Jurnal Ekonomi Malaysia 57(2) 2023 149-161
http://dx.doi.org/10.17576/JEM-2023-5702-11

Impact of Natural Disasters on House Prices: Evidence from Indonesia

(Kesan Bencana Alam ke atas Harga Rumah: Bukti dari Indonesia)

Ariyanto Adhi Nugroho
Universitas Sebelas Maret
Yunastiti Purwaningsih
Universitas Sebelas Maret
Lukman Hakim
Universitas Sebelas Maret
Suryanto
Universitas Sebelas Maret

ABSTRACT

This study examined how natural disasters affect house prices in Indonesia. The study used quarterly data from 16 provinces spanning 2012 to 2019, with the data set of natural disasters constructed as dummy variable. The regions were then clustered based on their disaster vulnerability. Panel data regression was conducted to test whether house prices in areas with different frequencies of natural disaster events adjust to market prices in the housing market. In moderate-risk regions with frequent earthquakes and volcanic eruptions, the higher regional income and greater minimum salaries were associated with increased housing prices. Conversely, higher population density led to a decline in house prices. However, areas prone to frequent floods, better economic conditions and increased minimum salaries were linked to declining house prices. The situation in high-risk regions was the reverse of that in moderate-risk areas. In regions with high disaster vulnerability, the rise in house prices is likely to decelerate. Regardless of this association, an increase in housing price was inevitable due to inherent regional factors even if the houses were located in a high disaster-risk area. This study extends the housing demand theory by explaining the influences of endogenous and exogenous factors on housing prices. The latter factors can influence through different responses depending on socio-economic conditions affected by the three major disasters, based on vulnerability of the clusters. Natural disasters and regional economic diversification offer potential benefits related to the policy of stakeholders' housing prices.

Keywords: Clustering; disaster vulnerability; house price; natural disaster; regional factor

ABSTRAK

Kajian ini bertujuan menganalisis sejauh manakah pengaruh bencana alam dapat mempengaruhi harga rumah di Indonesia. Metodologi: Kajian ini menggunakan data suku tahunan dari tahun 2012 hingga 2019 yang melibatkan 16 wilayah di Indonesia, dengan data bencana alam bertindak sebagai pemboleh ubah dami. Kajian ini mengelompokkan wilayah yang terjejas berdasarkan kepada tahap kerentanan bencana. Analisis regresi data panel telah digunakan untuk menguji sejauh manakah harga rumah di daerah yang mempunyai frekuensi bencana alam yang berbeza memberi kesan kepada harga pasaran rumah. Di kawasan risiko sederhana dengan kejadian gempa bumi dan letusan gunung berapi yang kerap, pendapatan wilayah yang lebih tinggi dan gaji minimum yang lebih besar dikaitkan dengan peningkatan harga rumah. Sebaliknya, kepadatan penduduk yang lebih tinggi mengakibatkan penurunan harga rumah. Walau bagaimanapun, kawasan yang cenderung mengalami banjir yang kerap, keadaan ekonomi yang lebih baik dan gaji minimum yang lebih tinggi dikaitkan dengan penurunan harga rumah. Situasi di kawasan berisiko tinggi adalah berlawanan daripada kawasan risiko sederhana. Di kawasan dengan frekuensi bencana yang tinggi, peningkatan harga rumah adalah agak perlahan. Namun begitu, kenaikan harga rumah tidak dapat dihindari kerana pengaruh faktor wilayah yang lebih dominan sehingga harga rumah menjadi lebih tinggi meskipun rumah tersebut berada di daerah yang berisiko tinggi mengalami bencana alam. Kajian ini meluaskan teori permintaan perumahan dengan menjelaskan pengaruh faktor endogen dan eksogen terhadap harga rumah. Faktor eksogen dapat mempengaruhi harga rumah melalui respon yang berbeza bergantung kepada keadaan sosio ekonomi berdasarkan tahap kerentanan yang *disebabkan oleh tiga bencana terbesar tersebut. Bencana alam dan kepelbagaian ekonomi di wilayah yang berisiko berhadapan dengan bencana mempunyai beberapa manfaat kepada pihak berkepentingan dalam merekabentuk dasar harga perumahan.*

Kata kunci: Pengelompokan; kerentanan bencana; harga rumah; bencana alam; faktor wilayah
JEL: R11, R31, Q54
Received 1 June 2023; Revised 30 August 2023; Accepted 21 September 2023; Available online 25 September 2023

INTRODUCTION

The housing sector basically aims for investment while fulfilling the primary human needs for shelter (Arrondel & Lefebvre 2001). Consequent to the global crisis triggered by the housing sector in the U.S. in 2007-2008, several countries had carried out macroprudential policies of their own. Housing price stability must be maintained, considering that housing is an investment instrument, and most home purchases are made through credit schemes. Differences in housing prices are generally influenced by endogenous factors related to house specifications and exogenous factors related to issues of location.

Housing prices are affected by several factors, including financial aspects, location, and environmental issues. Location is important in housing prices. Houses with good access, supporting infrastructure and without negative issues, such as disasters, may accentuate demand growth which can increase house prices accordingly. Considering the uniqueness of house locations, borrowers have the freedom to act differently in terms of foreclosure, for instance, through changes in mortgage rates that will affect default and prepayment loans (Fang & Munneke 2020; Kelly et al. 2018; Kelly & O'Toole 2018; Pong & Hook 2017).

Indonesia has a vast territory comprising thousands of islands with some strung along tectonic plate boundaries known as the volcanic "Pacific ring of fire". The potential for disaster in Indonesia is relatively high since geographically, the country is located at the confluence of three major tectonic plates, the Indian-Australian, Eurasian and Pacific. Regional differences in each province have their unique characteristics historically related to volcanic disasters which impact the populace through floods, earthquakes, and eruptions. Each occurrence of disaster leaves in its wake increased local poverty (Bui et al. 2014; Johar et al. 2022; Lopus et al. 2019; Silbert et al. 2012; Timar et al. 2018; Toya & Skidmore 2007). The community's income or wealth level plays a significant role in disaster vulnerability since the community will seek to rebuild shelter for security. In addition, natural disasters also compel stakeholders to decide on and set economic stimulus as mitigation measures.

