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Natural Disasters and Housing Prices: Fresh Evidence from a Global Country Sample

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Given that the literature on the impact of natural disasters on house prices is highly limited, this paper combines data on natural disasters and house prices from 117 countries, which span the period 2000-2018 and a panel regression method to estimate the effects of natural disasters on house prices. The findings document that natural disasters lead to lower house prices, with the results surviving a number of robustness tests. When examining the impacts of natural disasters by type, the findings highlight that geological disasters exert the strongest (negative) impact on house prices. The results also illustrate the negative impact of those disasters on house prices when also taking the distinction between small and large disasters into account. The findings provide important implications for policymakers and property investors. Lower house prices in countries that experience natural disasters events could significantly signify lower consumption and investment (the wealth effect), with further negative spillovers to the real economy. Economic policymakers could implement low-tax policies or quantitative easing schemes to support these areas/countries. The findings exemplify the need for governments and policymakers to mitigate climate change effects on housing by adopting new and more environmentally friendly technologies and energy sources.

Keywords

Natural Disasters, House Prices, Panel Data, 117 Countries

1. Introduction

The literature has indicated that the presence of natural disaster risk increases over time (Pachauri et al., 2014; Mechler and Bouwer, 2015). According to Dahl et al. (2019), the number of locations exposed to certain disasters, such as flooding, is expected to double over time. Therefore, there is an increasing concern over how natural disasters are expected to impact certain parts of the economy, such as the real estate sector.

The goal of our paper is to provide first-time evidence on the role of such natural disasters in determining housing prices across a wide sample of datasets on both natural disasters and housing prices. More specifically, this study extends the work on the role of natural disasters on house prices. Unlike previous studies that typically investigate the impact of a specific type of disaster on house prices, this paper explicitly examines the impacts of different types of disasters in a unified framework. Additionally, a novelty of the study is that it explicitly accounts on how the response of house prices differs across the different types of natural disasters.

The analysis makes use of a cross-country method to disentangle the link between housing prices and natural disasters. This is an approach that is not found in the relevant literature where previous studies suggest that the impact of natural disasters on house prices is most likely quite local. The employment of cross-country studies on this relevant topic seems highly appropriate in the sense that such natural disasters affect housing values due to changes in expected costs and risks of home ownership. Housing destructions induce substantial migration flows from one region/country to another and migrants update their decision priors based on information on disasters, which is likely conveyed in the media and more significant for severe disasters.

Alternatively, natural disasters can be taken as negative amenities or negative productivity shocks that might usually encourage existing residents to leave (or prevent prospective residents from moving in), thus leading to net out-migration to other regions/countries and changes in housing prices. In addition, natural disasters affect human capital due to their impact on school quality as measured by test scores (Black and Machin, 2011). These human capital effects have further repercussions on total factor productivity and partly on economic growth, which in a globalized world, generate (negative and indirect) spillovers to more countries.

At the same time, natural disasters corroborate poverty rates (which increase in areas/countries hit by disasters), which is consistent with the out-migration of households above the poverty line, in-migration of the poor, or a transition of the existing population into poverty. Furthermore, according to Deryugina (2017), disaster events significantly affect transfer payments, mainly in the form of unemployment insurance and medical spending, which also have spillover effects on various macroeconomic measures and, ultimately, on economic growth. Toya and Skidmore (2002) argue that even though natural disasters have effects mostly on the local economy, they usually carry spillovers for the growth path of the entire country and, therefore, for a number of international countries associated with the country of origin.

Therefore, we can also assume that changing growth patterns are expected to substantially influence the demand and supply conditions in the housing markets and, thus, eventually housing prices. Finally, there is a strand in the literature where studies show that natural disasters also affect labor markets. More specifically, Sarmiento (2007) highlights that aggregate local and national employment fall following a natural disaster event as workers flee the area. This is expected to affect disposable and aggregate income levels due to changes in labor demand and supply conditions in certain sectors, such as construction and building, with further spillovers in aggregate growth. Within the same context, the loss in public capital and changes in long-term wages in affected countries induce migration labor flows with more indirect spillovers to aggregate income and housing conditions and prices (Belasen and Polachek, 2009).

