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Rebuilding After Earthquakes: Steel Supply, Housing Capacity, and the Sustainability of Reconstruction

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Abstract

Earthquakes create substantial shelter and housing needs and increase pressure on the supply of reconstruction materials. This study examines the long-run relationships among earthquake-related housing needs, construction-material imports, and the global steel supply environment using annual worldwide data from 1988 to 2025, with the world-year as the unit of analysis. ARDL bounds testing and error-correction models estimate long-run and short-run relationships. Hatemi-J asymmetric causality analysis examines the direction of relationships between shocks. In the long run, prefabricated structure imports are positively associated with the homelessness indicator ($\beta = 9.3304$, $p = 0.0728$). This result is significant only at the 10% level and should be interpreted cautiously. Imports of iron or steel structural components are negatively associated with the homelessness indicator ($\beta = -8.2351$, $p = 0.0488$). Global crude steel production is positively associated with material import intensity per destroyed dwelling ($\beta = 2.2737$, $p = 0.0001$). The earthquake-related homelessness indicator is negatively associated with the same measure in the baseline model ($\beta = -0.2356$, $p = 0.0295$), but this relationship is not preserved in the alternative robustness specification. The findings highlight the importance of resilient and equitable material supply systems for sustainable post-disaster reconstruction and community recovery.

Keywords: construction materials; post-earthquake housing crisis; global steel production; earthquake; sustainability of reconstruction; disaster resilience

1. Introduction

Disasters occur when natural hazards interact with conditions of exposure, vulnerability and existing capacity, causing serious disruptions to the functioning of societies. An earthquake is one such natural hazard. Describing the resulting human, property and economic losses as purely natural overlooks the social and structural dimensions of disaster risk [1–5]. Homelessness can arise under different social, economic, and environmental conditions. Previous studies have examined different forms of homelessness, including chronic homelessness, child homelessness associated with informal labor, and homelessness resulting from economic crises [6–13]. Post-earthquake homelessness begins with the sudden loss of housing and the displacement of large numbers of people. This study focuses on people who lost their homes after major earthquakes. After major earthquakes, countries usually provide humanitarian assistance such as search-and-rescue teams, medical staff, equipment, technological support, and trained rescue dogs [14–17]. These efforts are essential during the emergency period. Once immediate life-saving operations are completed, the challenge becomes rebuilding housing in a way that supports long-term recovery.

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Disasters seriously disrupt the functioning of societies and cause major human, economic, and environmental losses [18]. In such situations, the affected society cannot cope with the damage through its own resources. National and international support is therefore needed [19]. Over the last two decades, natural disasters have caused 1.23 million deaths and more than USD 2.97 trillion in economic losses. They have also affected more than 4 billion people [20]. Earthquakes are especially severe because they cause large-scale housing loss, intense stress, and psychological harm. These effects make reconstruction a critical issue [21]. Housing is one of the main problems after an earthquake. The housing crisis lies at the center of homelessness [22]. The growing severity of natural disasters also increases the need for temporary housing [23]. The success of temporary and permanent housing depends on physical provision and attention to social needs [24].

Emergency shelter, transitional housing and the reconstruction of permanent housing do not refer to the same stage of post-disaster recovery [25–30]. This study does not examine emergency shelter or tent-based shelter services provided immediately after the earthquake. It focuses on the transitional period after the emergency response stage and especially on longer-term housing reconstruction capacity. This distinction is important because the steel and other construction materials examined in this study are more closely related to reconstruction activities than to emergency shelter. Sustainable housing also needs to be affordable, energy-efficient, safe, and based on local resources where possible [23]. Post-disaster housing research often discusses prefabricated systems. Their main limitations include poor attention to user needs, weak adaptation to local conditions, high costs, and sustainability problems [23,31]. The reconstruction literature also gives considerable attention to the debate between disaster capitalism and the idea of building back better [32].

The literature on the relationship between earthquakes and the economy does not appear to fit within a single analytical category [33–39]. Some research focuses on the effects of earthquake shocks on housing and real estate markets. Paudel examines changes in housing and property values [40]. A separate body of research deals with physical structural damage and direct economic losses. Zheng et al. assess building damage and total direct economic losses [41]. Property market effects, physical asset damage and direct economic losses therefore need to be treated as conceptually distinct. The effects of earthquakes on foreign trade and broader macroeconomic indicators form a third dimension that is separate from these two research areas. In this study, inferences drawn from earthquake-focused evidence are limited to earthquakes [42]. It is also recognized that any generalization to other types of disasters requires consideration of the broader disaster literature [5,43,44].

Post-earthquake recovery is too multidimensional to be assessed only through the availability of a particular construction material. Several factors are considered important in reconstruction. These include governance and institutional coordination, access to finance, the functioning of transport and other critical infrastructure, labor and equipment capacity, logistics systems, local production capacity, material availability and the resilience of supply chains to disruptions [45,46]. Disaster logistics, supply chain resilience, the security of critical material supply and the restoration of infrastructure are also treated as distinct but related aspects of post-disaster recovery [47–49]. Within this broader setting, the availability of construction materials can be considered one factor related to reconstruction capacity rather than a factor that explains the reconstruction process on its own. This also provides a basis for linking the post-earthquake housing crisis with material supply. Major earthquakes may destroy housing or make it unusable. This reduces existing housing capacity and may create additional housing needs. As these needs increase, demand for construction materials may also rise with reconstruction activity. Post-earthquake homelessness is used here as an indicator of the scale of earthquake-related shelter and housing needs. These needs can

translate into reconstruction demand for structural inputs. Homelessness is not treated as a direct determinant of imports. If local production and logistics capacity are insufficient to meet this demand, external supply sources and imports may become relatively more important [50,51]. Import capacity and international supply conditions can therefore be considered among the factors related to post-earthquake housing reconstruction capacity. The resilience of global supply chains may also be related to reconstruction through the availability of required materials in terms of quantity, cost and time.

Post-disaster housing reconstruction should not be understood only as the rebuilding of physical structures. It can also be viewed as a sustainability issue involving timely and equitable access to resources, resilient supply systems and long-term social recovery. Strengthening reconstruction capacity is therefore important for the resilience of disaster-affected communities and for sustainable development. Material supply is one part of this reconstruction process, and the present analysis focuses specifically on steel. The focus is on its global supply and trade conditions. Coccia considers the steel industry in relation to the concept of geoeconomics [52]. This shows the importance of steel products and the steel industry for countries. The industry is also one of the most heavily regulated sectors in global trade [53–55]. The main assumption of this study is that these trade and supply conditions can produce different outcomes for post-earthquake housing crises. Steel is treated as one of the main inputs used to examine the material supply dimension of the wider reconstruction system. Global crude steel production is used as an indicator of the broader international steel supply environment. It is not treated as a direct measure of material availability in a specific country or earthquake-affected area. This interpretation is also in line with the literature [45,56–58]. The variable reflects overall global production conditions and the capacity of international supply systems. Actual access at the local level also depends on trade, logistics, infrastructure, and institutional conditions. It is not considered the sole determinant of effective recovery. Rapid access to global steel supplies can support reconstruction capacity in earthquake-affected areas. Trade restrictions and supply chain bottlenecks can indirectly limit this process.

Research in recent years has discussed the allocation of limited construction resources in post-disaster reconstruction, the resilience of logistics networks, timely material delivery and bottlenecks in local material supply [42,50,51]. Material supply is generally examined in operational or local and regional reconstruction settings. Evidence from specific post-disaster cases also points to these constraints. Liu et al. examine reconstruction after the 2016 Kaikōura earthquake and report shortages and supply problems involving key construction materials [59]. These problems are linked to limited supply capability, freight capacity, and coordination problems. Zokaee et al. use an empirical reconstruction-supply-chain application [56]. Their findings show that limited access to construction resources and disruptions in distribution networks can materially affect post-disaster recovery planning. Empirical work linking post-earthquake housing shortages with global steel supply, construction material imports and reconstruction capacity remains limited [46,60,61]. These studies focus on infrastructure recovery planning, circular reconstruction strategies, and sustainability-oriented reconstruction decisions. None of them examines earthquake-related housing needs, construction-material imports, and the broader global steel supply environment together in the same empirical time-series analysis. The present research focuses on this less examined relationship. Some studies also draw attention to the role of local resource constraints, material supply, and different economic channels in post-disaster reconstruction. Mohan et al. state that the effects of disasters on different parts of the economy can be hidden under aggregated indicators [62]. They also note that reconstruction activities can affect demand for imported materials and services. Sai et al. identify limited material supply as one of the main constraints on post-disaster reconstruction [63].

The theoretical contribution of this study lies in bringing these two lines of the literature together. It treats post-disaster shelter and housing needs as a dimension related to access to international construction materials and the broader global steel supply environment. The study examines post-earthquake shelter and housing needs together with two separate construction-material import series. It also uses a material import intensity indicator based on the ratio of combined construction-material imports to the number of destroyed dwellings. As a robustness check, an alternative specification is also examined to assess whether the estimated relationship is sensitive to the construction of this ratio, using total material imports as the dependent variable and destroyed dwellings as a separate explanatory variable. In practical terms, the study does not test the effectiveness of a specific policy instrument. It points instead to international material access and global supply conditions as factors that need to be considered in planning post-disaster housing reconstruction. The relationship among these elements has received more limited attention in the literature.

The main aim of this study is to empirically examine the relationship between housing loss after major earthquakes and reconstruction capacity. The research covers the housing reconstruction stage following emergency response. Emergency shelter services are outside its scope. The study recognizes the importance of other factors in recovery, including governance, finance, labor, infrastructure and social needs. These factors are not measured directly. The analysis focuses on material supply and international access in the reconstruction process. The study examines two research questions:

- How does the relationship between post-earthquake homelessness and the import of construction materials take shape?
- How is global crude steel production related to material import intensity per destroyed dwelling?

The study examines earthquake-related housing needs together with two construction-material import channels and the broader global steel supply environment. The analysis uses annual worldwide data for 1988–2025, with the world-year as the unit of analysis. Long-run and short-run relationships are estimated with ARDL bounds testing and error-correction models. Hatemi-J asymmetric causality analysis is applied to directional relationships between shocks. Material import intensity per destroyed dwelling is also examined in relation to global crude steel production. The results are discussed in terms of material supply and international access in post-earthquake reconstruction planning. They are not interpreted as evidence of the effectiveness of any specific policy instrument.

2. Materials and Methods

This section first discusses the conceptual framework and the related literature. The dataset used in the empirical analysis, variable definitions and econometric methods are presented later. The conceptual framework considers the expected links among earthquake shocks, losses in the housing stock, resulting housing needs and demand for construction materials.

2.1. Conceptual Framework and Literature Review

Emergency shelter needs, transitional housing and longer-term housing reconstruction can be viewed as parts of a process with different time horizons, resource requirements and institutional arrangements. Tent-based and similar emergency shelter services provided immediately after an earthquake fall outside the scope of this study. The analysis covers the transitional period following the emergency response stage, with particular attention paid to longer-term sustainable housing reconstruction. This distinction is important because prefabricated structures and iron or steel building components are associated mainly with material inputs used in reconstruction [64–66]. The literature also stresses the need to

consider access to resources, infrastructure, planning and sustainability together in post-earthquake housing reconstruction [42,45,46,60,61].