The development of housing prices based on the Residential Property Price Index (RPPI) in 18 regions in Indonesia (Bank Indonesia) is subjected to fluctuation, creating gaps in house prices between regions. Over the last decade, the smallest movement in house prices in Indonesia occurred in 2016, with only a 0.30 percent increase whereas the highest house price index surge occurred in 2019, charting 348.15 points, in the East Java Province. These fluctuations are influenced by the respective endogenous and exogenous factors in each region, such as the diversity of geographical and socio-economic conditions. Exogenous factors may include the vulnerability to natural disasters in each region during which catastrophic earthquakes and volcanic eruptions may occur, as in East Java in 2014, with major impact on the populace. Past studies have yet to include disaster-induced vulnerable clusters to examine impact on house prices. These have included cluster research on house prices based on regional areas, analyses on cluster areas affected by floods (Bakkensen et al. 2019) and similar analyses on house prices affected by earthquakes and eruptions (Varga et al. 2012).

Given the above cognizance, this study aims to examine the response of housing prices to respective natural disasters in two provinces and compare this based on their disaster-vulnerability. According to Bakkensen et al. (2019), there were relatively minor house price differences between flood-prone and non-disaster-prone areas. Local governments need to be knowledgeable on regional factors that can affect housing prices in the event of disasters. In addition, regional groupings based on disaster vulnerability should provide empirical evidence necessary in drafting relevant policies. This can support decision-making in maintaining price stability and reducing price fluctuations affecting banking risk.

Housing is an important sector of economic activity in a country and economic stability can be disrupted when housing prices fluctuate. The majority of housing purchases are made through long-term bank credit facilities. If housing market conditions are unstable, credit risks may arise for banks, followed by economic turmoil in property-related sectors. This was proven by the global crisis caused by subprime mortgage in the the housing sector of the U.S., in 2007-2008. In consequence, several countries carried out macroprudential policies, especially on housing loans. Through the "Loan to Value" scheme (LTV) implemented by Bank Indonesia, the macroprudential policy aims to control the housing market. This can be effective considering that most of the population purchase houses through mortgages. Community response in areas that are vulnerable to disasters may vary between provinces.

The objective of this paper is to examine the effect of natural disasters such as floods, earthquakes, and volcanic eruptions on housing prices and to analyse the influence of regional factors. This novel perspective will elucidate whether the impact of these disasters displays regional differences. We used a distinctive fixed effect panel data analysis in our study which sets it apart from those reported in the existing literature. Our analysis encompasses three different categories of natural disasters, designed to enhance our understanding on how these catastrophic events influence housing prices.

This study should contribute to the growing literature on the subject to fill extant information gap. To the best of our knowledge, no prior studies have particularly focused on the interactions of all three types of natural disasters. For example, Bin & Polasky (2004) and Fang et al. (2023) only addressed two types of natural disasters (the impact of hurricanes that led to flooding) which affected housing prices. The remainder of the earlier studies have all focused on only one type of disaster in their research work. In addition, they utilised data from a purchase transaction survey. In comparison this study sourced house price data from information related to residential property development as an indicator of asset price inflation. This study sheds light on the complex interplay between natural disasters, regional factors and house prices. It potentially provides valuable insights for policymakers, real estate investors, and homeowners seeking informed decisions in the face of recurrent natural disasters. In addition, regional factors also play an important role in maintaining the stability of housing prices in disaster-affected areas.

LITERATURE REVIEW

The main factor influencing the housing market is house prices. According to the law of demand, the number of homes demanded increases when prices fall. The demand for housing also depends on household wealth, current income, and interest rates. Tsai (2019) found that in most areas, house prices tend to converge based on income levels, which reflect the demand for housing. Meanwhile, most house purchases are made using a credit scheme, so the tenor of housing loans impacts house prices. Housing demand conditions can react asymmetrically when housing prices are too high or too low because of their relationship to housing loans. The main factor affecting the housing supply is housing prices. When the price increases, the quantity supplied also increases. Changes in input prices and changes in technology shift the housing supply. The housing market equilibrium determines the quantity and price of traded housing.

The housing cycle may have national and regional elements (Del Negro & Otrok 2007). The diversity of regional factors that make up the advantages of each region cannot be considered as the aggregate of the housing market. This is consistent with Duran & Özdoğan (2020) and Tsai (2019; 2022) who posit that there are housing market characteristics in each region that cannot be measured in aggregate. Appreciation of house prices is very heterogeneous between regions. The causes of heterogeneity of the housing market that lead to appreciation can be due to high urbanization, population size, crime rate, openness to trade, location near the beach, population density and cultural diversity.

Tomal (2021) maintained that the housing cycle may depend on local factors, but national factors affect the cycle through the implementation of national policies. At the same time, monetary policy can be transmitted differently across a series of clusters. In fact, Adams & Füss (2010) identified specific demand and supply characteristics at the Metropolitan Statistical Area (MSA) level, that include population growth and elasticity of housing supply, are important relationships that translate national monetary policy and sentiment into housing price inflation. Therefore, identifying regional clusters of the housing cycle is relevant information for optimal monetary policy implementation.

Groupings in the housing market can be explained on several grounds, either by their characteristics, namely the price level or through the ripple effect phenomenon (Brzezicka & Wisniewski 2016), including socio-economic factors such as unemployment level, wages, the size and quality of the housing stock (Tomal 2021). The consumer's perspective in choosing a house should also be considered, and they have different preferences regarding structural characteristics, which can lead to a significant diversification of residential properties in different locations. Bin & Landry (2008); Cheung et al. (2018); Hallstrom & Smith (2005); and Kiel & Matheson (2018) indicated the difference in housing prices between areas with low or high natural disaster risk. Environmental disturbances caused by natural hazards will have a negative impact on the residential housing unit price. In this regard, Echegaray-Aveiga et al. (2020) concluded that consumers would be willing to pay higher prices to avoid the potential impact of a natural disaster such as volcanic eruption.

