

The Salience of Disaster: How Experience Outweighs Information in Pricing Earthquake Risk

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Abstract

This paper investigates how salience influences decision-making in earthquake-prone real estate markets in Türkiye, focusing on two critical events: the 2018 revision to the national earthquake hazard map and the catastrophic 2023 earthquake that resulted in over 50,000 fatalities. Our findings indicate that while the updates to the hazard map have little effects on property values, the actual occurrence of a disaster significantly reduces home prices and increases insurance uptake in high-risk but physically unaffected areas. A one-standard-deviation increase in baseline seismic risk is associated with a 4% decline in home prices after the earthquake. Additionally, the data show that areas with strong social connections to disaster-stricken regions experience more pronounced declines in home sale prices, highlighting the role of personal relationships in amplifying risk perception. Overall, these results suggest that the salience of a vivid, catastrophic event is far more impactful in shaping economic behaviors than abstract, probabilistic information in high-risk scenarios.

Keywords: Risk Salience, Housing Market, Natural Disaster Risk, Disaster Insurance, Earthquake Hazard Map

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1. Introduction

Decision-making in economic contexts is frequently marred by cognitive biases, particularly through the influence of salience on perceived outcomes. Salience bias causes individuals to overweight the most noticeable and memorable outcomes, often ignoring their statistical relevance or probability. This distortion is evident in real estate and insurance markets, where a fundamental question arises: "Do markets price natural disaster risk only after it becomes real?". In such environments, attention shifts from probabilistic information to realized experience, producing systematic deviations from rational behavior. While theoretical models predict such behavioral distortions (Bordalo et al., 2012), empirical tests examining both types of risk signals within the same market setting remain scarce.

To address this challenge, we provide direct evidence of attention asymmetry by examining how salience concerning natural disaster risk, specifically earthquake risk, impacts the real estate market in Türkiye, a country where many residential areas are susceptible to earthquakes. We compile a novel dataset that merges real estate listing prices, official seismic risk measures, earthquake insurance uptake, and regional socio-demographic indicators at the county-month level. Our quasi-experimental design exploits two clean, exogenous shocks observed in these markets: (i) the 2018 nationwide hazard-map revision, which delivered a probabilistic update, and (ii) the unexpected February 2023 earthquakes, which caused more than 50,000 fatalities and an estimated \$163 billion in losses.

First, we assess how the 2018 map update affected property values and insurance uptake. Next, we investigate the effects of a realized disaster. Although the 2023 disaster struck a specific region, we examine how its salience generated spillover effects in regions not directly affected but sharing similar underlying risk.¹ By comparing market responses across these events within the same empirical setting, we identify the role of salience in driving economic behavior under disaster risk while minimizing concerns about selection or anticipatory behavior.

¹One possible concern is whether the 2023 earthquake increased seismic risk in regions outside the immediate earthquake zone via fault line connections. While this hypothesis is plausible, post-event geological assessments so far indicate no such effect. Moreover, without updated hazard maps, it is unrealistic to expect market participants to evaluate fault line shifts, given the need for detailed and time-intensive ground research.

Our findings reveal a striking disparity in market response. The 2018 hazard map revision, despite updating probabilistic risk assessments, had no significant effect on housing prices. This muted market reaction suggests that in the absence of a vivid event, both homeowners and institutional actors, such as mortgage lenders, underreact to new risk information, leading to an underpricing of exposure. In other words, when heightened earthquake risk is conveyed only as an abstract probability on a map, it appears insufficiently salient to prompt repricing or increased precautionary demand.

By contrast, the 2023 earthquake triggered an immediate and substantial behavioral response. In regions with high seismic risk but no physical damage, home prices fell sharply following the disaster. The realization of risk through a catastrophic natural disaster made earthquake risk salient, prompting both households and market institutions to update their beliefs and decisions, resulting in a 4% decrease in home prices for each one standard deviation increase in the earthquake risk level and a moderate increase in insurance uptake. Notably, the response was especially pronounced in locations with strong social ties to the affected area. Even though these socially connected regions were geographically distant from the epicenter, they experienced declines in property values after the earthquake. This pattern suggests that personal connections, such as having friends or family in the disaster zone, amplified the salience of the event, transmitting fear and risk awareness.

We examine how behavioral adjustments differ across socio-economic and demographic dimensions to isolate variation in market response. The 2018 hazard map update elicited no measurable effect on rent prices, insurance uptake, or transaction volumes—even in counties with higher education levels or incomes. Mortgage-financed home sales reacted no differently than cash purchases, indicating that institutional actors were equally inattentive to the probabilistic information update. This pervasive inattention underscores the ineffectiveness of abstract risk disclosures in shifting market behavior.