The economic consequences of earthquakes also form part of the broader context in which reconstruction needs arise. Smith et al. report that positive economic growth was observed in the short term after the Tohoku earthquake and tsunami. They also find that post-disaster policy interventions were important during this period [67]. Research on earthquakes and the economy covers different aspects of this relationship. Some work examines housing values and direct economic losses. Paudel finds that the 2015 earthquake in Nepal reduced housing prices by about 40 points. Zheng et al. estimate that after the 2025 earthquake in Tibet, about 26% of buildings suffered minor damage and 3% were completely destroyed. They also estimate direct economic losses at 3.62 billion Yuan [40,41]. Other research examines the multidimensional effects of earthquakes on socio-economically and demographically vulnerable populations. Nasır et al. conclude that the Kahramanmaraş earthquake caused economic, psychological and social devastation among Syrian refugees at a level comparable to the wartime period [68]. Two main indicators are considered in assessing the severity of seismic disasters: these are human losses and economic losses [69]. Figure 1 presents the annual total economic losses associated with the earthquakes included in this study.

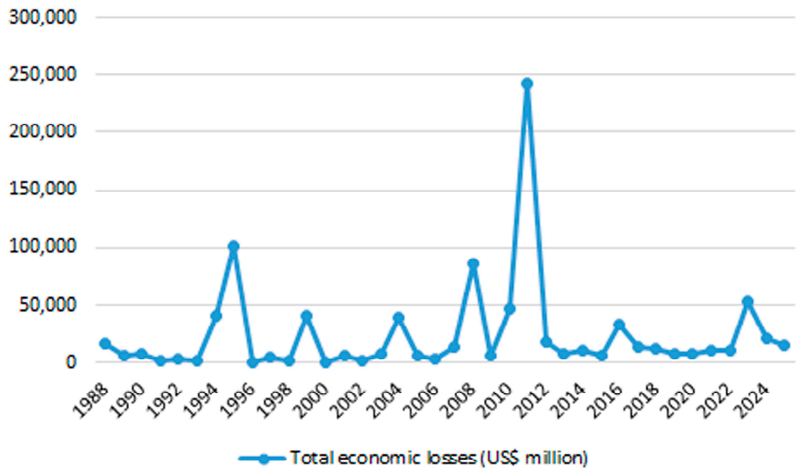


Figure 1. Total economic value of the damage. Source: Authors' own elaboration based on data from the National Centers for Environmental Information (NOAA) [70].

Figure 1 shows that economic losses vary across years and rise markedly in some periods, especially in the years of the earthquakes in Indonesia, India, Japan and Haiti. Total economic loss is not a direct measure of housing damage or post-earthquake homelessness. Physical losses to the housing stock may reduce the number of usable homes and be associated with an increase in unmet housing needs. In this study, the number of people left homeless after an earthquake does not indicate the duration of the housing crisis. It is used as an indicator of the scale of shelter and housing needs that emerge after the earthquake.

The destruction or loss of part of the housing stock after an earthquake is associated with a wider gap between usable housing and shelter needs [71–73]. In this study, this gap is treated as the post-earthquake housing demand gap. A larger housing demand gap may increase the need for prefabricated structures and other structural construction inputs during reconstruction [72]. The conversion of this material need into actual reconstruction inputs also depends on supply conditions. Local production capacity, functioning transport infrastructure, logistics, inventory management, delivery times and access to international sources are important in this process [45–47,50,65,66,74,75].

The theoretical mechanism of the study is based on several successive stages connecting earthquakes with steel trade. The first stage considers the link between an earthquake shock and physical losses in the housing stock. These losses may widen the gap between the existing housing supply and shelter needs. The resulting reconstruction need is then associated with additional demand for construction materials. The extent to which this demand can be met is linked to local production capacity, access to international material supply, the functioning of logistics systems and the resilience of supply chains. International trade channels become one possible source of access to reconstruction materials in cases where local supply is insufficient. This chain is used as a theoretical mechanism explaining why the variables examined in the study are considered within the same analytical framework. It is not treated as an empirically established sequence of causality.

Global supply chain resilience is important on the supply side of this mechanism. The global availability of materials needed after a disaster does not by itself ensure access. These materials also need to reach the affected area at the required time, quantity and cost [50,51]. Research on disaster logistics, infrastructure restoration, the resilience of production systems to disruptions and construction supply chain management examines different aspects of this access problem [46,47,50,66]. Recent work on sustainable reconstruction, circular material use and resilient supply systems also treats reconstruction as a process extending beyond the production of physical structures [51,60,61,76]. A similar approach can be applied to post-disaster reconstruction in relation to the security of critical material supply [77–81].

The conceptual framework in Figure 2 does not treat the whole reconstruction process as a single causal structure tested empirically. Post-disaster reconstruction is a multi-stage process shaped by physical damage, shelter and housing needs, material requirements, infrastructure, logistics, resource management, and institutional conditions. Yang et al. show that post-disaster reconstruction includes different stages such as emergency response, preparation for reconstruction, and the production of infrastructure and housing [82]. Serter and Gumusburun-Ayalp stress the need to consider resource management, governance, and different institutional mechanisms together during reconstruction [83]. In the cases examined by Bhusal et al., logistics problems, limited road access, and material shortages are also among the factors affecting reconstruction [71]. Figure 2 focuses on the material supply and international access dimension of this process. In the framework presented in Figure 2, steel is treated as one input within post-earthquake reconstruction. Global crude steel production represents the broader supply environment for the iron or steel structural components examined in this study. Changes in global steel production are therefore not assumed to directly determine the amount of construction material reaching a specific earthquake-affected area. Global production capacity is considered one of the conditions affecting the ability of international supply systems to provide materials needed for reconstruction. Research on the economic importance of the steel industry and the management of sustainable steel supply chains supports this approach [52,78,84]. The empirical counterparts of this process are defined using several variables. These are the number of people left homeless as an indicator of post-earthquake shelter and housing needs, imports of prefabricated structures, imports of iron or steel structural components, material import intensity per destroyed dwelling, and global crude steel production. In the empirical analysis, these variables represent the housing need, access to construction materials, and global supply dimensions shown in Figure 2.

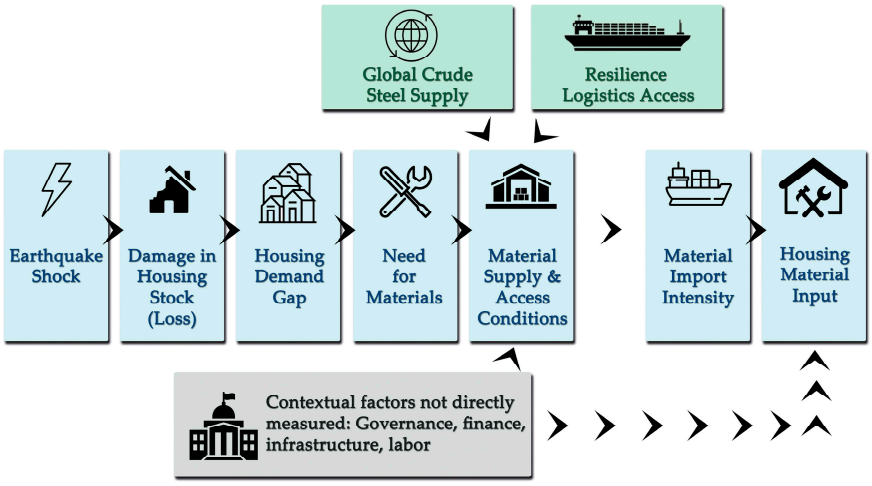


Figure 2. Conceptual framework. Note: Figure 2 shows only contextual mechanisms such as logistics, local production capacity, supply chain resilience, and trade barriers. The relationships tested empirically are defined in Equations (2) and (3) in the following sections. Source: Designed by the authors using Adobe Photoshop 7.0 [85].

Prefabricated structures and iron or steel structural components are both relevant to reconstruction. In international trade classification, however, they belong to different product groups. This study treats HS 9406 and HS 7308 as separate product groups. HS 9406 covers prefabricated buildings. HS 7308 covers structures and parts of structures made of iron or steel. Trade trends are examined separately for each group. Each product group is analyzed according to its own definition and data coverage. The operational definitions of the relevant HS codes, their data coverage and their links with the variables used in the study are explained in detail in the next section. International trade is treated as one possible channel for accessing external resources when local resources are insufficient to meet demand after an earthquake. Tariffs, quotas, anti-dumping measures and other trade policies have an important place in the international trade of steel products [53–55,86,87]. The study does not use a variable that directly represents trade barriers. These regulations are treated as institutional conditions that may shape international access to materials. They are not tested empirically as an independent mechanism.

The conceptual scope of the variables used in the study also needs to remain within this framework. The number of people left homeless after an earthquake does not directly measure the duration of the housing crisis or the time required for recovery. It is used as an indicator of the scale of shelter and housing needs after the earthquake. Material imports per destroyed dwelling are also not a direct measure of overall reconstruction capacity or housing efficiency. In this study, the ratio represents the relative intensity of prefabricated structures and iron or steel structural components supplied through international trade in relation to the destroyed housing stock. It is used as an indicator of material import intensity per destroyed dwelling. The variable therefore represents the material supply and international access dimension of reconstruction. It does not represent the reconstruction process as a whole.

Studies published in recent years have also examined post-earthquake reconstruction in relation to infrastructure restoration, resource allocation, logistics organization, supply chain resilience, prefabricated building systems and sustainable material use [45–47,50,51,60,61,65,66,75]. This literature suggests that reconstruction depends more on whether materials can reach the areas where they are needed on time and under suitable conditions than on their availability alone. The response of global supply chains to sudden disaster-related increases in demand and the security of critical construction material supply have also received

growing attention [42,88–90]. A large part of the existing literature examines post-disaster material and resource supply within local or regional reconstruction settings. Prefabricated building supply chains are mainly studied in operational and logistical terms. Studies that place post-earthquake housing needs, imports of prefabricated structures and iron or steel structural components, and broader global steel supply conditions within the same empirical framework remain limited [46,60,91–93]. The present study focuses on this less examined area through material supply and international access. The conceptual framework links post-earthquake shelter and housing needs with two separate construction-material import channels and the broader global steel supply environment. Its focus is limited to the material supply and international access dimensions of reconstruction. These relationships are separated because they can be tested empirically, without attempting to explain the entire reconstruction process. It does not seek to explain the reconstruction process as a whole. Following this conceptual framework, the empirical analysis examines the relationship between post-earthquake housing needs and imports of prefabricated structures and iron or steel structural components. It also examines the relationship between global crude steel supply and material import intensity per destroyed dwelling. These relationships are tested using the variable definitions and empirical model presented in the next section.

2.2. Data Set and Methodology

This study examines two related empirical models. The first evaluates the long-run and short-run relationships between the number of people left homeless after an earthquake and imports of prefabricated structures and iron or steel structural components. The second examines the relationship between global crude steel supply and material import intensity per destroyed dwelling. In the empirical analysis, post-earthquake shelter and housing needs are represented by the number of people left homeless. International access to construction materials is represented by imports of prefabricated structures and iron or steel structural components. Material import intensity is measured by imports per destroyed dwelling. The broader global supply environment is represented by global crude steel production. The number of people left homeless after an earthquake is used as an indicator of the scale of shelter and housing needs. It does not directly measure the duration of the housing crisis or the recovery period. The indicator refers to housing and shelter needs recorded in connection with earthquake events. It does not measure unresolved housing needs throughout the later reconstruction period. Later material imports therefore cannot be interpreted as reducing the number of people initially recorded as homeless. Material imports per destroyed dwelling are also not designed as a direct measure of overall reconstruction capacity or housing efficiency. This ratio represents the intensity of imports of prefabricated structures and iron or steel structural components relative to the destroyed housing stock. It therefore reflects the material supply and international access dimension of the reconstruction process.