Cortés & Strahan (2017) examined how financially integrated banks respond to natural disasters. Interest rates and credit are the most influential factors in the real estate sector, and housing construction is one of these. Furthermore, borrower behavior concerning the location's uniqueness provides the freedom to act differently regarding loan termination, for example, through changes in mortgage rates that will affect the default and prepayment loans (Fang & Munneke 2020; Kelly et al. 2018; Kelly & O'Toole 2018; Kepili 2020). Koetter et al. (2019) stated that banks with corporate customers in critical areas will experience direct impacts from the occurrence of flood damage.

Cheung et al. (2018) used repeat-sales and difference-in-differences models to examine the impact of earthquakes on Oklahoma's housing market. They found that the risk of natural disasters affects buyers and sellers to reassess property values based on their best estimate of the potential losses experienced by the house or the cost of insuring against these losses. The occurrence of a low-intensity earthquake that is unlikely to cause much damage will have little effect on house prices. However, sales prices may decline by around 3.5–10.3 percent with houses damaged by strong earthquakes.

The transformation of house prices at a regional level is highly dependent on regional factors (Apergis & Rezitis 2003; Duran & Özdoğan 2020a; Mallick & Mahalik 2015; Tomal 2021; Wang et al. 2011), especially in Indonesia. The country is known as the ring of fire, located between three large tectonic plates: the Eurasian, Indo-Australian, and Pacific Plates. In addition, Indonesia is an archipelagic country that has widely different geographical characters. These geological and geographic features characterized Indonesia as a disaster-prone country, especially with her sprawling size and hence diversity in disaster occurrences.

Indonesia has characteristics that are similar to areas studied in earlier research in terms of location, regional characteristics, and references to disaster routes. Such studies include Bin & Landry (2008) in Carteret County, North Carolina and Bin & Polasky (2004) in Pitt County, North Carolina, regarding flood hazards, Cheung et al. (2018) in Oklahoma and Alexander (1984) in Southern Italy regarding earthquakes, Hallstrom & Smith (2005) on hurricanes in the U.S. and Kiel & Matheson (2018) as related to canyon fires. All these natural disasters have an impact on house prices.

Research on the impact of natural disasters in Indonesia is normally related to the impact of earthquakes and flooding on the economy (Cameron Manisha Shah Cameron 2015; Gignoux & Menéndez 2016; Kirchberger 2017). As preparation, communities are required to be more responsive in determining the location of their residence. The study by Surjono et al. (2021) in Palu, Indonesia, stated that the populace were reluctant to relocate their residence due to reasons of family social structure, tsunami and flood-prone areas, land prices, road conditions, and the built area of the house. In addition, Priyanto et al. (2022) observed from the developer's point of view that certain regions in Indonesia offered expensive housing costs due to level of risk from natural disasters, as well as delays in providing utilities and building materials. The condition of the housing market in Indonesia is clearly influenced by natural disasters.

Research related to disasters in the housing market is normally focused on one type of natural disaster, such as earthquakes (Faenza & Pierdominici 2007; Mukhopadhyay et al. 2004; Toma´sˇfischer & Horaíek 2003; Varga et al. 2012), floods (Bin & Landry 2008; Bin & Polasky 2004; Kawasaki et al. 2020), and volcanic eruptions (Sukhwani et al. 2021). Research on clustering areas based on vulnerability to natural disasters is thus rarely carried out including investigations into the conditions of other types of natural disasters. This study identified differences in treatment in the housing market, as well as patterns that enable one to make informed decisions on how to mitigate risks and prepare for future events. The conditions in Indonesia offer advantages and uniqueness for each region that may enrich the literature on the housing market.

RESEARCH METHODOLOGY

DATA AND VARIABLES DESCRIPTIONS

In order to determine the response of housing price within the same area cluster, an analysis was conducted on a quarterly dataset spanning 2012 to 2019, for 16 regions. The regions were selected based on data availability from Bank Indonesia's Residential Property Price Survey (SHPR), which includes North Sumatera, Riau, West Sumatera, Riau Island, South Sumatera, and Lampung provinces from Sumatra Island. In West Java, DI Yogyakarta, Central Java, and East Java provinces were selected, including Bali province from Bali Island. In addition, West Kalimantan, South Kalimantan, and East Kalimantan provinces from Borneo, and North Sulawesi and South Sulawesi provinces from Sulawesi Island were also included. The incorporation of regional factors as research data in the determination of house prices was expected on socio-economic considerations. The independent variables used were regional factors consisting of gross regional domestic product (GRDP), salary (w), and density (d). In addition, we also included control variables, namely mortgage rate (r) and loan-to-value ratio (ltv), to control for most home purchases made through loans. These variables are represented in the home purchase scheme. The research data used are shown in Table 1:

TABLE 1. Variable definitions

Variables	Descriptions	Measurement
hp	House prices values: measured using an index developed based on the housing price in the selected regions	Index (Index 2012=100)
flood	Type of natural disaster (N.D.); measured in dummy variable, where (0) represents data before the flood occurred and (1) after the event.	dummy variable
earthquake	Type of natural disaster (N.D.); measured in dummy variable, where (0) represents data before the earthquake occurred and (1) after the event	dummy variable
eruption	Type of natural disaster (N.D.); measured in dummy variable, where (0) represents data before volcanic eruption and (1) after eruption	dummy variable
GRDP	Gross regional domestic product measured at constant market prices in unit price	log of GRDP
w	Provincial minimum wage or salary in unit price	log of wage
d	Population density measured by the total population in km2 in each region	log of density
r	Mortgage rate	percentage
ltv	Ratio of loan-to-value policy	percentage

Sources: Author's compilation

Data for this study were obtained from various sources. House price data were sourced from Residential Property Price Index published by Bank Indonesia. This index is one of the region's quarterly economic indicators of residential property developments, both in the current and upcoming quarters. Regional factor data were obtained from Statistics Indonesia (BPS), and natural disaster data from the National Disaster Management Agency (BNPB). The mortgage rate data were obtained from the Indonesian Financial Services Authority (OJK), and the loan-to-value ratio data, from Bank Indonesia.