In comparison, the response to the 2023 earthquake was immediate and persistent, yet not driven by domestic migration. Housing price declines did not correlate with distance from the epicenter, and voter registration data confirm that domestic migration does not account for the observed pattern. Instead, the salience of the catastrophic outcome alone drove widespread behavioral change. Disentangling insurance behavior shows that both new policy uptake and renewals increased, with renewal effects emerging more gradually but proving equally persistent, mirroring the durable decline in

home prices. Education does little to differentiate the market reaction, suggesting that heightened emotional salience compressed cognitive heterogeneity. Wealthier counties, however, showed stronger responses, highlighting liquidity as a key enabler of adjustment.

Earthquakes provide an ideal setting for studying responses to low-probability, high-impact risks compared to other natural disasters. Most studies examine geographically concentrated, seasonal, and partially predictable hazards such as floods, hurricanes, and wildfires.² These events typically affect specific areas with heterogeneous patterns.³ Unlike these hazards, earthquakes are spatially diffuse, structurally indiscriminate, and inherently unpredictable, posing systemic threats across entire communities regardless of socioeconomic status or property characteristics.⁴ Their lack of warning, seasonal pattern, or predictability minimizes selective migration and anticipatory behavior, creating a cleaner identification setting for studying risk perception and economic responses.

The stark contrast between market reactions to hazard map information and experienced disaster highlights the central role of salience in risk assessment and advances our understanding of economic behavior. Garmaise et al. (2024) show that households often overreact to salient financial news lacking genuine informational content, suggesting that attention, rather than information, drives many economic decisions. When hazard information remains probabilistic and abstract, market participants substantially underreact, failing to incorporate risk updates into asset prices and leading to systematic mispricing of exposure. Only when risk becomes concrete, emotionally charged, and personally meaningful through direct experience do markets adjust to more accurately reflect underlying fundamentals.⁵ While

²Bin and Landry (2013), Bernstein et al. (2019), and Issler et al. (2020) document price declines in home values following natural disasters.

³These hazards typically affect localized areas (e.g., coastal zones) or specific property types (e.g., ground-floor units), with ownership patterns that are often heterogeneous. Damage tends to be partial, involving belongings or limited structural harm. Because these hazards often recur with seasonal regularity, property owners may self-select into or out of risk zones, invest in mitigation, or learn to anticipate threats over time. Behavioral responses to these risks are often shaped by prior exposure, adaptation, or informational endogeneity, complicating causal interpretation.

⁴Giuliano and Spilimbergo (2024) show in their literature survey that exposure to aggregate shocks significantly shapes preferences and beliefs.

⁵This realized versus probabilistic losses effect is documented by Imas (2016), who

one could interpret the price response as an availability heuristic or an emotionally driven mispricing, the data suggest otherwise. The adjustment is neither short-lived nor erratic—it is persistent, consistent across high-risk areas, and aligned with fundamental reassessments of risk. This pattern implies that households were ex-ante inattentive to earthquake risk, and that the disaster served as a corrective event. In this sense, the salience of the earthquake induced a shift from behavioral inattention to rational repricing. Our analysis provides new evidence of this attention asymmetry and shows how social networks act as transmission channels for risk salience, triggering behavioral responses even in geographically unaffected but socially connected communities. Our contributions span several strands of literature, summarized as follows:

First, we contribute to the real estate finance literature by jointly analyzing an informational shock and a realized disaster within a unified empirical setting. Hazard maps aim to reduce information asymmetry by making geographic risk more transparent, but empirical studies report varying outcomes.⁶ Our findings add to this literature by showing that the update produced no detectable price effects in an emerging market. However, realized disasters often have pronounced and lasting impacts on housing markets. Prior studies show that earthquakes lead to substantial declines in property values (Murdoch et al., 1993; Naoi et al., 2009), and that even geographically distant disasters can alter market behavior in unaffected regions (Fekrazad, 2019). While prior studies typically examine either risk perception or realized damage in isolation, our dual-shock design uniquely captures how markets react to abstract probabilistic information versus lived experience. This is important because much of the existing evidence comes from developed economies, where housing markets are dominated by institutional investors, sophisticated insurers, and regulated lenders. On the other hand, our setting represents a more typical global housing structure, where individual households drive most transactions and where financial literacy and risk pricing are less advanced. We believe this context is more representa-

shows that experiencing actual financial losses leads to more conservative subsequent risk-taking compared to equivalent unrealized losses.