The findings of the empirical analysis in this study show that the majority of natural disaster events considered have a negative and statistically significant impact on house prices, with the geological and meteorological types of disasters exerting the strongest effect on those prices. Similar results are also obtained when a distinction is made between small and large disasters.

The results are crucial for economic inequality, given that property is a significant part of the wealth portfolio of households for the majority of the country populations considered here (low- and medium-income households), since housing offers financial security (Goodman and Mayer, 2018). Finally, the findings are imperative for the banking system, since through the lending (mortgages) process, natural disasters may jeopardize the capacity of lenders to repay their mortgage, thus, undermining the vulnerability of the system. Klomb (2014) uses data of more than 160 countries to investigate the impact of large-scale natural disasters on the default rates of commercial banks. Given that the financial consequences of natural disasters may stress and threaten the existence of a bank by adversely affecting their solvency, the findings in Klomb (2014) indicate that natural disasters increase the likelihood of the default rates of banks. More precisely, Klomb (2014) provides robust evidence that geophysical and meteorological disasters reduce the default rates, mostly due to the widespread damage caused, while the impact of a natural disaster depends on the size and scope of the disaster, rigorousness of financial regulations and supervision, and level of financial and economic development of a particular country. Moreover, Brei et al. (2019) construct a panel of banking data and historical losses due to hurricane strikes for islands in the Eastern Caribbean to explore the impact of such natural disasters on the banking system. Their results indicate that banks face deposit withdrawals and experience a negative funding shock due to these disasters. Their response to such a shock is to reduce the supply of lending and by drawing on liquid assets. These actions appear to play a substantial role in funding post-disaster recovery and thus, they signify the importance of active reserve requirement policies.

The link between natural disasters and housing prices exemplifies a tenure choice process, according to which, the occurrence of natural disasters motivates households to move from ownership to the rental market, potentially leading to lower housing prices. This shows that there is a prevailing demand driven phenomenon, characterized by declining housing prices and increasing rents. These facts draw attention to the presence of two theories: i) a wealth effect, in which households suffer from natural disasters, and ii) a risk effect, in which households realize the disaster risk, which increases their risk aversion towards owning a house as they are trying to mitigate their exposure to the risk of natural disasters. This happens because the majority of houses across many countries are not covered from the damages that they suffer caused by natural disasters. Therefore, the presence of such disasters causes an increase in the risk exposure that households can only hedge against by reducing their housing exposure. In addition, a third theoretical link between natural disasters and housing prices could be that the former cause changes in expected owner costs, which not only include property damage, but also expected fatalities, given that their information strength is very high as they appear in the news (Drakos and Kutan, 2003; Sheldon and Zhan, 2019). In terms of the supply side of the real estate market, natural disasters usually cause shortages in supply, which leads to rising housing prices, at least in the short run, which can be corrected later in the medium and long run (Strobl, 2009).

This paper is within the bounds of the strand of the literature that explores how housing prices are affected following natural disaster events (Bin et al., 2008; Daniel et al., 2009; Bin and Landry, 2013). Gibson et al. (2018) investigate how hurricanes have affected housing prices in New York. However, those studies have focused entirely on individual locations, mainly in the US. At the US aggregate level, Boustan et al. (2017) and Bernstein et al. (2019) have studied the impact of natural disasters on housing prices across the US. This paper is also related to the strand of the literature associated with the validity of the wealth effect mentioned above. Smith et al. (2006) and D'Acunto and Rossi (2017) explore how certain disasters, such as Hurricane Katrina, have affected housing prices in certain US locations (hit by the hurricane) by explicitly considering the impact of such disasters on household wealth. Moreover, the majority of papers presented in the relevant literature are associated with a particular type of natural disasters, which is that of flooding. According to this strand of the literature, flood events lead to lower housing prices, while a dissipating effect occurs over time (Gallagher, 2014; Atreya and Ferreira, 2015). Similar studies also explore how new environmental risk information affects housing prices, which have led to the same findings (Currie et al., 2013). Currie et al. (2014) provide evidence that the price of houses located within a mile radius of toxic pollutant-emitting industrial plants decreases when the plants open. Similarly, McCluskey and Rausser (2001) document through a hedonic property modelling approach that increased media coverage leads to high current risk perceptions, and, thus, lower property values.