TABLE 2. IRBI Index for cluster specification

Province	IRBI index					Cluster
	2015	2016	2017	2018	2019	
Riau Island	116.4	116.4	116.4	116.4	116.4	MODERATE
Bali	169.6	152.83	152.2	145.24	134.98	MODERATE
West Kalimantan	157.11	143.82	141.48	138.49	138.49	MODERATE
North Sumatera	151.04	151.04	146.19	141.45	139.47	MODERATE
South Sumatera	143.93	140.82	139.67	139.67	139.62	MODERATE
DI. Yogyakarta	165.28	146.87	145.18	142.24	140.92	MODERATE
East Java	171.39	168.94	165.79	152.4	143.07	MODERATE
Central Java	157.73	150.85	149.11	146.43	144.91	HIGH
North Sumatera	150.22	146.04	145.26	145.25	145.18	HIGH
South Kalimantan	151.6	147.31	147.31	145.37	145.37	HIGH
Lampung	156.72	153.26	152.71	148.44	146.78	HIGH
Riau	147.27	147.27	147.27	147.27	147.27	HIGH
West Sumatera	153.16	153.16	151.56	151.56	150.24	HIGH
West Java	168.15	163.18	158.52	152.13	150.46	HIGH
East Kalimantan	166.64	156.7	156.03	155.49	154.79	HIGH
South Sulawesi	166.77	164.45	162.59	160.05	159.49	HIGH

Source: National Disaster Management Agency (BNPB) report

The clusters were based on the disaster vulnerability (IRBI) level in each region (See Table 2). The cluster group was divided into two based on natural disaster vulnerability; namely high and moderate risk group.

The disaster risk level was assessed based on its components; hazard, exposure, and government and community capacity in dealing with disasters. Hazard (danger) was calculated based on spatial probability, frequency, and strength (magnitude) of a natural phenomenon, such as earthquakes, floods and volcanic eruptions. Exposure (vulnerability) was calculated based on socio-cultural, economic, physical, and environmental parameters, while capacity was computed using the regional resilience level approach. The risk index value for natural disaster vulnerability can be used as a valid basis for determining regional clusters. In this study, we used natural disasters comprising earthquakes, floods, and volcanic eruptions.

MODEL SPECIFICATION

Three models were used in the study. The first model tests the direct effect of each regional characteristic on the housing price. The second model includes natural disasters to elucidate its effect on the baseline model, and the third model examines the indirect impact of natural disasters on housing price. The specification in Equation 3 includes an interaction term between the variable of each disaster on t (years) in the area of occurrence. We did not use logarithm transformation of a variable that represents a house price index since it is inherently a ratio with a base year of 100 as the divisor. The equations for each model are multiple linear-log as follows:

$$hp_{it} = \alpha + \beta_1 \lg(grdp)_{it} + \beta_2 \lg(w)_{it} + \beta_3 \lg(d)_{it} + \beta_4 ltv_{it} + \beta_5 r_{it} + \mu_{it} \tag{1}$$

$$hp_{it} = \alpha + \beta_1 \lg(grdp)_{it} + \beta_2 \lg(w)_{it} + \beta_3 \lg(d)_{it} + \beta_4 \lg l\,tv_{it} + \beta_5 r_{it} + \beta_6 earthquake_{it} + \beta_7 flood_{it} + \beta_8 eruption_{it} + \mu_{it} \tag{2}$$

$$hp_{it} = \alpha + \beta_1 \lg(grdp) * flood_{it} + \beta_2 \lg(grdp) * earthquake_{it} + \beta_3 \lg(grdp) * eruption_{it} + \beta_4 \lg(w) * flood_{it} + \beta_5 \lg(w) * earthquake_{it} + \beta_6 \lg(w) * eruption_{it} + \beta_7 \lg(d) * flood_{it} + \beta_8 \lg(d) * earthquake_{it} + \beta_9 \lg(d) * eruption_{it} + \beta_{10} \lg(grdp)_{it} + \beta_{11} \lg(w)_{it} + \beta_{12} \lg(d)_{it} + \beta_{13} ltv_{it} + \beta_{14} r_{it} + \beta_{15} earthquake_{it} + \beta_{16} flood_{it} + \beta_{17} eruption_{it} + \mu_{it} \tag{3}$$

where α represents the intercept, β is coefficient regression, and m is the error term, *i* denotes provinces in quarterly time *t*.

To determine the best model for baseline regression, the study tested the fit model following the panel data estimations using Breusch Pagan Langrangian test and Hausman test to determine the use of random effect and fixed effect model. The data were first tested using the pooled (OLS) equation provided in Equation 1. Following the pooled regression, the model was fitted to the random effect model using the Breusch Pagan Langrangian test, following Equation 4.

$$hp_{it} = \alpha + \beta_1 \lg(grdp)_{it} + \beta_2 \lg(w)_{it} + \beta_3 \lg(d)_{it} + \beta_4 \lg(ltv)_{it} + \beta_5 r_{it} + \lambda_i + \mu_{it} \tag{4}$$

The fixed effect model was then tested to determine its suitability for adoption relative to the random effect model. For this objective a Hausman test was conducted following Equation 5. The results confirmed that fixed effect was the most appropriate model for the study.

$$hp_{it} = (\alpha + \lambda_i) + \beta_1 \lg(grdp)_{it} + \beta_2 \lg(w)_{it} + \beta_3 \lg(d)_{it} + \beta_4 \lg(ltv)_{it} + \beta_5 r_{it} + \mu_{it} \tag{5}$$

In addition, Table 3 presents the descriptive statistics from the data used to describe data distribution. The statistics shown include respective symbols, number of observations, mean, standard deviation, minimum value, and maximum value of the research data.

TABLE 3. Descriptive statistics (full sample)

Variable	Symbol	Obs	Mean	Std. dev.	Min	Max
Housing price	hp	478	203.956	56.11098	100	348.1549
Gross regional domestic product	GRDP	504	97552.92	98382.1	13208.24	425043
Minimum Salary	w	512	1772678	632441.2	745000	3355750
Population Density	d	512	405.0437	427.8894	18.39	1394
Mortgage rate	r	512	10.35656	0.78178	8.676064	11.3396
Loan to Value ratio	ltv	512	79.7125	6.958451	70	89.5
Natural disaster (dummy variable on year *t,* 1= yes, 0= no)	earthquake	512	0.1074219	0.3099517	0	1
	flood	512	0.7636719	0.4252415	0	1
	eruption	512	0.0820313	0.2746807	0	1

Sources: Processed data by author

Table 4 shows descriptive statistics on moderate-risk disaster clusters. The results showed that the mean value and standard deviation of each variable were higher or lower compared to the full sample. Both *GRDP* and *w* showed a lower mean value than the full sample. This observation was expected to give an overview of the results of analysis that compare the aftereffects of natural disasters in moderate clusters.