The analysis covers the period from 1988 to 2025 and consists of 38 annual observations. The starting year is 1988 because the Harmonized System (HS) nomenclature began to be implemented in that year [94]. The period also includes years in which many large-scale earthquakes occurred around the world [95–101]. The years from 1988 to 2025 also cover major economic disruptions that could affect global trade and steel production. These include the dissolution of the Soviet Union and Russia's transition to a market economy, the Latin American and Asian crises, the 2008 global financial crisis, trade wars and the pandemic [102–107]. The selected period therefore allows post-earthquake housing needs and changes in global trade and steel supply to be observed within the same time span.

The dataset was compiled from secondary and publicly available sources. Data on imports of prefabricated structures and iron or steel structural components were obtained

from UN Comtrade. For the prefabricated building series, the four-digit HS 9406 heading is used consistently for the full 1988–2025 period. No retrospective conversion to HS 9406.20 was applied. The data were also not harmonized across six-digit subheadings. Because the Harmonized System is revised over time, there are data limitations in comparing subheadings across different periods [108,109]. Jordan Exports reports HS 9406 under the main heading of prefabricated buildings [110]. Razzaque also states that prefabricated buildings are classified under the four-digit HS 9406 category [111]. The series was obtained at the four-digit HS 9406 heading level for the full sample period. HS 9406 is a broad product heading covering prefabricated buildings. The variable therefore represents prefabricated building imports in general and is not limited to steel modular building units. The same four-digit HS 9406 heading was used throughout the sample period. The series is interpreted as an aggregated indicator of prefabricated building imports. The number of people left homeless after earthquakes was taken from EM-DAT, and data on destroyed dwellings were obtained from NOAA. Global crude steel production data came from the World Steel Association [70,112,113].

The variables shown in Table 1 were selected to empirically represent the post-earthquake housing need, material supply and international access channels defined in the conceptual framework. *preb* is the import value of prefabricated buildings classified under the four-digit HS 9406 heading in UN Comtrade [108]. The variable reflects international trade in prefabricated buildings after a disaster. It is used as an indicator of access to this group of structures through international markets for reconstruction purposes. *sps* is the import value of structures and parts of structures of iron or steel classified under HS 7308. For both import variables, annual trade values reported by UN Comtrade in current US dollars are used. No conversion to constant prices or adjustment for inflation was applied. This product group has a different international trade classification from prefabricated structures. The HS 9406 and HS 7308 series are therefore kept separate. Each is examined within its own product coverage. *lhe* represents the number of people who lost their homes or whose homes became unusable because of an earthquake. It is used as an indicator of the scale of shelter and housing needs that arise after the earthquake. *tdh* represents the direct loss of physical housing stock caused by the earthquake. It is used to normalize material imports against the number of destroyed dwellings. This is intended to limit part of the scale effect arising from differences in the size of economies. *wsp* is total world crude steel production reported by the WSA. It is used as an aggregate indicator of the broader global steel supply environment. Its coefficient is interpreted within the statistical relationship between global supply conditions and the material import intensity defined in this study. It does not measure country-level steel availability or the direct effect of steel supply on reconstruction success. Based on these five variables, *lndr* is constructed as a separate derived indicator of material import intensity per destroyed dwelling. The ratio is calculated by dividing the combined import value of prefabricated structures and iron or steel structural components by the number of destroyed dwellings:

$$lndr = ln\left(\frac{preb + sps}{tdh}\right) \quad (1)$$

The indicator in Equation (1) is the natural logarithm of the ratio of the combined import value of prefabricated structures and iron or steel structural components to the number of destroyed dwellings. *lndr* indicates the monetary intensity of material imports supplied through international trade relative to the destroyed housing stock. In this way, part of the scale effect in total global import values is normalized by physical housing loss. For the robustness analysis, total material imports (*tmi*) are calculated as the sum of prefabricated structure imports (*preb*) and imports of iron or steel structural components (*sps*). An alternative model uses the logarithm of total material imports (*lntmi*) as the

dependent variable. Global crude steel production (*lnwsp*), the homelessness indicator (*lnlhe*), and the number of destroyed dwellings (*lntdh*) are included as explanatory variables. The model checks whether the estimated relationship with the homelessness indicator changes when the ratio-based dependent variable is replaced.

Table 1. Data set.

The Name of the Series	Short	Unit	Source
Import of prefabricated structures	*preb*	U.S. dollars	UNCOMTRADE
Imports of iron or steel construction components	*sps*	U.S. dollars	UNCOMTRADE
The number of people left homeless by the earthquake	*lhe*	Person	EM-DAT
Number of homes demolished	*tdh*	Number	NOAA
Crude steel production	*wsp*	Millions of tons	World Steel Association

Source: Prepared by the authors [70,108–113].

During data preprocessing, no statistical imputation, linear interpolation or deletion of observations was applied to missing or zero country-year observations. Earthquakes do not occur in every country or every year. Country-level earthquake indicators therefore have an intermittent time structure, and some country-year observations take a value of zero because no event occurred [70]. The analysis uses annual world totals reported by the data providers instead of constructing unbalanced and discontinuous country-level series. If more than one earthquake occurred in the same year, their effects are jointly represented in the annual world totals reported by the data providers. The authors did not carry out an additional event-level aggregation. Zero observations at the country-year level were not entered separately into the logarithmic models. Logarithmic transformations were applied to the positive annual world-level series used in the empirical analysis. The unit of analysis is defined as world-year. This allows the series to be combined at a common annual frequency and at a consistent level of observation. The starting year of the trade series under the Harmonized System was determined according to the year in which the HS classification began to be implemented [94]. No starting-year estimates or retrospective data were produced for these series. The reported measurement units of variables obtained from public databases were also retained. No additional unit conversion, rescaling or data imputation was carried out by the researcher. Logarithmic transformation was applied before the econometric analysis to reduce scale differences across the series and to facilitate interpretation of the coefficients in terms of proportional changes [114]. Log-transformed variables are denoted by adding ln before the relevant abbreviations. The first empirical model is specified as follows:

$$lnlhe_t = \alpha + \beta_1 lnpreb_t + \beta_2 lnsps_t + \varepsilon_t \quad (2)$$

In Equation (2), the dependent variable is *lnlhe*, while *lnpreb* and *lnsps* are the explanatory variables. The estimated coefficients are interpreted as relationships between imports of prefabricated structures and iron or steel structural components and the homelessness indicator representing the scale of shelter and housing needs recorded in connection with earthquake events. The coefficients in Equation (2) are not interpreted as evidence that the number of people left homeless determines imports. Possible directionality between the variables is examined separately using the asymmetric causality approach. Equation (2) shows the empirically tested relationships between post-earthquake shelter and housing needs and the two separate construction-material import channels presented in Figure 2. The second empirical equation is presented in Equation (3):

$$lndr_t = \alpha + \beta_1 lnwsp_t + \beta_2 lnlhe_t + \varepsilon_t \quad (3)$$

In Equation (3), the dependent variable is *lndr*, which represents material import intensity per destroyed dwelling. The explanatory variables are global crude steel production (*lnwsp*) and the number of people left homeless after an earthquake (*lnlhe*), which represents the scale of shelter and housing needs recorded in connection with earthquake events rather than unresolved housing needs during the subsequent recovery period. The model examines how the global steel supply environment and material import intensity relative to the destroyed housing stock move together. It does not assume that global steel production alone determines reconstruction success at the country level. It also does not assume that changes in homelessness arise directly from trade barriers. Equation (3) shows the empirically tested relationships among the global steel supply environment, post-earthquake shelter and housing needs, and material import intensity per destroyed dwelling presented in Figure 2. The robustness model described above replaces the ratio-based dependent variable with total material imports and enters destroyed dwellings separately. The model is specified as follows:

$$lntmi_t = \alpha + \beta_1 lnwsp_t + \beta_2 lnlhe_t + \beta_3 lntdh_t + \varepsilon_t \quad (4)$$

In Equation (4), lntmi is the dependent variable. lnwsp, lnlhe, and lntdh are the explanatory variables. Figure 3 provides a descriptive view of the temporal relationships among the variables included in the first empirical model by illustrating the joint evolution of prefabricated structure imports, iron or steel structural component imports, and post-earthquake housing needs over the 1988–2025 period.

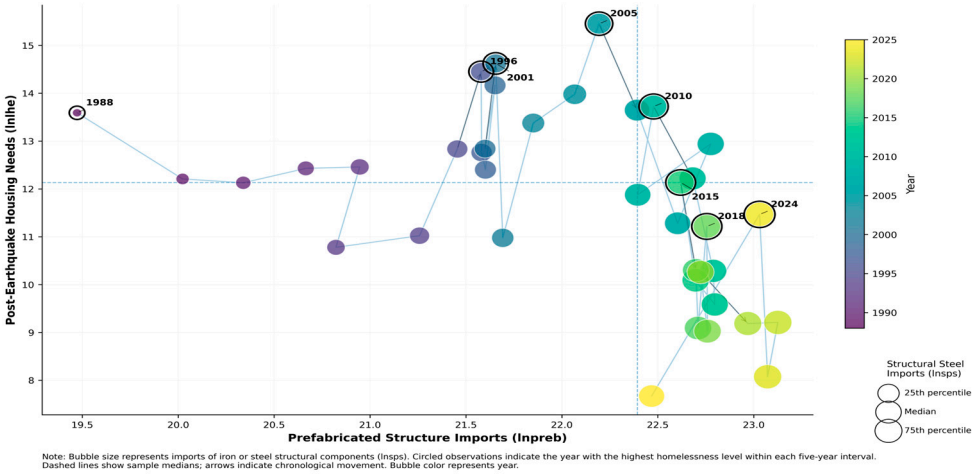


Figure 3. Temporal patterns in construction material imports and post-earthquake housing needs. Source: Prepared by the authors using Python 3.13 in Visual Studio Code 1.141 [115,116].

Figure 3 shows that prefabricated structure imports generally increase over time, while post-earthquake housing needs fluctuate considerably across years. The changing bubble sizes also indicate variation in imports of iron or steel structural components, with higher housing needs occurring under different combinations of the two import channels. This pattern provides a descriptive basis for examining the relationships specified in Equation (2). A similar descriptive visualization for the variables included in the second empirical model is presented in Figure 4.

Figure 4 shows that global crude steel production generally increases over time, while material import intensity per destroyed dwelling exhibits greater variation across years. The distribution of larger bubbles also indicates that higher post-earthquake housing needs occur under different combinations of global steel supply and material import intensity. This pattern provides a descriptive basis for examining the relationships specified in Equation (3).

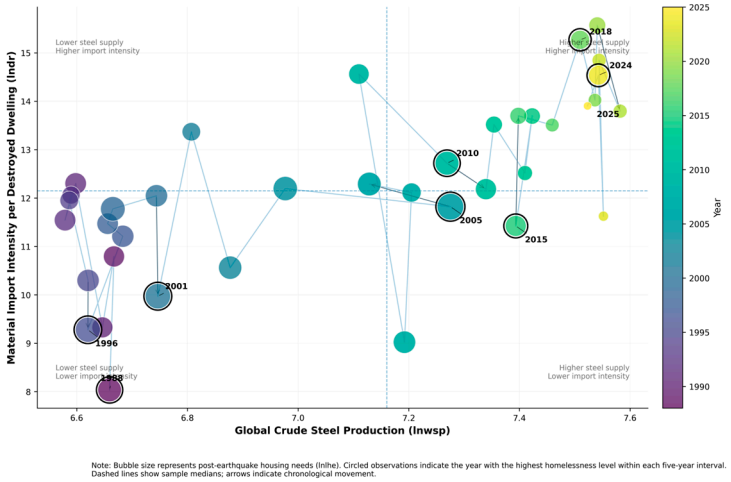


Figure 4. Global crude steel production, material import intensity, and post-earthquake housing needs. Source: Prepared by the authors using Python 3.13 in Visual Studio Code 1.141 [115,116].