⁶Research on flood risk documents modest to significant price effects (Hino and Burke, 2021; Shr and Zipp, 2019). Seismic risk studies find evidence of both price declines in high-risk areas and price resilience where mitigation measures are strong (Singh, 2019; Hidano et al., 2015; Kawabata et al., 2022).

tive of the majority of the world’s housing markets. Moreover, in emerging markets, housing prices carry heightened economic significance: real estate assets often serve as primary collateral for small and medium-sized enterprises, which rely heavily on collateral-based lending in the absence of deep, structured financial systems.

Second, we introduce a behavioral mechanism by showing how social networks amplify the salience of disaster risk. Unlike previous studies that focus on spatial proximity, we demonstrate that familial ties to the disaster zone can transmit risk perception across geographically separated markets. Empirical evidence highlights that perceptions of risk—and resulting economic decisions—are not confined geographically but can diffuse through shared media, visual cues, and networks⁷. This approach helps explain why asset price movements sometimes appear disconnected from local economic fundamentals.

Third, we contribute to the behavioral finance literature by documenting persistent inattention to probabilistic risk. Building on the theoretical foundations of salience theory (Bordalo et al., 2012), we extend its empirical application to disaster risk pricing in housing and insurance markets. Salience distorts attention and valuation across various financial settings.⁸ In the context of natural disasters, salient events drive significant behavioral responses beyond objective risk levels⁹. Fairweather et al. (2024) show that providing salient flood risk information through a real estate platform significantly alters homebuyer behavior throughout the purchasing process. While their experiment demonstrates that clearly presented risk information can drive proactive adaptation in housing markets, our study reveals that official earthquake hazard maps fail to generate similar responses without the experience of an actual disaster.

This salience-driven pattern extends to insurance markets as well. Subjec-

⁷See, for example, Fogli and Veldkamp (2021); Blumenstock et al. (2025); Gallagher (2014); Hu (2022); McCoy and Walsh (2014)

⁸See, for example, Cosemans and Frehen (2021), Cakici and Zaremba (2022), Chetty et al. (2009), Bordalo et al. (2015).

⁹Managers increase cash holdings after nearby hurricanes despite unchanged risks Des-saint and Matray (2017), CEOs’ early-life disaster experiences shape corporate risk-taking Bernile et al. (2017), firms enhance ESG disclosures following nearby disasters Huang et al. (2022), and institutional investors support environmental proposals after hurricane exposure Fich and Xu (2025).

tive risk perception drives earthquake insurance decisions (Palm and Hodgson, 1992), with even minor earthquake experiences temporarily boosting uptake through availability bias (Lin, 2020). Disaster experiences significantly alter insurance purchasing when outcomes differ from expectations (Gao et al., 2020), demonstrating that experiential salience shapes insurance behavior more powerfully than statistical information.

Collectively, our findings underscore a central insight: risk pricing is driven more by perceived immediacy than by objective probability. Market reactions to disaster risk reflect not just the availability of information, but how that information is experienced, internalized, and socially transmitted. By directly comparing abstract probabilistic updates with realized shocks within a unified empirical setting, our study advances research on attention constraints, limited belief updating, and disaster myopia in financial markets. This design reveals the limitations of hazard disclosures and demonstrates how salience, personal exposure, and social connectivity jointly shape housing market and insurance outcomes in ways that conventional risk communication often fails to capture.

The remainder of the paper is organized as follows. Section 2 provides background on the institutional settings and earthquakes. Section 3 describes the data. Section 4 outlines our empirical strategy. Section 5 presents the main results, and Section 7 concludes.

2. Institutional Background

Earthquake hazard maps are critical tools for communicating seismic risk and informing structural design, insurance pricing, and policy. In Türkiye, the first comprehensive earthquake risk map was released in 1996 and remained in effect until a major revision was introduced in 2018. These maps use a probabilistic seismic hazard assessment (PSHA) framework, which estimates the likelihood of various levels of ground shaking over a given time horizon. Specifically, Türkiye’s maps adopt a 10% probability of exceedance in 50 years, corresponding to a return period of 475 years.

Seismic risk is measured using Peak Ground Acceleration (PGA), which quantifies the maximum expected acceleration of the ground during an earthquake. PGA is internationally standardized and serves as a key input in the design of earthquake-resistant infrastructure. In Türkiye, PGA values are used both in the Turkish Building Earthquake Code (TBDY 2018) and in

the pricing of compulsory earthquake insurance. Higher PGA values imply more intense shaking, stricter building standards, and higher insurance premiums.

