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Post-Disaster Loss Amplification (PLA) Effect

Prepared by Wang Xueying

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Actuaries Institute
ABN 69 000 423 656
Level 2, 50 Carrington Street, Sydney NSW 2000
P +61 (0) 2 9239 6100 | actuaries.asn.au

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Wang Xueying

Insurance Australia Group

sylvia.wang@iag.com.au

Abstract

Natural catastrophes can result in substantial losses for re/insurers which can amount to a significant proportion of the local economy. The phenomenon of post-loss amplification (PLA), characterized by unexpectedly high losses following severe disasters, must not be overlooked.

To date, there exists limited literature and publications comprehensively modelling PLA on a quantitative basis. Existing studies tend to focus on either a single major driver or several minor drivers of PLA, lacking a holistic and straightforward solution for insurance loss modelling. Although major catastrophe modelling companies such as Verisk (formerly known as AIR) and RMS demonstrate sophistication in PLA estimation, their respective methodologies do not consistently align with observed PLA in historical events. This research systematically reviews important drivers of PLA and derives a universal relationship between PLA and economic measures accessible to insurers. Through this approach, we provide a comprehensive framework applicable across different countries and regions, enhancing the accuracy and reliability of insurance loss modelling in the face of post-disaster amplification phenomena.

Key findings can be summarised as:

a) Post-disaster loss amplification (PLA) demonstrates a direct correlation with the size of the loss relative to the affected economy, indicating that larger losses tend to result in greater amplification effects.

b) Connectivity of the economy, including distance between economic centres, efficiency and coverage of railway and road transportation network, as well as population density plays a crucial role in adjusting to the accessible economy size. These considerations are vital for accurately assessing the economic impact of disasters.

c) The remoteness of the impacted region emerges as a significant driver of PLA, highlighting the importance of geographical factors in shaping post-disaster economic dynamics.

d) Addressing inconsistencies between short-term price surges and overall PLA requires standardization. Our study proposes leveraging models that incorporate price surge decay and reconstruction volume throughout the reconstruction cycle. This approach facilitates the closure of the gap between anecdotal information and economic statistics, thereby enhancing the accuracy and reliability of PLA assessments.

Keywords: post-disaster loss amplification (PLA), economic connectivity, remoteness, loss estimation, reconstruction volume, demand surge, regression analysis, resilience and preparedness.

1. Defining PLA

Post-loss amplification (PLA) refers to a situation in the insurance and risk management industry where the financial consequences of a disaster substantially increase the economic losses experienced by property owners, businesses, insurers, and other stakeholders beyond the initial estimates of property damage caused directly by the disaster itself. It is particularly relevant in context involving natural disasters, large-scale accidents, or other catastrophic events, underscoring how the aftermath of a disaster can intensify the economic burden associated with property damage, leading to escalated costs and challenges for affected individuals and entities in recovering and rebuilding. PLA can occur for various reasons, among which the most well-known and of often explicitly quantified is demand surge, which is caused by increased demands for construction and rebuild materials and services after disasters while the supply is limited. Besides this, PLA can also be driven by supply chain disruptions due to extreme weather or infrastructure failure, prolonged business interruptions, social inflation during the recovery phase, and sometimes inflationary pressures due to a widespread catastrophe event (also referred to as super-cat effect).

Despite the complex nature of risk and challenges in accurately predicting the financial impact of large-scale events, it is crucial to adequately account for PLA in catastrophe modelling, actuarial assessments, disaster planning and financial preparedness.

PLA is sometimes employed as a catch-all term for various factors contributing to higher-than-expected event losses. To avoid ambiguity in the definition of post-disaster loss amplification, this study will focus solely on PLA resulting from disasters. This means insurance practices that could lead to biased initial event loss estimates, such as exposure data errors, misestimation of catastrophe models, or underestimation of losses due to underinsurance, missed event-specific reconstruction cost components, and updates of building standards, are not considered part of post-disaster loss amplification. Non-disaster-driven factors, such as economic cycles, economic policies, construction industry cycles, and non-disaster events or projects co-occurring with disasters, should also be separated from the study.

2. Existing studies on PLA

Three streams of literature contribute to the study of PLA. Firstly, there are industry papers that identify drivers of PLA and quantify PLA from past events significant enough to observe a noticeable PLA effect. These papers are exclusively qualitative and do not quantify the relationship between PLA drivers or general indicator for PLA. The second category encompasses papers with quantitative studies on one or several factors contributing to PLA. Examples include an economic study covering focusing only on increasing wages that drives higher reconstruction costs (Hallegatte, S. et al., 2008), multilevel regression models focusing on the correlation between demand surge and physical variabilities without considering economic mechanisms (Olsen,A.H.& Porter, K.A., 2011), Botzen,W.W. et.al.'s economic modelling focusing on the impact of natural disaster on the economy, and Döhrmann,D. et.al.(2013)'s paper validating hypothesis on the association between PLA and economic cycles, constraining variabilities in number of contractors or high levels of wages. Given this is a niche area of study, there is usually a trade-off between the depth of quantitative modelling within a limited number of factors and the range of causal effect uncovered. The complexity of econometric modelling means most of the studies focus on examining the supply or the demand that contributes partially to PLA. Another limitation of these papers is the lack of an established link between economic inflationary pressure demonstrated by economic statistics and PLA evidenced and quantified in the insurance industry in the past. The third category of study come from large third-party modelling companies such as Verisk, RMS and EQECAT. Their catastrophe models have built-in modules to quantitatively estimate PLA effects. However, due to intellectual property rights, the methodologies are usually qualitatively captured, and access to details is subject to licencing. The empirical events used, and technical details are not publicly available.