This paper also touches the strand of the literature that investigates how natural disasters affect home ownership, and subsequently, housing prices (Haurin and Morrow-Jones, 2010). According to this strand of the literature, natural disasters cause damage to existing housing stock, and create increased risk for homeowners, ultimately leading to lower housing prices (Moriizumi and Naoi, 2011). Another strand of the literature that is associated with this paper includes studies that have focused on the effect of global warming and its impact on property prices. The analysis in those studies documents that global warming substantially undermines property prices. More specifically, Butsic et al. (2011) provide evidence that global warming reduces property prices in locations with proximity to ski resorts in the US and Canada, while Huang et al. (2015) illustrate that extreme weather conditions, such as extreme temperatures, precipitation and humidity, lead to rising housing prices in China.

Finally, this paper is closely associated with the literature that considers that the analysis of housing prices determinants is highly important because of the housing impact on various economic and social aspects. For instant, house prices have an effect on residential mobility and resident health (Dietz and Haurin, 2003), while housing is closely related to the performance and vulnerability of the financial/banking sector. Moreover, changes in housing prices impact the construction market, as well as other macroeconomic variables, such as growth, unemployment and inflation. Overall, the related literature has identified factors, such as gross domestic product (GDP) or personal income, unemployment, interest rates and credit conditions (i.e., macroprudential variables, such as loan-to-value ratios and debt-to-income ratios) as important drivers of housing prices (Adams and Fuss, 2010; Agnello and Schuknecht, 2011; Crowe et al., 2011; Chu, 2014). Additional determinants are associated with the demand and supply conditions in the housing sector, such as construction costs (Adam and Fuss, 2010) and demographic variables, such as population, ageing and migration (Takats, 2012; Chen et al., 2012).

2. Theoretical Links Between House Prices and Natural Disasters

Understanding the extent that climate change risks act as a barrier to reach permanent home decisions has important effect on house prices. The literature basically offers two main mechanisms/effects through which natural disaster events can impact house prices. The first mechanism is known as the wealth effect. Houses are a crucial means of wealth accumulation and serve as a measure of financial security, especially for low- and mid-income households (Goodman and Mayer, 2018). Thus, changes in housing value in response to natural disasters may impact long-run economic inequality, growth and racial disparity. The impact is more prominent on low- and mid-income households who suffer more from natural disasters. Once they experience less wealth, they cannot afford ownership, thus, leading to a lower demand for housing and, therefore, lower prices. Smith et al. (2006) use household-level data from the Dade County in Florida to show that, following Hurricane Katrina, low-income households moved into low-rent housing, mid-income households moved out of the area, while wealthy households were insensitive to this particular shock. On the contrary, wealthy households filled more mortgage applications. Nevertheless, the difficulty with empirically measuring the long-term wealth changes from housing wealth destruction is that there is no quantifiable variable that captures the expectations imbedded in wealth. The long-term losses of wealth effects from natural disaster shocks are hard to detect because they are likely to be smoothed over many years. Finally, the climate change adaptation literature argues that there is a broad consensus that the wealthy can access a wide range of strategies, which range from owning a second home to accessing better quality food, medical care and housing to protecting themselves from shocks. The poor are, thus, more likely to bear the incidence of natural disasters (Smith et al. 2006; Barreca et al., 2016). The poor may also be more willing to trade off a lower housing price for a heightened risk of disaster activity.

The second channel is the risk channel, according to which, low- and mid-income households learn about disaster risk. They then become less willing to take risks (i.e., become more risk averters), and reduce their exposure to homeownership to minimize exposure to natural disaster risks. In addition, certain insurance policies do not cover the damage from natural disasters, unless households can pay a high risk premium. As such, natural disasters cause increases in risk exposure that households can only hedge by reducing their housing exposure, thus leading to lower house prices (Smith et al., 2006; Bin and Landry, 2013). Moreover, natural disasters can change the beliefs of people. Individuals who experience a natural disaster perceive the world to be a much riskier place. Accordingly, they report unrealistically high probabilities that another disaster will occur in the (near) future and that it will be severe, with these perceptions persisting for several years (Di Tella et al., 2007; Malmendier and Nagel, 2011). In a world of perfect information, individuals are able to accurately form expectations as to the probability of such an event occurring. However, natural disasters impart new information and hence, affect behavior through their impact on estimates of background risk. Alternatively, natural disasters constitute a 'shock' that contains new information and probably causes estimates of background risk to be updated. If this 'shock' is incorporated in expectations of background risk, then it has a long-term effect on behavior. Additionally, natural disasters are likely to affect risk-taking behavior through their effect on income and wealth. Disasters destroy physical property and reduce income-earning opportunities. It is well established in the economics literature that wealth is negatively associated with risk aversion. Theoretically, the anticipated effect of a natural disaster on risk aversion remains unclear. On the one hand, adding background risk to wealth increases risk aversion to other independent risks (Guiso and Paiella, 2008). Empirically, the evidence that can be used to test the risk behavior theory is quite limited. Guiso and Paiella (2008) report that the environment of a consumer affects risk aversion and that individuals who are more likely to face income uncertainty or become liquidity constrained show a higher degree of absolute risk aversion. Overall, natural disasters provide new information on the 'riskiness' of living in a given area, but individuals are unable to adequately assess the underlying risk of such shocks and therefore, consider the experience of a disaster as providing new information.