The stationarity properties of the series were examined using the Augmented Dickey–Fuller (ADF) test [117], the KPSS stationarity test [118] and the Lee–Strazicich unit root test with two structural breaks [119]. The ADF and KPSS tests are based on different null hypotheses. Using both provides complementary evidence on the stationarity properties of the series. The structural break test was included to account for the possible role of major economic and disaster-related disruptions during the sample period. After confirming that none of the series is integrated of order two, $I(2)$, the ARDL bounds testing approach developed by Pesaran et al. was used to examine short-run and long-run relationships [120]. To further assess the validity of the long-run relationships, Wald tests were used to examine the joint significance of the lagged levels of the explanatory variables in both ARDL models. This additional test was used to assess whether the bounds-test results could reflect a degenerate case associated with a level-stationary dependent variable. Information criteria were used to determine the lag lengths in the ARDL models. Model selection was based on the Akaike Information Criterion (AIC). When the information criteria suggested different lag structures, the more parsimonious specification selected by AIC was used to limit overparameterization in the small sample. VAR lag length results were also considered in the preliminary assessment. Keeping the lag structure relatively low helps limit unnecessary parameterization in a sample of 38 annual observations. Possible directional asymmetries associated with positive and negative shocks were examined using the Hatemi-J asymmetric causality approach [121]. The Hatemi-J asymmetric causality test was performed using GAUSS 14.0 [122]. Following the procedure of the method, positive and negative shocks in the series were separated. The directional relationships between these shocks were then tested separately. In this test, causality is interpreted in the time-series sense as statistical directionality or predictive relationships between shocks. Two additional checks were used to assess the robustness of the main findings. Structural break dates identified by the Lee–Strazicich test were added to the ARDL models as exogenous control variables. Earthquake economic losses as a share of GDP, the number of people affected by earthquakes, and the number of earthquakes were also used as alternative measures of disaster severity. Contemporaneous, one-year lagged, and two-year lagged relationships were examined using Newey–West robust standard errors.

Meeting housing needs during post-disaster reconstruction is closely related to timely and adequate access to the required construction materials. Chang et al. show that resource shortages and rising construction-material costs after major disasters can slow reconstruction [123]. They also report that the costs of non-local materials such as steel can be affected

by broader economic conditions and national strategies. Sai et al. identify limited material supply, skilled labor, and planning capacity among the main factors that delay reconstruction in resource-constrained post-disaster settings [63,123]. H_1 and H_2 test the relationships defined in Equation (2) between construction-material imports and post-earthquake shelter and housing needs. H_3 and H_4 test the relationships defined in Equation (3) between global crude steel production, post-earthquake shelter and housing needs, and material import intensity per destroyed dwelling. The hypotheses tested in this study are as follows:

H_1: *A negative long-run statistical relationship is expected between prefabricated structure imports and the homelessness indicator representing post-earthquake shelter and housing needs.*

H_2: *A negative long-run statistical relationship is expected between imports of iron or steel structural components and the homelessness indicator representing post-earthquake shelter and housing needs.*

H_3: *A positive long-run statistical relationship is expected between global crude steel production and material import intensity per destroyed dwelling.*

H_4: *A negative long-run statistical relationship is expected between the homelessness indicator representing post-earthquake shelter and housing needs and material import intensity per destroyed dwelling.*

Microsoft Excel 16.0, EViews 11.0, and Gauss 14.0 were used to carry out the analyses [122,124,125].

3. Results

This section reports the statistical relationships among the homelessness indicators representing post-earthquake shelter and housing needs, construction material imports, material import intensity per destroyed dwelling and global crude steel production. The analysis follows the research questions and hypotheses of the study. The findings are presented through descriptive statistics and stationarity checks, ARDL long-run and short-run estimates, Hatemi-J asymmetric directionality analysis, diagnostic tests and robustness analyses.

3.1. Common Practices

This subsection presents the basic distributional properties of the series used in the analysis. Stationarity and unit root tests are then reported to assess whether the series are suitable for the time-series analyses that follow.

Table 2 presents the main descriptive statistics for the logarithmic series used in the analysis. Among the 38 observations, global crude steel production has the lowest standard deviation at 0.3787. The highest standard deviation is observed for the number of people left homeless after an earthquake at 1.9085. Material import intensity per destroyed dwelling has a standard deviation of 1.7856. All series have negative skewness coefficients, indicating left-skewed distributions to varying degrees. According to the Jarque–Bera test, the normality assumption is rejected at the 5% significance level for prefabricated structure imports ($JB = 6.4782$, $p = 0.0391$). For the other series, the normality assumption is not rejected at the 5% significance level.

Table 3 reports the regression results used to assess the deterministic components for the unit root analyses. The statistical significance of the constant and trend terms was considered in selecting the appropriate specification for the stationarity tests. The level unit root tests included a constant and a linear trend. The trend was excluded from the first-difference tests. The ARDL bounds tests were estimated under Case III, with an unrestricted constant and no trend. The negative trend coefficient for the homelessness indicator shows the direction of the deterministic trend within the relevant test specification.

Table 2. Descriptive statistics.

	lndr	*lnlhe*	*lnpreb*	*lnsps*	*lnwsp*
Mean	12.2329	11.7309	22.0261	23.5662	7.0791
Median	12.1491	12.1314	22.3933	24.0436	7.1604
Maximum	15.5686	15.4548	23.1257	24.8204	7.5819
Minimum	8.0359	7.6694	19.4729	20.7409	6.5788
Std. Dev.	1.7856	1.9085	0.9096	1.1057	0.3787
Skewness	−0.2519	−0.2257	−0.9993	−0.7881	−0.0805
Kurtosis	2.6524	2.3261	3.3111	2.6517	1.3267
Jarque–Bera	0.5933	1.0416	6.4782	4.1261	4.4741
Probability	0.7432	0.5940	0.0391	0.1270	0.1067
Obs.	38	38	38	38	38

Source: Prepared by the authors using EViews 11.0 [125].

Table 3. Model selection regression results for unit root tests *.

	lndr	*lnlhe*	*lnpreb*	*lnsps*	*lnwsp*
Stable	10.1161 [0.0000]	13.7483 [0.0000]	20.6493 [0.0000]	21.8529 [0.0000]	6.4733 [0.0000]
Trend	0.1144 [0.0000]	−0.1090 [0.0000]	0.0747 [0.0000]	0.0926 [0.0000]	0.0327 [0.0000]

* The values represent coefficients. The values in square brackets represent probabilities. Source: Prepared by the authors using EViews 11.0 [125].

Table 4 reports the results of the ADF, KPSS and Lee–Strazicich unit root tests with two structural breaks. According to the ADF results, the series representing the number of people left homeless after an earthquake and material import intensity per destroyed dwelling appear stationary at level. The remaining series become stationary after first differencing. In the KPSS results, the test statistics for $\Delta lnpreb$ and $\Delta lnsps$ are 0.6602 and 0.6416, respectively, and both are above the 5% critical value of 0.4630. In contrast, the ADF first-difference results for lnpreb and lnsps are −3.8519 and −3.2265, respectively, rejecting the null hypothesis of a unit root. For this reason, the orders of integration were determined by evaluating the ADF, KPSS, and Lee–Strazicich results together. The findings were interpreted as showing a mix of $I(0)$ and $I(1)$ processes and as not supporting the classification of any series as $I(2)$. These results satisfy the condition required to examine long-run and short-run relationships using the ARDL bounds testing approach.

3.2. Assessing the Socioeconomic Network: Imports as a Crisis Buffer

Equation (2) examines the long-run and short-run statistical relationships between the homelessness indicator representing post-earthquake shelter and housing needs and imports of prefabricated structures and iron or steel structural components. The coefficients in Table 5 are interpreted according to this model specification.

Model selection was based on the AIC, taking into account the results of the unit root tests and the subsequent tests. The appropriate lag length was set to two. Based on the model selection results obtained using EViews, ARDL (1,2,2) was selected as the appropriate model.

Table 6 presents the ARDL bounds test results for Equation (2). The F-Bounds test statistic is 6.1513, and the t-Bounds test statistic is −4.2480. Both statistics exceed the relevant upper critical bounds at the 5% significance level. The F-Bounds statistic of 6.1513 and the t-Bounds statistic of −4.2480 reject the null hypothesis for the lagged level terms in the conditional error-correction model. These results provide statistical evidence of a long-run cointegration relationship among the variables in Equation (2). Imports of prefabricated

structures, imports of iron or steel structural components, and the homelessness indicator representing post-earthquake shelter and housing needs therefore move together in the long run.

Table 4. Unit root and stationarity test results *.

	UR_{ADF}	UR_{KPSS}	UR_{LS}^{2SB}
lnlhe	−4.2173	0.2105	−6.3062 [1992; 1997]
lnpreb	−2.4219	0.2080	−4.2922 [1994; 2004]
lndr	−7.9606	0.0897	−8.7097 [1992; 1996]
lnwsp	−2.2811	0.1097	−5.1758 [1994; 2003]
lnsps	−1.3755	0.2051	−4.3018 [1994; 2004]
Δ*lnlhe*	*	0.2377	*
Δ*lnpreb*	−3.8519	0.6602	−6.5677
Δ*lndr*	*	*	*
Δ*lnwsp*	−6.2124	*	−9.4161
Δ*lnsps*	−3.2265	0.6416	−6.5103

* The Δ symbol represents the difference operator. The values for the ADF test are t-statistics (τ). In the KPSS test, it represents the LM statistic, and in the LS test, it represents the minimum test statistic (τ). In the ADF test, the user-specified value was set to 0. Critical values were determined according to MacKinnon. For level analyses, the critical values at the 1%, 5%, and 10% significance levels are −4.2268, −3.5366, and −3.2003, respectively. For difference series, the critical values are −2.6307, −1.9503, and −1.6112. In the KPSS test, critical values were taken from Kwiatkowski et al. [118]. For level values, they are 0.2160, 0.1460, and 0.1190. For difference series, they are 0.7390, 0.4630, and 0.3470. The Newey–West bandwidth was considered. Since annual data were used in the KPSS test, maxlag was set to 2 and end of percent to 0.05. The critical values for the level series of lnlhe, lnwsp, and lndr are −6.7500, −6.1080, and −5.7790, respectively. For lnpreb and lnsps, they are −7.1960, −6.3120, and −5.8930. For the difference series of lnpreb and lnsps, the critical values are −6.6910, −6.1520, and −5.7980. For lnwsp, they are −6.8630, −6.2680, and −5.9560. In the unit root analyses, the trend was removed during the differencing process. The AIC was considered as the information criterion. Source: Prepared by the authors using EViews 11.0 [125].

Table 5. Results of the VAR analysis for Equation (2).