Despite limitations in individual studies, collective knowledge from various approaches suggested common drivers of PLA effects.

Event size relative to the economy size. Event sizes are directly associated with number of claims and the amount of repair and reconstruction required after the event. Event sizes can be quantified by economic loss or insurance industry losses incurred. Economic loss is a preferred measurement for assessing the repairs required in the economy, as it is not biased by insurance take-up rates, underinsurance, or any factors specific to the features of insurance products in certain jurisdictions. The size of the surrounding economy is crucial for providing relief during disasters, and the relative size of between disaster events and the size of economy reflects the strain. With adequate stocks available, a sufficient labour force providing services, and strong production power, an economy can cope with disaster recovery with less impact on its usual economic activities. Economic indices such as Gross Domestic Product or Gross National Product, with nuanced difference determined by international trade, can be used as reliable measurements for the size of the economy.

Demand and supply of building material. The sudden increase in demand for repair materials creates a strain on the availability of building materials. This is often coupled with disruptions in the transportation storage of building materials, collectively leading to price increases. The demand and supply of building materials are primary drivers considered in PLA modelling for catastrophe modelling agencies and in existing literature.

Demand and supply of labour. Immediately after disasters, there is a huge demand for disaster event management staff, engineers, and claims adjusters within a short period, ranging from a few days to a few weeks. The high demand and short of supply of these expert staff, often requiring overtime working during this period, add significant costs for insurers. Additionally, there is a strong demand for reconstruction and repair labour during the rebuilding period. Unlike materials, labour is immobile, and shortages cannot be addressed as simply as transporting materials into the region. Introducing labour from other regions would require substantial subsidies and benefits, such as transportation and temporary accommodation subsidies, as well as certain incentives to encourage mobility. The demand and supply of labour are primary drivers considered in PLA modelling for catastrophe modelling agencies and in existing literature.

Connectivity and Remoteness. Economic connectivity significantly influences the extent of loss surge. Countries with well-connected economic centres, efficient logistics networks, large freight capacity through multiple transportation modes, and robust supply chains tend to experience less loss amplification. For nations with modern road, railway and airfreight networks, factors such as the distance between economic centres, transportation efficiency, and accessibility of remotes regions serve as good proxies for connectivity. Disasters occurring in remote regions often incur significantly higher repair cost and labour costs due to long distances required to complete repairs and extended travel times, especially in regions inaccessible by paved roads or requiring access through multiple modes of transportation. The Insurance Council of Australia estimated a 42% higher repair cost in North Australia compared to the south (ICA, 2018) due to remoteness.

Concurrence of events. The concurrence of events with spatial and temporal proximity tends to lead to higher PLA (Döhrmann ,D.et.al, 2013). This phenomenon was exemplified by the simultaneous occurrence of Hurricane Harvey and Hurricane Irma in 2017. While Hurricane Harvey struck Texas in August 2017, resulting in a loss of $125 billion and a 4% demand surge (Verisk, 2020), Hurricane Irma hit Florida in September of the same year, resulting in a $50 billion loss, significantly smaller than Harvey's. However, despite the smaller loss, Hurricane Irma experienced a higher demand surge of 5% compared to Harvey, attributable to the close spatial proximity and only a one-month gap between the two events (Verisk, 2020)

In the category of disaster-driven PLA, other factors can include compounding losses from disasters, such as non-damage business interruption caused by infrastructure failure.

3. PLA in catastrophe models

3.1 RMS methodology

Global catastrophe modeler RMS considers factors including economic demand surge, claims inflation, super Cat scenarios and compounding factors in successive events to model country-specific PLA. The

RMS Australian model is based on economic data from 15 clusters or individual historical events, and this estimation allows for granular estimation tailored to specific locations and coverages.

3.2 Verisk methodology

Another global catastrophe modeler, Verisk, started with a US-specific PLA model and expanded to establish new PLA models for regions such as Europe and New Zealand. Like RMS, Verisk develops country-specific and peril-specific models. Verisk tends to take a conservative view in the measurement of demand surge, which incorporates inflationary signals observed from national economic statistics. It also only considers demand surge as loss amplification although its documentation clearly outlines the distinction between the demand surge and loss amplification.

4. Empirical study

4.1 Collection of Historical Events

The insurance industry closely monitors large catastrophes and events with substantial observed loss amplification. Various entities, including professional services firms, reinsurers, financial industry regulators, and central banks, frequently release publications on Post-Loss Amplification (PLA) and event loss estimates to illuminate the intricate dynamics of managing and mitigating risks associated with such large-scale events. This study on PLA estimation investigates historical events with documented PLA and economic losses. The analysis encompasses a diverse array of global events spanning North America, Asia, New Zealand, and Australia, ensuring that the findings are relevant and applicable within a global context.

Hurricane Katrina (with Rita, Wilma happening in the same year). Hurricane Katrina, which occurred in 2005, was one of the costliest tropical cyclones on record. The destructive Category 5 Atlantic hurricane impacted the Bahamas, Florida, Cuba, Louisiana, Mississippi, Alabama, as well as causing flooding and storms in Eastern United States and Canada. It caused around $125 billion damage in 2005 and **30%** pf PLA estimated by Munich Re.

Northbridge Earthquake. The 1994 Northbridge earthquake, with a moment magnitude of 6.7, impacted the San Fernando Valley and the City of Los Angeles, causing widespread damage. An economic loss of $35 billion in 2019 value was estimated, with a 20% increase in costs observed (Larsen T., 2005).

Indian Ocean earthquake and Tsunami. The 2004 Indian Ocean earthquake struck the western coast of northern Sumatra, Indonesia, with a magnitude of 9.1-9,3, also causing a massive tsunami with waves up to 30m high. The event impacted Tamil Nadu in India, Sri Lanka, Khao Lak in Thailand, and also affected Malaysia, Maldives, Myanmar, and Somalia. The total loss of $10 billion and a 60% of demand surge were recorded.