Finally, both the theoretical and empirical literature emphasize that the human costs associated with natural disasters pose an additional link to housing prices. Baez et al. (2010) present evidence that natural disasters affect human development by bringing about substantial damages, including deaths, to human assets. In that sense, they can dramatically reduce education, human capital, income growth and, thus, housing prices. Furthermore, destruction to schools and other infrastructures, along with teacher and student casualties, affect the supply of education in the aftermath of a disaster, while children who lose a parent have lower investments in human capital as a result of losing their source of income to attain their education level (Cuaresma, 2010), thus ending up again with lower housing prices.

3. Methodology

The modelling approach that we use here considers the dependent variable housing indexes as a function of certain housing prices determinants. In particular:

$$\Delta \log(P_{it}) = a\Delta Control_{i,t-1} + \sum_{k=1}^{p} b_k ND_{i,t+1-k} + c\Delta \log\left(P_{i,t-1}\right) + \eta_i + \eta_t + v_{it} \quad (1)$$

where i denotes the country, t the year, P is an indicator of the housing prices (index), ND is natural disasters, $Control$ is a vector of the determinants of housing prices, such as aggregate personal income, the unemployment rate, population size, real interest rates (Adams and Fuss, 2010), construction costs, and the Gini index. η_i and η_t denote country and year fixed effects, respectively, capturing potential discrepancies across country locations and over time which are not taken into account by the country characteristics or country housing conditions. Finally, v is the error term. For the estimation of Equation (1), the analysis uses the general method of moments (GMM) estimation, as recommended by Arellano and Bover (1995) and Blundell and Bond (1998). This particular method addresses the potential presence of endogeneity which may come either through reverse causality between house prices and natural disasters (not likely), or correlation between the drivers of house prices and the error term.

A novelty of the paper is that the estimation will take place not only in terms of aggregate natural disasters, but also by disaster type. The reason is that the impacts of natural disasters on housing prices may differ as the informational priors and expected losses of potential homeowners may differ across disaster type, i.e., due to the differentiated national institutional contexts and major policymakers (i.e., central banks or fiscal authorities), as well as the reaction of insurance makers to the natural disaster (Browne and Hoyt, 2000). In addition, news coverage and information may be more comprehensively available for certain types of disasters.

4. Data

The analysis considers 117 countries (see Appendix) and spans the period 2000-2018. The analysis uses housing price indexes as proxies for housing prices. House price data are obtained from various sources, such as the Bank for International Settlements (BIS) and the Organisation for Economic Co-operation and Development (OECD) databases for the case of developed countries, and the Global Market Information Database for the remaining countries. In terms of the natural disasters measure, we follow the structure introduced by Noy (2009), according to which, the impact of a specific natural disaster depends on the magnitude of the disaster relative to the size of the economy, and the analysis standardizes the disaster measure. More specifically, we need to divide the measures for the number of people affected by the population size in the year prior to the disaster year, and then divide the direct cost measure of the disaster by the GDP of the previous year (since the current year population and GDP have been affected by the disaster itself). Furthermore, since it is likely that a disaster that occurred in one month is expected to have a greater impact on the macroeconomy in the same year than a disaster that occurred in the previous year, the empirical analysis weighs this measure based on the month in which the disaster occurred. As a result, the natural disasters measure is calculated based on the cost measure and the month that the disaster is based on is M (Klomp and Valckx, 2014), so that Cost (12–M)/12. Moreover, the natural disasters measure is divided by the land area of each country, given that larger countries have a higher probability of being hit by a natural disaster. The data are obtained from the Emergency Events Database (EM-DAT), which is an international disaster database provided by the Center for Research on the Epidemiology of Disasters (CRED).