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−71.60770	NA	0.014260	4.263297	4.396613	4.309318
1	−0.072241	126.7200	0.000401	0.689842	1.223105 *	0.873924
2	14.11408	22.69811 *	0.000302 *	0.393481 *	1.326690	0.715625 *
3	18.74838	6.620433	0.000401	0.642950	1.976105	1.103155

* in the table footer. indicates the lag order selected by each criterion. Source: Prepared by the authors using EViews 11.0 [125].

Table 6. ARDL model estimation results for Equation (2) *.

$f(lnlhe \mid lnpreb, lnsps)$ ARDL (1,2,2) k:2, m:2, effective n = 36					**Test Stats**		**Result**
					$F_{OVERALL}$	6.1513 **	Cointeg.
					t_{DV}	−4.2480 **	
CV	1%		5%		10%		
Tests	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
$F_{OVERALL}$	6.140	7.607	4.183	5.333	3.393	4.410	n = 35
t_{DV}	−3.43	−4.10	−2.86	−3.53	−2.57	−3.21	

* The estimates were made according to Case III. ** Denotes the 5% significance level; k denotes the number of independent variables; m denotes the maximum lag length; and n denotes the number of observations. Finite-sample F-Bounds critical values for n = 35 were used because this is the closest available tabulated sample size to the effective estimation samples (n = 36 for Equation (2)). Source: Prepared by the authors using EViews 11.0 [125].

Table 7 reports the long-run and short-run coefficient estimates for Equation (2). The coefficient of the error correction term is −0.6438 and is statistically significant at the 1% level ($p = 0.0001$). Its negative and significant value is compatible with the error correction mechanism of the long-run relationship identified in Equation (2). The estimated coefficient indicates that about 64% of a short-run disequilibrium is corrected in the following period. The long-run estimate for prefabricated structure imports is positive in relation to the homelessness indicator ($\beta = 9.3304$, $p = 0.0728$). The coefficient is statistically significant at the 10% level but not at the 5% level. The result should therefore be interpreted with caution. Equation (2) indicates a positive long-run association between prefabricated structure imports and the homelessness indicator. Higher prefabricated structure imports are associated with higher values of the indicator representing the scale of shelter and housing needs recorded in connection with earthquake events. The long-run coefficient for imports of iron or steel structural components is negative and statistically significant at the 5% level ($\beta = -8.2351$, $p = 0.0488$). The magnitude of the coefficients should be interpreted cautiously because of the logarithmic form of the variables and the small sample. The results indicate long-run statistical relationships and should not be read as precise estimates of effect size. Higher imports of iron or steel structural components are associated in the long run with lower values of the homelessness indicator recorded in connection with earthquake events. This statistical relationship should not be interpreted as evidence that subsequent imports reduce the number of people initially recorded as homeless. Equation (5) is defined as follows:

$$ECT_t = lnlhe_t - (9.3304 \times lnpreb_t - 8.2351 \times lnsps_t) \quad (5)$$

The long-run results for Equation (2) indicate that the two import variables are not related to the homelessness indicator in the same direction. The positive coefficient for prefabricated structure imports, which is statistically significant only at the 10% level, does not support the negative relationship predicted in H_1. By contrast, the negative coefficient for imports of iron or steel structural components is statistically significant at the 5% level and is consistent with the negative relationship predicted in H_2. Accordingly, H_1 is not supported, whereas H_2 is supported.

Table 7. ARDL long- and short-run coefficient estimates for Equation (2) *.

Long Run	Coefficient	Std. Error	t-Stat.	Prob.
lnpreb	9.3304	5.0044	1.8644	0.0728 *
lnsps	−8.2351	3.9972	−2.0602	0.0488 **
Short Run				
C	−0.2283	0.2846	−0.8023	0.4291
Δ*lnpreb*	4.0718	3.4064	1.1954	0.2420
Δ*lnpreb*(−1)	−12.8506	3.3716	−3.8115	0.0007 ***
Δ*lnsps*	−0.3111	3.3813	−0.0920	0.9273
Δ*lnsps*(−1)	11.6725	3.5318	3.3050	0.0026 ***
ECT_{t-1}	−0.6438	0.1448	−4.4465	0.0001 ***

* The symbols *, **, and *** correspond to significance levels of 10%, 5%, and 1%, respectively. Effective estimation sample: n = 36. Source: Prepared by the authors using EViews 11.0 [125].

3.3. Global Commodity Flows and Local Reconstruction Needs: A Macro-Level Connection

Equation (3) examines the long-run and short-run statistical relationships between global crude steel production and material import intensity relative to physical housing loss caused by earthquakes. The results are interpreted in terms of the estimated relationships between material import intensity, global supply conditions and the homelessness indicator.

Table 8 indicates that the appropriate lag length is one based on the AIC. According to the model selection results obtained using EViews, we see that the appropriate model is ARDL (1,0,0).

Table 8. Results of the VAR analysis for Equation (3).

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−134.2796	NA	0.512203	7.844550	7.977865	7.890570
1	−67.22451	118.7833 *	0.018620 *	4.527115 *	5.060377 *	4.711197 *
2	−60.32880	11.03315	0.021282	4.647360	5.580569	4.969503
3	−53.97178	9.081450	0.025574	4.798388	6.131543	5.258593

* in the table footer. indicates the lag order selected by each criterion. Source: Prepared by the authors using EViews 11.0 [125].

Table 9 presents the ARDL bounds test results for Equation (3). The F-Bounds test statistic is 22.1953, and the t-Bounds test statistic is −8.0682. Both test statistics exceed the relevant upper critical bounds at the 1% significance level. The F-Bounds statistic of 22.1953 and the t-Bounds statistic of −8.0682 provide strong evidence for the lagged level terms. These results provide statistical evidence of a long-run cointegration relationship among global crude steel production, the homelessness indicator representing post-earthquake shelter and housing needs, and material import intensity per destroyed dwelling.

Table 10 reports the long-run and short-run coefficient estimates for Equation (3). The coefficient of the error correction term is −1.2525 and is statistically significant at the 1% level. Its negative and significant value indicates an error correction mechanism compatible with the long-run cointegration relationship identified in the model. Since the absolute value of the coefficient exceeds one, the short-run adjustment process may involve corrective movements across periods. Monotonic convergence should not be assumed. Equation (6) is defined as follows:

$$ECT_t = lndr_t - (2.2737 \times lnwsp_t - 0.2356 \times lnlhe_t) \quad (6)$$

Table 9. ARDL model estimation results for Equation (3) *.

$f(lndr \mid lnwsp, lnlhe)$ ARDL (1,0,0) k:2, m:2, effective n = 37					**Test Stats**		**Result**
					$F_{OVERALL}$	22.1953 ***	Cointeg.
					t_{DV}	−8.0682 ***	
CV	1%		5%		10%		
Tests	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
$F_{OVERALL}$	6.140	7.607	4.183	5.333	3.393	4.410	n = 35
t_{DV}	−3.43	−4.10	−2.86	−3.53	−2.57	−3.21	

* The estimates were made using Case III. *** denotes a 1% significance level; k denotes the number of independent variables; m denotes the maximum lag length; and n denotes the number of observations. Finite-sample F-Bounds critical values for n = 35 were used because this is the closest available tabulated sample size to the effective estimation samples (n = 37 for Equation (3)). Source: Prepared by the authors using EViews 11.0 [125].

The coefficient for global crude steel production is positive and statistically significant at the 1% level ($\beta = 2.2737$, $p = 0.0001$). Within the analysis period and the world-year data structure used in the study, this result indicates a positive long-run statistical relationship between global crude steel production and material import intensity per destroyed dwelling. Periods of higher global crude steel production are associated with higher values of material import intensity within the model. The long-run coefficient of the homelessness indicator representing the scale of shelter and housing needs recorded in connection with earthquake

events is negative and statistically significant at the 5% level ($\beta = -0.2356$, $p = 0.0295$). With the other variable in the model held constant, periods with higher values of the homelessness indicator are associated with lower material import intensity per destroyed dwelling. This result indicates a negative long-run statistical relationship between the earthquake-related homelessness indicator and material import intensity per unit of physical housing loss. It does not imply that subsequent material imports reduce the number of people initially recorded as homeless. The positive long-run relationship expected between global crude steel production and material import intensity per destroyed dwelling is statistically supported. This supports H_3. The negative and statistically significant relationship between the homelessness indicator and material import intensity per destroyed dwelling is consistent with H_4 in the baseline specification. The robustness of this result is examined further in Section 3.6.

Table 10. ARDL model estimation results for Equation (3).

Long Run	Coefficient	Std. Error	t-Stat.	Prob.
lnwsp	2.2737	0.5250	4.3308	0.0001 ***
lnlhe	−0.2356	0.1036	−2.2755	0.0295 **
Short Run				
C	−1.3213	0.2595	−5.0913	0.0000 ***
ECT_{t-1}	−1.2525	0.1491	−8.4036	0.0000 ***

The symbols ** and *** correspond to significance levels of 5% and 1%, respectively. Effective estimation sample: n = 37. The ARDL(1,0,0) specification does not generate additional differenced explanatory-variable terms in the ECM. Source: Prepared by the authors using EViews 11.0 [125].

3.4. The Causality Approach

The Hatemi-J asymmetric causality test was applied to examine possible asymmetric directional relationships between positive and negative shocks in the variables [121]. In this approach, the term causality refers to the statistical directionality and predictive information carried by shocks in one variable for shocks in another variable within a time-series setting.

Table 11 reports the statistically significant directional relationships identified by the Hatemi-J asymmetric causality test. The results for all directions examined in the Hatemi-J asymmetric causality test are presented in Table A1 in Appendix A. A statistically significant directional relationship is found from negative shocks in imports of iron or steel structural components to positive shocks in prefabricated structure imports ($MWald = 12.729$). The test statistic exceeds the 5% bootstrap critical value, supporting this directional relationship at the 5% significance level. This result indicates that shocks in the two product groups do not move completely independently. In some periods, negative shocks in one product group carry predictive information for positive shocks in the other product group. A statistically significant directional relationship is also found at the 5% level from positive shocks in global crude steel production to positive shocks in material import intensity per destroyed dwelling ($MWald = 8.655$). Positive changes in global crude steel production therefore carry predictive information for positive changes in material import intensity within the time-series setting. There is also a significant directional relationship at the 5% level from positive shocks in the homelessness indicator representing post-earthquake shelter and housing needs to positive shocks in material import intensity per destroyed dwelling ($MWald = 5.251$). Positive shocks in the homelessness indicator carry statistical directionality and predictive information for positive shocks in material import intensity. A statistically significant directional relationship is also found at the 1% level from negative shocks in the homelessness indicator to negative shocks in material import intensity. ($MWald = 10.775$). These results indicate asymmetric directional dynamics between the positive and negative shocks of the two variables. The statistically significant directional relationship from negative shocks in imports of iron or

steel structural components to positive shocks in prefabricated structure imports provides empirical evidence of an asymmetric relationship between shocks in the two product groups.

Table 11. Results of the Hatemi-J asymmetric causality test.

			Bootstrap CV		
Directions	**Lag**	**MWald Stat**	**1%**	**5%**	**10%**
$lnsps^{-}_{Eq1} \rightarrow lnpreb^{+}_{Eq1}$	2	12.729 **	20.301	8.935	6.821
$lnwsp^{+}_{Eq2} \rightarrow lndr^{+}_{Eq2}$	1	8.655 **	14.404	4.750	2.873
$lnlhe^{+}_{Eq2} \rightarrow lndr^{+}_{Eq2}$	1	5.251 **	9.108	4.608	2.984
$lnlhe^{-}_{Eq2} \rightarrow lndr^{-}_{Eq2}$	1	10.775 ***	10.322	4.429	3.058

The sub-indices indicate the model under examination. The symbols ** and *** denote statistical significance at the 5% and 1% levels, respectively. Lag lengths were selected using the Hatemi-J Criterion (HJC), with dmax = 1. Leveraged bootstrap critical values were obtained using 1000 bootstrap replications. Source: Prepared by the authors using Gauss 14.0 [122].