Christchurch Earthquake. A series of three earthquakes occurred over 9 months between 2010 and 2011, resulting in $40billion NZD losses and causing an **80%** demand surge due to a shortage of resources. On 4th September, a magnitude 7.1 earthquake struck near the city of Christchurch. After many buildings were weakened, a more devastating earthquake occurred on 22nd February with a magnitude of 6.2. This earthquake struck only 6.7 km from the city centre and at a shallower depth, resulting in widespread destruction and loss of life. The Eastern suburbs experienced significant liquefaction. On 13th June, a magnitude 6.3 aftershock occurred, further exacerbating the damage caused by the previous earthquakes and complicating recovery efforts.

Wenchuan Earthquake. The 2008 Wenchuan earthquake, measuring 8 Ms with aftershocks exceeding 6 Ms continuing for months after the main shock, was one of the deadliest earthquakes in China since the 1976 Tangshan earthquake killing 242 thousand people, and the strongest in the country since the 1950 Assam-Tibet earthquake. It had a focal depth of 19km, ruptured the fault for over 240km, and was also felt as far away as both Beijing and Shanghai –1500 and 1700 km away, respectively, where office buildings swayed with tremors. To the south, it was felt in Bangkok, Thailand, and Hanoi, Vietnam. An 80% demand surge was estimated after the earthquake, despite the central government budgeting an economic stimulus program of $1trillion RMB over a three-year period to support recovery of impacted regions. The total loss estimate was $150 billion USD.

Cyclone Tracy. Cyclone Tracy caused nearly destruction of the city of Darwin city in 1974, destroying 70% of the buildings, including 80% of houses. All Defence Force personnel throughout Australia, along with the entire Royal Australian Air Force fleet of transport planes, were recalled from holiday leave and deployed to evacuate civilians from Darwin as well as to bring essential relief supplies to the area. Thirteen Royal Australian Navy ships were used to transport supplies to the area as part of Operation Navy Help Darwin, which is the largest humanitarian or disaster relief operation ever performed by the Royal Australian Navy. The event had $6.85 billion in losses using 2022 estimates, with a 75% demand surge (Miles, 2013), which was likely mitigated by the nation-wise emergency support.

Cyclone Larry. Cyclone Larry was a Category 5 tropical cyclone made landfall in Far North Queensland near Innisfail in 2006. The severe damage to infrastructure and crop is estimated to be **$1 billion** AUD at 2022 value, leading to significant food price soaring, especially bananas and sugar. The demand surge has been estimated at a **50%** increase in prices (Miles, 2013, & AISC, 2007), especially due to remoteness of the impacted region.

Newcastle Earthquake. The 1989 Newcastle earthquake (magnitude 5.6) caused 50,000 damaged buildings and 300 demolished buildings. The total loss estimated at $4.25 billion as 2019 and cause a 35% increase in building costs (Miles, 2013).

Canberra bushfire. The 2003 Canberra bushfire caused severe damage to the suburbs and outer areas of Canberra, causing severe damage to 70% of ACT pastures, pine plantations, and nature parks, and destroying 470 homes. The event was estimated to incur near $840 million in insured losses, causing a 50% increase in building material prices immediately after the event (Miles, 2013).

4.2 Methodology

4.2.1. Standardising estimate for loss amplification over whole reconstruction cycles

Literature describing demand surge or PLA tends to take different basis, and there is little evidence of a universal standard defining PLA. Some focus on total loss amplification over the whole recovery time of an event, whereas others, such as Cyclone Larry and Canberra Bushfire, tend to focus on immediate demand surge or price increase seen in within a shorter period describing the highest observed price surges. When only the short-term price surge information is available, price surge decay and reconstruction volume throughout the recovery cycle are considered with the method below to estimate standardised PLA across the whole recovery cycle.

Events that result in acute shortages of resources such as rebuild materials and labour tend to lead to price surge shortly after the event. Such price surges often do not represent demand surge for the whole recovery cycle following the event and are likely to decay over time to adjust back to a level close to normal price in the latter half of the recovery cycle. Industry publications on the initial price surge can be calibrated with economic indices such as the construction cost index and labour cost index in the aftermath of events. These adjustments are then further refined and revalued using inflation indices to establish the surge function. Reconstruction activities, on the other hand, occur over a span of months to years following the event, often peaking at a different time than price surge (Lloyd-Jones, T., 2006). The interplay between price surge and rebuild activities ultimately shapes the final loss amplification outcome, which is integrates over the reconstruction period to establish the standardised loss amplification.

