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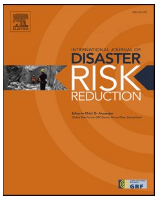

Evaluating the impacts of earthquake disasters on the building construction sector: a SARIMA-based counterfactual analysis

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ABSTRACT

Disasters have a dual effect on the construction industry. While their initial impact disrupts construction activities, the resulting damage also stimulates construction demand. Existing scholarly literature predominantly adopts qualitative approaches in examining the impacts of disasters on the sector. This study introduces a quantitative methodology to assess the impacts of disasters on building construction activity. Utilizing counterfactual time series analysis, trajectories of the construction sector in the absence of disasters are simulated and subsequently compared with actual observed trajectories. Building consent datasets were obtained from Statistics New Zealand and time series analysis was employed to investigate the effect of the Canterbury and Kaikoura earthquakes on the building construction sector, examining impacts at both national and regional levels. The findings reveal that the Canterbury earthquake had a significant national impact, initially decreasing construction activity but subsequently leading to more rapid growth in the medium to long term than anticipated. In contrast, the Kaikoura earthquake's impact was largely confined to the Canterbury region, slowing the local building construction sector. This study highlighted the usefulness of counterfactual time series analysis in assessing the impacts of disasters on the construction sector, and its findings are useful for simulating the impacts of disasters and other shocks in forecasting future trajectories of the sector.

1. Introduction

Disasters exert a dual influence on the construction sector. While they often cause significant disruption [1], damaging infrastructure [2–4], human resource strains [5,6], and straining supply chains [7,8], they also generate a surge in demand for building services, as communities mobilize to repair and rebuild. The construction sector is, thus, not only impacted by disaster shocks but also a critical driver of recovery. Understanding how construction activity evolves in response to major disasters is essential for informing recovery strategies, strengthening sectoral resilience, and supporting long-term planning.

Existing literature, for instance Refs. [2–5,7–9], has extensively explored the impact of disaster shocks on the construction sector, yielding rich insights into both the challenges faced during recovery and the opportunities for sectoral adaptation. Most of these studies, however, have focused on qualitative approaches, thereby underscoring the need for a more robust quantitative comprehension of the subject matter. The nuanced contextual understanding offered by qualitative studies could be made more robust when complemented by quantitative empirical studies, a knowledge gap that this study aims to fill.

This paper presents a robust counterfactual time series methodology for quantifying disaster impacts on the construction sector. The approach is demonstrated using data from New Zealand, which experienced major earthquake events in recent decades. While grounded in this context, the method is broadly applicable to other regions and disaster scenarios where comparable time series data exists.

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Seasonal Autoregressive Integrated Moving Average (SARIMA) models are employed to generate counterfactual scenarios. These models are well suited to long univariate time series with pronounced seasonal patterns, such as those observed in construction sector activity. By comparing actual and counterfactual outcomes across spatial and sectoral dimensions, this approach offers novel insights into disaster recovery dynamics.

2. Evaluating the impacts of shocks on the construction industry

The effects of disasters on the construction sector have been widely discussed in the literature, particularly through qualitative studies. A significant portion of this literature has focused on the immediate aftermath of disasters, highlighting the surge in demand for construction services [3,4,9] during the recovery phase. Chang et al. [9] conducted semi-structured interviews and document reviews to surface the challenges and key issues in resourcing for post-disaster reconstruction projects in the Canterbury earthquakes' aftermath. Their findings revealed significant logistical and coordination challenges, including difficulties in workforce mobilization and material supply, which constrained recovery timelines and underscored the need for integrated resourcing frameworks. Further to this, Chang-Richards et al. [5] also investigated how post-disaster workforce shifts and skills shortages in the construction industry could be addressed. Their study highlighted that disasters can exacerbate existing labor market tensions, and that targeted training, better workforce planning, and flexible immigration policies are essential to overcoming post-disaster skills gaps. Sapeciay et al. [7], on the other hand, explored how construction organizations may enhance their resilience to the impacts of natural hazards. They identified that proactive leadership, adaptive capacity, and knowledge management are key enablers of organizational resilience in the construction sector.

Government reports [10,11], which typically provide quantitative perspectives, have been instrumental in tracking the actual trends and trajectories of the sector. Yet, these reports fall short in quantifying the potential value losses attributable to disaster shocks.