3.5. Diagnostic Tests

A series of diagnostic tests was applied to assess the statistical properties of the estimates obtained from the ARDL models. The tests examined serial correlation, heteroskedasticity, ARCH effects, residual normality and functional form misspecification. The results are presented in Table 12.

Table 12. Diagnostic findings.

	Equation (2)		**Equation (3)**	
Diagnostic Tests	**Test Value**	**Probability**	**Test Value**	**Probability**
χ^2_{SC}	2.0126	0.3656	0.0417	0.9794
$\chi^2_{HET(BPG)}$	1.7464	0.9725	0.4796	0.9233
$\chi^2_{HET(ARCH)}$	0.0016	0.9677	0.1090	0.7412
χ^2_{NORM}	1.9695	0.3735	3.8302	0.1473
χ^2_{FF}	2.7253	0.0988	0.0647	0.7991

Source: Prepared by the authors using EViews 11.0 [125].

For the Breusch–Godfrey serial correlation LM test in Table 12, the test statistics are 2.0126 for Equation (2) and 0.0417 for Equation (3). The corresponding probability values are 0.3656 and 0.9794. Since both probability values are above 0.05, the null hypothesis of no serial correlation cannot be rejected at the 5% significance level. The probability values from the Breusch–Pagan–Godfrey and ARCH tests are also above 0.05 for both models. At the 5% significance level, no statistical evidence of heteroskedasticity or ARCH effects is found in the error terms of the models. For the Jarque–Bera test, the probability values are 0.3735 for Equation (2) and 0.1473 for Equation (3). The normality null hypothesis cannot be rejected at the 5% significance level. The Ramsey RESET test statistic is 2.7253 for Equation (2) ($p = 0.0988$) and 0.0647 for Equation (3) ($p = 0.7991$). At the 5% significance level, there is insufficient statistical evidence of functional form misspecification in either equation.

Parameter stability in the ARDL models over the sample period was also assessed using the CUSUM and CUSUMSQ tests [126]. Figure 5 shows that the CUSUM and CUSUMSQ test statistics for Equations (2) and (3) remain within the critical bounds at the 5% significance level. No evidence of clear parameter instability is found in either model over the sample period. An additional Wald test was also applied to both ARDL models to examine the joint significance of the lagged levels of the explanatory variables. The results are reported in Table 13.

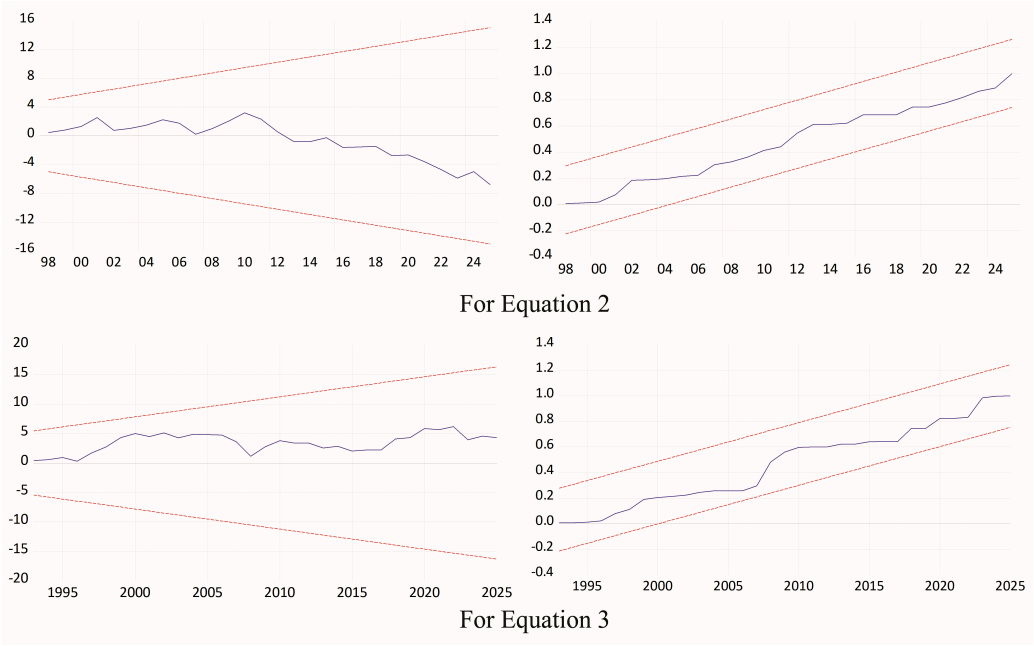


Figure 5. CUSUM and CUSUMSQ plots. Source: Prepared by the authors using EViews 11.0 [125].

Table 13. Joint significance tests for lagged explanatory-variable levels.

Model	F-Statistics	*p*-Value	Decision
Equation (2)	3.3356	0.0407	Reject H_0
Equation (3)	14.4648	0.0000	Reject H_0

H_0 states that the lagged levels of the explanatory variables are jointly equal to zero. The Wald tests were applied to the same ARDL specifications and estimation samples used in the baseline models. Source: Prepared by the authors using EViews 11.0 [125].

As shown in Table 13, the null hypothesis that the lagged levels of the explanatory variables are jointly equal to zero is rejected for both models. The Wald test is statistically significant at the 5% level for Equation (2) and at the 1% level for Equation (3). These results provide additional support for the long-run relationships identified by the bounds tests and reduce the concern that the rejections are driven only by level stationarity of the dependent variables. Therefore, the long-run interpretation of both ARDL models remains supported.

3.6. Robustness Analyses

The robustness analysis first examines the sensitivity of Equation (3) results to the construction of the ratio-based dependent variable. Equation (4) uses total material imports as the dependent variable and includes destroyed dwellings as a separate explanatory variable.

Table 14 reports the results for the alternative robustness specification in Equation (4). The F-Bounds statistic is 9.0048, which is above the upper critical bound at the 1% level. The error correction term is negative and statistically significant. These results indicate a long-run relationship among the variables in the alternative specification. Global crude steel production has a positive and statistically significant long-run coefficient. The coefficient for destroyed dwellings is also positive but is significant only at the 10% level. The homelessness coefficient is positive and statistically insignificant in this specification. The negative coefficient found in Equation (3) is therefore not preserved after total material imports are used as the dependent variable and destroyed dwellings are entered separately. This result shows that the relationship underlying H_4 is sensitive to the construction of the ratio-based dependent variable. H_4 is therefore supported by the baseline specification

but is not supported by the alternative robustness specification. This result is considered further in the discussion and conclusion sections.

Table 14. ARDL robustness results for Equation (4) *.

Bounds Test	**Test Statistics**	**Value**	**Result**	
	F-Bounds	9.0048 ***	Cointeg.	
	t-Bounds	−4.7252 ***	Cointeg	
Long-run estimates	**Coef.**	**Std. Error**	**t-Stat**	**Prob.**
lnwsp	2.1097	0.3302	6.3898	0.0000 ***
lnlhe	0.0843	0.0661	1.2764	0.2110
lntdh	0.1312	0.0766	1.7123	0.0965 *
Error correction	**Coef.**	**Std. Error**	**t-Stat**	**Prob.**
ECT_{t-1}	−0.2637	0.0420	−6.2766	0.0000 ***

* The estimates were made according to Case III. The selected model is ARDL(1,0,0,0), with lntmi as the dependent variable and an effective estimation sample of n = 37. For the newly introduced series, the unit root results classify *lntmi* as $I(1)$ and *lntdh* as $I(0)$. The ADF, KPSS, and Lee–Strazicich tests were used for this assessment. For the F-Bounds test, the finite-sample critical values for n = 35 were used, with $I(0)$ and $I(1)$ bounds of 5.198 and 6.845 at the 1% level. For the t-Bounds test, the corresponding 1% asymptotic bounds are −3.43 and −4.37. The diagnostic tests produced the following results: Breusch–Godfrey LM, F = 0.5868 (p = 0.5624); Breusch–Pagan–Godfrey, F = 1.2339 (p = 0.3162); ARCH, F = 0.0634 (p = 0.8027); and Ramsey RESET, F = 1.4797 (p = 0.2330). The CUSUM and CUSUMSQ statistics remained within the 5% critical bounds. * and *** indicate statistical significance at the 10% and 1% levels, respectively. Source: Prepared by the authors using EViews 11.0 [125].

The robustness of the ARDL results was also examined using structural break controls. These additional analyses assessed whether the main long-run relationships and coefficient directions were generally preserved under different model specifications. Given the relatively limited size of the annual sample, the findings in this section were interpreted as complementary analyses supporting the main results. The break dates endogenously identified by the Lee–Strazicich unit root test with two structural breaks were included in the ARDL models as exogenous control variables. The break dates were 1992–1997 for Equation (2) and 1992–1996 for Equation (3). The analysis examined whether the main ARDL results remained similar in terms of coefficient direction, long-run relationship and the error correction mechanism after accounting for structural changes during the sample period. The results are presented in Table 15.

Table 15. ARDL estimation results with structural break controls *.

Model	**Long-Run Coefficients**	**F-Bounds**	**ECT(−1)**
Equation (2)	lnpreb: 6.4314 lnsps: −6.3469	5.9710	−0.6913 ***
Equation (3)	lnwsp: 1.8366 ** lnlhe: −0.2689 **	20.7069	−1.2623 ***

* The symbols **, and *** denote statistical significance at the 5%, and 1% levels, respectively. For the structural-break-controlled specifications, the Breusch–Godfrey LM, Breusch–Pagan–Godfrey, ARCH, and Ramsey RESET tests yielded p-values above 0.05 based on the F-statistics (Model 1: 0.3316, 0.4660, 0.8488, and 0.0970; Model 2: 0.9852, 0.8844, 0.7286, and 0.9370, respectively), indicating no evidence of serial correlation, heteroskedasticity, ARCH effects, or functional-form misspecification at the 5% level. Source: Prepared by the authors using EViews 11.0 [125].

Adding the structural break controls slightly reduced the F-Bounds statistics in Table 15. However, the test statistics remained above the upper critical bound at the 5% significance

level in both models, and the long-run relationships were preserved. The inclusion of the structural break controls also did not change the ARDL lag structures selected by the AIC in either model. For Equation (2), the directions of the long-run coefficients remained the same as those in the baseline model. For Equation (3), both the coefficient directions and their statistical significance were preserved. The CUSUM and CUSUM2 controls are presented in Figure 6.

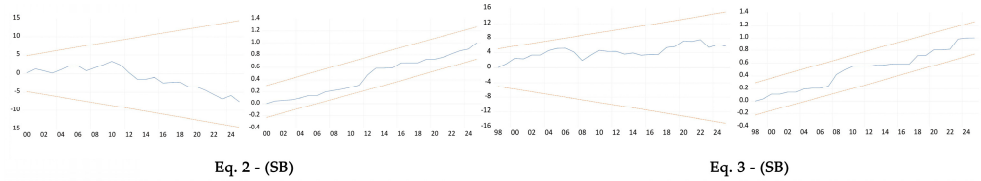


Figure 6. CUSUM and CUSUMSQ plots with structural break controls. Source: Prepared by the authors using EViews 11.0 [125].