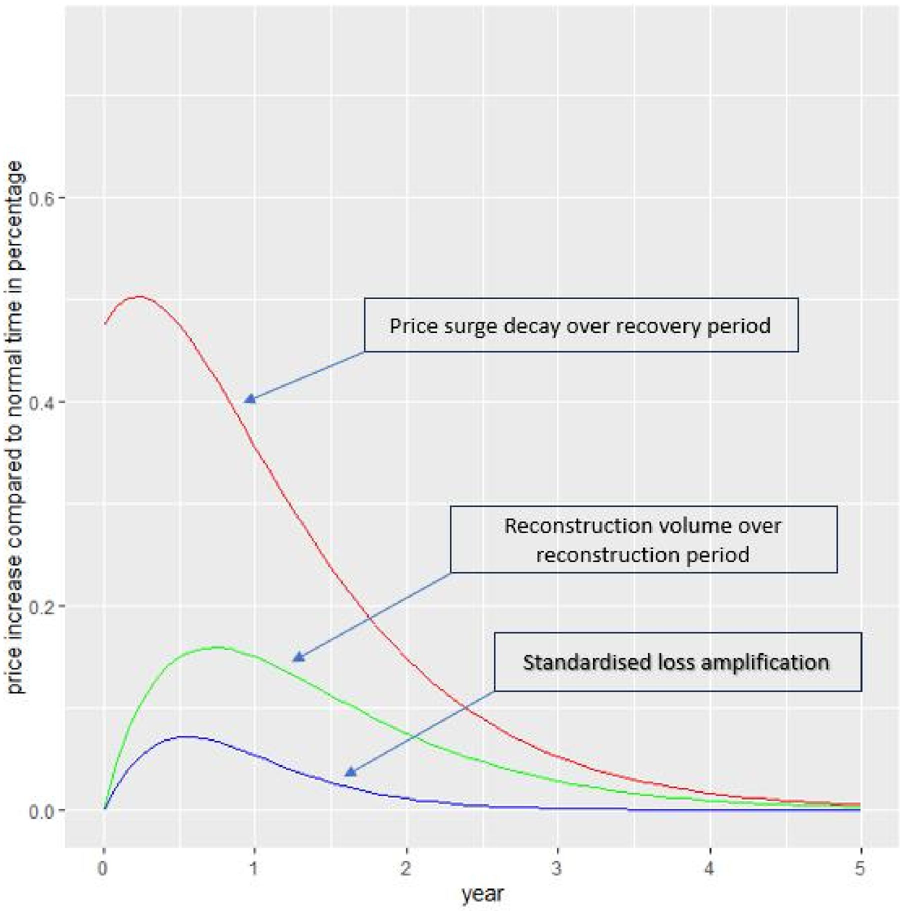


Figure 1: Price surge decay and reconstruction volume over the entire reconstruction cycle

Surge function to assess price surge decay throughout the entire recovery cycle:

$$P_t = a(t + \mu) * b^{(-c(t+\mu))} * (1 + i)^t$$

P_t is price increase compared to normal price at time t,

i is the long-term inflation for the country.

a, b, c, μ are parameters determining size, shape, and position of the surge curve.

Function to determine reconstruction volume over the reconstruction cycle can also be derived using a similar surge function, albeit with different parameters.

$$C_t = a'(t + \mu') * b'^{(-c'(t+\mu'))}$$

Where C_t represents the reconstruction volume at time t

Loss amplification is calculated as the price increase multiplied with the reconstruction volume integrated over the entire recovery cycle.

$$Loss\ Amplication = \int_{t=0}^{t=t_{max}} P_t * C_t \ dt$$ [i]

where t_{max} represents the end of recovery cycle.

Each event exhibits a unique price surge pattern, and the reconstruction cycle duration varies based on the size and extent of damage, ranging from several months for smaller secondary events to over 12 years for major events like the Christchurch earthquake. Parameters in the price surge function and the reconstruction volume function must be determined individual for each event based on available information. Standardization alone has adjusted the described 50% immediate price surge for the Canberra Bushfire to 31% standardized loss amplification, for Cyclone Larry from 50% to 37%, and for the Christchurch Earthquakes from 80% to 66%.

4.2.2. Relationship between PLA and economic factors

Intuitively, one would expect a positive correlation between PLA and the size of event losses. However, this correlation is predominantly observed when comparing events within a specific region, and it does not hold true when examining a global sample of events across different economies (Figure 2). Therefore, the relationship between PLA and economic factors needs to be re-examined on the global event set to model PLA. The data presents a positive correlation between PLA and event loss prior to PLA effect as a percentage of state GDP for the impacted region, as depicted in Figure 3, with 'loss as percentage of state GDP' on logarithmic scale.

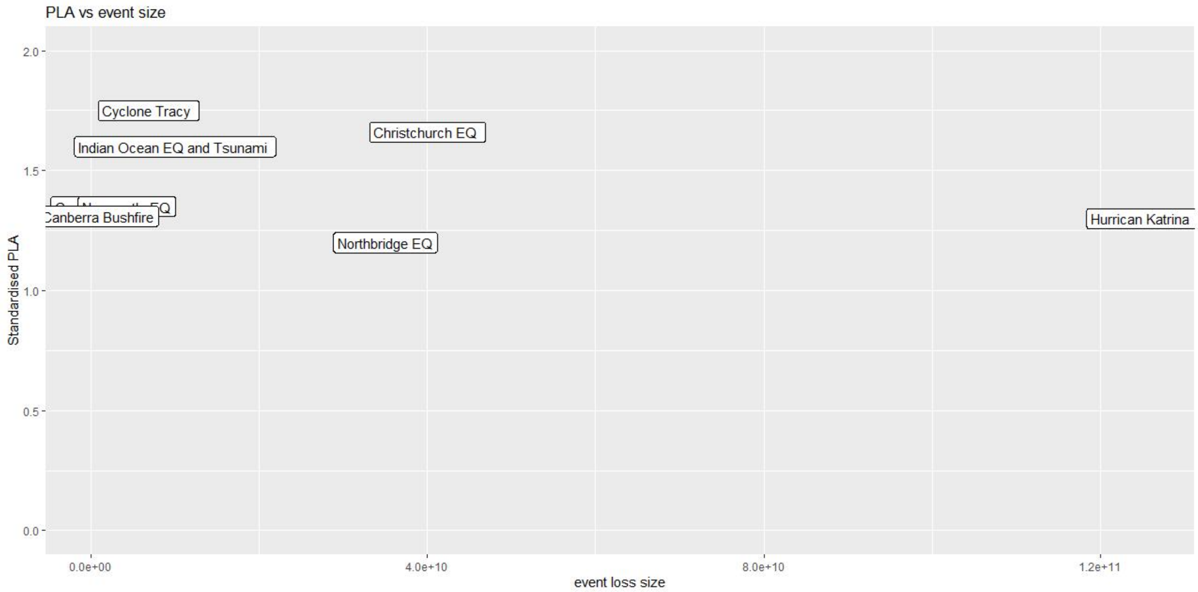


Figure 2: Plot of PLA against event on global events.