For a disaster to be entered into the EM-DAT, at least one of the following criteria must be satisfied: a) 10 or more people are reported to be killed, b) 100 people are reported to be affected, c) declaration of a state of emergency, or d) call for international assistance. The data span the period 2000-2018 and include geophysical (earthquakes, volcanic activity), meteorological (extreme temperatures, fog, storms/hurricanes), hydrological (floods, landslides, wave actions), climatological (drought, glacial lake outburst, wildfires), and biological (epidemic, insect infestation, animal accidents) disasters. A detailed breakdown of the disasters is shown in Table 1. This variable has been used frequently in the literature as a proxy for natural disasters (Toya and Skidmore, 2007; Cavallo et al., 2013). Given that the remaining control variables are on a quarterly basis, natural disasters variables are turned into quarterly values by taking the average of the three months that correspond to the relevant quarter.

Table 1 Types and Occurrence of Natural Disasters in Percentage

Types of disasters	Percentage
Geophysical	34%
Meteorological	22%
Hydrological	12%
Climatological	14%
Biological	8%

Source: Based on natural disaster events that occurred in the 117 countries and over the time span under study.

In terms of the control variables, quarterly data on: i) personal income per capita (defined as the income received from all sources, and constitutes the sum of the net earnings, and rental, personal dividend and personal interest incomes); all nominal values are turned into real values by dividing them by the consumer price index, ii) real interest rates for construction and housing loans (measured as the difference between nominal interest rates and inflation), iii) housing construction costs (measured as construction materials and labor costs per square meter), iv) unemployment rate, and v) the Gini coefficient: obtained from the Standardized World Income Inequality Database (SWIID) offered by Solt (2014) as the preferred measure of income inequality due to its superiority in terms of availability and comparability for cross-country research purposes (Bergh and Nilsson, 2010). Furthermore, the SWIID data take into consideration the uncertainty in the predicted measures of inequality by using multiple imputed estimation methods that automate the Monte Carlo simulation process and average the results to arrive at the final measure of inequality (Solt, 2014). Given that the Gini is bounded between 0-100, the coefficient is transformed into an unbounded measure by using [Gini/(100-Gini)], and subsequently the unbounded measure is converted into a natural log value. Higher values of the Gini coefficient denote values closer to maximal inequality and vice versa.

5. Empirical Analysis

Table 2 presents the empirical results, with columns that indicate certain specifications. In particular, Column (1) displays the bivariate estimates between house prices and natural disasters, when no other control variable is included, while Column (2) shows the estimates when all control variables are allowed to enter. Throughout the analysis, we cluster standard errors at the country level to allow for correlations in the idiosyncratic shocks to all transactions that occur in the same country over the entire sample period, while the Akaike criterion suggests zero lags across all variables involved and across both specifications. The results of both columns clearly document the negative and statistically significant impact of natural disasters on house prices. In that sense, the findings validate the negative effect from less demand for ownership housing.

Table 2 GMM (Baseline) Estimates

Variable	(1)	(2)
Natural disasters	-0.163***	-0.142***
	[0.00]	[0.00]
ΔPersonal income per capita		0.271***
		[0.00]
ΔReal interest rates		-0.079**
		[0.03]
ΔHousing construction costs		-0.138**
		[0.04]
ΔUnemployment rate		-0.218***
		[0.00]
ΔIncome inequality		-0.254***
		[0.00]
Diagnostics		
Adj. R^2	0.18	0.62
LM test	[0.00]	[0.00]
Hansen test	[0.95]	[0.99]
No. of instruments	8	26
No. of countries	117	117
No. of observations	8,892	8,892

Notes: Figures in brackets denote *p*-values. LM stands for the Lagrange multiplier test for random effects (Breusch and Pagan, 1980). Hansen is the instrument validity test. The number of lags in both tests is determined through the Akaike criterion. All estimations are performed with time dummies. **: $p<0.05$; *** $p<0.01$.

