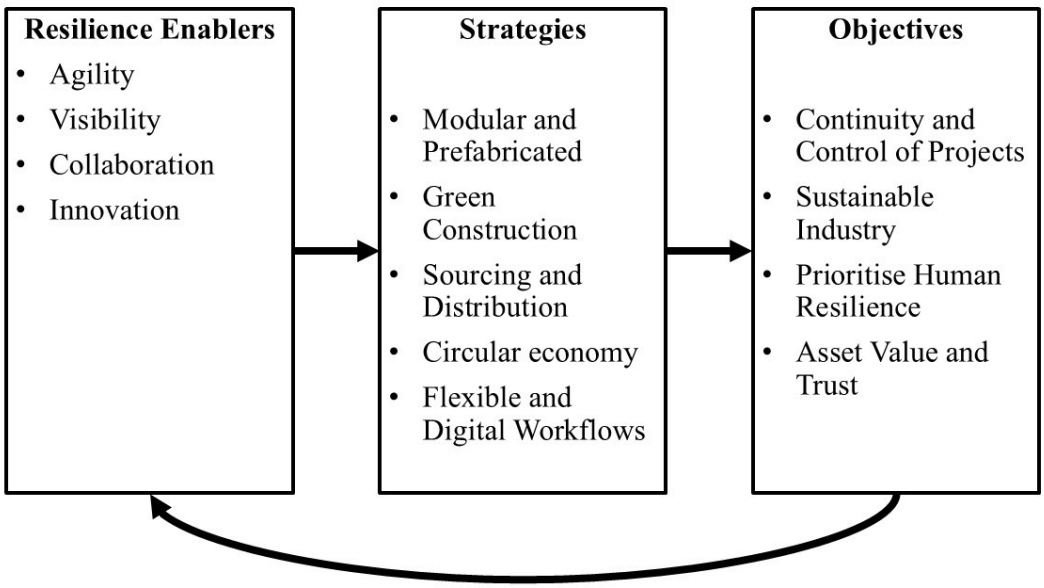


Figure 27 Productivity improvement of the construction industry.

4.6.7. Economic Scenarios for Construction: Alternative Construction Outcomes Under Disruption

A statistical scenario appeared when transportation restrictions impeded machinery and slowed project deliveries. The lack of materials and machinery, combined with difficulties transporting goods to project locations, forced suspension and cancellations of projects[56]. A situation developed in regions where labour was furloughed, while in other areas, labour shortages appeared because active construction sites had infection outbreaks. The pandemic of COVID-19 affected older workers, with accentuated repercussions for the construction industry[57].

Intensive investment required labour that was often unavailable, or legislation prohibited the participation of at-risk populations, including individuals over 65 years of age or those with pre-existing health conditions [DD]. These constraints forced companies to choose between delaying projects, reducing scope or absorbing operational risks[58].

[DD] High-risk workers were often legally restricted from on-site work, reducing available labour pools.

4.6.8.Automation as a Potential Construction Resilience Mechanism

The construction industry involves processes with large-scale energy consumption. Either by moving structural elements or by implementing detailed activities such as surface finishing, the construction industry has been categorised as a slow adopter of technological innovation[59]. If the extraction of raw materials, their processing, manufacturing, transportation, and on site assembly were automated, the entire construction supply chain could work with minimal human presence during emergencies[EE].

Automation is considered here as a potential resilience mechanism, not as evidence that construction can imminently operate without human workers[60]. Extraction, processing, manufacturing, transportation and assembly can be progressively automated in selected applications, but physical variability, capital requirements, regulation, skills and safety constraints limit immediate full automation[FF].

4.6.9.Adaptation Period: Flexible and Hybrid Work

After the lessons from the COVID-19 experience, the post pandemic construction economy still requires guidance on how to implement industrial procedures that support both recovery and resilience against pandemics[61]. For instance, the construction economy must find work patterns that allow quick and efficient adoption of remote working and hybrid patterns. The lessons learned from the global events show that the initial adaptation period reduced the efficiency of working activities. Previous literature documented the modifications of the economy during the global events caused by the pandemic in 2019. As an example, changes in work patterns in the United States transitioned from a fully remote work pattern, which initially caused a short downturn, to a more reliable hybrid work mode. Together with changes in labour demand, it required an adaptation to work patterns and sometimes to relocation from one job to another. An example of this was the increase in demand for workers on health related constructions and services, while the demand for industry and workers related to public transport decreased.

The flexible work patterns showed that the industry required adaptive human capital; it also required responsive administrative structures to secure stable supply systems that minimise delays and strengthen overall readiness. These principles were consistent with previous

[EE] Automated production relies on tools that partially work autonomously and require fewer workers on site. Automated machinery can also increase efficiency by performing excavation, assembly, and structural tasks in a more synchronised and predictable manner. This is particularly relevant because construction accounts for 40% of global CO_2 emissions, despite contributing 13.4% to global GDP.

[FF] Automation work displacement requires updates of the welfare models.

understanding of how hybrid work practices and secure supply continuity can further enhance resilience. Moreover, the analysis from earlier events says that hybrid work arrangements during normal periods will reduce the need for preparations and training when emergencies arise[GG]. These considerations, together with non-atmospheric emissive methods, highlight the value of embedding flexible labour and logistical strategies into long-term planning to enhance the industry's resilience to disruptions.

Work on site requires physical presence and cannot be moved to the home environment. Achieving remote capability for different work types only becomes possible with advances in robotics and automation. Just as the internet and computing technologies enabled distant work for administrative occupations, emerging technologies could automate supply chain processes. From extraction and processing to manufacturing, transport and distribution, reducing the need for in-person activity requires remote operation of machines to run the industry during global risks. Although concerns persist about job displacement, different industrial approaches are necessary to ensure continuity of products and services during crises[HH].

4.6.10. The Path Towards an Automated Construction Industry

Disruption mechanisms identified in the literature include labour unavailability, financial contraction, demand changes, transport restrictions, regulatory intervention and material shortages. These mechanisms are treated as interacting inputs rather than independent chronological events. During COVID-19, approximately 64% of construction workers were employed under temporary contracts, with the least stable roles concentrated among manual and artisanal occupations. One approach to stabilising household income during crises is to reduce working hours while increasing wage rates to balance the use of automatic methods. Higher wages and reduced working hours can occur with management methods that reduce delays, minimise overlaps, and optimise resource allocation during global events[62].

Response mechanisms include workforce flexibility, supplier diversification, buffer inventory, public financial support, digital monitoring, automation and alternative logistics. The review compares these mechanisms according to the disruption they address, the stage at which they

[GG] Hybrid work can reduce commuting requirements, which can be offset through alternative transportation for recreation and other purposes.

[HH] The use of those technologies will require updated regulations and taxation frameworks for companies employing autonomous systems.

become effective, and the consistency of the construction outcome and how it was affected by other variables.

The reviewed evidence indicates that an analytical approach addressing systemic construction disruption should be able to represent simultaneity, endogeneity, temporal lags, nonlinear or changing effects, structural breaks, feedback relationships, uncertainty, competing specifications and nested interactions. These requirements do not imply that FCE is the only possible solution; they provide the criteria against which FCE and alternative approaches are considered[63].

4.6.11. Responses to International Events

As discussed in Section 2, the COVID-19 pandemic required extensive policy intervention to stabilise public health systems and maintain economic activity. In the construction sector, public investment played a critical role in preserving project continuity, supported by the industry's capacity to adapt to evolving operational constraints[II]. This section synthesises the response mechanisms identified in the literature. Institutional responses are classified according to their contribution to liquidity protection, demand stimulation, contractual adaptation, supply chain continuity and labour protection. Their effectiveness is interpreted in relation to different stages of a crisis[64].

The responses observed during the pandemic were heterogeneous across construction subsectors. While residential and commercial construction contracted in some regions, healthcare facilities, telecommunications infrastructure, logistics networks and automated warehouse developments often experienced increased or redistributed demand. External shocks do not necessarily reduce construction activity uniformly but instead reallocate demand between subsectors. Aggregate construction indicators conceal opposing trends occurring simultaneously within different segments of the industry. A decline in overall activity coexists with dynamic functions with rapid expansion in strategically prioritised infrastructure sectors. Analytical models and administrative processes should preserve subsector heterogeneity whenever sufficient data are available[65].

Differences between countries further influence construction performance during crises. Previous research demonstrated that productivity effects varied in the construction economies. The magnitude and direction of these effects were influenced by differences in fiscal capacity,

[II] Although the effectiveness of pre-pandemic preparedness in reducing emergency expenditure remains debated, evidence suggests that countries with established contingency frameworks generally implemented faster and more effective responses during periods of emergency.

regulatory frameworks, healthcare responses, institutional quality and workforce characteristics[JJ]. Within the Full Causal Effect framework, those differences are represented as part of the broader system of interacting causal relationships and not as isolated influences.

The complexity of construction systems during crises highlights the importance of analytical approaches capable of representing multiple interconnected relationships simultaneously. Automated managerial analysis can support stability by evaluating statistically admissible pathways before interventions are implemented[66]. The objective is not to replace managerial judgement but to strengthen resource allocation, risk and performance management decisions using quantitative evidence when operating conditions change rapidly.

Labour shortages, financial instability, mobility restrictions and supply chain disruptions form an interconnected network of relationships. Disruptions propagate through construction systems via multiple interacting channels, generating effects that vary with the time and economic conditions. Unlike physical systems, governed by fixed laws, socioeconomic systems exhibit behaviour in which structural relationships evolve as policy environments, market conditions and organisational responses change.

The proposed framework examines individual mechanisms while preserving the interconnections among the variables that constitute the broader construction system. Within this context, cause and effect identification refers to the estimation of systems of equations that satisfy endogeneity controls, instrument validity requirements (if any) and equation comparability conditions. Relationships that remain statistically significant under these requirements are interpreted as plausible causal pathways. Although any individual equation captures only a partial representation of the system, the combined analysis of multiple admissible configurations provides a more comprehensive understanding of the dynamic processes through which disruptions propagate and influence industrial performance.

From this perspective, the principal advantage of methods like the Full Causal Effect approach is not the replacement of existing analytical methods but the systematic exploration of multiple valid causal structures. By retaining alternative statistically admissible configurations, the framework allows decision makers to evaluate how different combinations of labour, financial, regulatory and supply chain conditions influence construction outcomes under both normal and extreme operating environments.

[JJ] These factors act as boundary conditions that shape how external shocks propagate through construction systems.

4.6.12. Liquidity Protection

Governments provided financial resources to sustain industry, infrastructure and services to preserve the supply system. Infrastructure projects were prioritised by their relevance, with public funding ensuring continuity. Public-Private Partnerships (PPAs) became a mechanism for keeping investment flows. These arrangements, which structure the delivery and financing of infrastructure[67], proved resilient due to their flexibility. During the pandemic, adjustments like renegotiation, temporary guarantees and accelerated procurement processes enabled projects to continue while mitigating financial risk [KK].

Public support extended beyond firms to households and vulnerable workers. Housing stimulus programmes, like Australia's homebuilder scheme, sustained residential construction demand, while emergency funding in countries like India supported rural and migrant labour, and uneven access to support persistent inequalities in labour protection[68].

Despite these interventions, the crisis exposed structural imbalances. Public spending increased, often under constrained fiscal conditions. Private investment declined by 50% in 2020. This link between pandemic control and the supply system contributed to insolvencies and delayed construction sectorial recovery[69]. The pandemic reduced productivity and profitability, compounding financial pressures on construction firms [LL].

Public intervention has properties of a multidimensional resilience mechanism. Tax relief primarily protects firm liquidity; direct liquidity assistance protects solvency; infrastructure spending stimulates demand and preserves project pipelines; household support protects labour income and consumption; accelerated procurement shortens administrative lead times; and contractual renegotiation reallocates financial risk. These mechanisms operate through different causal channels and should therefore be analysed separately.

Separating these mechanism channels also improves the interpretation of public intervention because each policy instrument can enter the construction system through a distinct pathway affecting demand, liquidity, labour availability, project continuity or investment.

[KK] PPA flexibility included renegotiation of timelines, temporary financial guarantees, and accelerated procurement for construction works.