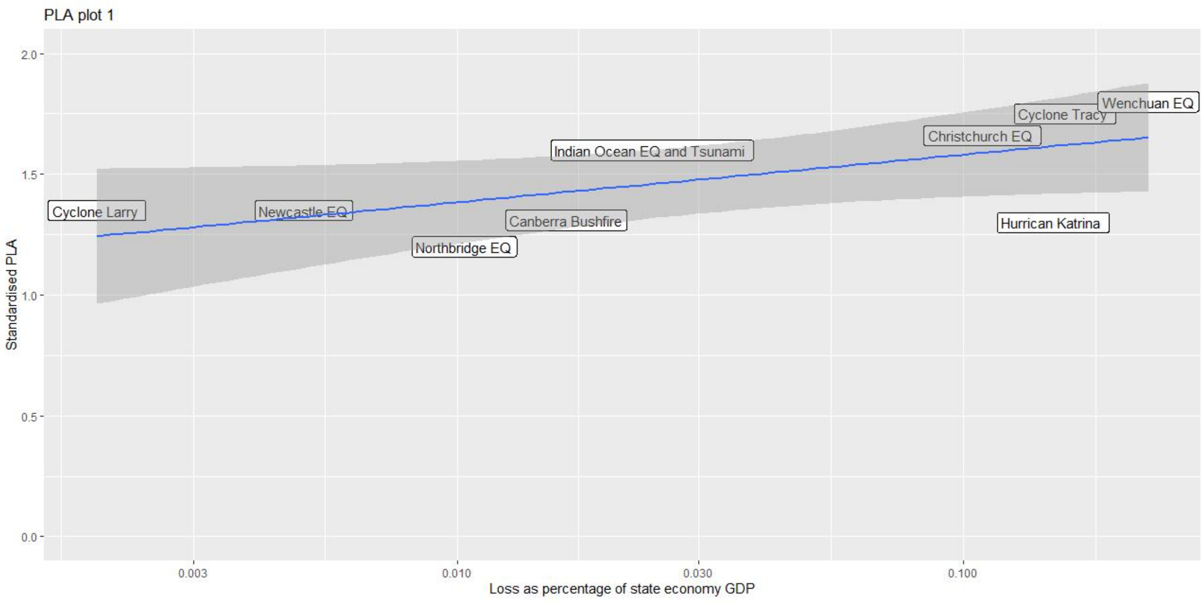
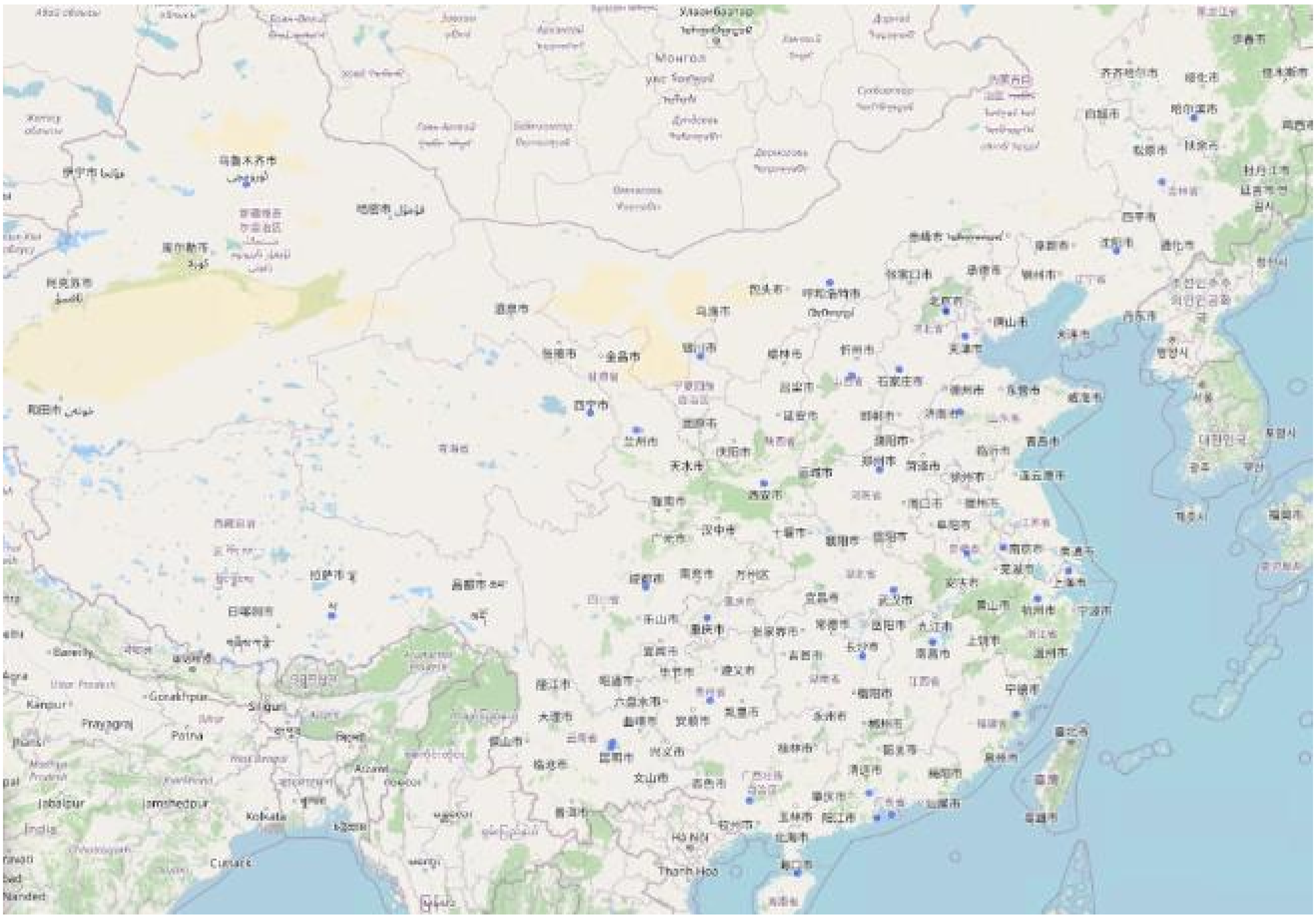