In terms of the remaining determinants of house prices, the estimates are in accordance with theoretical expectations; more specifically: i) personal income per capita exerts a positive effect on house prices, ii) real interest rates for construction and housing loans have a negative impact on house prices, iii) housing construction costs have a negative effect on house prices, iv) higher (lower) unemployment rates affect house prices in lower (higher) house prices, and v) higher (lower) income inequality (proxied by the Gini coefficient) exerts a negative (positive) effect on house prices. Finally, the relevant diagnostics are reported at the bottom of Table 1. In particular, the findings document that for the validity of the instruments used, we need to reject the test for second-order autocorrelation, AR(2), in disturbances. It is evident that the test for the AR(2) of disturbances fails to reject the respective null. Thus, this test supports the validity of the instruments used. The diagnostics also report the Hansen test for over-identifying restrictions. In the estimation process, a total of 23 and 28 instruments have been used across both specifications, respectively. The reported Hansen test results fail to identify any problems in the validity of the instruments used in the estimation approach.

6. Robustness Check: The Impact by Type of Natural Disaster

Table 3 reports the results for each type of natural disaster. A multivariate framework has been used to obtain the new findings. The findings provide robust support to those reported in Table 2, not only in terms of the primary control variable, that is, natural disasters, but also in terms of the remaining drivers. Moreover, the impact of natural disasters on house prices is higher in the case of geological types of disasters, followed by meteorological and climatological disasters. The impact of meteorological disasters (in which hurricanes have the largest share) is positive, a result which contrasts with the remaining types of natural disasters that show a negative effect on housing prices. Theoretically, a large exogenous shock to housing, such as a hurricane, may have considerable implications for housing values, although the a priori net effect is not clear. On the one hand, the shortage in supply is likely to cause increases in housing prices. In other words, markets surge from a housing shortage following a hurricane storm, and then correct in the more distant future as supply gradually returns to previous levels. At the same time, however, hurricanes may cause enough disruption to economic activity so as to negatively affect income and consequently the demand for housing (Strobl, 2009). Moreover, if potential homeowners update their subjective probability of a hurricane strike occurring in response to a hurricane strike, this may reduce the attractiveness of hurricane-prone areas and reduce housing demand even in the long-run. Therefore, our findings potentially provide support to the first round of implications mentioned above by emphasizing the supply side channel of the hurricane effects. In addition, meteorological disasters can be easily predicted (due to better advancements in related technology), for example, in contrast to earthquakes. In this case, the expected net losses in terms of health and productivity, as well as property damages, should be lower than the expected losses from other types of disaster events. As a result, the housing values do not receive as much pressure to drop. Finally, differential media coverage could also drive heterogeneity in the impact of the type of disaster on housing prices. Certain types of disasters such as hurricanes, tend to receive extensive (inter)national news coverage. This speeds up the response of policymakers to compensate the population who suffer from this event, while allowing people to return to their homeland faster. Thus, the demand for housing is increased, which leads to higher prices.

Table 3 GMM Estimates by Type of Natural Disaster and When All Controls are Included

Variable	Geophysical	Meteorological	Hydrological	Climatological	Biological
ND	-0.189***	0.144***	-0.093**	-0.106***	-0.062*
	[0.00]	[0.00]	[0.03]	[0.01]	[0.07]
Δ*Pincome*	0.233***	0.198***	0.165***	0.176***	0.149***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Δ*Rinter.rates*	-0.094**	-0.077**	-0.056**	-0.068**	-0.042*
	[0.03]	[0.04]	[0.05]	[0.04]	[0.07]
Δ*Hconstr costs*	-0.159***	-0.136***	-0.124***	-0.140***	-0.106**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]
Δ*Unempl rate*	-0.246***	-0.228***	-0.201***	-0.211***	-0.143**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]
Δ*Income ineq*	-0.283***	-0.248***	-0.215***	-0.230***	-0.163**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.03]
Diagnostics					
Adj. R^2	0.71	0.64	0.62	0.63	0.49
LM test	[0.65]	[0.59]	[0.53]	[0.56]	[0.47]
Hansen	[0.99]	[0.99]	[0.99]	[0.99]	[0.97]
No. instruments	27	26	26	25	25
No. of countries	86	109	67	110	58
No. of obs.	6,536	8,284	5,092	8,360	4,408

Notes: Figures in brackets denote *p*-values. The Akaike criterions zero lags across all variables. Hansen is the test for over-identifying restrictions and LM stands for the Lagrange multiplier test for random effects (Breusch and Pagan, 1980).
**: p<0.05; *** p<0.01.