[LL] Firms with diversified portfolios and stronger liquidity buffers recovered faster than those dependent on single-project revenue streams.

4.6.13. Demand Stimulation

Transport infrastructure was among the most affected subsectors. Investment in touristic and recreational buildings declined, and existing projects were delayed due to reduced demand and financial uncertainty. Although public support mitigated immediate job losses, it was insufficient to offset the scale of disruption[70].

Lockdowns and mobility restrictions required a fast reassessment of project feasibility; often, it required tracking financial behaviour[MM]. The effectiveness of demand stimulation policies depended on their timing, scale and interaction with broader economic conditions. Because policy measures influence investment behaviour, labour demand, project viability and supply chain performance simultaneously, their effects are difficult to evaluate using simpler analytical approaches. The Full Causal Effect framework addresses this challenge by examining multiple statistically admissible causal configurations, allowing the assessment of alternative policy outcomes under differing economic conditions. Firms faced rising costs, contractual uncertainty and volatile conditions[71]. Besides the efforts to respond to previous events, evidence suggests that an initial scepticism slightly delayed responses; e.g. tax adjustments could have improved resource allocation and reduced imbalances in the industry[NN]. Besides the negative and positive evidence for the previous responses, an important remaining question is how an automated supply chain will react to major external disruptions and how regulatory and fiscal mechanisms would need to adapt to the next regulatory procedures.

4.6.14. Contractual Adaptation

Contractual flexibility became a critical component of project resilience during the pandemic. Renegotiation of delivery schedules, temporary modifications to risk-sharing arrangements, and force majeure provisions enabled projects to continue despite unprecedented uncertainty. The experience demonstrated the value of contractual frameworks capable of accommodating rapid changes in economic and operational conditions. The pandemic reduced the value of infrastructure partnerships and increased project risk. Small and medium scale enterprises showed valuation losses, reflecting declining demand, disrupted systems and heightened uncertainty[72].

[MM] In terms of real time tracking, it is limited by data availability and analytical resources.

[NN] A multidimensional tax approach could have redistributed fiscal pressure more equitably across sectors experiencing asymmetric impacts.

Demand sensitive sectors, like aviation, rail and hospitality infrastructure, were affected, leading to widespread delays and cancellations. Major projects, like the New International Airport of Mexico City, were abandoned[73]. In Europe, more than €3 billion in transport projects were cancelled during the pandemic[74].

Although construction activity did not fully cease, productivity declined with a complex operating environment characterised by simultaneous pressures on costs, timelines and low availability. Limited analytical capacity among smaller firms[75] further constrained their ability to respond effectively, contributing to delays and insolvencies[OO].

4.6.15. Supply Continuity

Infrastructure investment during COVID-19 reflected a dual dynamic of contraction and adaptation. While projects were delayed or cancelled [PP], projects around healthcare, digital infrastructure and coordination had increased demand[76]. Despite this apparent divergence, the global downturn in infrastructure investment was estimated at US$15 trillion in 2020[77], although recovery was supported by renewed public spending and gradual private sector re-engagement, supportive of industry recovery but requiring substantial investment for recovery.

The external event reinforced the counter-cyclical role of infrastructure investment in economic recovery. Governments introduced regulatory reforms, strengthened risk management frameworks, and expanded PPC models to attract private capital for infrastructure [QQ]. Countries adopted varied strategies, including fiscal stimulus, institutional reform and long term investment planning, reflecting differences in fiscal capacity and governance structures[78].

Fig. 29 shows the level of functionality of the construction industry during the COVID-19 pandemic. Despite an initial decline in construction productivity, the industry showed resilience, with recovery supported by public demand and supply balances. Within two years of the first outbreak, returns in the sector exceeded pre-pandemic levels in markets, indicating a rebound to pre-pandemic conditions[79]. While countries supported stable efficiency, others experienced volatility or persistent inefficiency. Capital efficiency improved temporarily during the pandemic but declined unevenly afterwards: 90 countries saw post-COVID drops, while only 28 improved.

[OO] Many cancellations were driven not only by reduced demand but also by the inability to renegotiate PPA terms under extreme uncertainty.

[PP] Projects dependent on foreign direct investment was disproportionately vulnerable due to cross-border labour and material constraints.

[QQ] Sustainable-infrastructure projects often require long-term financing, making them sensitive to short-term fiscal shocks.

Although countries remained efficient and stable, others experienced volatility or structural inefficiencies, highlighting fragile and inconsistent recovery patterns.

4.6.16. Labour Protection

Labour protection measures extended beyond direct financial support. Construction firms implemented distancing requirements, personal protective equipment protocols, workforce segmentation, health screening, and revised scheduling arrangements to reduce workplace transmission. These measures helped maintain operational continuity but often reduced productivity and increased project costs.

The global spread emphasised the importance of internationally coordinated policy responses. Countries that implemented early containment measures and economic support mechanisms had more stable outcomes in both health and economic indicators. Delays in response increased uncertainty, disrupted investment patterns and intensified labour-market impacts, contributing to a global loss of approximately 9% of working hours[80] in 2020 [RR]. Effective emergency management requires integrating health, economic and infrastructure policies. Key performance indicators, embracing hospital capacity, mortality rates and economic activity, provided a basis for evaluating response effectiveness and guiding adaptive strategies[81].

4.6.17. Construction as a Driver of Recovery

Despite the disruptions, the construction sector played a leading role in economic recovery. Its capacity to generate employment and support interconnected industries positioned it as a key instrument for post pandemic stabilisation. Increased demand for infrastructure, particularly in healthcare, housing and digital systems, partially offset the negative impacts of the crisis.

However, the pandemic also exposed structural vulnerabilities, like the reliance on global supply chains, limited financial resilience among firms and gaps in regulatory frameworks. Addressing those weaknesses required enhanced risk preparedness, more inclusive labour protections and stronger integration of public and private investment strategies.

The evidence reviewed demonstrates that construction resilience emerged through the interaction of financial support, contractual flexibility, labour protection, supply chain adaptation, and demand stimulation measures. Because these mechanisms operate simultaneously and influence one another through multiple causal pathways, effective risk

[RR] Outdoor work environments reduced infection risk, making construction more resilient than indoor-dependent industries.

management requires analytical approaches capable of representing interconnected and evolving construction systems.

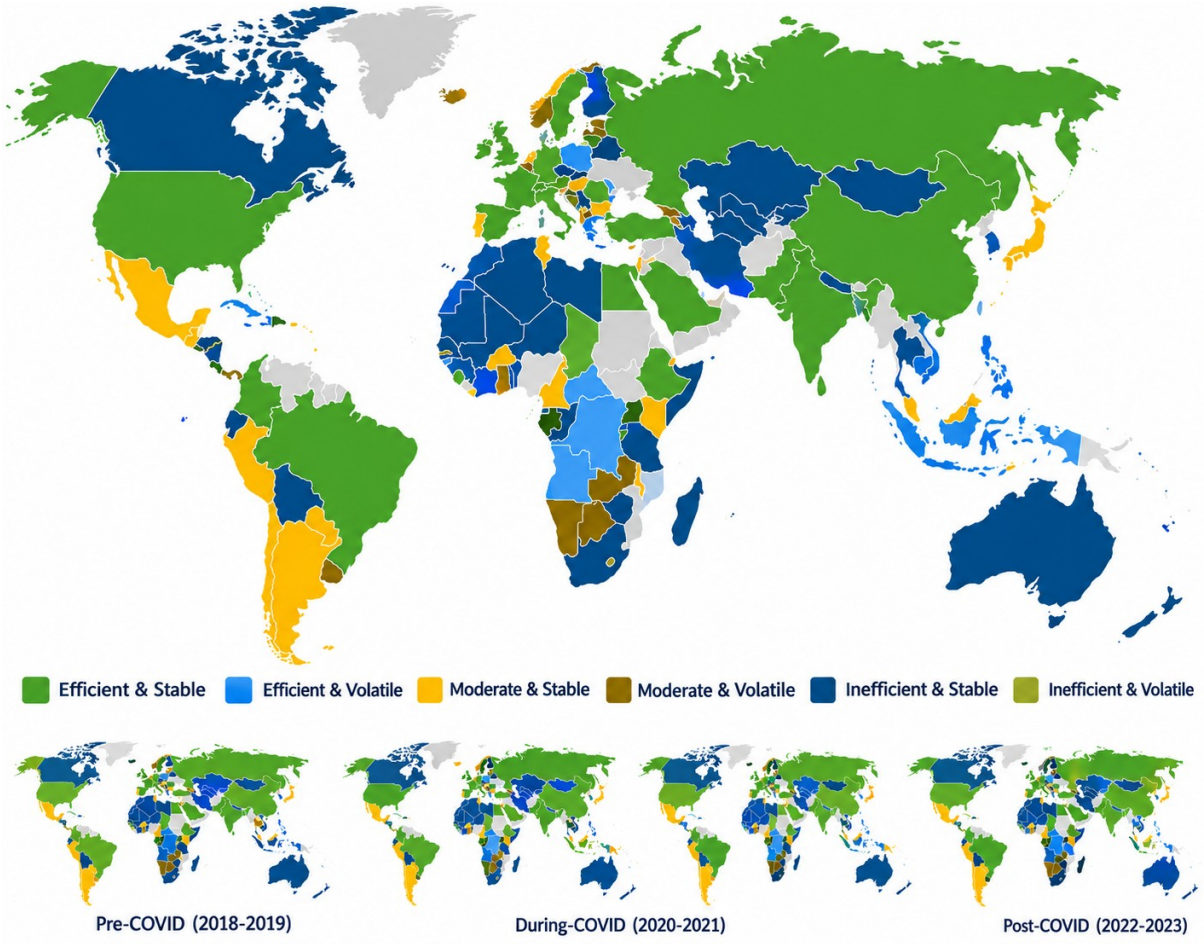


Figure 28 Global efficiency classifications for 141 countries (2018–2023) show how performance and stability evolved. Adapted from[79].

4.7. Risk Management in Construction

During COVID-19, construction supply chains and the policies governing them relied increasingly on advanced analytical tools. Beyond procedural adjustments, the pandemic reshaped innovation paradigms, raising questions about whether progress should be driven by competition or by broader societal and global goals. In the post COVID-19 era, the functionality, competitiveness and scope of supply chains remained central to supporting equilibrium in the construction sector.

Global organisations reaffirmed their responsibility to preserve supply-chain capabilities that underpin resilience[SS]. The pandemic proved that keeping supply chain stability requires a stable

[SS] Sustained performance depends on continuous monitoring of interdependencies that shape competitiveness and the allocation of global capital.

level of technical sophistication, combining evidence analysis with coordination among stakeholders[82].

Public institutions played a critical role in mitigating disruptions by providing infrastructure and regulatory support. In this context, governments had to balance short- and long-term risk distribution, particularly when shocks exceeded the capacity of firms to respond independently[TT]. Section 4 consolidates the preceding evidence into a construction risk architecture organised around five categories—demand, supply, regulatory, infrastructure, transport and risk levels—and then examines how these categories interact at crisis stages.

4.7.1.Trade and Construction During Major External Disruptions

The pandemic exposed structural vulnerabilities in global supply chains. While re-localisation of production was proposed as a mitigation strategy, it would require substantial domestic investment and remain vulnerable to localised disruptions. At the same time, geopolitical tensions and policy instability amplified uncertainty in the international trade networks[83].

Measuring supply-chain interconnectedness remains challenging, as available data often capture only partial sectoral dynamics. Both business and consumer uncertainty increased significantly: business sentiment strongly fluctuated, while consumer expectations adjusted more slowly, prolonging demand instability. Supply-chain stress peaked during the first stages of the pandemic before declining below pre-crisis levels[84].

The interaction of non-economic factors, like health policies, political priorities, and geographic constraints, with market dynamics complicates risk assessment. There is a need for more robust criteria to show and quantify risks objectively. During COVID-19, tracking critical goods and assessing their strategic importance became standard practice, with disruptions in major economies producing disproportionate global effects[85].

A comprehensive vulnerability assessment must therefore consider trade concentration, political and geographic risks, natural hazards and the likelihood of disruption in the supply-chain[UU].

[TT] During COVID-19, governments shifted from reactive to anticipatory risk-distribution models to stabilise relevant economic sectors.