In parallel, counterfactual time series analysis has been used in other disciplines to evaluate the impacts of interventions and shocks. In this method, counterfactual or "what-if" scenarios are generated from historical datasets to represent what would have happened in the absence of intervention or an intervening event. This is then compared with the actual records to establish and quantify the impact of the event or intervention. Counterfactual forecasts developed from time series regression have been used to evaluate the effect of policy changes, and aided in developing alternative policies [12]. The method has been used to simulate the effect of economic shocks such as the impact of oil supply shock on the global economy [13] and the effect of the pandemic on employment [14,15]. In the context of environmental health, Dey et al. [16] used counterfactual time series analysis to model the reduction in air pollution following the Covid lockdowns. Furthermore, the method has been used to establish causal inference in the field of public health [17,18]. These studies presented counterfactual analysis as a robust framework for estimating what would have happened in the absence of the intervention or event. Hernan [18] further asserts the importance of establishing counterfactual theories in order to affirm causality in the context of public health interventions.

An increasingly used alternative in impact evaluation is the Synthetic Control Method (SCM), which constructs a weighted combination of unaffected units, known as the "donor pool," to approximate the counterfactual trajectory of a treated unit had the intervention or shock not occurred. Introduced by Abadie and Gardeazabal [19] and further developed by Abadie, Diamond, and Hainmueller [20,21], SCM has become a valuable tool for estimating causal effects in comparative case studies, where randomized control trials are infeasible. By optimally selecting weights to minimize pre-treatment discrepancies, SCM produces a synthetic control that closely tracks the treated unit's behavior before the intervention, thereby providing a credible counterfactual for post-treatment impact estimation.

SCM has demonstrated strong potential in policy and disaster impact assessments. For example, duPont and Noy [22] applied SCM to reassess the economic effects of the 1995 Kobe earthquake, highlighting its capability to isolate disaster impacts by leveraging unaffected control units. Moreover, methodological advancements such as the Augmented Synthetic Control Method [23] have improved inference robustness and addressed limitations related to imperfect pre-treatment fits, enhancing SCM's practical applicability.

However, the utility of SCM depends critically on the existence of unaffected or minimally affected units to serve as a valid donor pool. This assumption becomes challenging in settings like New Zealand, where large-scale disasters often generate widespread ripple effects, disrupting supply chains, workforce mobility, and investment decisions across multiple regions simultaneously. In such contexts, identifying unaffected control units is difficult, if not impossible, which limits SCM's direct applicability. Recent work [24,25] has highlighted the risks of biased estimates when pre-treatment fit is imperfect or when spillover effects contaminate the donor pool, underscoring the need for caution and potential methodological adaptations when applying SCM in nationwide disaster contexts.

Given the constraints on data availability and frequency, and the presence of a long, consistent univariate time series, this study employs a SARIMA-based approach. While multivariate methods such as Vector Autoregression (VAR) [26] or Vector Error Correction (VEC) [27] models are capable of modeling dynamic relationships among multiple variables, they require consistent covariate data at the same temporal resolution as the primary series. Key economic indicators such as GDP, employment, and interest rates are typically available only at annual frequencies, whereas this study aims to analyze disaster impacts at a more granular quarterly level to capture shorter-term post-disaster effects. Incorporating lower-frequency covariates would necessitate either interpolation, which can distort the true time series dynamics, or aggregation to annual resolution, which would reduce the granularity essential for precise impact assessment.

SARIMA models are well-suited for this context because they explicitly model seasonal variation and structural changes in a univariate time series, producing reliable forecasts when accompanied by rigorous diagnostic validation. SARIMA's strength lies in its ability to capture complex autocorrelation structures and seasonal cycles, which are common features in economic and construction activity data [28]. When checked for stationarity, residual independence [29], and residual normality, SARIMA models yield statistically sound and interpretable results [30]. This methodological rigor ensures that the model accurately reflects the underlying data patterns and provides a transparent, statistically grounded counterfactual baseline for estimating sectoral impacts. Recent studies have employed SARIMA models for counterfactual time series analysis across a range of fields, demonstrating the method's versatility and credibility. For example, SARIMA has been used to estimate the impact of policy interventions or external shocks on air pollution levels [16,31], public health outcomes [32], employment trends [14], and tourism activity [33]. These applications underscore SARIMA's ability to model seasonality and temporal dependencies accurately, making it a reliable tool for isolating the effects of shocks in settings where long univariate time series are available but multivariate data may be limited or inconsistent. Given the single-variable focus and the robustness of SARIMA modeling, this approach balances complexity and interpretability, supporting effective disaster recovery planning.