In Figure 6, SB denotes the structural-break-controlled specification in which dummy variables representing the structural break dates are included in the model. The CUSUM and CUSUMSQ test statistics for the SB models remain within the 5% significance bounds. They do not indicate clear parameter instability after the inclusion of the structural break controls. An additional robustness analysis examined the main findings using alternative measures of disaster severity and possible lags in the reconstruction process. Annual earthquake economic losses as a share of GDP, the number of people affected by earthquakes, and the number of earthquakes were used as alternative disaster severity indicators [112]. Their relationships with material import intensity were examined for the same year and with one-year and two-year lags. Newey–West standard errors robust to heteroskedasticity and autocorrelation were used in the estimations. Figure 7 shows the distribution of these alternative indicators over time. It also shows the different dimensions of disaster impact represented by each indicator.

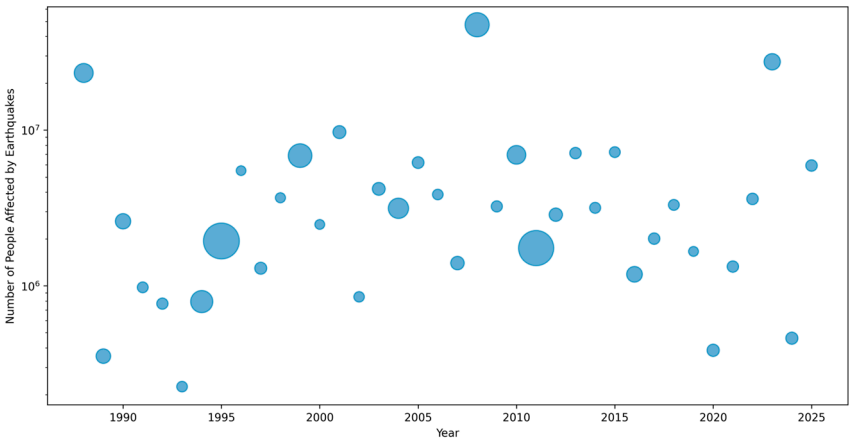


Figure 7. Annual global earthquake impacts based on affected population and economic damage. Note: Bubble size represents annual earthquake economic damages as a share of GDP. Source: Prepared by the authors using Python 3.13 in Visual Studio Code 1.141 [115,116].

As shown in Figure 7, country-level earthquake indicators are not observed continuously for every country and year. They have an intermittent structure. Annual world totals were therefore used to create a common and consistent time dimension for the study. The results of the additional robustness analyses using alternative disaster severity indicators and possible reconstruction lags are presented in Table 16.

Table 16. Robustness results using alternative earthquake severity indicators *.

Alternative Severity Indicator	Timing	Coef.	*p*-Value	R^2	N
People affected by earthquakes (ln)	Contemporaneous	−0.799 ***	<0.001	0.717	38
	1-year lag	0.200	0.264	0.452	37
	2-year lag	−0.320 **	0.043	0.466	36
Economic damage/GDP	Contemporaneous	−4.797 *	0.061	0.482	38
	1-year lag	−1.496	0.593	0.436	37
	2-year lag	−2.781 *	0.071	0.434	36
Number of earthquakes	Contemporaneous	0.368	0.649	0.448	38
	1-year lag	0.194	0.748	0.433	37
	2-year lag	−0.311	0.603	0.421	36

* The dependent variable is material import intensity per destroyed dwelling. All specifications include global crude steel production as an explanatory variable. Newey–West heteroskedasticity- and autocorrelation-consistent standard errors are used with a maximum lag of two. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Source: Authors' calculations using Python 3.13 in Visual Studio Code 1.141 [115,116].

Table 16 summarizes the additional robustness estimates based on alternative earthquake severity indicators and their contemporaneous, one-year lagged, and two-year lagged values. The results are presented to examine whether the main relationships remain under different measures of disaster severity and possible reconstruction lags.

Table 16 and Figure 8 show that the main negative relationship is partly preserved, especially for the number of people affected by earthquakes and the economic loss indicators. The contemporaneous and two-year lagged values of the number of people affected by earthquakes show negative relationships with material import intensity. Some lagged values of earthquake economic losses as a share of GDP also show negative relationships. The number of earthquakes is not statistically significant. This suggests that disaster impact should be considered together with the scale of the disaster and the size of the affected population, not only with the number of events. The additional analysis examines whether the main relationships remain under alternative measures of disaster severity and possible reconstruction lags. Because the data are based on world totals, the results should not be interpreted as showing direct material access at the country level.

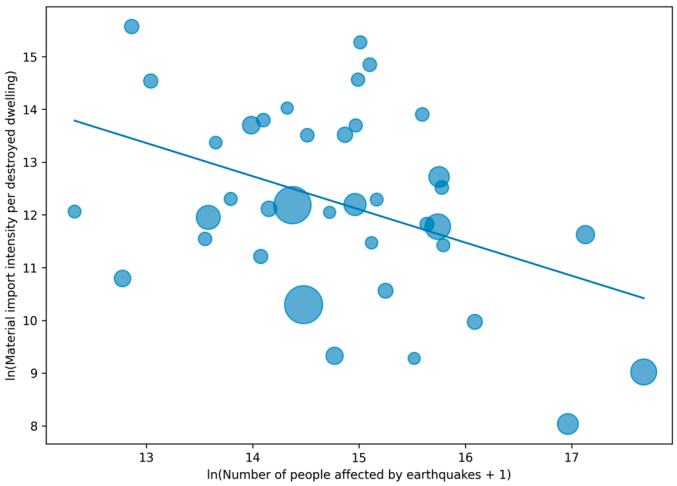


Figure 8. Relationship between earthquake severity and material import intensity. Note: Bubble size represents annual earthquake economic damages as a share of GDP. Source: Authors' calculations using Python 3.13 in Visual Studio Code with the Statsmodels [115,116].

4. Discussion

The findings indicate long-run statistical relationships between post-earthquake shelter and housing needs, construction material imports, and the global steel supply environment. These relationships represent long-run statistical associations among globally aggregated series. As reported in Tables 6 and 7, Equation (2) shows that prefabricated structure imports have a positive relationship with the homelessness indicator, although the coefficient is significant only at the 10% level. Imports of iron or steel structural components have a negative relationship with the homelessness indicator and are significant at the 5% level. Figure 3 provides complementary descriptive context for the temporal behavior of these three series. Accordingly, H_1 is not supported, whereas H_2 is supported. As reported in Tables 9 and 10, Equation (3) shows a positive long-run relationship between global crude steel production and material import intensity per destroyed dwelling, while the homelessness indicator has a negative long-run relationship with the same variable. Figure 4 provides complementary descriptive context for the temporal behavior of these variables. These results support H_3. The negative coefficient for the homelessness indicator is consistent with H_4 in Equation (3). However, this result is not preserved in the alternative specification in Equation (4). As reported in Table 14, the homelessness coefficient becomes positive and statistically insignificant when total material imports are used as the dependent variable and destroyed dwellings are included separately. H_4 is therefore not supported by the alternative specification.

The break dates identified by the Lee–Strazicich test were included in the models as exogenous control variables in the robustness analyses. This step was used to assess the sensitivity of the main ARDL results to structural changes. After these controls were added, the long-run relationship remained in both models. The coefficient directions in Equation (2) also remained unchanged. In Equation (3), both the coefficient directions and their statistical significance were preserved. These results indicate that the main findings are generally robust to structural breaks. The second set of additional robustness analyses shows that the main findings are generally preserved when alternative earthquake severity indicators and possible reconstruction lags are taken into account. The corresponding robustness results are reported in Table 16, while the baseline and structural-break-controlled parameter-stability results are presented in Figures 5 and 6, respectively. These results are treated as methodological checks on the robustness of the main findings. The alternative specification in Equation (4) is also used to assess whether the support for H_4 depends on the construction of the ratio-based dependent variable.

The results for Equation (2) indicate a long-run relationship between the homelessness indicator representing post-earthquake shelter and housing needs and imports of prefabricated structures and iron or steel structural components. The two product groups are therefore not related to the homelessness indicator in the same direction. Post-disaster housing provision involves material availability, as well as costs, planning, implementation and adaptation to local conditions [127–129]. The Türkiye case also shows the importance of implementation and use conditions in the assessment of prefabricated temporary housing [130]. The relationships found here should be interpreted as empirical findings on the material supply and international access dimension of reconstruction. They represent the material supply and international access dimension of reconstruction.

The findings for Equation (3) indicate a positive and statistically significant long-run relationship between global crude steel production and material import intensity per destroyed dwelling. A negative and statistically significant long-run relationship is found between the homelessness indicator and the same variable. These results support H_3. The result for H_4 is therefore sensitive to model specification. The negative relationship should be interpreted as an association between the scale of earthquake-related homelessness

recorded in a given year and material import intensity per destroyed dwelling. Because the homelessness indicator records needs arising from earthquake events rather than unresolved needs throughout the subsequent recovery period, this result does not imply that later material imports reduce the number of people initially recorded as homeless. The literature also treats resource provision and allocation as important issues in post-disaster housing reconstruction. Recovery also involves wider factors such as the resettlement of displaced populations and local conditions [74,131,132]. The relationship between global steel supply and material import intensity should therefore be interpreted as a finding on the material supply and international access channel within the broader reconstruction process. The logistical, financial, institutional, and supply-side mechanisms behind this relationship were not tested directly in this study. The study examines post-earthquake shelter needs, construction-material imports, and the global steel supply environment together within a common world-year time-series setting for 1988–2025.

The Hatemi-J asymmetric directionality results reported in Table 11 indicate dynamic relationships in different directions between positive and negative shocks in the variables. A statistically significant directional relationship is found from negative shocks in imports of iron or steel structural components to positive shocks in prefabricated structure imports. This suggests that shocks in the two product groups do not move completely independently. Directional shocks in global crude steel production and the homelessness indicator are also related to shocks in material import intensity per destroyed dwelling. In the time-series setting, these relationships contain predictive information. Post-disaster shelter, temporary housing and permanent housing recovery form a multidimensional process with different stages and requirements [30]. Housing quality, implementation time, planning and institutional coordination are also important in this process. Temporary housing practices can involve cost and use problems [130]. The housing needs of displaced populations can differ across time and location [129]. Recovery also has institutional and social dimensions [131]. The directional relationships found in the analysis should therefore be interpreted as limited empirical evidence that different material channels in the reconstruction process can move differently over time.

The findings indicate that the material dimension of post-earthquake housing reconstruction needs to be considered together with actual patterns of access to construction materials in relation to housing loss and shelter needs. The empirical findings are limited to the observed statistical relationships among earthquake-related housing needs, material imports, material import intensity, and global steel supply. The empirical models do not test broader recommendations on coordination, logistics, financing, equitable access, or trade facilitation. These recommendations come from the wider post-disaster reconstruction literature. They should be read as policy implications and not as findings established directly by the present analysis. The sustainability relevance of these findings lies in the material access dimension of post-disaster reconstruction. Resilient and equitable access to construction materials is discussed in the wider reconstruction literature as part of sustainable recovery, although these dimensions are not directly tested in the present study. Previous studies have discussed institutional coordination problems in post-disaster response and the role of collaborative governance networks in recovery. The relationship between humanitarian assistance and long-term social vulnerabilities has also been examined [132–135]. Resource supply difficulties in housing reconstruction have been discussed as well [74].