[UU] Countries with concentrated import sources, single supplier economy, experienced severe construction-sector disruptions during COVID-19.

4.7.2.The Relevance of Anticipating Supply-Chain Shocks

Understanding supply-chain disruptions requires analysing the multiple linkages between local and global actors. However, disaggregated analysis of individual products and services often produces fragmented or contradictory insights, limiting effective decision making.

Despite these challenges, risk-anticipation efforts during the pandemic focused on finding disruption sources, implementing coordinated policies, restoring confidence and reinforcing international cooperation[86]. The complexity of cascading effects requires integrated modelling approaches capable of capturing cross-sectoral dependencies.

The pandemic underscored that effective anticipation requires combining economic modelling with political-risk analysis, geographic assessment and real-time monitoring of global trade flows[VV].

4.7.3.Cause–Effect Dynamics in Construction Markets

Construction is a major global industry and plays a stabilising role in supply–demand dynamics. COVID-19 revealed that disruptions were not driven by demand shocks or input shortages, but by systemic limitations in adjusting production and distribution at the required speed[87].

Firms were compelled to reorganise their workloads and procedures with the use of Personal Protective Equipment (PPE), and at the same time the most experienced workers on site were at special risk, requiring skill acquisition and investment in training. This accelerated structural changes, including digitalisation, supplier diversification and improved management of environmental and fiscal impacts[88].

Maintaining the supply of raw materials was particularly challenging due to labour intensity and geographic concentration. These challenges worsened with the early transitions to low-carbon technologies. For instance, clinker production for cement stays energy-intensive and resource-dependent[89]. The industry, therefore, faced the dual task of sustaining material flows while ensuring worker safety and environmental performance [WW].

[VV] Integrated risk-anticipation frameworks are now adopted by several governments to improve resilience against future global disruptions.

[WW] Cement and steel production account for a significant share of global industrial emissions, making optimisation crucial during crises.

4.7.4.Infrastructure and Risk Management in the Supply Chain

Resilience refers to the capacity to absorb disruption and maintain or restore performance. Vulnerability refers to exposure and sensitivity to adverse events. Stability refers to persistence of performance under changing conditions[XX]. Five primary risk categories appeared during COVID-19. The five categories are presented as a synthesis of recurring mechanisms identified in the reviewed studies and are used here to organise the evidence for subsequent analytical comparison. These stages are analytical categories with no fixed durations. The review identifies five interacting categories of risk:

- Demand Risk: sudden changes in infrastructure requirements, project cancellations, shifts between subsectors.
- Supply Risk: material shortages, labour shortages, production interruptions.
- Regulatory Risk: emergency restrictions, compliance requirements, policy uncertainty.
- Infrastructure and Transport Risk: planning bottlenecks, border closures, coordination failures.
- Catastrophic Risk: pandemics, wars, natural disasters, systemic shocks.

A key finding is that these risks rarely occur independently. Instead, construction outcomes emerge from their interaction with different stages of disruption and recovery.

4.7.5.Reducing Risk in Construction Firms During Pandemics

While most risks can be mitigated operationally, some risks require systemic responses. Key firm-level strategies include supporting buffer inventories, enhancing workforce flexibility and implementing early warning and rapid response systems. These measures, though resource-intensive, significantly improve resilience and recovery speed [YY].

4.7.6.Regulations for Construction Projects

Large-scale disruptions need fast cycle regulatory adaptation during major external disruptions; every three months is not an optimal period when a global event occurs. During COVID-19,

[XX] Adaptability refers to the capacity to alter processes, resources or configurations in response to changed conditions. Continuity refers to maintaining critical activity during disruption. Recovery refers to the process of restoring or establishing a state of balance after disruption.

[YY] Firms with pre-existing contingency plans recovered faster during COVID-19 than those relying on ad-hoc responses.

governments reduced trade frictions, eased coordination and supported material production to sustain construction activities.

The crisis also accelerated the need for automation in construction processes. Technologies like 3D concrete printing and robotic steel processing can reduce labour dependency and improve efficiency[90]. Integrating causal modelling with optimisation techniques further enables more precise risk allocation and resource management [ZZ].

4.7.7.Building Supplies: Border Closure and Maritime Transportation

The review synthesis suggests that supplier diversification can improve resilience under specific disruption mechanisms but is not universally optimal. Diversification reduces vulnerability where supplier concentration creates single points of failure, whereas localisation provides greater resilience when border restrictions, transportation interruptions, or geopolitical constraints dominate risk exposure. Consequently, sourcing strategies should be adapted to the specific disruption mechanism affecting the supply chain.

The evidence reviewed throughout this study can be represented through a linked analytical sequence consisting of event type, disruption mechanism, observable variables, analytical inference, response strategy, performance outcome, crisis stage, and recovery trajectory. This sequence provides an integrative framework that connects findings from individual studies into a coherent representation of construction system behaviour during external shocks[91].

Unlike isolated empirical analyses, this synthesis emphasises the interconnected nature of construction systems and the dynamic relationships among labour, supply chains, finance, regulation, infrastructure demand, and technological adaptation. The principal analytical challenge is therefore determining whether a modelling approach can simultaneously represent these interconnected elements while allowing their relationships to evolve. This challenge motivates the use of analytical frameworks capable of examining multiple admissible causal configurations and assessing their implications under different crisis conditions.

The literature reviewed demonstrates that construction-sector disruptions emerge through the interaction of demand fluctuations, supply constraints, regulatory interventions, infrastructure dependencies, and major external disruptions. These mechanisms operate simultaneously, generate feedback effects, and change in significance over time. Consequently, effective risk management requires analytical approaches capable of representing interconnected systems,

[ZZ] Causal-inference models help find structural vulnerabilities, while combinatorial methods optimise resource allocation.

evolving causal relationships, and multiple plausible pathways of disruption and recovery. The following discussion evaluates the implications of these findings for construction resilience and the application of Full Causal Effect modelling.

The comparative network diagrams presented in Fig. 30 show the interactions identified in this synthesis by depicting how economic and pandemic related agents reconfigure under contrasting conditions. During normal periods, Construction Industry Productivity (PCI) is primarily shaped by economic determinants—foreign direct investment, employment rate, total spending, and inflation. Under lockdown, pandemic variables like transmission rate and recovery rate exert dominant causal influence[AAA]. The diagrams provide a graphical synthesis of the reviewed evidence, translating complex causal relationships into an integrated representation of construction sector behaviour at different phases.

4.8. Discussion

The synthesis of the reviewed articles identifies three recurring findings. First, disruption mechanisms interact and do not operate independently. Second, their relative influence can reconfigure over event stages. Third, the magnitude and sign differ between countries and construction subsectors because institutional, economic, regulatory and supply chain conditions differ.

The literature review indicates that disruption mechanisms interact, that resilience is conditional on organisational and institutional circumstances, that supply chain configurations influence construction outcomes, that policy responses vary in effectiveness between contexts and that pandemic impacts differ between countries and construction subsectors[BBB]. The FCE analysis identified multiple statistically admissible systems of equations, showed that coefficient values vary within identifiable ranges of valid configurations, found that foreign direct investment (FDI), share prices and total spending generally exert a positive statistically admissible causal configuration on construction productivity, identified inflation as frequently having a negative effect, and demonstrated how pandemic variables influence productivity.

[AAA] This regime change underscores the adaptive reorganisation of causal pathways within the construction system, demonstrating that resilience depends on recognising how interdependencies among financial, regulatory and epidemiological factors evolve during crises.

[BBB] The FCE provides methodological findings concerning the statistical representation of these relationships.

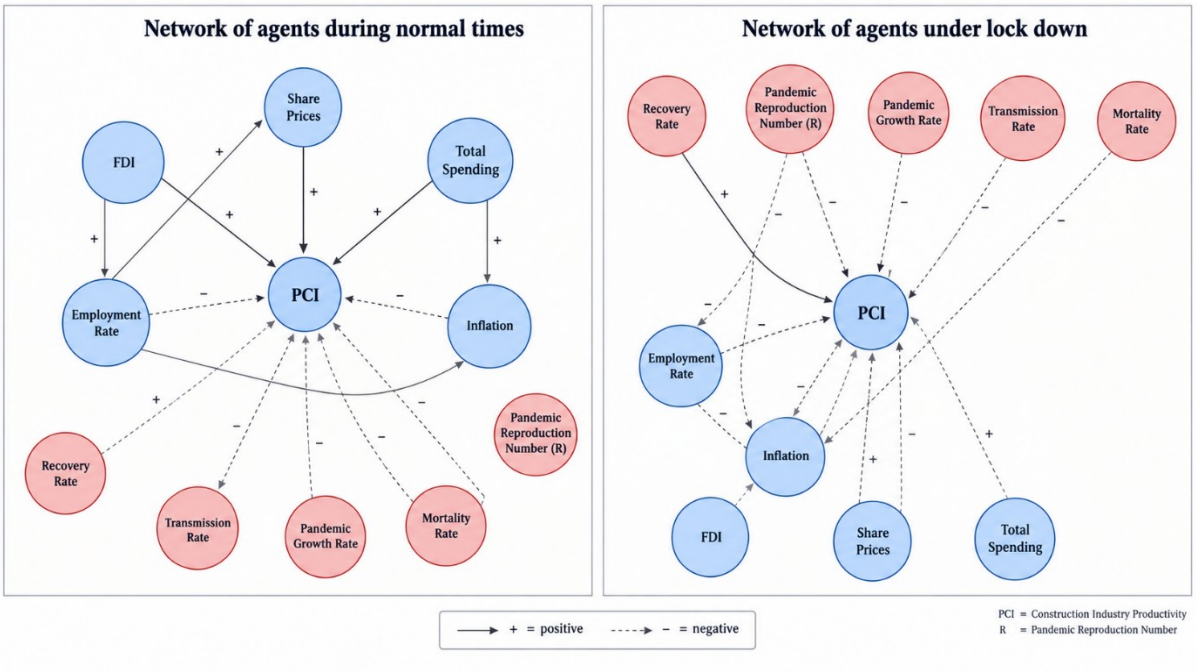


Figure 29 Network diagrams comparing the interaction of economic and pandemic information during two stages of the proper time; the occurrences varied with specific spatial location and specific time.

The review demonstrates that construction performance during external shocks emerges from the interaction of work on site, supply chain, financial, regulatory and technological mechanisms. These mechanisms combine in changing configurations whose influence varies with the event stages, countries and subsectors. The central analytical challenge is therefore not merely identifying individual risks but understanding how multiple interacting mechanisms jointly influence construction outcomes under changing conditions.

An open question is whether global and local economic forces, including their temporal and spatial variation, can be represented adequately using systems of probabilistic equations. The comparison indicates that the relationships reported in the reviewed studies are represented within the distributions of coefficients generated by the FCE framework. As an additional dimension to the literature review, its interpretation focuses on when and where the groups of explanatory models, each one with comparable explanatory variables, reveal a drive of the fluctuating system.

National economic results should not be interpreted as direct project-level decisions. They provide sector-level signals about changing labour, inflation, mobility, investment and supply conditions. Translation into procurement, workforce or inventory decisions requires firm- or project-level information and additional validation. The managerial translation of the reviewed evidence should proceed at the level at which the data are observed. At sector level, changes in labour availability, inflation, mobility restrictions, FDI and procurement conditions can inform

policy and portfolio planning. At firm level, identified configurations can inform sourcing, staffing, inventory and contingency decisions. At project level, these implications require project-specific data and should not be inferred automatically from national coefficients[CCC].

The review findings indicate that construction resilience is not a single state but a capacity to maintain or restore performance while the configuration of interacting risks changes. The distinction made in this work is between stability, continuity, resilience, adaptability, vulnerability and recovery: stability concerns persistence of performance; continuity concerns maintaining critical activity; resilience concerns absorbing disruption and restoring performance; adaptability concerns changing processes or resource allocation in response to altered conditions; vulnerability concerns exposure and sensitivity to adverse events; and recovery concerns the process of returning toward or establishing a system that evolves to its optimal equilibrium.

A narrower methodological interpretation of the review is that industrial-crisis research requires detailed representation of interdependence. The reviewed approaches demonstrate different capabilities; the unresolved requirement is the simultaneous representation of multiple relationships and their changing configurations. FCE is evaluated as one response to that requirement.