The following section outlines the data, model development, and validation process used to implement this counterfactual time series analysis.

3. Methodology

This study employs counterfactual time series analysis to quantitatively assess the impact of major disasters that occurred in New Zealand's Canterbury region on the building construction sector, both at the regional and national scales. In this study, an event is deemed major if it resulted in an impact worth over a billion New Zealand dollars. During the decade from 2010 to 2020, two disasters resulted in damages exceeding One Billion New Zealand Dollars: Canterbury and Kaikoura earthquakes [34].

Canterbury earthquakes was a series of earthquakes triggered by the M7.1 Darfield earthquake, which occurred on September 4, 2010 [10]. This was followed by numerous significant aftershocks, including the more devastating M6.9 Christchurch Earthquake, which happened on February 22, 2011. The second disaster is the M7.8 Kaikoura Earthquake which struck New Zealand's South Island on November 14, 2016. Its epicenter was in Kaikoura, a coastal town in the Canterbury Region.

Despite the Kaikoura earthquake being stronger in terms of magnitude, the Canterbury earthquakes caused a more significant devastation due to its epicenter being situated in an urban center, whereas the former occurred in a largely rural area. Table 1 outlines the pertinent details of the two major disasters that affected the region.

3.1. Data acquisition and preparation

Quarterly data on the value (in NZD) of building consents issued were obtained from Statistics New Zealand [35]. The dataset spans from 1990 to 2023, representing the full range of available quarterly building consent data. This comprehensive time frame was chosen to leverage the maximum historical context for model training and validation. Utilizing the complete dataset allows the SARIMA models to effectively capture long-term trends, seasonal patterns, and structural breaks critical for accurate counterfactual forecasting. Shorter time periods would limit the pre-disaster data available, potentially reducing the robustness of the impact assessments.

Consent data was used in lieu of data on building construction activity due to the insufficiency of the available data on the latter for training the model, which is only available from 2003, leaving only 8 years of pre-shock, i.e. pre-Canterbury earthquake data, to train and test the model with. In the case of the building consent data, the available dataset covers the period from 1990 to 2023. The Granger causality test indicates that building consents have significant predictive power on building activity, with an F-statistic of 5.72 and a p-value of 0.02, suggesting that past values of building consents provide useful information in forecasting building activity at a lag of 4 quarters.

The time series datasets initially visually analyzed for trends, seasonality, fluctuations, and anomalies. Visual inspection and statistical tests indicated the presence of heteroskedasticity in the building consent datasets, characterized by increasing variance over time. This heteroskedasticity violates key assumptions of SARIMA modeling and can adversely affect parameter estimation and forecast accuracy. To mitigate this, a log-transformation was applied to stabilize the variance, resulting in more consistent variance levels and improving model performance [36]. Furthermore, spectral analysis revealed peaks at $f = 0.25$ confirming a quarterly seasonality in annual cycles.

3.2. Development of counterfactual scenarios

Subsequently, counterfactual time series trajectories simulating without-disaster scenarios were developed by fitting a Seasonal Autoregressive Integrated Moving Average (SARIMA) model on the pre-disaster time series and subsequently generating forecasts over the succeeding quarters. SARIMA was deemed appropriate because of the presence of seasonal patterns in the data.

Table 1
Details of major disasters in the study area.

Event	Canterbury Earthquakes	Kaikoura Earthquake
Epicenter	Darfield (main), Christchurch (major aftershock)	Kaikoura, Canterbury Region, NZ
Date	September 4, 2010 (Darfield EQ), February 22, 2011 (Christchurch EQ)	November 14, 2016
Magnitude	7.1 (Darfield EQ), 6.9 (Christchurch EQ)	7.8
Estimated loss	NZD 22.9 Billion	NZD 2.27 Billion

The Augmented Dickey-Fuller test was used on various combinations of regular and seasonal differencing to determine the differencing orders to use for the SARIMA model. In order to come up with a parsimonious model, the minimum combined seasonal and regular differencing orders that would make the time series stationary ($p < 0.05$) were selected. All the datasets have achieved stationarity after one seasonal differencing and one regular differencing ($d = 1$, $D = 1$).