The results that are relevant to earthquakes disasters are supported in Prentice (2005) and Naoi et al. (2009) who analyze the effect of earthquake risks on house prices. Their findings document the presence of substantial price discounts associated with earthquake activities. The findings with respect to meteorological disasters are also in accordance with certain studies in the literature, such as Bin and Polasky (2004). They are, however, in contrast with those by Graham and Hall (2001) and Beracha and Prati (2008) who find no discernable effect of hurricanes on house prices. Finally, with respect to hydrological disasters, the findings are also in accordance with the majority of the studies in the literature (Tobin and Newton,1986; Tobin and Montz, 1994) which suggest that there are different profiles that depict the impacts of floods on house prices, depending on how often they occur. When rare flooding is the case, house prices fall immediately after a flood event and then recover fully after repairs are complete. By contrast, when floods occur very frequently, housing utility has insufficient time to recover and thus, house prices remain low, given the incomplete and imperfect capitalization of flood damages. Similar results are provided by Harrison et al. (2001) and Bin et al. (2008). They are, however, against those provided by the proponents of the efficient market hypothesis who suggest that this type of disaster reflects a transitory phenomenon. Given rapid repairs are made on damaged properties, house prices are characterized by rapid rebounds (Lamond and Proverbs, 2006).

7. Robustness Check: The Role of Fatal Disasters

Following Boustan et al. (2017), this section repeats the estimates of Table 2, but this time, the variable of natural disasters contains only disasters with at least one fatal event with multiple direct deaths. The new results are presented in Table 4 and provide robust evidence to the previous findings, but this time, the impact on house prices is higher. In other words, life-threatening disasters lead to the strong decline in the demand for home ownership, thus leading to large reductions in house prices.

Table 4 GMM Estimates (Only Fatal Natural Disasters Included)

Variable	(1)	(2)
Natural disasters	-0.236***	-0.186***
	[0.00]	[0.00]
ΔPersonal income per capita		0.278***
		[0.00]
ΔReal interest rates		-0.093**
		[0.02]
ΔHousing construction costs		-0.152**
		[0.03]
ΔUnemployment rate		-0.226***
		[0.00]
ΔIncome inequality		-0.262***
		[0.00]
Diagnostics		
Adj. R^2	0.2	0.69
LM test	[0.00]	[0.00]
Hansen test	[0.98]	[0.99]
No. of instruments	10	25
No. of countries	63	63
No. of observations	4,788	4,788

Notes: Figures in brackets denote *p*-values. The Akaike criterions zero lags across all variables. Hansen is the test for over-identifying restrictions and LM stands for Lagrange multiplier test for random effects (Breusch and Pagan, 1980). **: p<0.05; ***: p<0.001.

8. Robustness Check: The Role of the Frequency of Disasters

Finally, this section explores the role of the frequency of natural disasters. To this end, the analysis differentiates, in terms of frequency, between large and small natural disasters. More specifically, the analysis replaces the overall natural disaster variable with two new disaster variables, large natural disasters (LNDs) and small natural disasters (SNDs). LNDs are defined as those that equal 1 if the frequency of disasters is above the year median in terms of the damages (large disaster), while SNDs are defined as those that equal 1 if the frequency of disasters is below the year median in terms of damages (small disasters). The threshold level that differentiates between LNDs and SNDs is damage that is worth 100 thousand US dollars. The new findings (in the multivariate framework) are reported in Table 5 and clearly show that LNDs have a more pronounced effect on house prices.