This study has several limitations. The small sample may also limit the statistical power of the estimates. Results that are only marginally significant should therefore be interpreted with caution. The analysis is based on annual world totals and does not separate differences across countries in trade regimes, institutional capacity, disaster scale, industrial infrastructure or economic structure. The findings should therefore not be interpreted

as country-level effects or average country behavior. Global import totals also include ordinary construction demand and imports by countries not directly affected by major earthquakes. For this reason, disaster-related material demand cannot be fully separated from general construction activity. The scope of the indicators also limits their interpretation. The post-earthquake homelessness indicator represents the scale of shelter and housing needs. It does not measure the duration of the crisis or the speed of recovery. Material import intensity per destroyed dwelling is not a direct indicator of reconstruction capacity or housing efficiency. Global crude steel production represents the global supply environment and does not measure actual material access in a specific region. The study focuses on products classified under HS 9406 and HS 7308. Because HS 9406 covers a broad category of prefabricated buildings that includes more than steel modular building units, this variable should be interpreted as an aggregated indicator of prefabricated building imports. Other construction materials and local production are outside the empirical model. Import values are measured in current US dollars and are not adjusted for inflation. Changes in the general price level and fluctuations in international construction-material prices may therefore partly affect their movement over time. The import variables may reflect price effects, as well as changes in physical quantities. Governance, finance, infrastructure, labor, logistics and trade barriers are also not directly modeled. These mechanisms cannot therefore be interpreted as empirically verified causes. The Hatemi-J results also do not indicate structural causality or complete substitution between the product groups. The analysis covers 38 annual observations from 1988 to 2025. A parsimonious model structure, lag selection based on information criteria, structural break controls and CUSUM/CUSUMSQ tests help assess the effect of this limitation. They do not eliminate the small-sample problem. The findings should therefore be interpreted as statistical relationships among global aggregate series. The findings should therefore not be generalized directly to specific countries, individual earthquakes, or local reconstruction processes.

5. Conclusions, Policy Recommendations and Future Research

This study examined the long-run statistical relationships among post-earthquake shelter and housing needs, construction material imports and the global steel supply environment using two empirical models. The study links post-earthquake shelter and housing needs with two different construction-material import channels and the broader global steel supply environment in the same empirical framework. It also uses a material import intensity indicator that normalizes construction-material imports by the number of destroyed dwellings. This allows global supply conditions and the material access dimension of reconstruction to be examined together. The findings point to international material access and global supply conditions as factors that need attention in post-disaster reconstruction planning. The additional robustness results show that several observed relationships remain under alternative measures of disaster severity and structural-break controls, but the result for H_4 is not preserved when total material imports replace the ratio-based dependent variable and destroyed dwellings are entered separately.

The empirical findings concern statistical relationships among earthquake-related housing needs, material imports, material import intensity, and the global steel supply environment. The study did not directly test policy measures related to governance, financing, logistics, infrastructure, local production capacity, procurement arrangements, customs procedures, or equitable access. Framework supply agreements, emergency procurement planning for product groups such as HS 9406 and HS 7308, and expedited customs and logistics procedures come from the broader literature. They should be read as policy implications and not as effects established empirically in this study. The robustness results also suggest caution in linking the homelessness indicator directly to these policy implications.

The positive long-run relationship between global steel supply and material import intensity provides context for considering these procurement, customs, and logistics arrangements as policy options drawn from the literature. The sustainability relevance of the findings lies in the material access and supply resilience dimensions of post-disaster reconstruction. These dimensions are related to sustainable recovery in the broader literature, but they are not directly measured in the present analysis. The study does not directly measure environmental performance, carbon emissions or life-cycle effects. Its conclusions regarding sustainability are therefore limited to the scope examined here.

Research using country-level or higher-frequency data, where available, could examine institutional and economic differences across countries. Variables such as customs clearance times, port efficiency, trade facilitation indicators, financial capacity, local production, infrastructure and labor could also be included directly in the models. These mechanisms can be tested directly using country-level or disaster-level panel data or event-based designs. Their effects on material imports and reconstruction outcomes can then be examined. This would allow empirical testing of mechanisms that are considered only as possible explanations in this study. Such analyses could provide a more detailed assessment of the relationships between post-disaster material access, supply chain resilience, efficient resource use and long-term sustainable reconstruction. This approach will also allow a closer examination of the extent to which the relationships identified at the global level apply to specific countries and disaster settings.

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Abbreviations

The following abbreviations are used in this manuscript:

ADF	Augmented Dickey–Fuller
AIC	Akaike information criterion
ARCH	Autoregressive conditional heteroskedasticity
ARDL	Auto regressive distributed lag
CUSUM	Cumulative sum of recursive residuals
CUSUMSQ	Cumulative Sum of Squares of Recursive Residuals
CV	Critical values
ECM	Error Correction Model
ECT	Error correction term
EM-DAT	Emergency Events Database

FPE	Final Prediction Error
GDP	Gross Domestic Product
HJC	Hatemi-J Criterion
HQ	Hannan–Quinn Information Criterion
HS	Harmonized system
JB	Jarque–Bera
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LM	Lagrange multiplier
LR	Likelihood Ratio
LS	Lee–Strazicich
NOAA	National Centers for Environmental Information
RESET	Ramsey Regression Equation Specification Error Test
SB	Structural-Break-Controlled specification
SC	Schwarz Criterion
UN	United Nations
UR	Unit root
US	United States
USD	United States Dollar
VAR	Vector autoregression
WSA	World Steel Associations
WTO	World Trade Organization

Appendix A

Table A1. Hatemi-J Asymmetric Causality Test Results for All Tested Directions.

			Bootstrap CV		
Directions	**Lag**	**MWald Stat**	**1%**	**5%**	**10%**
Equation (1)					
$lnlhe^{+} \rightarrow lnpreb^{+}$	1	0.154	8.884	4.932	3.520
$lnlhe^{+} \rightarrow lnpreb^{-}$	1	0.482	10.480	5.136	3.380
$lnlhe^{-} \rightarrow lnpreb^{-}$	1	0.000	13.190	5.793	3.660
$lnlhe^{-} \rightarrow lnpreb^{+}$	1	1.375	9.618	4.911	3.150
$lnpreb^{+} \rightarrow lnlhe^{+}$	1	2.421	8.876	4.767	3.480
$lnpreb^{+} \rightarrow lnlhe^{-}$	1	0.171	8.682	4.749	3.180
$lnpreb^{-} \rightarrow lnlhe^{-}$	1	0.002	12.710	5.431	3.610
$lnpreb^{-} \rightarrow lnlhe^{+}$	1	0.234	9.446	5.273	3.220
$lnsps^{+} \rightarrow lnlhe^{+}$	1	2.262	9.232	4.957	3.430
$lnsps^{+} \rightarrow lnlhe^{-}$	1	0.006	9.447	4.846	3.310
$lnsps^{-} \rightarrow lnlhe^{-}$	1	0.023	11.180	5.592	3.610
$lnsps^{-} \rightarrow lnlhe^{+}$	1	0.052	8.781	4.925	3.230
$lnlhe^{+} \rightarrow lnsps^{+}$	1	0.284	10.630	4.949	3.350
$lnlhe^{+} \rightarrow lnsps^{-}$	1	0.234	9.778	4.895	3.180
$lnlhe^{-} \rightarrow lnsps^{-}$	1	0.003	14.020	6.347	3.780
$lnlhe^{-} \rightarrow lnsps^{+}$	1	0.712	10.030	4.829	3.240
$lnsps^{+} \rightarrow lnpreb^{+}$	1	0.692	9.780	4.797	3.170
$lnsps^{+} \rightarrow lnpreb^{-}$	2	0.408	21.120	10.850	7.160
$lnsps^{-} \rightarrow lnpreb^{-}$	1	1.850	12.940	5.807	3.570
$lnsps^{-} \rightarrow lnpreb^{+}$	2	12.729 **	20.300	8.935	6.820
$lnpreb^{+} \rightarrow lnsps^{+}$	1	0.065	8.692	4.369	2.900
$lnpreb^{+} \rightarrow lnsps^{-}$	2	0.937	20.480	10.570	7.340
$lnpreb^{-} \rightarrow lnsps^{-}$	1	0.706	16.160	5.842	4.090
$lnpreb^{-} \rightarrow lnsps^{+}$	2	2.474	19.150	8.840	6.200

Table A1. *Cont.*

Directions	Lag	MWald Stat	Bootstrap CV		
			1%	5%	10%
Equation (2)					
$lnwsp^{+} \rightarrow lndr^{+}$	1	8.655 **	14.400	4.750	2.870
$lnwsp^{+} \rightarrow lndr^{-}$	1	0.001	19.240	7.467	4.310
$lnwsp^{-} \rightarrow lndr^{-}$	1	0.013	14.490	4.381	2.930
$lnwsp^{-} \rightarrow lndr^{+}$	1	0.587	10.800	4.729	2.970
$lndr^{+} \rightarrow lnwsp^{+}$	1	0.859	11.520	4.887	3.430
$lndr^{+} \rightarrow lnwsp^{-}$	1	0.002	9.705	4.952	3.300
$lndr^{-} \rightarrow lnwsp^{-}$	1	0.053	16.170	5.778	3.610
$lndr^{-} \rightarrow lnwsp^{+}$	1	0.107	13.200	5.693	3.630
$lnlhe^{+} \rightarrow lndr^{+}$	1	5.251 **	9.108	4.608	2.980
$lnlhe^{+} \rightarrow lndr^{-}$	1	0.034	13.510	5.464	3.250
$lnlhe^{-} \rightarrow lndr^{-}$	1	10.775 ***	10.320	4.429	3.060
$lnlhe^{-} \rightarrow lndr^{+}$	1	1.644	12.700	5.207	3.060
$lndr^{+} \rightarrow lnlhe^{+}$	1	0.613	7.743	4.408	3.090
$lndr^{+} \rightarrow lnlhe^{-}$	1	0.021	9.360	5.277	3.110
$lndr^{-} \rightarrow lnlhe^{-}$	1	2.804	9.711	4.825	3.240
$lndr^{-} \rightarrow lnlhe^{+}$	1	0.247	9.012	4.764	3.280
$lnwsp^{+} \rightarrow lnlhe^{+}$	1	0.375	9.045	4.630	3.100
$lnwsp^{+} \rightarrow lnlhe^{-}$	1	0.161	9.662	4.583	3.330
$lnwsp^{-} \rightarrow lnlhe^{-}$	1	0.011	11.400	4.881	3.220
$lnwsp^{-} \rightarrow lnlhe^{+}$	1	0.046	9.383	4.793	3.100
$lnlhe^{+} \rightarrow lnwsp^{+}$	1	0.080	10.150	5.338	3.600
$lnlhe^{+} \rightarrow lnwsp^{-}$	1	2.523	10.520	4.521	3.080
$lnlhe^{-} \rightarrow lnwsp^{-}$	1	0.002	12.290	5.992	3.540
$lnlhe^{-} \rightarrow lnwsp^{+}$	1	0.073	14.020	5.042	3.340

The sub-indices indicate the model under examination. The symbols ** and *** denote statistical significance at the 5% and 1% levels, respectively. Lag lengths were selected using the Hatemi-J Criterion (HJC), with dmax = 1. Leveraged bootstrap critical values were obtained using 1000 bootstrap replications. Source: Prepared by the authors using Gauss 14.0 [122].

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