TABLE 4. Descriptive statistics moderate risk

Variable	Symbol	Obs	Mean	Std. dev.	Min	Max
Housing price	hp	217	209.8008	59.21891	100	348.1549
Gross regional domestic product	GRDP	224	78813.77	110862.2	13208	425043
Minimum Salary	w	224	1756687	670435.1	745000	3355750
Population Density	d	224	456.5322	403.8467	30.25	1206
Mortgage rate	r	224	10.35665	0.782657	8.676064	11.34
Loan to Value ratio	ltv	224	79.7125	6.967221	70	89.5
Natural disaster (dummy variable on year *t,* 1= yes, 0= no)	earthquake	224	0.102679	0.304218	0	1
	flood	224	0.660714	0.474527	0	1
	eruption	224	0.09375	0.292133	0	1

Sources: Processed data by author

Further, Table 5 illustrates the descriptive statistics in the high-risk disaster cluster. The values of variables in this cluster are inversely proportional to moderate-risk values. This allows us to analyze regional factors and the impact of natural disasters on housing prices in two clusters that produce different results.

TABLE 5. Descriptive statistics high risk

Variable	Symbol	Obs	Mean	Std. dev.	Min	Max
Housing price	hp	261	199.0966	53.01472	100	332.8616
Gross regional domestic product	GRDP	284	112360.8	83790.14	22059	362445
Minimum Salary	w	288	1785116	602127.8	765000	3355750
Population Density	d	288	364.9971	442.2518	18.39	1394
Mortgage rate	r	288	10.3567	0.782208	8.676064	11.34
Loan to Value ratio	ltv	288	79.7125	6.963752	70	89.5
Natural disaster (dummy variable on year *t,* 1= yes, 0= no)	earthquake	288	0.111111	0.314817	0	1
	flood	288	0.84375	0.363724	0	1
	eruption	288	0.072917	0.260452	0	1

Sources: Processed data by author

RESULTS AND DISCUSSION

Table 6 shows the estimation results for the three models. Based on these findings, we can identify the general factors affecting housing prices. Differences between the models indicate the influence of regional characteristics (Model 1) and also that of natural disasters (Model 2). For Model 3, we added a moderation test between the natural disaster variable and the independent variable. Models 1 and 2 showed similar variables that significantly affect house prices. The study thus verified that the influence of regional factors on housing prices is different (Model 3) following interaction with natural disasters. It is known that the GRDP and density variables have a greater effect on house prices in Model 3 than in the other models. Additionally, wages significantly and positively affect housing prices in Models 1 and 2.

Turner and Fichter (1992) said that demand occurs when there is a desire and ability to acquire an item, such as a house, as a consumer product. These needs can be fulfilled in lieu of the price factor. The rise and fall of house prices are affected by many factors, as explained in the previous section. As indicated in Table 3, the results are consistent with those of past research in that regional factors in interaction with natural disasters, influence housing prices.

The occurrence of natural disasters, especially due to earthquakes and volcanic eruptions, disrupts socio-economic activities and this will consequently require a rapid recovery period that will also greatly affect housing prices. Our main results specifically show that the house prices increased by 4.29 unit when the GRDP rose by 1 unit. The interaction between floods and GRDP has a coefficient of -2.522. This suggests that the influence of GRDP on house prices diminishes when moderated by flood occurrence. Earthquakes and volcanic eruptions affect GRDP to house price and are greater by 0.1888 point and 0.1137 point respectively. However, the effect of floods and volcanic eruptions on wages to house price are stronger than that of earthquakes. The effect of population density on house prices after moderation by flood disasters will grow stronger. However, this impact becomes weaker following earthquakes and eruptions.

Interest rates have a significant effect on housing prices. In contrast to GRDP and density, the magnitude of the effect of interest rates on house prices in Model 3 is lower than those in Model 1 and 2, although they have a positive and significant effect on house prices. The outcome is mainly due to the greater influence of risk management under natural disaster conditions. The results in Model 3 show that regional factors, following a natural disaster, exert a greater influence on housing prices, except where salary is concerned.

TABLE 6. Result regression full sample

Variables	Model 1	Model 2	Model 3
GRDP	399.9***	413.6***	429.0***
	(35.82)	(36.00)	(36.47)
flood*GRDP			-2.522
			(4.983)
earthquake*GRDP			18.88***
			(6.671)
eruption* GRDP			11.37*
			(6.385)
Minimum Salary, w	30.94***	28.32***	15.67
	(8.594)	(8.560)	(13.04)
flood*w			17.37
			(10.86)
earthquake*w			-1.404
			(13.15)
eruption*w			5.912
			(17.79)
Population Density, d	-20.72	-18.34	-4.357
	(48.97)	(48.55)	(48.78)
flood*d			3.043
			(3.630)
earthquake*d			-9.074
			(7.772)

continue ...

... continued

eruption*d			-8.587
			(7.944)
ltv	0.231	0.198	0.0359
	(0.293)	(0.291)	(0.292)
Mortgage Rate, r	7.611***	7.595***	7.466***
	(1.145)	(1.136)	(1.147)
earthquake		0.405	-61.87
		(2.388)	(94.66)
flood		3.529**	-99.84
		(1.720)	(73.89)
eruption		-7.058***	-76.10
		(2.567)	(131.5)
constant	-1,956***	-2,011***	-2,024***
	(187.4)	(187.3)	(191.3)
Observations	474	474	474
R-squared	0.713	0.720	0.730
Number of prov	16	16	16

Notes: Estimates of the general effect before and after natural disasters on house price are presented. The result is robust against multicollinearity and autocorrelation problem. Standard errors (in parentheses) are also robust. All regressions include time.
*** Significant at <1%. ** at <5%. * at <10%

To elucidate whether regional clusters influence housing prices, we conducted a test-parm test. Results showed the presence of regional cluster effect. Comparisons of two regional clusters on their response to housing prices based on vulnerability to disaster risk are presented in Table 7.