Autocorrelation (ACF) and partial autocorrelation function (PACF) correlograms were plotted to gain insights into which autoregressive (AR), moving average (MA), seasonal autoregressive (SAR), and seasonal moving average (SMA) values to use.

The models' fit was then validated using the Ljung-Box test and Shapiro-Wilk tests on the residuals. The goal was to ensure that the residuals behaved as white noise, indicating a good fit of the model. The Ljung-Box test checks for remaining significant autocorrelations; a $p > 0.05$ indicates that there is no autocorrelation among the residuals. Shapiro-Wilk test, in contrast, evaluates the normality of the residuals; a W-value close to 1.0 indicates normality, and $p > 0.05$ is preferable as it rejects the null hypothesis that the residuals are not normally distributed. Akaike Information Criterion (AIC) was used to weigh the goodness of fit of the model against its complexity; hence addressing concerns on underfitting and overfitting while achieving model parsimony. Iterations across sensible combinations of the ARIMA parameters were conducted to achieve the lowest AIC value. The counterfactual, i.e. without-disaster scenario, trajectories, were thus generated using the SARIMA models that minimize the AIC, while ensuring that the residuals are white noise. Fig. 1 illustrates the process for tuning the SARIMA parameters.

For the Canterbury Earthquake, time series data spanning from 1990 up to the second quarter of 2010, just prior to the disaster, was utilized. This pre-disaster data was instrumental in generating a robust forecast. Similarly, for the Kaikoura Earthquake, a pre-disaster model was fitted using data from 1990 through to the second quarter of 2016. This allowed for accounting of any trends or patterns present in the data before the earthquake occurred. Counterfactual forecasts were generated both at the regional and national levels. This enabled a comparative assessment of the impact of the shocks at different scales.

3.3. *Evaluating the impact of disaster shocks through time*

The generated counterfactuals were then compared with the actual trajectories to observe the difference between the without and with disaster scenarios in terms of building construction activity. The counterfactual trajectories may be set as the baseline, as these would have been the performance of the sector had the disaster event not occurred. The performance ratio, $p(t)$, through time may then be measured using the following equation:

$$p(t) = \frac{y(t)}{\widehat{y}(t)}$$

where $y(t)$ is the actual value at any given time t, while $\widehat{y}(t)$ is the value projected for time t from the counterfactual model.

The counterfactual trajectories are constructed under the assumption that external influences on the construction sector would have continued following their historical pre-disaster patterns. This baseline therefore isolates the estimated impact of the disaster by holding other drivers constant, as captured through the pre-disaster data. While this assumption simplifies the complex interplay of sectoral drivers, it is necessary to quantify the disaster's net effect and is consistent with standard practice in counterfactual time series analysis.

4. Results and discussion

Table 2 shows the best-fit SARIMA models, which were subsequently used to generate the counterfactual forecasts for the Canterbury and Kaikoura earthquakes, respectively, along with the results of the model diagnostics.

Fig. 2 shows the juxtaposed actual and counterfactual trajectories following the Canterbury earthquake at the regional and national scales. At the regional level, the counterfactual trajectory projected a building sector growth of approximately 6 % with seasonal

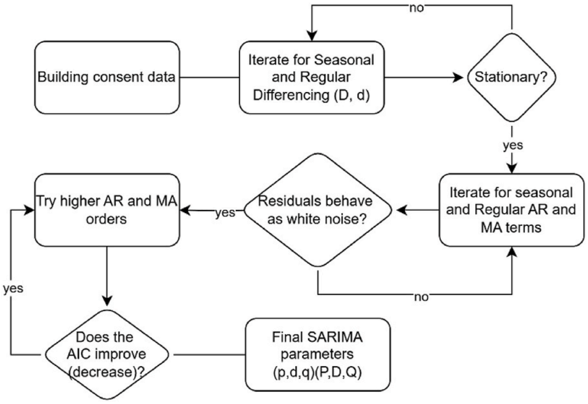

Fig. 1. SARIMA modeling process.

Table 2
SARIMA model parameters used for counterfactual generation.