Table 5 GMM Estimates (Role of Large and Small Natural Disasters)

Variable	Large disasters	Small disasters
Natural disasters	-0.289***	-0.147***
	[0.00]	[0.01]
ΔPersonal income per capita	0.299***	0.236***
	[0.00]	[0.00]
ΔReal interest rates	-0.109***	-0.066**
	[0.01]	[0.04]
ΔHousing construction costs	-0.186***	-0.124**
	[0.00]	[0.05]
ΔUnemployment rate	-0.261***	-0.194***
	[0.00]	[0.00]
ΔIncome inequality	-0.294***	-0.229***
	[0.00]	[0.00]
Diagnostics		
Adj. R^2	0.74	0.56
LM test	[0.00]	[0.00]
Hansen test	[0.99]	[0.97]
No. of instruments	27	24
No. of countries	86	71
No. of observations	6,536	5,396

Notes: Figures in brackets denote *p*-values. The Akaike criterions zero lags across all variables. Hansen is the test for over-identifying restrictions and LM stands for the Lagrange multiplier test for random effects (Breusch and Pagan, 1980).
**: $p<0.05$; *** $p<0.01$.

9. Conclusion

This study has added some new and fresh information to current understanding on how natural disasters impact house prices. The previous literature has focused on specific types of natural disasters and how certain types of natural disasters, mostly floods, have influenced house prices. The findings offer a more complete picture of the impact of disastrous events on housing markets, while including a variety of natural disaster types across 117 countries that span the period 2000-2018. The findings show that natural disasters lead to lower house prices, with the results surviving a number of robustness tests. When examining the impacts of natural disasters by type, the findings document that geological disasters have the strongest (negative) impact on house prices. Similar results are obtained when fatal and large disasters are used.

The findings provide important implications for policymakers and property investors. More specifically, in terms of insurance policies, natural hazards are expected to increase in severity and occur more frequently everywhere as a result of global climate change, thus, exerting severe impacts on house prices. Insurance efforts should explicitly consider the role of insurance within a framework where natural disasters lead to lower house prices and thus cater to the needs of such problems and start providing new solution strategies by improving awareness of natural hazards across the globe. Swift steps also need to be taken in national policies to adjust natural hazard insurance systems in relation to the housing sector. Only then can the involved parties arrive at the systematic risk transfer needed to tackle climate change. The insurance system landscape across the globe (as well as across many types of insurances) varies greatly given that global insurances are rooted in the cultures of different societies in combating natural hazards. It is to be expected that any adjustments needed to new weather conditions should comply with the 'change in diversity' approach that offers the best chance across countries to achieve systems that are perfectly adapted to climate change (Huber and Amodu, 2006).

Moreover, the results can offer substantial guidance on the effects on banking institutions. In particular, lower house prices can motivate individuals and business owners who suffer from such losses to withdraw deposits and apply for loans at banks to obtain additional funding for reconstruction efforts. Banks can, therefore, play a significant supporting role through the provision of greater liquidity and credit in response to the disaster effects. Overall, these natural disasters can generally lead to increases in the demand for loans from banks that usually respond by raising deposit rates to obtain additional funding to provide greater lending in line with such disasters (Bos et al., 2018; Dlugosz et al., 2018; Koetter et al., 2019). Our results also offer a caveat for certain implications on house ownership and potential derived migration effects. Lower house prices may, especially for households with no easy access to credit funding, compel reconsiderations around home ownership and rent choices that will eventually generate migration flows with further repercussions to sectoral and aggregate economies. Overall, changes in home ownership choices seem to reflect priors of households on natural disaster risks given new information provided by the disaster event (Gallagher, 2014; McCoy and Zhao, 2018).

Lower house prices in countries hit by natural disasters could also lead them to significantly experience lower consumption and investment (the wealth effect), with further negative spillovers to the real economy. In that case, economic policymakers could implement low-tax policies and/or quantitative easing schemes that provide liquidity to support areas hit by natural disasters.

Finally, a limitation of this current research effort is that further empirical analysis could have explored the impact of various types of natural disasters on house prices, by replacing house prices with house supply indexes, such as new sales and house transactions. This would have been substantially interesting as a potential research venue. Nevertheless, such research has to cope with two methodological difficulties. First, it is difficult to track the availability of such data for the majority of the countries involved. Second, in order for this type of analysis to be as accurate as possible, the data should be focused on the areas where the disasters have occurred and not on the entire country domain, which makes it practically impossible in terms of data availability.

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Appendix

Country Sample (117 Countries)
Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, China, Colombia, Costa Rica, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Fiji, Finland, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guinea, Guyana, Honduras, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Laos, Latvia, Lebanon, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Congo, Romania, Russia, Saudi Arabia, Senegal, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Zambia, and Zimbabwe.