TABLE 7. Regression result by regional cluster

Variables	High-risk Regions			Moderate-risk Regions		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GRDP	417.0***	429.6***	463.4***	371.1***	374.1***	370.3***
	(36.59)	(36.25)	(39.08)	(67.42)	(69.04)	(68.97)
GRDP*flood			-11.25			-3.836
			(7.709)			(8.601)
GRDP*earthquake			19.98			33.98***
			(25.91)			(10.23)
GRDP*eruption			50.35**			13.10
			(24.56)			(12.11)
Minimum Salary,w	21.96**	19.98**	10.37	37.63**	34.72**	18.68
	(9.405)	(9.326)	(21.63)	(14.94)	(14.91)	(19.06)
w*flood			13.07			33.83**
			(18.78)			(16.05)
w*earthquake			-3.563			30.80
			(13.83)			(31.34)
w*eruption			-30.74			54.42*
			(20.25)			(31.55)
Population Density, d	141.1	150.6	116.5	-49.85	-48.79	-19.31
	(108.7)	(107.2)	(112.0)	(65.17)	(64.29)	(64.02)

continue ...

... continued

d* flood			9.597			1.636
			(7.195)			(5.189)
d*earthquake			-8.219			-17.74
			(22.42)			(14.64)
d*eruption			-36.23**			-1.341
			(16.33)			(14.61)
ltv	-0.114	-0.144	-0.254	0.521	0.565	0.295
	(0.313)	(0.309)	(0.314)	(0.555)	(0.552)	(0.551)
Mortgage Rate, r	7.417***	7.519***	7.950***	8.129***	7.806***	7.800***
	(1.206)	(1.192)	(1.219)	(2.088)	(2.066)	(2.112)
earthquake		-2.482	-60.99		5.209	-305.2
		(2.436)	(95.95)		(4.461)	(231.4)
flood		6.145***	-41.62		1.923	-195.7*
		(2.070)	(126.9)		(2.752)	(107.7)
eruption		-2.206	22.82		-11.95***	-406.2*
		(2.883)	(161.4)		(4.340)	(231.5)
Constant	-2,387***	-2,462***	-2,486***	-1,754***	-1,754***	-1,686***
	(271.9)	(269.0)	(292.1)	(324.6)	(327.8)	(327.7)
Observations	257	257	257	217	217	217
R-squared	0.797	0.806	0.815	0.649	0.664	0.692
Number of prov	10	10	10	6	6	6

Notes: Estimates of the effect of natural disasters on regional factors are represented in Model 3 by cluster (high-risk and moderate-risk), using the fixed-effects model in Eq. (1, 2, and 3). This result is robust against multicollinearity and autocorrelation problem. Standard errors (in parentheses) are robust. All regressions include time.
*** Significant <1%. ** <5%. * <10%

Three models were established for statistical estimation to determine their response to each condition. Model 1 is the baseline model before inclusion of natural disasters as an independent variable. Model 2 is established to include natural disaster estimates on the baseline model, and Model 3 examines the moderating effect of natural disasters and regional factors. The estimation results revealed a differential impact on groups in high-risk and moderate-risk areas.

The effect of GRDP on housing prices in the high-risk cluster was more significant than that for low-risk cluster. This outcome was due to the higher vulnerability to natural disaster risk in an area, which generates more disruptive economic and social activities. Natural disasters cause damage to infrastructure, business, and human resources. However, post-disaster recovery and reconstruction efforts were carried out to rehabilitate the economic conditions of affected areas. If the recovery efforts are successful and GRDP increases accordingly, it may positively impact purchasing power of the population. This increase may consequently boost demand for housing leading to increase in prices.

A negative relationship exists between population density and house prices in areas with moderate level of disaster occurrence. Based on provincial data, moderate disaster areas have a higher average population density than the high disaster areas. With higher population densities and disaster level, it is expected that the residents will seek for safer locations which are not too crowded. Therefore, following disasters in such areas, property prices tend to decrease due to resultant reduction in residential comfort.

It is also known that salary has a significant effect on house prices in Model 1 and 2. But when interacting with natural disasters, salary does not have a significant effect (Model 3). Housing as a commodity requires substantial funds, to which most of the residents' salaries are invested. However, a house owner's salary does not significantly affect housing prices after a natural disaster has occurred leading to a shift in priorities in allocating his finances. Thus, there is a trade-off in income allocation preference, leading to a decrease in the effect of salary on housing prices.

Densely populated areas negatively affect house prices, even though these areas are categorized as moderate-risk. Price reductions will further be exacerbated in high-density areas with high-risk disaster potential. However, for a region with lower density and high-risk potential, the study showed no reduction in housing prices, especially in areas with low-risk condition.

The effect of a natural disaster on housing prices will differ with the actual disaster risk involved, and a house owner's disaster risk perceptions may differ with the actual flood risk in their resident location. A study by Echegaray-Aveiga et al. (2020) showed that environmental damage caused by natural disasters will harm the price of residential housing units, and consumers will be willing to pay a higher price to avoid potential property damage. When making rational purchasing decisions, the individual will prioritize for the complexity of meeting housing needs and focus on the costs associated with the house purchase process, but will tend to neglect the risk due to future flooding (Matêjka & McKay 2015; Reis 2006; Sallee 2014). Such imprudent decisions may expose the consumer to much greater costs in case unforeseen natural disasters were to occur in the future.

The loan-to-value ratio adopted in this study is the ratio of home loans that need to be paid by individuals excluding their down payments. This policy is carried out at the national level and as such it has little bearing on house prices in local regions. Findings from this study support the need for a loan-to-value policy based on regional factors. Conversely, interest rates significantly affect house prices. Higher interest rates can make mortgage repayments more expensive, increasing buyers' difficulty in buying houses. However, lower interest rates can make mortgage repayments more affordable, thus housing prices may increase proportionally as demand increases due to more buyers.