Earthquake	Scale	Best-fit SARIMA model	AIC	Ljung-Box p-value of residuals	Shapiro-Wilk test W statistic of residuals
Canterbury	Regional	(0,1,1)(0,1,1)[4]	−74.81	0.6053	0.98946
Canterbury	National	(0,1,0)(0,1,1)[4]	−143.72	0.3383	0.98106
Kaikoura	Regional	(0,1,1)(0,1,1)[4]	−83.81	0.2274	0.99147
Kaikoura	National	(0,1,0)(0,1,1)[4]	−207.33	0.3448	0.98554

fluctuations. In contrast, actual trajectory post-Canterbury earthquake showed a substantial dip in the earthquake's immediate aftermath, followed by an average of 20 % annual growth in the years that ensued. This steeper annual growth resulted in the actual trajectory overtaking the counterfactual by the fourth quarter of 2011, three quarters after the major earthquake event. Nationally, the annual growth forecast in the counterfactual scenario was estimated to be at 2 %. Mirroring the regional trend, there was also an initial dip in the national building sector output for two quarters following the earthquake but had rebounded with an average of 16 % growth afterwards, overtaking the counterfactual trajectory by 2012 Q3. This is indicative of the expansion of the building construction sector post-Canterbury earthquake. A similar trend of construction sector growth has been observed in the aftermath of the Great East Japan Earthquake where job vacancies decreased as a result of publicly funded reconstruction projects [37]. In contrast, the initial momentary decrease may be attributed to the shock resulting in temporary shortage in the capacity, in terms of [37] and capability [5] of the sector.

The rapid recovery and growth in building construction activity following the Canterbury earthquake can be attributed to several factors. Firstly, extensive government-funded reconstruction programs injected substantial resources into the sector, stimulating demand. Secondly, the urgent need to repair and replace damaged buildings, along with heightened community and investor confidence, accelerated project initiations. Thirdly, the recovery period saw increased labor mobilization and material supply chain adjustments that facilitated rebuilding efforts. Together, these elements created a surge in construction activity that outpaced what the counterfactual scenario, based on pre-disaster trends, would have predicted.

Fig. 3 shows the impact of Kaikoura earthquake on the building construction sector in the Canterbury region and the entire New Zealand. Counterfactual projection for the region suggests that there would have been growth in regional building construction. In contrast, the actual trajectory showed decline in the disaster's aftermath. This means that the earthquake event resulted in a decrease in construction activity in the region than what would have been expected if a disaster did not happen.

Such an impact, however, is not evident at the national scale where there is a match between actual and counterfactual trajectories. The impact of the Kaikoura earthquake at the national scale was characterized as insignificant because the actual construction activity closely followed the counterfactual trajectory, with deviations generally within a ±2 % range, well within normal seasonal and economic fluctuations. This contrasts with the more pronounced regional decline of up to 22 % observed in Canterbury. The limited national effect can be attributed to the earthquake's localized epicenter and lower population density in the affected areas, which mitigated spillover effects on the broader national construction sector. This affirms that the impact of the Kaikoura earthquake on the construction sector is largely confined within the Canterbury region.

The impact of the two disasters could be more easily appreciated when the ratio of the with and without-disaster trajectories, i.e.

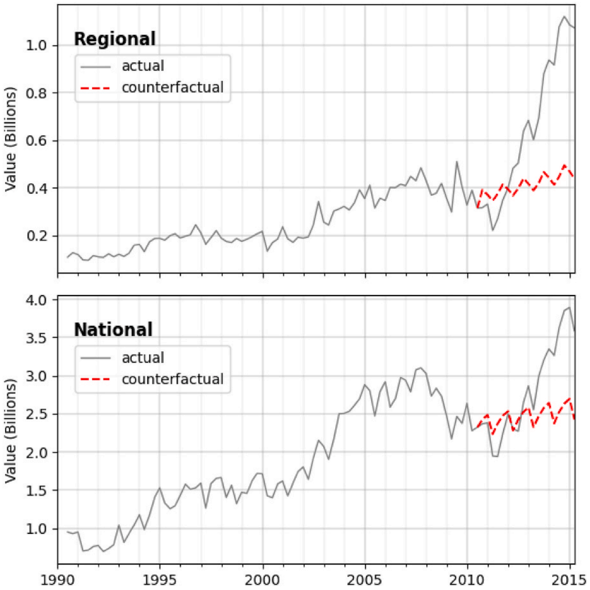

Fig. 2. Counterfactual versus actual trajectories in the aftermath of Canterbury earthquake.