Analytical approaches are compared using the following criteria: ability to represent simultaneity, endogeneity, temporal change, structural breaks, feedback, uncertainty, interpretability, predictive performance, data requirements and computational complexity. The purpose is not to rank all methods universally, but to identify which capabilities are relevant to the construction crisis prevention problem and where FCE provide additional coverage[DDD].

These findings verified that even in non-crisis periods, construction productivity is shaped by a complex and changing interplay of financial, labour and investment conditions. The FCE framework therefore provides a tool for strategic planning, enabling firms and policymakers to anticipate how shifts in macroeconomic conditions influence project viability, supply-chain stability and workforce availability in the space of statistical actions. By finding the most influential variables and their causal directions, the framework supports informed decisions

[CCC] For example, a detected reduction in labour availability can signal the need for staffing or automation decisions; rising inflation can alter procurement timing and inventory strategy; mobility restrictions can increase the value of local or diversified suppliers; and longer procurement lead times can justify earlier purchasing or alternative sourcing.

[DDD] Under these criteria, FCE provides a capability in the reviewed prior work for enumerating statistically simultaneous equation configurations.

about investment timing, procurement strategies and labour-force management. The analytical requirements identified above represent interacting mechanisms, changing configurations, endogeneity, temporal dependence, structural change and uncertainty. Only after establishing these requirements can FCE be assessed as a response[EEE]. Alternative methods remain relevant where they satisfy the requirements more efficiently or with lower data and computational demands. Within the search strategy and inclusion criteria adopted in this review, no directly comparable framework was identified that combines these capabilities in the same configuration.

4.8.1.FCE During Periods of Global Health Emergencies

The onset of COVID-19 and later developments towards global movements introduced exogenous shocks that altered the behaviour of economic systems. Epidemiological variables including pandemic growth, transmission rate and R exerted strong negative causal pathways on productivity. The negative effects of the pandemic on the construction industry affected labour availability, transport restrictions and material supply disruptions. These findings align with broader evidence that pandemics reduce economic activity by constraining workforce participation, limiting access to materials and increasing operational uncertainty [92]. Recovery rates functioned as stabilising forces, mitigating inflationary pressures and supporting employment in construction.

This dynamic between pandemic and industry reflects the broader macroeconomic pattern seen during COVID-19, where improvements in public health conditions helped gradual economic reopening and restored confidence in labour markets and supply chains. The FCE framework captures these evolving relationships by modelling the economy during distinct crisis phases: the initial shock, the adaptive period and the post-vaccination restructuring phase. Each phase is characterised by different causal configurations, showing that the economic system reorganises itself in response to changing epidemiological and policy conditions[93]. This finding changes the interpretation of construction risk from a list of isolated factors to a configuration problem. The management question is not only which risks exist, but which combination is active and how that combination changes the outcome under current conditions.

[EEE] The argument of the statistical significance in the spatial analysis is therefore circular: interconnectedness establishes the modelling requirement, while the comparative criteria determine whether FCE provides useful additional capability.

4.8.2.Full Causal Effect Modelling for Construction Management

Integrating FCE into the construction sector offers information that was less evident in previous approaches. This is because the FCE identifies the mathematical conditions under which labour shortages, infection rates and recovery dynamics will most strongly affect productivity by occurring simultaneously. The FCE can detect when the forces will cause multiple conditions of interest for the available workforce.

The FCE estimates how inflation, mobility restrictions, FDI and external-event indicators are statistically associated with changes in the modelled construction system variables, materials, machines and labour, and their impacts on the economy of construction. This enables firms to implement proactive procurement strategies, diversify suppliers and develop contingency plans for transportation and inventory management before the effects can be seen [94].

The characteristic of the FCE consists of its widespread application. Rather than a purely novel statistical approach, it is a process assembling statistical bits to maximise the extraction of causal effects. It provides benefits by obtaining and grouping coefficients of explanatory variables, verifying which internal and external elements consistently exert positive, negative, or varying effects depending on dynamic momentum and emerging regimes within the industrial and economic system. The second application is temporal reconfiguration. Prior FCE evidence shows that the influence of pandemic growth, transmission, recovery and R differed with the conditions of the periods of study. The review therefore supports distinguishing initial shock, adaptation and recovery with more than one causal configuration throughout the event. A risk can remain present while its statistical influence changes as other mechanisms, policies and resource constraints become active and the risk is taken to its minimal expression with fewer repercussions[FFF].

4.8.3.Changing Interactions Under Pandemic Conditions

Previous FCE applications included five epidemiological variables—pandemic growth, transmission rate, mortality rate, recovery rate and R—because these variables were statistically relevant to construction productivity during COVID-19. The FCE was widely applied to other variables—employment, trade, investment, inflation, international trade, pricing—finding ten systems of equations for the broad economy. This was achieved using standard validation tests and combinatory cumulative empirical evidence. If an external event does not produce a

[FFF] This supports a conceptual shift from static risk inventories toward temporally contingent configurations of interacting risks.

statistically relevant effect on construction within the observed data, the FCE procedure does not force that event into the resulting causal configuration[GGG].

Although developed in the context of COVID-19, the FCE framework applies to a range of global events, including geopolitical conflicts, energy crises and climate related disasters. Wars, for example, influence commodity prices, labour mobility, supply chains and investment flows, which can be incorporated into the FCE structure. Natural disasters introduce sudden shocks to infrastructure, labour markets and coordination, which can be studied using similar spatial principles. The FCE can be applied to normal conditions to track every interaction within a system. This allows the best allocation of resources and provides significant information on the evolution of economic interlinks in the industry. This finding is conditioned on effectiveness. Local sourcing, supplier diversification, public support, automation, flexible working and inventory buffers are not expected to produce identical benefits in every context[HHH]. This study can only ensure that the described preventive measures are effective for pandemic events like COVID-19. Relevant boundary conditions include country institutions, project type, organisational size, supply concentration, financial capacity and crisis stage. Resilience strategies should therefore be selected conditionally and temporally, and not as universal prescriptions.

By providing an adaptable analytical tool, the FCE framework enables the construction industry to prepare for and respond to diverse forms of systemic risk. The Full Causal Effect provides holistic modelling, considering every statistical path of action and preventing bias when considering only one statistical scenario, increasing statistical certainty and preventing multiple potential outcomes across a space of multiple paths that can be activated according to the economic conditions and their evolution. Its ability to integrate epidemiological, economic and operational variables makes it suitable for studying the challenges during unforeseen events [95,96,97].

The framework is relevant to other major external disruptions when the event and its effects are observed over time and represented by measurable variables. Similarity in affected variables does not by itself establish identical causal structures, but it can identify relationships that are supported by the data[III]. Continuity is resilient under conditions that preserve safe operation,

[GGG] Transfer to other events therefore represents conceptual potential requiring empirical testing.

[HHH] Their effectiveness depends on the active mechanism and on organisational, economic and institutional conditions.

[III] The effect of a specific external event on construction therefore remains an empirical question for FCE.

resource availability and economic viability. The managerial objective is to identify the conditions under which continuity remains beneficial.

The theoretical implication of the FCE is that construction resilience should be conceptualised as a capacity to respond while the causal configuration of interacting risks changes. This extends a static preparedness perspective by emphasising when and how the relationships among existing risks reconfigure. Resilience in this formulation is not equivalent to recovery speed alone. It includes the capacity to maintain or restore performance while adapting to changes in the structure connecting labour, finance, supply, policy and operational mechanisms to their optimal configurations for every period. These distinctions are necessary because a system can be stable while being resilient, continuous while being safe, adaptable while fully recovering, and less vulnerable by remaining operational.

4.8.4.Limitations of the FCE

The current evidence is derived from the COVID-19 pandemic. Although the conceptual framework is transferable to wars, energy crises and climate related disruptions, empirical validation remains necessary before assuming similar causal configurations under different external shocks.

FCE requires sufficient data, substantial computation and careful variable selection. Its interpretation depends on valid instruments, appropriate equation restrictions and a causal structure able to defend its equations. Large candidate spaces of equations create implementation and interpretability challenges. Scalability and computational cost limit its use by smaller organisations. These limitations mean that FCE should be implemented with precise diagnostics and compared with simpler methods where the analytical problem does not require the additional complexity.

It is relevant to mention that prediction and causal explanation are distinct objectives. Prediction evaluates how accurately future outcomes can be forecast, whereas causal analysis seeks to identify how changes in one mechanism affect another under the model assumptions. A strong causal configuration need not be the strongest short term forecasting model, and forecasting performance alone does not establish causality. For this review, causal explanation has priority because the principal contribution sought is identification of changing causal configurations that can support resilience decisions[JJJ]. Operational feasibility will differ by organisation. Large public

[JJJ] Predictive performance is a secondary implementation objective and should be evaluated independently through out-of-sample validation.

agencies and major contractors can possess the data, computing infrastructure and analytical staff required for FCE, whereas SMEs, subcontractors and project-specific enterprises require simplified interfaces, shared analytical services or sector level decision support tools.

The practical application should therefore be distinguished by level: FCE can support policy and portfolio planning; applications can support procurement, staffing and contingency planning, requiring specific project information. The same model output should not be assumed to have identical meaning at all three levels. During adaptation, management should use updated evidence to reconfigure sourcing, operations, workforce and project priorities as the causal configuration changes. During recovery, successful emergency practices should be evaluated and embedded selectively and not retained automatically.

Supplier diversification, emergency planning, digital monitoring, workforce flexibility and related practices are established resilience mechanisms in the literature. They are not claimed as original practices in this review. The contribution instead concerns how these established mechanisms interact, when they become important and how their relationships reconfigure with the different crisis stages and contexts[KKK]. This review reframes construction resilience around changing configurations of interdependent events. It assesses analytical tools according to their ability to represent these configurations and considers FCE as a candidate framework. The analysis translates the findings into stage specific decision support implications.

4.9. Conclusions

The evidence reviewed in this study suggests that construction performance during periods of disruption cannot be explained by isolated factors. Instead, outcomes emerge from the interaction of economic, labour- market, supply chain, organisational and policy mechanisms whose influence varies with the stages of crisis and recovery. This finding highlights the need to understand how causal relationships evolve under changing conditions and how analytical frameworks can capture these dynamic interactions.

The literature confirms that construction operates within an interconnected economic and institutional system in which labour availability, supply chain performance, investment, financial

[KKK] FCE is relevant to this contribution because it provides a process for examining multiple admissible configurations.

conditions, public policy and operational outcomes interact simultaneously[LLL]. The review indicates that while conventional analytical methods remain valuable and robust within their respective assumptions, the complexity of extreme conditions requires analytical approaches capable of representing multiple interacting pathways, structural changes, feedback effects and uncertainty.

The economic losses observed during the early stages of the COVID-19 pandemic demonstrated that effective disruption management requires more than the identification of individual risk factors. The principal challenge is understanding how multiple mechanisms interact and how their combined effects change throughout the lifecycle of a crisis. Evidence from previous applications of Full Causal Effect modelling suggests that the approach can capture a broader range of statistically admissible multi equation configurations than approaches relying on a single selected specification[MMM].

The review also demonstrates that construction can continue operating during emergencies and contribute to employment stability, infrastructure delivery and economic continuity. However, these benefits are accompanied by increased vulnerabilities, including health risks, trade disruptions, logistical constraints, productivity losses and financial uncertainty. Resilience should not be understood as the elimination of risk but as the capacity to adapt effectively while maintaining essential functions.

Three principal inferences emerge from the literature:

A) Pandemic impacts are multivariate and dynamic

The effects of major disruptions on construction are shaped by interacting epidemiological, economic, financial and operational variables. Evidence from the pandemic demonstrates that disease transmission, mobility restrictions, labour availability and supply chain conditions collectively influence sector performance, with relationships varying with the countries, industries and stages of the events.

B) Resilience requires proactive rather than reactive planning

The literature indicates that productivity losses were often amplified by delayed implementation of emergency procedures and adaptation strategies. Organisations that integrated contingency

[LLL] External shocks therefore propagate through multiple mechanisms affecting a multiple risk factor simultaneously.