Figure 3: Plot of PLA against event loss as a percentage of state GDP.

4.2.3 Economic connectivity and remoteness adjustments

Economic connectivity significantly influences the magnitude of loss surge following disasters. Countries with well-connected economic centers, efficient logistics networks, ample freight capacity across various modes of transportation, and robust supply chains tend to tend to experience lower levels of loss amplification. However, there is considerable variation in the distances between economic centers across different countries. By comparing the distances between state or provincial capital cities in Australia, the United States, and China (refer to Map 1, Map 2, and Map 3, respectively, which are set on the same scale), one can observe a notably lower density of key economic centers in Australia. For instance, the shortest distance between state capitals in Australia, from Canberra and Sydney, is equivalent to the average distance between contiguous state capitals in the US. Furthermore, the distance between Perth and its nearest capital city, Adelaide, exceeds 2000 kilometers, surpassing even the distance between Urumqi, the most remote provincial capital in China, and its neighbouring provincial capital. This contrast highlights the vast distances and relatively sparse distribution of major urban centers across Australia compared to the United States and China, resulting in less interconnected economic centers in the country. Given the modern road, railway, and airfreight networks in these nations, the distance between economic centers serves as a simplifying factor. Consequently, this study will adopt a distance-weighted approach to determine the economy size among economic centers accessible to disaster-affected regions, updating the previous experiment's economy size to consider connectivity.

Map1: Map of the US state capital cities.



Map 2: Map of China provincial capital cities.

Map 3: Map of Australia state capital cities.

The refined relationship between PLA and event loss as a percentage of accessible GDP is presented in Figure 4.

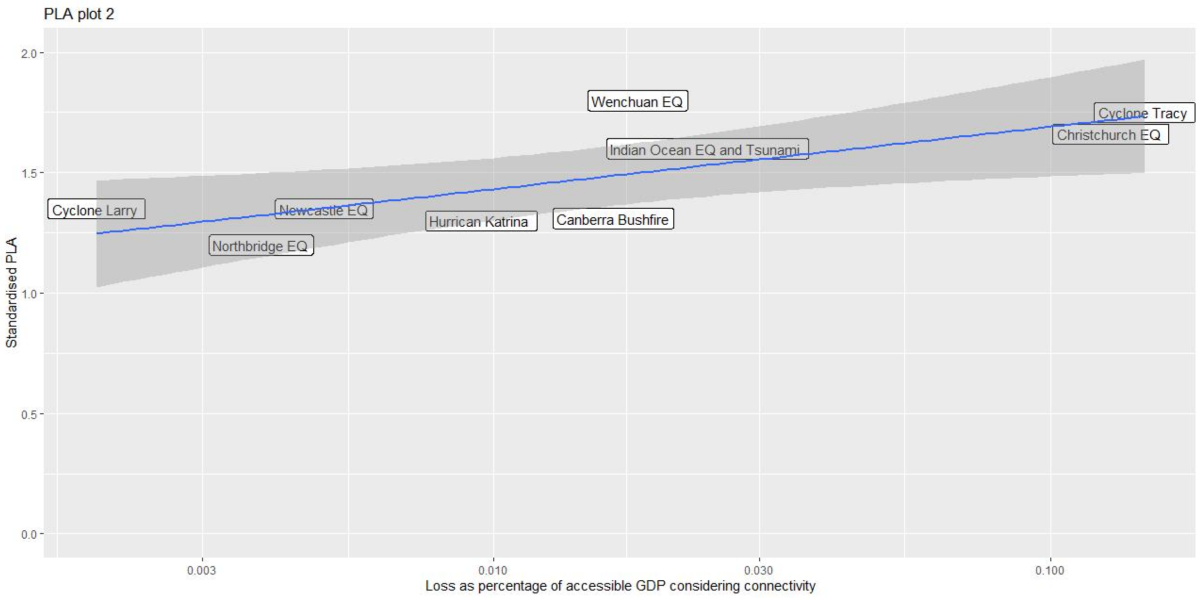


Figure 4: Plot of PLA against event loss as a percentage of accessible GDP considering connectivity.

Another quantitative adjustment factor to consider is remoteness, which significantly impacts the estimation of post-disaster loss amplification (PLA) by potentially inflating event losses. Disasters occurring in remote regions often incur substantially higher repair and reconstruction costs. This is primarily attributable to the considerable distances required to travel to complete repair works, increased transportation expenses, and extended travel times, especially in areas that are not easily accessible via paved roads or necessitate access through multiple modes of transportation.

For instance, in 2018, the Insurance Council of Australia reported repair cost estimates that were 42% higher in North Australia compared to southern regions, primarily due to the challenges posed by remoteness. To account for these additional challenges in completing construction work, a remoteness loading is added when estimating loss amounts and loss amplification.