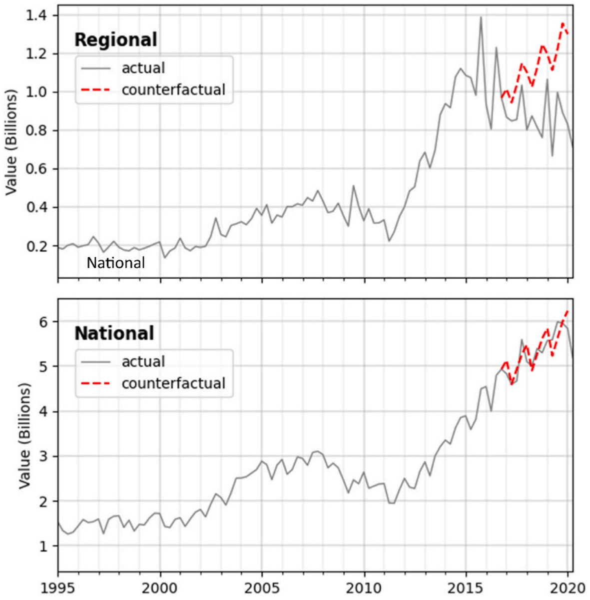

Fig. 3. Counterfactual versus actual trajectories in the aftermath of Kaikoura earthquake.

performance metric for the sector, $p(t)$, are visualized in Fig. 4. A value of 1.0 indicates that the sector is performing at par with the without-shock scenario. Values less than 1.0 would mean lost potential, i.e., fewer buildings than expected are constructed in the aftermath of the shock event, while values greater than 1.0 indicate gained potential, i.e. building construction increased because of the disaster compared to a scenario without the disaster. The deviation from the unit line may be interpreted as loss or gain of the sector for that given period, in this case, quarter.

The resulting performance metric is analogous to Bruneau et al.'s [38] temporal parameter for measuring the resilience of infrastructure systems. In this framework, the area bounded by the sector's performance and the unit line constitutes loss. Resilience, on the other hand, is defined by the ability to minimize loss in the face of shocks. There are two dimensions to this: the sector's robustness, which reduces the magnitude of the performance drop as the shock occurs, and the ability to recover quickly after the shock. Losses may be reduced by mitigating the drop in the performance level and by shortening the recovery time. Recovery point may be defined as the point where the $p(t)$ plot re-intersects the unit line and turns positive. Consequently, the length of recovery period may be measured as the time between the onset of the shock and the recovery point.

As shown in Fig. 4a, the Canterbury earthquakes resulted in value losses for the construction sector, both within the Canterbury region and at the national level. The ratio of actual to counterfactual construction activity dropped below 1.0 in the immediate aftermath, indicating that performance fell short of what would have been expected in the absence of the disaster. In Canterbury, the ratio declined to a low of 0.72, representing a 28 % reduction relative to the counterfactual baseline. This reflects severe disruption,

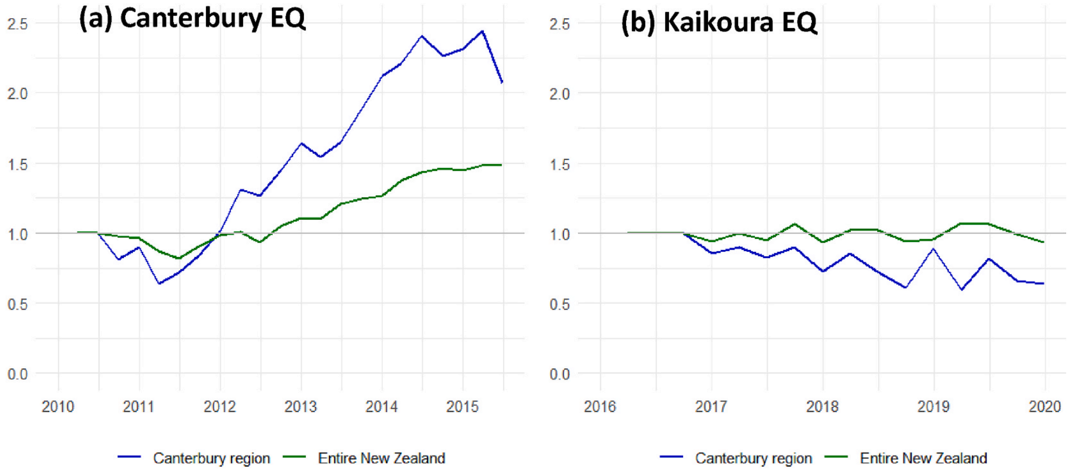

Fig. 4. Construction sector performance ratio, p(t), in the aftermaths of Canterbury and Kaikoura earthquakes.

including halted construction, infrastructure damage, and delays in mobilizing labor and materials. Nationally, the ratio reached a minimum of 0.82, or an 18 % drop, signaling broader economic impacts, albeit less intense than those experienced in the directly affected region.