[MMM] This capability is valuable in industries like construction, where economic, operational and external variables interact simultaneously.

planning, digital capabilities and risk management procedures into routine operations were better positioned to respond to rapidly changing conditions. Resilience should therefore be embedded within normal management practice rather than developed only after disruptions occur.

C) Analytical frameworks should accommodate changing configurations

Because construction operates within a highly interconnected and externally sensitive environment, analytical models should be capable of representing evolving relationships and not assuming a single configuration remains valid under all conditions. The literature suggests that approaches capable of examining multiple statistical pathways provide valuable support for decision-making during both normal operations and periods of disruption[NNN].

A particularly important implication of the review is that relationships observed during normal conditions do not remain stable during periods of shock, adaptation and recovery. Coefficients, causal pathways and dominant mechanisms change as external conditions evolve. The central analytical requirement identified by this review is the ability to recognise and evaluate changing configurations of operating environments[OOO].

Future research should evaluate FCE alongside alternative modelling approaches using numerical criteria, like causal identification, predictive performance, interpretability, treatment of structural change, computational requirements and practical implementation. Future research would help clarify the circumstances under which FCE can most effectively support construction management and event control measures.

The significance of this work lies in consolidating structural equations into a set of mathematically defined system configurations that can be applied to panel systems spanning multiple countries and time periods. The main contribution is the comparison between existing approaches in the literature and the proposed method, demonstrating that the Full Causal Effect (FCE) framework encompasses the relationships identified in previous studies. This outcome is expected when researchers analyse similar parameters and economic relationships.

[NNN] FCE represents one potential implementation of this principle and warrants further evaluation against alternative modelling approaches.

[OOO] Resilience strategies should therefore be tailored to contextual conditions, institutional capacity, project characteristics, organisational capability, supply-chain structure, financial resources and the stage of disruption. No single response strategy is likely to be universally effective across all contexts.

4.9.1.Novelty and Contribution

The FCE framework considers systems whose properties may vary across different conditions. Rather than allowing these properties to vary without defined limits, the proposed systems of equations identify the possible configurations that an economy can adopt while excluding configurations that are inconsistent with the observed economic variables. A configuration is therefore excluded when one of its constituent equations is invalid or when the properties of the overall system are inconsistent with those of the economy under investigation.

4.9.2.Remarks on the primary questions

RQ1 — Which interconnected mechanisms influence construction performance during major external disruptions?

The review shows that construction performance is influenced by a simultaneous interaction of epidemiological, labour, economic/financial, supply chain, mobility, regulatory and technological mechanisms[PPP]. For example, health restrictions can reduce labour availability and mobility; labour shortages can reduce productivity; material and transport disruptions can delay projects and increase costs; and reduced demand and investment can create financial pressure on firms. Public investment, financial support, contractual flexibility, digitalisation and supply chain adaptation can mitigate these effects. The evidence therefore supports a multivariate and interconnected interpretation of construction resilience, rather than treating individual risks as isolated factors.

RQ2 — How do these mechanisms change across normal, disruption, adaptation and recovery conditions, countries and subsectors?

The review indicates that the relative importance and configuration of causal mechanisms change across crisis stages and contexts[QQQ]. During the initial disruption, epidemiological conditions, mobility restrictions, labour availability and supply chain interruptions become particularly important. During adaptation, workforce reorganisation, digitalisation, health and safety measures and alternative coordination become more prominent. During recovery, public investment, demand stimulation, financial conditions and infrastructure activity become increasingly important. The effects also differ between countries and subsectors because of

[PPP] These mechanisms do not operate independently.

[QQQ] Relationships observed under normal conditions cannot necessarily be assumed to remain stable during disruption, adaptation and recovery.

differences in fiscal capacity, regulation, institutional quality, healthcare systems, supply-chain dependence and project characteristics.

RQ3 — What analytical capabilities are required, and to what extent can FCE provide them?

The review identifies the need for analytical methods capable of addressing simultaneity, endogeneity, temporal lags, changing/nonlinear effects, structural breaks, feedback, uncertainty and competing model configurations. FCE appears aligned with these requirements because it systematically evaluates multiple statistically admissible equation configurations rather than relying on a single selected specification. The reviewed FCE evidence also indicates that coefficient values can vary across valid configurations and that pandemic influence differs across phases. The review itself states that comparative empirical evaluation against alternative approaches remains necessary, and that an equivalent multidimensional study does not exist in previous reports[RRR].

4.9.3.Limitations

This review is subject to the following limitations. First, the evidence base is heavily concentrated on the COVID-19 pandemic, whereas evidence relating to wars, energy crises, climate related events and natural hazards remains more heterogeneous. The conclusions should therefore be interpreted primarily within the context of pandemic related disruptions.

Second, the reviewed literature reflects substantial variation in institutional capacity, economic development, regulatory systems, project characteristics and supply-chain structures. These contextual differences influence both the magnitude and direction of observed relationships, limiting the generalisability of some findings.

Third, the review was conducted primarily through searches of Google Scholar using construction and management related keywords, with publications from 2019 onwards forming the principal temporal boundary. Although systematic screening procedures were applied, the review should not be considered exhaustive of all construction literature.

Finally, the reviewed studies employ heterogeneous methodologies and research designs, meaning that not all findings provide equivalent levels of causal evidence. Furthermore, the discussion of Full Causal Effect modelling builds on existing applications reported in the literature and verified empirical estimations generated from the review dataset. Future empirical studies

[RRR] However, the manuscript does not automatically claim that FCE has been definitively demonstrated to be superior to alternative methods.

are therefore required to validate the practical performance of FCE in different construction and crisis management contexts.

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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5. DISCUSSION

5.1. Integrated Theoretical and Empirical Synthesis

This thesis synthesises three interconnected published contributions to establish a novel data driven paradigm for disaster risk reduction in major global construction economies during health emergencies. Traditional disaster management approaches historically treated epidemiological outbreaks and macroeconomic downturns as isolated or exogenous shocks. By bridging mathematical epidemiology, dynamic panel econometrics and predictive risk modelling, this research demonstrates that global pandemics induce systemic risk that propagates through complex and multivariate transmission channels across macro level infrastructure sectors.

The theoretical architecture constructed across the three published works operates as a unified multi stage framework:

Epidemiological Dynamics & Parameterisation (SIRDi Model): Mathematical formulation of viral transmission (γ), recovery (α), mortality (τ), and isolation dynamics (σ, where $i = 1 - \sigma$), providing time varying epidemic parameters extracted from daily public health data.

Full-Causal Econometric Modelling (Dynamic Panel GMM): High Performance Computing combinatorial estimation utilising the Generalised Method of Moments with Arellano-Bond specifications to isolate unconfounded, endogenous and exogenous macroeconomic and pandemic predictors of construction industry productivity across 14 major economies representing ~75% of global GDP.

Risk Indexing & Non-Linear Predictive Systems: Formulation of global and continental Relative Risk Indices and high order polynomial forecasting models ($RPCI = f(RRI)$) that quantify sectoral vulnerability and enable automated crisis response strategies aligned with international DRR frameworks (e.g., the United Nations Sendai Framework).

5.1.1. Epidemiological-Economic Interdependencies and Full Causality

A primary contribution of this thesis is providing advanced econometric analysis from simple or subjective causality to full causal effect detection. Traditional econometric studies often rely on single regression models or selected regressors, which run the risk of model misspecification, omitted variable bias and heteroskedasticity. By testing 967 combinatorial sets of regressors against 7 orthogonal instrumental variables (Z) under strict moment conditions ($corr(z_j, \epsilon_{i,k}) \leq 0.100$), this research identifies 10 statistically significant explanatory variables that govern construction productivity during a pandemic and presents them in Table 11:

Table 11 Types of variables, sign and mechanicms of action within the systems.

Variable Category	Explanatory Regressor	Symbol / Measurement	Observed Global Causal Effect (θ)	Theoretical & Structural Mechanism
Epidemiological	Recovery Rate	α (1/day)	Positive (Global RI driver)	Refinement of healthcare response; accelerates safe workforce re-entry.
	Mortality Rate	τ (1/day)	Negative ($\theta = -3.0$ in RI)	Fatalities in skilled labour, severe site disruptions, direct loss of Human Capital.
	Pandemic Growth Rate	$\frac{dI}{dt}$ (1/day)	Negative ($\theta = -2.5$ in RI)	Rapid outbreak spread triggers emergency lockdowns and project suspensions.

Variable Category	Explanatory Regressor	Symbol / Measurement	Observed Global Causal Effect (θ)	Theoretical & Structural Mechanism
	Reproduction Number	R (dimensionless)	Negative ($\theta = -1.556, p < 0.01$)	Sustained community spread ($R > 1$) forces strict social distancing on sites.
	Transmission Rate	γ (1/day)	Negative ($\theta = -3.0$ in RI)	High contagious potential disrupts labour intensive procurement and supply lines.
Macroeconomic	Inflation Rate	$2015 = 100$	Negative ($\theta = -0.713, p < 0.01$)	Drives up raw material, energy, and labour costs, causing project cost overruns.
	Share Prices	$\mathbf{2015 = 100}$	Positive ($\boldsymbol{\theta = 0.473, p < 0.01}$)	Strong capital markets provide liquidity and

Variable Category	Explanatory Regressor	Symbol / Measurement	Observed Global Causal Effect (θ)	Theoretical & Structural Mechanism
				equity financing for infrastructure.
	Employment Rate	% of labour force	Negative ($\boldsymbol{\theta = -0.391, p < 0.05}$)	Reflects volatile labour reallocation, furloughs, and severe structural shifts.
	Foreign Direct Investment	FDI (US$Millions)	Positive ($\boldsymbol{\theta = 0.637, p < 0.01}$)	Inflows of foreign capital stabilise construction funding during domestic crises.
	Total Spending	US$Trillions	Positive ($\boldsymbol{\theta = 1.189, p < 0.01}$)	Public counter-cyclical stimulus and private

Variable Category	Explanatory Regressor	Symbol / Measurement	Observed Global Causal Effect (θ)	Theoretical & Structural Mechanism
				capital expenditure fuel demand.

The empirical modelling demonstrated that excluding statistically independent pandemic variables prevented the convergence of valid GMM regressors. This finding underscores that macro-level infrastructure models cannot accurately reflect economic realities during biological disasters without incorporating time series epidemiological metrics.

5.1.2.Regional Vulnerabilities and Continental Heterogeneity

The empirical application of the unified framework across America, Asia, Europe, and Oceania revealed key regional divergences in risk sensitivity and productivity trajectories, driven by differing institutional, fiscal and containment policies:

5.1.2.1. The Americas

America demonstrated high sensitivity to both epidemiological severity and fiscal intervention. The mortality rate and pandemic growth rate imposed strong negative impacts on productivity, aggravated by stringent initial state level shutdowns. However, unlike the global trend, the employment rate exhibited a positive relationship with productivity ($\boldsymbol{\theta = 0.194, p < 0.01}$), reflecting the rapid deployment of wage protection programs (e.g., PPP in the United States) and targeted infrastructure stimulus that preserved site employment.

5.1.2.2. Asia

Asian economies (dominated by China, Japan, and India) displayed wider statistical dispersion and dynamic variations. In China, early and aggressive non pharmaceutical interventions (zero-COVID lockdowns) effectively suppressed epidemiological transmission rates ($\boldsymbol{\gamma}$), allowing a rapid reopening of industrial construction. Asia's models showed a slightly positive coefficient for the reproduction number $\boldsymbol{R}$, as construction activity rebounded sharply under strict health protocols. However, labour market volatility and supply chain bottlenecks created prolonged challenges across South Asian construction sectors.

5.1.2.3. Europe

European models highlighted the dominant role of financial market performance and institutional safety nets. Share prices ($\boldsymbol{\theta = 1.7}$ in $\boldsymbol{RI}_{\text{Europe}}$) and inflation ($\boldsymbol{\theta = 2.862, p < 0.05}$) had positive associations with construction value added creation. This counterintuitive inflationary finding indicates that elevated material prices coincided with high value infrastructure projects backed by European Union recovery funds (e.g., NextGenerationEU). Furthermore, European sites rapidly adapted via digital procurement, BIM integration and strict site isolation, enabling operations to persist even during elevated viral transmission phases.