The design of the remoteness loading should be customized for each event location, considering factors such as the distance from major economic centers, road conditions, speed limits, and accessibility. This study proposes a practical guideline recommending the incorporation of a remoteness loading for travel duration surpassing 7 to 8 hours using the most efficient mode of transportation, approximately equivalent to a full day's travel. It is essential to adjust PLA for events such as Cyclone Larry, the Wenchuan Earthquake, and the Indian Ocean tsunami, as these events impacted remote and less accessible regions.

In this study, the estimated post-disaster loss amplification (PLA) will undergo adjustments to mitigate the impact of remoteness loading. By applying remoteness adjustments alongside previously mentioned adjustments, the resulting remoteness-adjusted PLA and loss as a percentage of connected economy demonstrate a closely fitting logarithmic relationship. This relationship serves as a suitable foundation for modelling purposes (Figure 5).

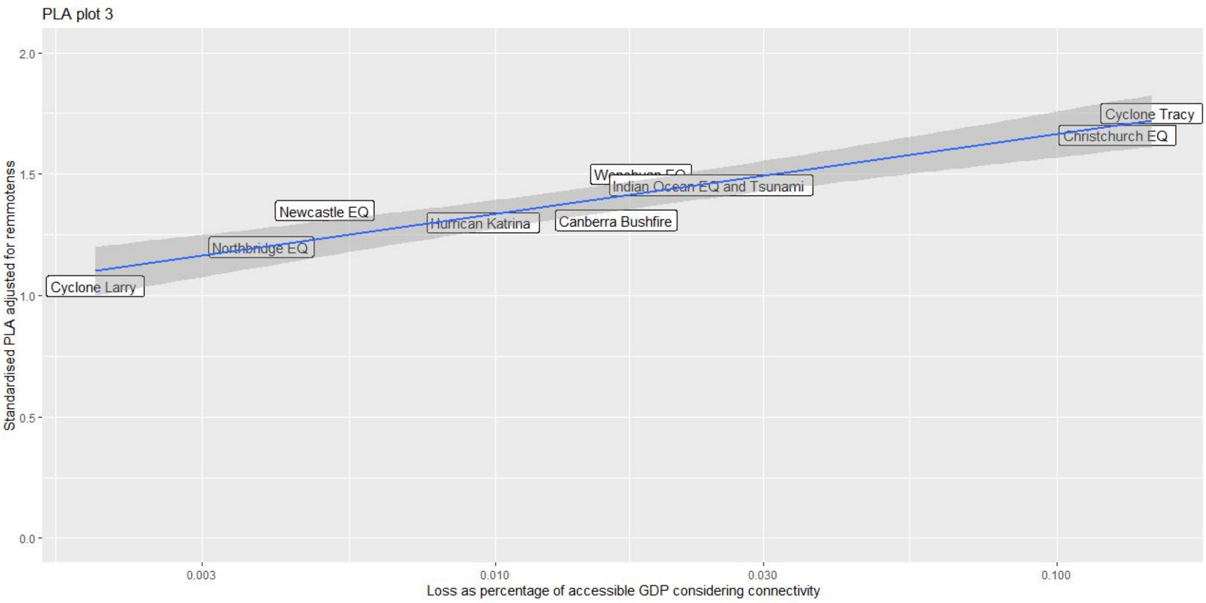


Figure 5: Plot of remoteness adjusted PLA against event loss as a percentage of accessible GDP considering connectivity.

4.3 The PLA model

A linear regression can be performed between PLA and $log_{10}(pc\_loss)$ based on empirical data points after connectivity and remoteness adjustments.

$$PLA = 1.99164 + 0.32848 \times log_{10}(pc\_loss)$$

where PLA is PLA factor adjusted for remoteness and pc_loss is event loss as a percentage of accessible GDP.

The model summary indicates statistically significant coefficients, an adjusted R-squared value close to 0.9, indicating a strong goodness-of-fit.

```
Coefficients:
                                                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                                                    1.99164    0.07521  26.479 2.81e-08 ***
log10(pc_economy_before_accounting_for_PLA_adjusting_US_and_CHN_economy_size)  0.32848    0.03932   8.353 6.91e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07166 on 7 degrees of freedom
Multiple R-squared:  0.9088,	Adjusted R-squared:  0.8958
F-statistic: 69.77 on 1 and 7 DF,  p-value: 6.911e-05
```

4.4 Further consideration on scope of application

The losses observed in the events utilized in this PLA model range from 0.19% to 14.76% of the connected economy, corresponding to monetary losses ranging from $500 million USD to $150 billion USD. While this relationship between PLA and loss as a percentage of accessible GDP remains validated within a similar range, it may not necessarily be applicable to events of significantly larger or smaller scales.

Loss amplification is not ubiquitous across all event magnitudes; rather, it occurs when an event reaches a critical threshold, causing price surges beyond normal levels. For instance, in a quantitative study on demand surge, Döhrmann D. (2013) indicates that their analysis only includes events with loss thresholds exceeding $500 million USD for statistical assessment. Similarly in our regression model, we recognize positive loss amplification for events surpassing 0.0957% of accessible GDP, or $670 million AUD if occurring in the capital city of the most populated state.

It is also crucial to note that estimated relationship between PLA and event loss as a percentage of accessible GDP considering connectivity in this paper may not hold for extreme catastrophe events. When disaster loss reaches a significant proportion of GDP, there is likely to be a deeper imbalance between demand and supply which is not observed in events covered in this study. Furthermore, there is a greater likelihood of deeper disruption to the economy, financial system and social stability, leading to compounded losses.