In regions with moderate to high flood risks, there is a positive relationship between minimum salary levels and house prices under flood occurrence. The same trend holds for areas with high population density. However, areas where economic conditions were improving, a flood event will reduce housing prices. Conversely, areas under moderate risk regions, with frequent earthquakes, the higher the local minimum salary, the higher will be the house price, and vice versa. House prices tend to weaken following earthquake occurrence in densely populated areas. In regions with moderate to high earthquake risk, the better the economic conditions, the more house prices will tend to rise. Volcanic eruptions tend to reduce house prices in areas with high population density and with moderate to high earthquake risk. House prices are stable in high-income areas including those with high risk and frequent eruptions.

Following a natural disaster, there will be a decrease in the number of available houses because most of these are damaged or destroyed, especially those in high-disaster-risk areas, thus resulting in a decrease in the supply of houses in the market. However, the demand for housing will still persist among the affected population. They need to either find a new residence or rehabilitate their damaged properties. This would consequently drive up the demand for housing, and with limited supply, may result in higher house prices. In addition, other factors such as interest rates, government regulations, and property market conditions may also affect house pricing in post-natural disaster areas.

CONCLUSION

Regional disparities can result in divergent responses in house prices, particularly in Indonesia, which, as the world's largest archipelago, exhibits considerable geographical variation. Creating disaster cluster groups in the housing market is an important step in disaster preparedness and response since the intensity and severity of disasters cannot be predicted. These groups are typically created to anticipate and mitigate the risks of natural disasters such as floods, earthquakes, and volcanic eruptions. Results from this study indicate a significant difference between such clusters in their response to changes in house prices.

The regional factors that significantly influence house prices are GRDP and the minimum salary. In moderate-risk regions with earthquakes and eruptions, the higher the regional income with minimum salary level, the higher will be the housing prices in regions with more frequent floods. With larger minimum salary, house prices will also be higher. Volcanic eruptions tend to reduce house prices in high population density and high-risk region. House price is stable in higher income regions even in areas with high risk and frequent eruptions. Therefore, it is important for the authority in areas with frequent volcanic eruptions to increase the income level and reduce the population density in order to stabilize the house prices. Furthermore, the impact of house prices differs depending on the type of disaster. This study shows that house prices following flood event are weaker than in areas with recent earthquakes and volcanic eruptions. The study observes that flooding is a seasonal natural disaster, where the probability of flooding during the monsoons is high in specific areas. As such, the handling and intervention of stakeholders in stabilizing house prices can be anticipated. The primary objective is to identify vulnerable areas and implement policies and measures to reduce disasters' potential impact on communities and thereby to stabilize the housing price.

The uniqueness of a region and its economic opportunities present a stimulus for house prices. Regional factors have the capacity to strengthen or weaken real estate values including house pricing. This study suggests that the government should formulate and enact a post-disaster housing price control policy. The banking sector is also important since banks are the third party in meeting housing needs. Thus, the sector needs an indicator to serve as an index of disaster vulnerability, especially in disaster-prone areas, to assist in the disbursement of housing loans.

ACKNOWLEDGEMENTS

The first author wishes to thank Universitas Sebelas Maret for funding this research under the Research University Grant Scheme Penelitian Disertasi Doktor (PDD-UNS) No. 228/UN27.22/PT.01.03/2023.

REFERENCES

Adams, Z. & Füss, R. 2010. Macroeconomic determinants of international housing markets. *Journal of Housing Economics* 19(1): 38–50.

Alexander, D. 1984. Housing crisis after natural disaster: The aftermath of the November 1980 southern Italian earthquake. *Geoforum* 15(4): 489–516.

Arrondel, L. & Lefebvre, B. 2001. Consumption and investment motives in housing wealth accumulation: A French study. *Journal of Urban Economics* 50(1): 112–137.

Bakkensen, L.A., Ding, X. & Ma, L. 2019. Flood Risk and Salience: New Evidence from the Sunshine State. *Southern Economic Journal* 85(4): 1132–1158.

Bin, O. & Landry, C. E. 2008. Flood hazards, insurance rates, and amenities. *Journal of Risk and Insurance* 75(1): 63–82.

Bin, O. & Polasky, S. 2004. Effects of flood hazards on property values: Evidence before and after hurricane Floyd. *Land Economics* 80(4): 490–500.

Brzezicka, J. & Wisniewski, R. 2016. Translocality on the real estate market. *Land Use Policy* 55: 166–181.

Bui, A.T., Dungey, M., Nguyen, C.V & Pham, T. P. 2014. The impact of natural disasters on household income, expenditure, poverty and inequality: Evidence from Vietnam. *Applied Economics* 46(15): 1751–1766.

Cameron Manisha Shah Cameron, L. 2015. *Risk-Taking Behavior in the Wake of Natural Disasters*.

Cheung, R., Wetherell, D. & Whitaker, S. 2018. Induced earthquakes and housing markets: Evidence from Oklahoma. *Regional Science and Urban Economics* 69: 153–166.

Cortés, K.R. & Strahan, P.E. 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics* 125(1): 182–199.

Del Negro, M. & Otrok, C. 2007. 99 Luftballons: Monetary policy and the house price boom across U.S. states. *Journal of Monetary Economics* 54(7): 1962–1985.

Duran, H.E. & Özdoğan, H. 2020. Asymmetries across regional housing markets in Turkey. *Journal of Economic Asymmetries* 22.

Echegaray-Aveiga, R.C., Rodríguez-Espinosa, F., Toulkeridis, T. & Echegaray-Aveiga, R.D. 2020. Possible effects of potential lahars from Cotopaxi volcano on housing market prices. *Journal of Applied Volcanology* 9(1): 1-11.

Faenza, L. & Pierdominici, S. 2007. Statistical occurrence analysis and spatio-temporal distribution of earthquakes in the Apennines (Italy). *Tectonophysics* 439(1–4): 13–31.

Fang, L., Li, L. & Yavas, A. 2023. The impact of distant hurricane on local housing markets. *Journal of Real Estate Finance and Economics* 66(2): 327–372.

Fang, L. & Munneke, H.J. 2020. A spatial analysis of borrowers' mortgage termination decision – a nonparametric approach. *Regional Science and Urban Economics* 86.

Gignoux, J. & Menéndez, M. 2016. Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia. *Journal of Development Economics* 118: 26–44.