5.1.2.4. Oceania

Oceania (principally Australia) demonstrated strong reliance on capital inflows and spending stimulus. FDI exerted an extraordinary positive influence ($\boldsymbol{\theta = 8.375, p < 0.01}$), alongside total spending ($\boldsymbol{\theta = 3.2}$ in $\boldsymbol{RI}_{\text{Oceania}}$). Australia's geographically isolated position and strict border biosecurity successfully mitigated early mortality impacts, allowing targeted public infrastructure spending to act as the primary engine of economic recovery.

5.1.3. Mathematical Modelling of Sectoral Resilience: Risk Index & RPCI

To translate econometric estimations into operational disaster risk tools, this thesis formulated the Sectoral Risk Index (RI) and the Relative Risk Index. Defined as the inverse of the weighted sum of valid regressor coefficients, the general global risk index formulation is established as:

Normalising this index relative to historic limits produces the dimensionless Relative Risk Index ($RRI \in [0,1]$). The empirical trajectory during COVID-19 revealed a clear inverse relationship between RRI and the Relative Productivity of the Construction Industry:

Key Empirical Observation: In Q1–Q2 2020, RRI spiked to maximum levels ($RRI \rightarrow 1.0$) across all continents, driving a severe synchronous collapse in $RPCI$. As governments implemented fiscal stimulus, vaccination campaigns, and modified work practices from 2021 onwards, RRI stabilised, facilitating a non linear recovery in Relative Productivity of the Construction Industry.

High-order polynomial regression equations (6th to 10th degree) were fitted to model $RPCI = f(RRI)$ across regions, achieving exceptional explanatory power ($R^2 = 0.960$ to 0.980). This non linear formulation enables real-time stress testing: policymakers can input projected macroeconomic and epidemiological shifts into the model to forecast infrastructure productivity trajectories up to 8–12 quarters in advance.

5.1.4. Academic, Methodological, and Policy Implications

5.1.4.1. Theoretical Advances

This research redefines disaster risk literature by demonstrating that systemic biological hazards cannot be decoupled from macroeconomic dynamic systems. It extends the Sendai Framework for Disaster Risk Reduction (Priority 1: Understanding disaster risk; Priority 3: Investing in DRR for resilience) into the domain of quantitative macroeconomics.

5.1.4.2. Methodological Contributions

The thesis demonstrates the efficacy of High-Performance Computing combined with dynamic panel GMM to solve high-dimensional causal search problems. It establishes that orthogonality conditions and moment tests (Hansen's $\boldsymbol{J}$-test) allow researchers to extract robust causal structures from observational time-series data without relying on restrictive theoretical assumptions.

5.1.4.3. Practical & Policy Applications

Public Sector & International Financial Institutions (IMF/World Bank): Provides an early-warning diagnostic tool to evaluate sovereign infrastructure exposure, sovereign debt risks during crises, and the required fiscal stimulus sizing.

Project Managers & Corporate Executives: Enables construction firms to dynamically hedge material procurement, adjust labour allocations based on regional $\boldsymbol{RRI}$ scores, and maintain capital liquidity during emerging crisis phases.

5.1.5. Limitations of the Research

Data Granularity Mismatch: High-frequency epidemiological data (recorded daily) required temporal aggregation to align with quarterly macroeconomic reports ($\boldsymbol{Q1 - Q4}$), potentially smoothing out short-term micro-surges in virus transmission.

Instrument Power in Extreme Outliers: In periods of extreme structural breaks (e.g., initial global lockdown in March 2020), standard linear moment conditions risk weak instrumentation, requiring strict filtering via Hansen's $\boldsymbol{J}$-test.

Data Availability in Developing Economies: The analysis was bounded by 14 major economies due to data completeness requirements, omitting low-income countries where informal labour dominates construction sectors.

6. CONCLUSIONS

This doctoral research successfully established an integrated computational framework for evaluating, quantifying, and mitigating disaster risks within major global construction economies during health crises. The principal achievements of this thesis are summarised below:

Formulation of an Integrated Macro-Epidemiological Model: Successfully coupled the compartmental SIRDi epidemic model with macroeconomic dynamic panel regressions, proving that independent pandemic indicators are essential for convergent causal modelling of industrial productivity.

Full Causal Identification via HPC & GMM: Identified 10 key explanatory variables across 967 combinatorial model spaces, demonstrating that positive drivers (FDI, share prices, total spending, recovery rate) and negative drivers (mortality rate, pandemic growth rate, R number, transmission rate, inflation, labour volatility) govern global infrastructure resilience.

Establishment of the Relative Risk Index: Developed standardised mathematical formulations for global and continental risk indices, providing a dynamic metric to quantify sectoral vulnerability in real time.

Non-Linear Predictive Forecasting Systems: Constructed high accuracy polynomial regression models ($R^2 \geq 0.960$) capable of forecasting construction productivity drops and recovery trajectories based on fluctuating risk index parameters.

6.1. Directions for Future Research

The methodologies established in this thesis open several promising avenues for future scientific inquiry:

Extension to Broader Macroeconomic Sectors: Applying the full-causal GMM-SIRDi framework to other labour intensive or capital-intensive sectors, such as manufacturing, transportation, energy, and agriculture.

Integration of Machine Learning & Deep Learning: Utilising Recurrent Neural Networks and Physics-Informed Neural Networks to capture hyper-dimensional non-linear interactions without relying on polynomial expansions.

Compound Disaster Risk Modelling: Expanding the framework to model multi-hazard scenario disruptions simultaneously—such as climate-induced extreme weather events occurring concurrently with biological pandemics.

Real-Time Automated Streaming Analytics: Coupling cloud computing infrastructures with live economic APIs and public health feeds to maintain a continuous, autonomous early-warning system for global infrastructure markets.

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7. APPENDICES

7.1. Appendix A

The SIRDi model, standing for Susceptible-Infected-Recovered-Death with Isolation, is a compartmental model used to analyse the spread of a pandemic within a population, particularly considering the effects of isolation measures [47]. This model divides the total population (N) into four categories: susceptible (S), infected (I), recovered (R) and deceased (D) individuals due to the pandemic. The isolation factor, denoted by σ, represents the proportion of the population under isolation due to various control measures implemented to mitigate the spread of the virus. When σ equals 1, it indicates complete isolation, while σ equals 0 signifies no isolation measures in place. The term $i = 1 - \sigma$ is relevant for controlling the virus spread in a population.

In the SIRDi formulation, the flow of individuals between these compartments is governed by various rates denoted by Greek letters. These rates represent the interactions between different groups within the population during the pandemic. Specifically, the transmission rate (γ) determines the rate at which susceptible individuals become infected, with higher values indicating a greater likelihood of contracting the virus. After the implementation of isolation measures, new infections occur at a reduced rate of $(1 - \sigma)\gamma$. Once individuals are infected, they have the option to transition to either the recovered (R) or deceased (D) compartments at rates represented by α (recovery rate) and τ (death rate), respectively.

Fig. 31 illustrates a flow diagram of the SIRDi epidemic model, depicting the interactions between the various groups and the flow of individuals between compartments. This schematic representation aids in visualising how different factors, such as transmission, recovery and mortality rates, explain the compartmental spread of the pandemic within the population. By studying these interactions, researchers can better understand the effectiveness of isolation measures and other interventions in controlling the spread of the virus and mitigating its impact on public health. Fig. 32 shows the key pandemic variables for the studied countries.

7.2. Appendix B

Table 12 Sign Concordance Across Benchmark Models

Economic Relationship	Proposed SUR–GMM Systems	Reduced-Form Panel (GMM with lags)	SUR	SUR (with lags)

Employment Rate → Employment Rate (t-1)	n/a	Positive	n/a	Positive
Government Spending → Employment Rate	Positive	Negative	Positive	Positive
House Prices → Employment Rate	Positive	Positive	Positive	Positive
Inflation → Employment Rate	Positive	Negative	Positive	Positive
Production Prices → Employment Rate	Positive	Positive	Positive	Positive
Exports (t-1) → Exports	n/a	Positive	n/a	Positive
Government Spending → Exports	Positive	Positive	Positive	Positive
Inflation → Exports	Positive	Positive	Positive	Positive
Mobility Rate → Exports	Positive	Negative	Positive	Positive
Private Spending → Exports	Positive	Positive	Positive	Positive
FDI (t-1) → FDI	n/a	Positive	n/a	Positive
Government Spending → FDI	Positive	Negative	Positive	Positive
Mobility Rate → FDI	Positive	Negative	Positive	Positive
Private Spending → FDI	Positive	Positive	Positive	Positive
Share Prices → FDI	Positive	Negative	Positive	Positive
Inflation (t-1) → Inflation	n/a	Positive	n/a	Positive
Employment Rate → Inflation	Positive	Negative	Positive	Positive
House Prices → Inflation	Positive	Positive	Positive	Positive
M5 → Inflation	Positive	Positive	Positive	Positive
Mortality Rate → Inflation	Positive	Positive	Positive	Positive
Pandemic Growth → Inflation	Positive	Negative	Positive	Positive
Pandemic Number → Inflation	Positive	Positive	Positive	Positive

Private Spending → Inflation	Positive	Negative	Positive	Positive
Production Prices → Inflation	Positive	Negative	Positive	Positive
Recovery Rate → Inflation	Positive	Negative	Positive	Positive
Share Prices → Inflation	Positive	Negative	Positive	Positive
Private Spending (t-1) → Private Spending	n/a	Positive	n/a	Positive
Transmission Rate → Private Spending	Positive	Positive	Positive	Positive
Mobility Rate → Private Spending	Positive	Positive	Positive	Positive
Imports → Private Spending	Positive	Positive	Positive	Positive
Pandemic Growth → Private Spending	Positive	Negative	Positive	Positive
M3 → Private Spending	Positive	Negative	Positive	Positive
Production Prices → Private Spending	Positive	Positive	Positive	Positive
FDI → Private Spending	Positive	Negative	Positive	Positive
Employment Rate → Production Prices	Positive	Positive	Positive	Positive
House Prices → Production Prices	Positive	Positive	Positive	Positive
Mortality Rate → Production Prices	Positive	Negative	Positive	Positive
FDI → Production Prices	Positive	Negative	Positive	Positive
Employment Rate → Production Prices	Positive	Positive	Positive	Positive
Production Prices (t-1) → Production Prices	n/a	Positive	n/a	Positive
Share Prices (t-1) → Share Prices	n/a	Positive	n/a	Positive
Pandemic Number → Share Prices	Positive	Negative	Positive	Positive
Mobility Rate → Share Prices	Positive	Negative	Positive	Positive

Employment Rate → Share Prices	Positive	Negative	Positive	Positive
Recovery Rate → Share Prices	Positive	Negative	Positive	Positive
M3 → Share Prices	Positive	Negative	Positive	Positive
Employment Rate → Share Prices	Positive	Negative	Positive	Positive
Government Spending → Share Prices	Positive	Positive	Positive	Positive

"Positive" ("Negative") indicates that the estimated effect is consistently positive (negative) across statistically valid specifications within each modelling framework.

Table 12 summarises the sign concordance of selected pandemic–economic relationships across benchmark models and the proposed SUR–GMM framework. The reduced form panel regressions, classical SUR systems, and Panel VAR models recover directional effects consistent with the core relationships identified in the SUR–GMM systems. In particular, improvements in recovery rates are associated with higher employment and lower inflation, while increased mortality and mobility exert adverse effects on labour markets and price stability.