These value losses may be attributed to the susceptibility of the resources and dynamics the construction sector rely on. Directly, ongoing construction efforts in disaster-stricken areas are often plagued by significant delays and disruptions [2–4]. Disasters have the potential to inflict damage upon structures being constructed [39–41], thereby necessitating rework and impeding project progress. Additionally, the machinery and supplies essential for construction may become damaged and unusable in the wake of a disaster. Moreover, the construction workforce is also susceptible to the impacts of disasters [5,42], as workers may need to attend to personal matters or relocate, consequently resulting in labor shortages. Furthermore, the aftermath of a disaster may trigger disruptions in supply chains [9,43], resulting in a scarcity of available construction materials. This scarcity, in turn, propels the prices of construction materials upwards [8].

On the other hand, recovery and reconstruction efforts in the aftermath of disasters translate directly into construction sector activity. Furthermore, once the situation has stabilized, these catastrophic events prompt property owners to contemplate proactive measures such as retrofitting [44], aimed at strengthening structures against hazards they may be exposed to. Consequently, these initiatives serve to boost construction activity in the aftermath of disasters.

By early 2012, both the Canterbury and national construction sectors began to recover. The ratio for Canterbury returned to and then exceeded 1.0 earlier than the national trend, indicating a faster rebound. This likely reflects the rapid onset of reconstruction efforts in the region, supported by insurance payments, government-led recovery initiatives, and sustained private sector investment. In contrast, the national recovery occurred more gradually, as the wider industry responded to increased demand without experiencing direct disruption. The earlier recovery in Canterbury points to a responsive and concentrated mobilization of resources in the wake of the disaster.

Following the recovery threshold, Canterbury's construction sector experienced a prolonged phase of outperformance. The ratio climbed steadily, reaching approximately 2.5 by 2015, indicating that construction activity was 150 % higher than it would have been without the earthquakes. This sustained growth reflects the intensity and duration of the region's reconstruction program, encompassing residential, commercial, and infrastructure development. Nationally, the ratio also rose above 1.0, peaking at around 1.5, or a 50 % increase. While this suggests some positive spillover effects, the gains remained more modest compared to Canterbury. The contrast between regional and national trends underscores the importance of disaggregated analysis when evaluating the spatial impacts of disasters on the construction sector.

As shown in Fig. 4b, the Kaikōura earthquake did not lead to a sharp immediate decline in construction activity but rather coincided with a gradual and sustained decline in the Canterbury region's performance relative to the counterfactual forecast. The ratio of actual to counterfactual values consistently remained below 1.0, fluctuating between 0.6 and 0.9 throughout the post-earthquake period. This indicates a prolonged period of underperformance in the region's construction sector, without any clear signs of recovery during the observed timeframe.

In contrast, construction activity at the national level remained largely unaffected, with the ratio staying close to 1.0. This suggests that the Kaikōura earthquake did not produce significant spillover effects on the broader New Zealand construction sector, likely due to the smaller geographic scope and lesser scale of damage compared to the Canterbury event.

The absence of a recovery pattern in Canterbury may indicate that recovery, if any, extended beyond the counterfactual forecast horizon, or alternatively, that the event did not generate sufficient reconstruction activity to lift the sector back to its expected trajectory. It is also important to note that the observation window ends just before the onset of the COVID-19 pandemic, a significant subsequent shock that may have further influenced sectoral performance in ways that extend beyond the scope of this analysis.

While the Canterbury earthquakes spurred medium-to-long-term growth in the building construction sector, the same cannot be said for Kaikoura earthquake's effect. The difference in the primarily affected areas may have influenced this difference in effects. Canterbury earthquakes affected an urban center, thereby affecting more people and properties, compared to Kaikoura earthquake, which primarily impacted a largely rural area. While Koerniadi et al. [45] demonstrated the positive impact on the construction sector of multiple disaster events including earthquakes, tsunamis, floods, hurricanes, tornadoes, and volcanic eruption, New Zealand's experience in the aftermath of Kaikoura earthquake reveals that such impact is also influenced by the relative scale of the disaster, whether or not it is massive enough to stimulate the expansion of the sector. The timing of the disaster event, as well as the socio-economic significance of the most affected area may also affect this trend. The second major earthquake that heavily affected the Canterbury region within a decade, Kaikoura earthquake may also have interrupted the momentum built up in the region in light of the Canterbury earthquake recovery.