Hallstrom, D.G. & Smith, V.K. 2005. Market responses to hurricanes. *Journal of Environmental Economics and Management* 50(3): 541–561.

Johar, M., Johnston, D.W., Shields, M.A., Siminski, P. & Stavrunova, O. 2022. The economic impacts of direct natural disaster exposure. *Journal of Economic Behavior and Organization* 196: 26–39.

Kawasaki, A., Kawamura, G. & Zin, W.W. 2020. A local level relationship between floods and poverty: A case in Myanmar. *International Journal of Disaster Risk Reduction* 42.

Kelly, R., McCann, F. & O'Toole, C. 2018. Credit conditions, macroprudential policy and house prices. *Journal of Housing Economics* 41:153–167.

Kelly, R. & O'Toole, C. 2018. Mortgage default, lending conditions and macroprudential policy: Loan-level evidence from UK buy-to-lets. *Journal of Financial Stability* 36: 322–335.

Kepili, E.I.Z. 2020. The impact of macroeconomic factors on the house prices during liberalisation. *Jurnal Ekonomi Malaysia* 54(2): 1-12.

Kiel, K.A. & Matheson, V.A. 2018. The effect of natural disasters on housing prices: An examination of the Fourmile Canyon fire. *Journal of Forest Economics* 33: 1–7.

Kirchberger, M. 2017. Natural disasters and labor markets. *Journal of Development Economics* 125: 40–58.

Koetter, M., Noth, F. & Rehbein, O. 2019. Borrowers under water! Rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation* 43(1).

Lopus, J.S., Amidjono, D.S. & Grimes, P.W. 2019. Improving financial literacy of the poor and vulnerable in Indonesia: An empirical analysis. *International Review of Economics Education* 32.

Matêjka, F. & McKay, A. 2015. Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review* 105(1): 272–298.

Mukhopadhyay, B., Dasgupta, S. & Dasgupta, S. 2004. Clustering of earthquake events in the Himalaya - Its relevance to regional tectonic set-up. *Gondwana Research* 7(4): 1242-1247

Pong, C.S. & Hook, L.S. 2017. Roles of housing wealth and financial wealth in monetary transmission mechanism in Malaysia. *Jurnal Ekonomi Malaysia* 51(1): 77–86.

Priyanto, B., Sahid, M.N., Solikin, M. & Faruqi, J. Al. 2022. Investigation of critical risk factors and level of risk for environmentally damage induced by house projects. *Caspian Journal of Environmental Sciences* 20(2): 413–421.

Reis, R. 2006. Inattentive consumers. *Journal of Monetary Economics* 53(8): 1761–1800.

Sallee, J.M. 2014. Rational inattention and energy efficiency. *Journal of Law and Economics* 57(3): 781-820.

Silbert, M., Del, M. & Useche, P. 2012. *Repeated Natural Disasters and Poverty in Island Nations: A Decade of Evidence from Indonesia*. .https://bear.warrington.ufl.edu/centers/purc/docs/papers/1202_Silbert_Repeated_Natural_Disasters.pdf

Sukhwani, V., Napitupulu, H., Jingnan, D., Yamaji, M. & Shaw, R. 2021. Enhancing cultural adequacy in post-disaster temporary housing. *Progress in Disaster Science* 11(5): 1-10.

Surjono, S., Wardhani, D.K., Yudono, A. & Muluk, M.R.K. 2021. Residential preferences of post great disaster in Palu City, Indonesia. *Evergreen* 8(4): 706–716.

Timar, L., Grimes, A. & Fabling, R. 2018. That sinking feeling: The changing price of urban disaster risk following an earthquake. *International Journal of Disaster Risk Reduction* 3: 11326–1336.

Toma´sˇfischer, T.T. & Horaíek, J. 2003. Space-time distribution of earthquake swarms in the principal focal zone of the NW Bohemia/Vogtland seismoactive region: Period 1985-2001. *Journal of Geodynamics* 35(1-2): 125-144.

Tomal, M. 2021. Housing market heterogeneity and cluster formation: Evidence from Poland. *International Journal of Housing Markets and Analysis* 14(5): 1166–1185.
Toya, H. & Skidmore, M. 2007. Economic development and the impacts of natural disasters. *Economics Letters* 94(1): 20–25.
Tsai, I.C. 2019. Relationships among regional housing markets: Evidence on adjustments of housing burden. *Economic Modelling* 78: 309–318.
Tsai, I.C. 2022. Changes in social behavior and impacts of the COVID-19 pandemic on regional housing markets: Independence and risk. *Journal of Behavioral and Experimental Finance* 35(14).
Turner, J.F.C. & Fichter, R. 1992. Housing as a verb. In *Freedom to Build, Dweller Control of the Housing Process.* New York: Macmillan Company.
Varga, P., Krumm, F., Riguzzi, F., Doglioni, C., Süle, B., Wang, K. & Panza, G.F. 2012. Global pattern of earthquakes and seismic energy distributions: Insights for the mechanisms of plate tectonics. *Tectonophysics* 530–531(8): 80–86.

Ariyanto Adhi Nugroho*
Faculty of Economics and Business
Universitas Sebelas Maret,
Jalan Ir. Sutami 36 Kentingan,
57126 Surakarta, Jawa Tengah. INDONESIA.
E-mail: ariyanto_an@staff.uns.ac.id

Yunastiti Purwaningsih
Faculty of Economics and Business
Universitas Sebelas Maret,
Jalan Ir. Sutami 36 Kentingan,
57126 Surakarta, Jawa Tengah. INDONESIA.
E-mail: yst_stm13@staff.uns.ac.id

Lukman Hakim
Faculty of Economics and Business
Universitas Sebelas Maret,
Jalan Ir. Sutami 36 Kentingan,
57126 Surakarta, Jawa Tengah. INDONESIA.
E-mail: lukmanhakim@staff.uns.ac.id

Suryanto
Faculty of Economics and Business
Universitas Sebelas Maret,
Jalan Ir. Sutami 36 Kentingan,
57126 Surakarta, Jawa Tengah. INDONESIA.
E-mail: suryanto_feb@staff.uns.ac.id

* Corresponding author