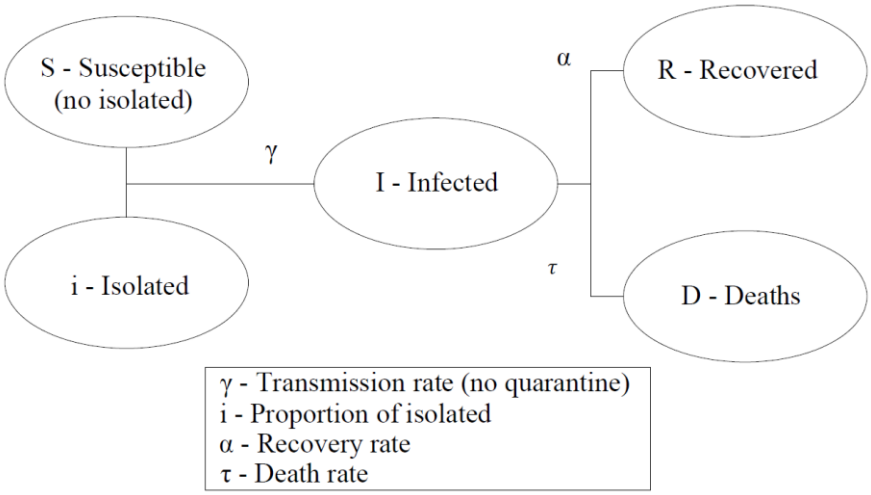
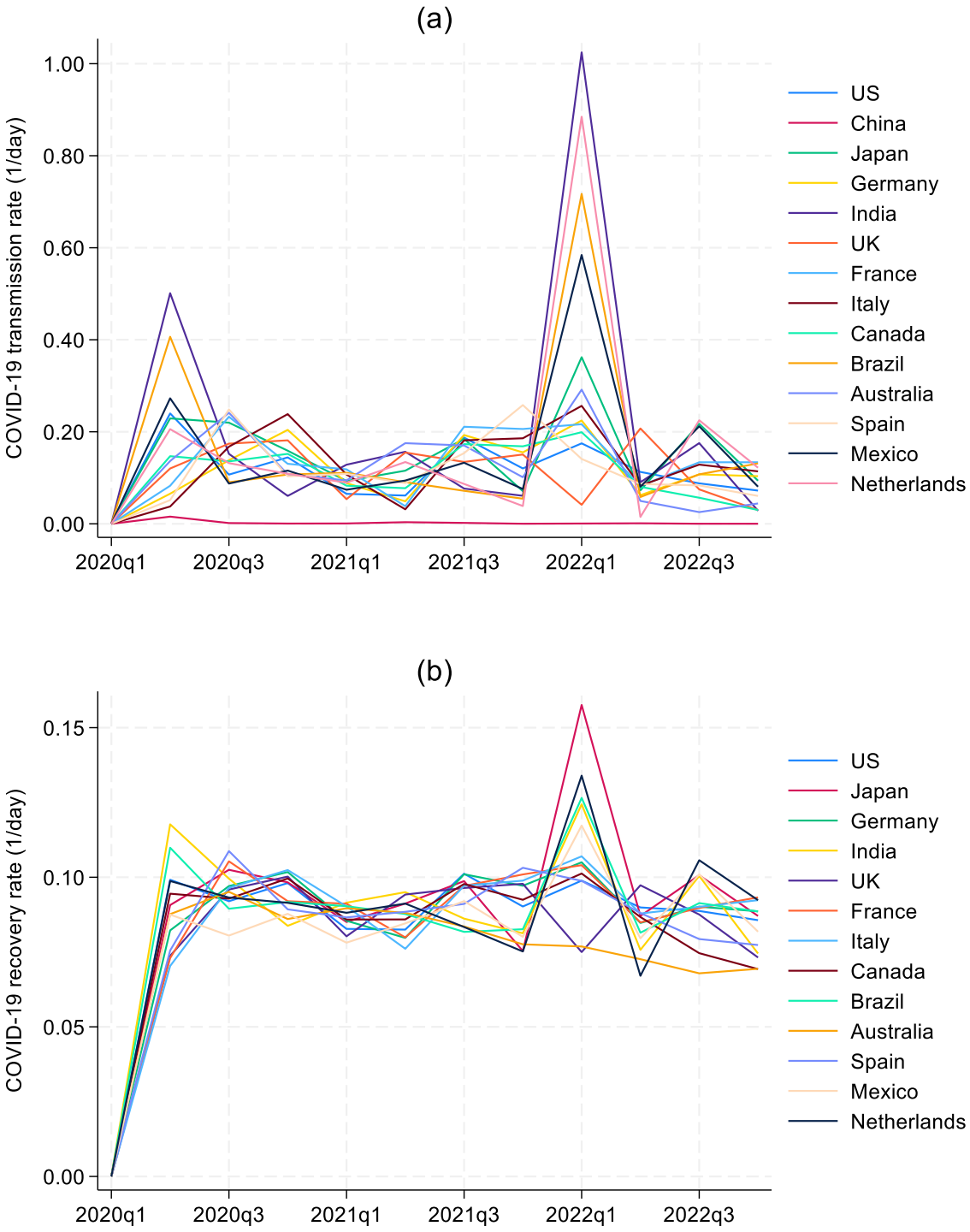


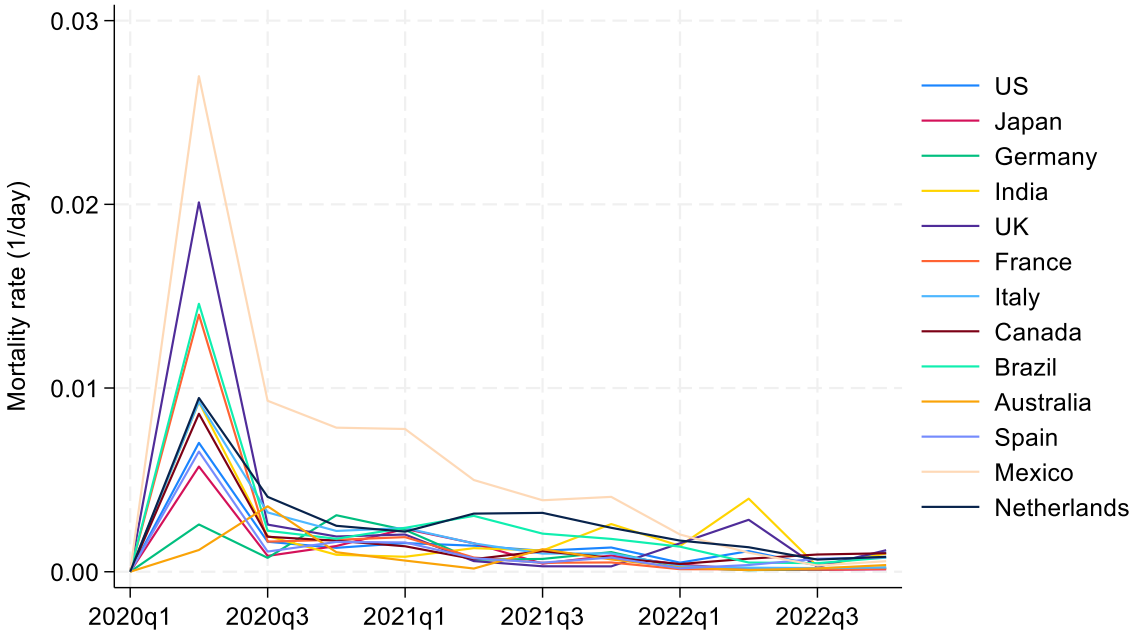
Figure 30 SIRDi epidemic model diagram. The coefficient γ is the transmission rate from S with no quarantine to the I compartments. The I corresponds to the portion of the population in quarantine. The coefficients α and τ are the recovery and death rates, respectively, within the described pandemic model.

The main difference across approaches lies not in the direction of estimated effects, but in the inferential structure. Reduced form and VAR models capture average or lag based dynamics at the equation level, whereas the SUR–GMM framework identifies contemporaneous systems of equations that are jointly and individually statistically valid. The consistency in sign across benchmarks supports the empirical credibility of the system level results, while the SUR–GMM methodology reveals how

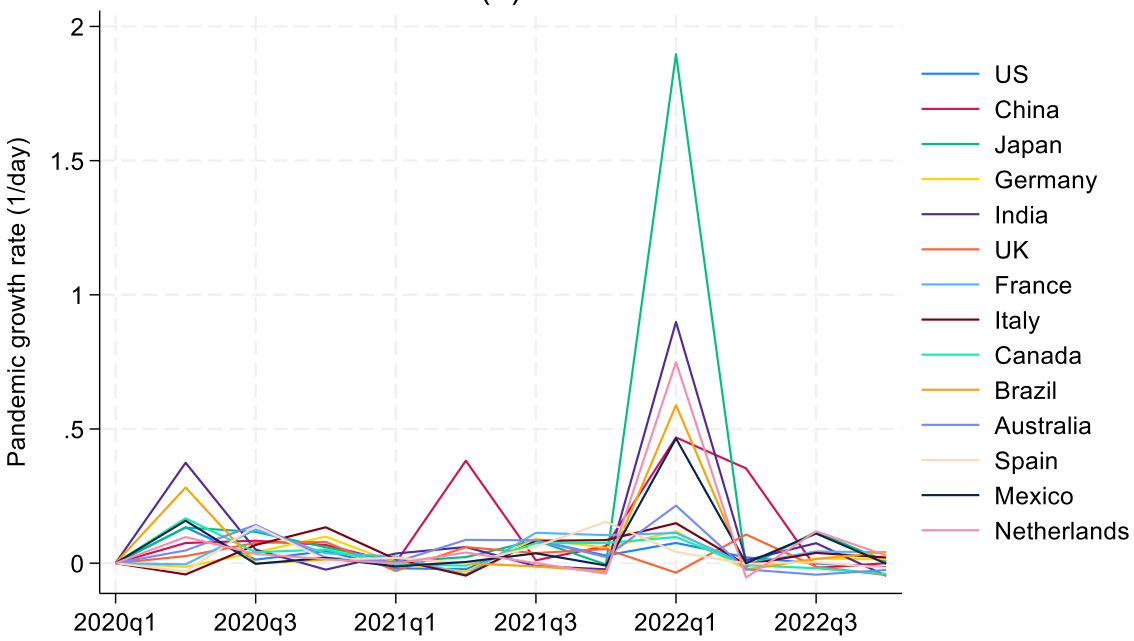
these relationships coordinate simultaneously across multiple sectors of the economy during different pandemic phases.



(c)


Mortality rate (1/day)
0.03
0.02
0.01
0.00
2020q1
2020q3
2021q1
2021q3
2022q1
2022q3
US
Japan
Germany
India
UK
France
Italy
Canada
Brazil
Australia
Spain
Mexico
Netherlands

(d)


Pandemic growth rate (1/day)
2
1.5
1
.5
0
2020q1
2020q3
2021q1
2021q3
2022q1
2022q3
US
China
Japan
Germany
India
UK
France
Italy
Canada
Brazil
Australia
Spain
Mexico
Netherlands

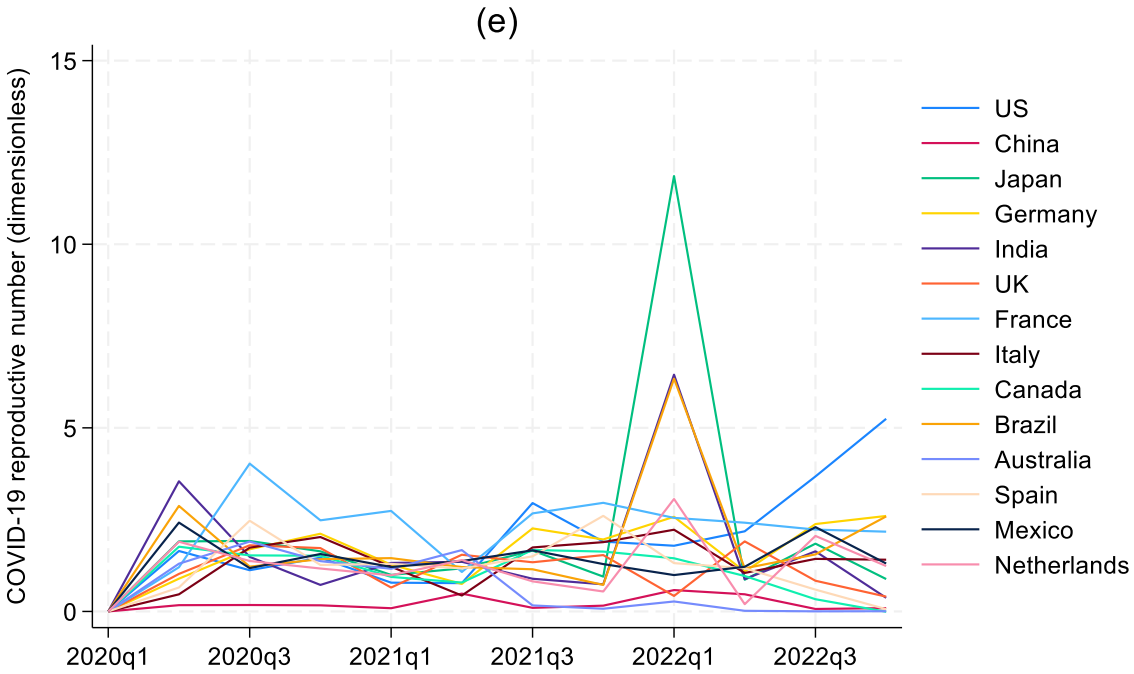


Figure 31 The Figs. (a), (b), (c), (d) and (e) correspond to the pandemic transmission, recovery and mortality rate, pandemic growth rate and pandemic reproductive number of COVID-19.