5. Conclusions, Limitations, and Future Directions

5.1 Conclusion

This study presents an integrated framework for comprehensively understanding and modelling post-disaster loss amplification (PLA), incorporating predictive variables such as the event loss magnitude and economic scale. Additionally, it proposes standardized quantification of PLA, integrating adjustments for economic connectivity and disaster location remoteness to establish a universally applicable approach for PLA estimation. Through an extensive literature review and analysis of empirical data across different countries, we have developed a global framework applicable to various disaster types and economic contexts. This model not only bridges the gap between anecdotal evidence from industry reports and formal economic statistics but also addresses deficiencies and limitations observed in previous PLA studies and models. Furthermore, the proposed framework offers a pragmatic approach for implementation within the insurance context.

5.2 Limitations

While our study offers a promising solution for estimating post-disaster loss amplification (PLA), it is important to recognize several inherent constraints. Firstly, the absence of a universally accepted definition of post-loss amplification within the industry, government agencies, or other published event information leads to debate regarding the historical data points. PLA, as defined in some reports, serves as a catch-all factor encompassing various reasons for unexpected loss increases. Secondly, our analysis relies on historical events marked by significant levels of observed PLA within the insurance industry and regulatory frameworks, resulting in a dataset consisting of only nine historical events used in PLA modelling. This limitation in sample size may impact the reliability of the model. Thirdly, there is a potential bias in the selection of events with reported PLA, as they tend to skew towards larger-scale disasters. This bias may overlook events with smaller loss amplification, which could exhibit different relationships with economic factors. Fourthly, the historical events included in our sample predominantly occurred in countries with well-established financial systems, reasonable institutional quality. As a result, our study does not encompass jurisdictions in Least Developed Countries (LDCs), Small Island Developing States (SIDS), or Landlocked Developing Countries (LLDCs), thereby limiting the generalization of our findings to these specific contexts.

5.3 Future Directions

Several critical areas in the estimation of post-disaster loss amplification (PLA) warrant further attention and refinement. Firstly, addressing the scarcity of PLA data from disaster events and forming a standard PLA definition requires concerted efforts to encourage the compilation of loss information by stakeholders such as the insurance industry, government agencies, and non-state organizations. Forming a consistent definition and expanding the scope of data collection to encompass a wider range of events will enhance the accuracy and reliability of PLA estimations. In addition, gap-filling data is imperative to overcome the limitations of government and industry reports, as well as economic statistics, including issues related to timeliness, coverage, and granularity. Utilizing big data analytics and high-frequency data to discern retail price fluctuations and supply chain activities is essential. Additionally, delving into greater detail regarding infrastructure and transportation networks' vulnerability during catastrophic events is necessary. Secondly, there is a pressing need to explore the compounding effects of disasters, including non-damage business interruption, social disruptions, civil unrests, and displacement, which can exacerbate post-disaster losses. Understanding these complex interactions is essential for developing a more comprehensive framework for assessing PLA in extreme events and in the global context. Thirdly, qualitative factors such as the maturity of financial markets, institutional quality, and the effectiveness of state or national disaster response mechanisms are likely to significantly influence post-disaster loss amplification. Integrating these nuanced considerations into PLA prediction models is essential for improving their predictive power and practical implementation.

By addressing these overlooked aspects and refining our approach to PLA estimation, we can better anticipate and mitigate the economic impacts of disasters, fostering greater resilience and preparedness in vulnerable communities and economies and ultimately helping to build a more robust response system to future catastrophic events.

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Appendix

Event information for empirical study

Event	Year	Country	Region	Currency	Event Loss	Loss as Percentage of Economy	Loss as Percentage of Accessible Economy	PLA	PLA Adjusteed for Remote	State GDP	Accessible GDP Considering Connectivity
Hurrican Katrina	2005	US		USD	$ 125,000,000,000	0.15052	0.00950	1.3	1.30	$ 638,800,000,000	$ 10,122,327,975,000
Northbridge EQ	1994	US		USD	$ 35,000,000,000	0.01031	0.00382	1.2	1.20	$ 2,830,000,000,000	$ 7,631,666,427,493
Cyclone Tracy	1974	AU		AUD	$ 6,850,000,000	0.15878	0.14763	1.75	1.75	$ 24,653,000,000	$ 26,514,153,000
Cyclone Larry	2006	AU	remote	AUD	$ 1,000,000,000	0.00193	0.00193	1.35	1.04	$ 383,096,000,000	$ 383,096,000,000
Newcastle EQ	1989	AU		AUD	$ 4,250,000,000	0.00496	0.00496	1.35	1.35	$ 635,000,000,000	$ 635,000,000,000
Canberra Bushfire	2003	AU		AUD	$ 840,000,000	0.01640	0.01640	1.31	1.31	$ 39,102,000,000	$ 39,102,000,000
Wenchuan EQ	2008	CHN	remote	USD	$ 150,000,000,000	0.23213	0.01814	1.8	1.50	$ 359,000,000,000	$ 4,594,000,000,000
Christchurch EQ	2011	NZ		NZD	$ 40,000,000,000	0.10888	0.12833	1.66	1.66	$ 221,301,775,148	$ 187,773,461,582
Indian Ocean EQ and Tsunami	2004	IND	semi-remote	USD	$ 10,000,000,000	0.02423	0.02423	1.6	1.45	$ 257,919,000,000	$ 257,919,000,000

[i] *This formulation is intended to provide a universal framework that encompasses the entire input space and connects seamlessly with earlier defined continuous functions for surge decay and construction volume.*

It is acknowledged that, in practical scenarios, data for price and construction volume often exist in discrete forms and may lack uniformity in temporal units. Consequently, while the presented function is continuous, it is recommended that practitioners adapt this model to discrete approximations as dictated by the availability and characteristics of specific data sets.