The counterfactual time series analysis enabled the quantification of lost or gained potential of the sector following a shock. The generated performance function, $p(t)$, further finds its utility in scenario-based analysis on the impact of shocks on the forecast trajectories of the sector. The function may be used as a multiplier to simulate the potential impact of an event with the scale of Canterbury earthquakes or Kaikoura earthquake, the potential differential trajectories between local and national scales. Such may be useful in providing quantitative evidence for policy development for enhancing the resilience of the sector. The presented methodology may also be extended to the analysis of the impact of other events such as hydrometeorological disasters, pandemics, or economic shocks, on the construction sector. Likewise, the methodology may also be used to simulate the impacts of shocks on other economic sectors.

One key limitation of the counterfactual time series analysis is its inability to separate the overlapping effects of multiple concurrent or cascading shocks affecting the sector. This challenge arises because the method estimates impacts based on deviations from the expected baseline without isolating individual causes. As a result, if multiple shocks occur close in time, their combined effects may be conflated, potentially biasing the estimated impact attributed to any single event. Recognizing this limitation is important when interpreting results, particularly in complex disaster contexts where economic, environmental, or policy shocks may interact. In the context of the demonstrated use cases in this study, the underlying assumption is that the effects of other shocks are negligible compared to those of the mega-disasters studied.

5. Conclusion

The study delved into the application of time series analysis methods for assessing the effects of significant disasters on the building construction sector. The difference between the actual trajectory and the trajectory without the disaster generated from the counterfactual analysis offers a quantifiable measure of the disaster's impact on the building construction sector. The study underscores the substantial economic impact of the earthquake and subsequent recovery efforts on the construction industry.

The research findings reveal that the Canterbury earthquakes, which mainly impacted an urban center, generally bolstered building construction activity not only at the regional level but also nationwide. Conversely, the Kaikoura earthquake, which significantly affected rural parts of New Zealand's Canterbury region, disrupted the momentum of the construction sector and led to a decline in building construction activity in its aftermath. However, this decline was confined to the Canterbury region and was not observed on a national scale.

The study introduced a robust method for quantifying the effects of a shock on the construction industry, which may be extended in the analysis of comparable situations and scenarios. The method demonstrated in this study facilitates a deeper understanding of the potential risks to the construction industry, thereby enabling a more informed development of risk management strategies. It also aids in policymaking towards construction industry resilience by providing quantitative evidence that may serve as a foundation for regulatory recommendations and guidelines.

Beyond demonstrating a robust methodology for quantifying disaster impacts on the construction sector, our findings provide important insights into the resilience and recovery dynamics at both regional and national scales. This contributes to the literature by offering empirical evidence of how large-scale shocks can differentially affect sectors and regions, informing targeted resilience-building and recovery strategies.

The counterfactual time series approach presented here offers a replicable framework for future studies assessing the impact of diverse shocks, including pandemics and economic crises, on construction and other sectors. This method contributes to broader disaster risk reduction efforts by strengthening the evidence base for risk-informed planning, allowing for the quantification of deviations from expected performance, and enabling forward-looking assessments to enhance sectoral resilience. It also informs recovery planning by highlighting how construction sector performance varies across regions and disaster types. By comparing actual activity to counterfactual trajectories, the framework helps identify where recovery has lagged or diverged from expectations, supporting more responsive and context-specific strategies. Policymakers and industry stakeholders can leverage these insights to better anticipate, plan for, and mitigate the impacts of future shocks, primarily on economic and built environments, ultimately contributing to more effective and evidence-based disaster risk reduction and recovery efforts.

Further research may be explored in developing a methodology for the decomposition of the effects of concurrent shocks on the sector in order to disentangle the juxtaposed effects of multiple shocks.

CRediT authorship contribution statement

Diocel Harold M. Aquino: Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Niluka Domingo:** Writing – review & editing, Supervision. **Chinthaka Atapattu:** Writing – review & editing, Visualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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