7.3. Appendix C

The equations of the chord diagrams are presented here. Table 13 includes the systems of equations with all the explanatory variables. All the variables of X work as a system to explain the seven variables. These coefficients were computed with GMM and verified with SUR. As described in section 3, the results were also compared with another research. Given the level of parameter constraints and the intensive search engines, the results were consistent on every test. In this work, we presented the GMM systems.

Table 13 The structural systems for the periods of study.

Q1 2020

Employment Rate = - 0.926*Mortality Rate - 0.402*M3 - 0.849*Share Prices + 0.482*Production Prices + 0.368*FDI

Exports = - 0.358*Mobility Rate + 0.506*Private Spending

FDI = 0.416*Mortality Rate + 0.244*Mobility Rate + 0.199*Employment Rate + 0.874*Exports + 0.231*Terms of Trade

Inflation = - 0.84*Recovery Rate + 0.552*M3 + 0.644*Mobility Rate + 0.17*House Prices - 0.433*Government Spending + 0.313*Exports

Private Spending = 0.921*Transmission + 0.643*Mortality Rate + 0.439*Mobility Rate + 1.205*Imports

Production Prices = - 0.292*Mortality Rate + 0.439*M3 + 0.83*Mobility Rate + 0.373*House Prices - 0.553*Government Spending + 0.386*Exports

Share Prices = - 0.729*Recovery Rate + 0.279*M3 + 0.341*Mobility Rate - 0.261*Employment Rate

Q2 - Q4 2020

Employment Rate = 0.811*Recovery Rate - 0.857*Mortality Rate + 0.668*House Prices - 0.341*Production Prices - 0.424*FDI

Exports = - 0.717*Mobility Rate + 0.395*Production Prices

+ 0.463*Government Spending

FDI = - 0.529*Mobility Rate + 0.187*Production Prices + 0.685*Private Spending

Inflation = - 0.473*Mortality Rate + 0.556*M3 - 0.649*Employment Rate + 0.639*House Prices - 0.359*Private Spending - 0.306*Terms of Trade

Private Spending = 0.921*Transmission + 0.643*Mortality Rate + 0.439*Mobility Rate + 1.205*Imports

Production Prices = - 0.475*Mortality Rate + 0.595*M3 - 0.489*Employment Rate + 0.807*House Prices - 0.51*Private Spending - 0.415*Terms of Trade

Share Prices = - 0.729*Recovery Rate + 0.279*M3 + 0.341*Mobility Rate - 0.261*Employment Rate

Q1 2021 - Q3 2023

Employment Rate = 0.811*Recovery Rate - 0.857*Mortality Rate + 0.668*House Prices - 0.341*Production Prices - 0.424*FDI

Exports = - 0.675*Mobility Rate + 0.306*Production Prices + 0.516*Private Spending

FDI = - 0.537*Mobility Rate + 0.266*Inflation + 0.526*Government Spending

Inflation = - 0.779*Recovery Rate + 0.661*M3 - 0.428*Employment Rate + 0.533*House Prices - 0.369*Private Spending - 0.333*Terms of Trade

Private Spending = 0.818*Transmission + 0.772*Mortality Rate - 0.412*Pandemic Growth + 0.496*Mobility Rate + 1.192*Imports

Production Prices = - 0.475*Mortality Rate + 0.595*M3 - 0.489*Employment Rate + 0.807*House Prices - 0.51*Private Spending - 0.415*Terms of Trade

Share Prices = - 0.867*Recovery Rate + 0.553*M3 - 0.324*Employment Rate - 0.262*Government Spending

The information here corresponds to the full systems of causal contemporaneous equations. Adding or reducing elements of X may carry uncertainty. If further algebra is expected to be done, it must include the entire system.

7.4. Appendix D

Equations obtained with the GMM and validated using Hansen's J Statistic corresponding to the 13 analysed variables in this study. The list of equations presented in this appendix was permuted to form systems of linear equations, which were subsequently validated using the conditions presented in this work and presented in Table 14.

Table 14 The CSoE for the period 2020-2023.

D.1
Employment Rate = 0.494*House Prices - 0.573*Inflation
Exports = - 0.702*Mobility Rate + 0.33*Inflation + 0.46*Private Spending
FDI = - 0.151*Share Prices + 0.638*Private Spending
Inflation = 0.376*Share Prices + 0.687*Production Prices
Private Spending = 0.921*Transmission + 0.643*Mortality Rate + 0.439*Mobility Rate + 1.205*Imports
Production Prices = - 0.458*Employment Rate + 0.635*House Prices - 0.35*Terms of Trade
Share Prices = - 0.725*Pandemic Number + 0.439*Mobility Rate - 0.463*Employment Rate
D.2
Employment Rate = 0.5*House Prices - 0.393*Production Prices

Exports = - 0.333*Mobility Rate + 0.419*Government Spending

FDI = - 0.343*Mobility Rate + 0.648*Private Spending

Inflation = - 0.698*Recovery Rate + 0.554*M3 - 0.523*Employment Rate + 0.479*House Prices - 0.362*Private Spending

Private Spending = 0.818*Transmission + 0.772*Mortality Rate - 0.412*Pandemic Growth + 0.496*Mobility Rate + 1.192*Imports

Production Prices = - 0.458*Employment Rate + 0.635*House Prices - 0.35*Terms of Trade

Share Prices = - 0.729*Recovery Rate + 0.279*M3 + 0.341*Mobility Rate - 0.261*Employment Rate

D.3

Employment Rate = 0.5*House Prices - 0.393*Production Prices

Exports = - 0.333*Mobility Rate + 0.419*Government Spending

FDI = - 0.529*Mobility Rate + 0.187*Production Prices + 0.685*Private Spending

Inflation = - 0.44*Pandemic Number + 0.767*M3 - 0.412*Employment Rate + 0.527*House Prices - 0.51*Private Spending

Private Spending = 0.293*M3 + 1.059*Imports

Production Prices = - 0.528*Mortality Rate - 0.672*Employment Rate + 0.829*House Prices - 0.399*FDI

Share Prices = - 0.724*Pandemic Growth - 0.665*Employment Rate

D.4

Employment Rate = 0.5*House Prices - 0.393*Production Prices

Exports = - 0.358*Mobility Rate + 0.506*Private Spending

FDI = - 0.343*Mobility Rate + 0.648*Private Spending

Inflation = - 0.822*Mortality Rate + 0.517*Pandemic Growth - 0.871*Employment Rate + 0.549*House Prices

Private Spending = 0.646*Mobility Rate - 0.217*Production Prices + 1.294*FDI

Production Prices = - 0.529*Pandemic Number - 0.584*Employment Rate + 0.698*House Prices - 0.283*Private Spending

Share Prices = - 0.867*Recovery Rate + 0.553*M3 - 0.324*Employment Rate - 0.262*Government Spending

D.5

Employment Rate = 0.628*House Prices - 0.572*Inflation - 0.224*Government Spending

Exports = - 0.805*Mobility Rate + 0.463*Inflation + 0.394*Government Spending

FDI = - 0.309*Mobility Rate + 0.477*Government Spending

Inflation = - 0.698*Recovery Rate + 0.554*M3 - 0.523*Employment Rate + 0.479*House Prices - 0.362*Private Spending

Private Spending = 0.646*Mobility Rate - 0.217*Production Prices + 1.294*FDI

Production Prices = 0.743*M3 + 0.548*House Prices - 0.474*Exports - 0.544*Terms of Trade

Share Prices = - 0.728*Pandemic Number - 0.593*Employment Rate

D.6

Employment Rate = 0.65*House Prices - 0.515*Inflation - 0.287*Private Spending

Exports = - 0.702*Mobility Rate + 0.33*Inflation + 0.46*Private Spending

FDI = - 0.343*Mobility Rate + 0.648*Private Spending

Inflation = 0.466*Share Prices + 0.136*House Prices + 0.536*Production Prices

Private Spending = 0.646*Mobility Rate - 0.217*Production Prices + 1.294*FDI

Production Prices = - 0.634*Employment Rate + 0.77*House Prices - 0.343*FDI

Share Prices = - 0.703*Employment Rate + 0.242*Exports

D.7

Employment Rate = 0.675*House Prices - 0.362*Production Prices - 0.383*Private Spending

Exports = - 0.333*Mobility Rate + 0.419*Government Spending

FDI = - 0.25*Employment Rate + 0.51*House Prices - 0.299*Inflation

Inflation = - 0.488*Mortality Rate + 0.426*M3 - 0.767*Employment Rate + 0.611*House Prices - 0.329*Private Spending

Private Spending = - 0.617*Employment Rate + 0.595*Share Prices + 0.744*House Prices - 0.893*Production Prices

Production Prices = - 0.556*Mortality Rate - 0.745*Employment Rate + 0.852*House Prices - 0.274*Private Spending - 0.335*Terms of Trade

Share Prices = - 0.998*Mortality Rate - 0.729*Employment Rate

D.8

Employment Rate = - 0.38*Share Prices + 0.488*House Prices - 0.198*Government Spending

Exports = - 0.393*Mortality Rate - 0.435*Mobility Rate + 0.545*Private Spending

FDI = - 0.151*Share Prices + 0.638*Private Spending

Inflation = - 0.698*Recovery Rate + 0.554*M3 - 0.523*Employment Rate + 0.479*House Prices - 0.362*Private Spending

Private Spending = 0.229*Share Prices + 1.23*FDI

Production Prices = - 0.724*Mortality Rate + 0.566*Pandemic Growth - 0.479*Employment Rate + 0.649*House Prices - 0.328*Terms of Trade

Share Prices = - 0.729*Recovery Rate + 0.279*M3 + 0.341*Mobility Rate - 0.261*Employment Rate

D.9

Employment Rate = - 0.516*Mortality Rate + 0.477*House Prices - 0.413*Production Prices

Exports = - 0.358*Mobility Rate + 0.506*Private Spending

FDI = - 0.151*Share Prices + 0.638*Private Spending

Inflation = - 0.613*Mortality Rate + 0.425*M3 - 0.591*Employment Rate + 0.604*House Prices - 0.293*Exports - 0.37*Terms of Trade

Private Spending = 0.818*Transmission + 0.772*Mortality Rate - 0.412*Pandemic Growth + 0.496*Mobility Rate + 1.192*Imports

Production Prices = - 0.663*Employment Rate + 0.787*House Prices - 0.222*Private Spending - 0.334*Terms of Trade

Share Prices = - 0.793*Recovery Rate + 0.45*Mobility Rate - 0.355*Employment Rate

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D.10

Employment Rate = - 0.593*Mortality Rate + 0.594*House Prices - 0.55*Inflation - 0.269*Private Spending

Exports = - 0.675*Mobility Rate + 0.306*Production Prices + 0.516*Private Spending

FDI = - 0.343*Mobility Rate + 0.648*Private Spending

Inflation = - 0.822*Mortality Rate + 0.517*Pandemic Growth - 0.871*Employment Rate + 0.549*House Prices

Private Spending = 0.33*M3 + 1.111*FDI

Production Prices = - 0.556*Mortality Rate - 0.745*Employment Rate + 0.852*House Prices - 0.274*Private Spending - 0.335*Terms of Trade

Share Prices = - 0.789*Mortality Rate + 0.478*Mobility Rate - 0.433*Employment Rate + 0.196*Private Spending

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Using the mathematical process described in Section 2, 23 CsoE was found with a probability of 10^{-7} between multiple combinations of *X*.