The 2018 revision of Türkiye’s Earthquake Hazard Map, developed by the Disaster and Emergency Management Authority (AFAD), replaced the earlier map with a continuous, site-specific PGA model. This update incorporated advances in seismic science, added newly identified fault lines, and removed outdated ones. As a result, many counties experienced significant reclassification, with previously similar-risk areas now exhibiting sharply different levels of hazard. The map was officially published in March 2018. The revised system enables more granular risk evaluation and is expected to enhance the accuracy of building codes and insurance assessments.

To quantify county-level earthquake risk in our analysis, we use these location-specific PGA values. We match geographical coordinates from the hazard maps to county centroids, allowing for precise risk measurement across space. The average distance between measurement points and county centers does not exceed 6 km, ensuring a high level of accuracy in spatial mapping.

On February 6, 2023, Türkiye experienced two catastrophic earthquakes: a magnitude 7.8 quake centered near Kahramanmaraş, followed nine hours later by a magnitude 7.7 event near Elbistan. These twin earthquakes affected 11 provinces and caused over 59,000 fatalities in Türkiye alone, with millions displaced and massive destruction of housing and infrastructure. The economic cost is estimated to exceed \$200 billion. The disaster emphasized systemic vulnerabilities in construction standards and disaster preparedness, triggering both domestic and international calls for reform and reconstruction.

The Turkish Catastrophe Insurance Pool (DASK), established in 2000 after the 1999 İzmit earthquake, plays a central role in Türkiye’s risk-sharing infrastructure. The insurance is legally required for all urban homes, particularly for accessing public services such as title deed registration, electricity, and water connections. However, in practice, many residents do not maintain continuous coverage unless they engage in a transaction that enforces it—such as moving to a new home or transferring ownership. This results in low continuous coverage rates, especially among older and lower-income properties. Since the policy is mandatory during the first year of occupancy for all homeowners, public awareness of DASK remains very high, even if many allow their coverage to lapse afterward.

Despite enforcement gaps, DASK remains a cornerstone of Türkiye’s dis-

aster response framework. Following the 2023 earthquakes, it disbursed over \$1.2 billion in claims. Nonetheless, the system’s long-run effectiveness is constrained by weak enforcement and behavioral inertia among residents. This uneven insurance behavior, coupled with the low pricing of earthquake risk before the disaster, underscores the challenges in translating risk awareness into consistent market behavior.

Türkiye’s housing market is suitable for our setting since nearly half of the population lives in earthquake-prone zones. Additionally, the relatively low switching costs in the Turkish housing market—due to the fact that mortgage sales account for only 10-15% of total sales—allow people to move quickly between risky and non-risky areas. This unique setting enables our sample to be robust in managing endogeneity concerns, particularly as we examine price differentials within cities, where risk gradients are stark, as observed in Istanbul, where the northern part has significantly lower risk than the southern part and price adjustments were immediately reflected after the 2023 earthquake (Figure 6) despite not altering fault lines or changing the pre-existing risk levels associated with the city.

3. Data

We construct a monthly panel of county-level home prices in Türkiye using publicly available data on real estate listings. The data provide detailed information on property listings, including price records, and neighborhood characteristics. They also offer monthly, county-level information on listing sale and rent prices for both commercial and residential properties.

To assess seismic risk over time, we incorporate the 1996 Earthquake Hazard Map developed by the Disaster Management Implementation and Research Center and its updated 2018 version by the Disaster and Emergency Management Authority (AFAD). We obtain seismic risk assessments from Türkiye’s official earthquake hazard maps, published in 1996 and updated in March 2018 by AFAD. Importantly, neither version of the map assigns risk directly to counties or cities; instead, they provide risk values at a grid of geographic coordinates. We spatially match these coordinates to the administrative centers of Türkiye’s 350 counties using geolocation tools. The maximum distance between a county center and its nearest risk data point is 6 kilometers, ensuring high geographic precision and justifying our county-level assignment of seismic risk. To quantify information updates, we

compute the percentage change in risk values between the old and new maps for each county.

Additionally, the Turkish Catastrophe Insurance Pool’s data is crucial for understanding insurance uptake and earthquake-related claims, shedding light on financial preparedness and risk mitigation among homeowners. Demographic statistics from the Turkish Statistical Institute, particularly educational attainment and family structures, are also utilized. These statistics are instrumental in examining the socio-economic factors that influence property valuation and risk decisions.

Moreover, our analysis incorporates data on individuals’ hometown origins, which is provided by Turkish Statistical Institute. This dataset reports how many residents in each county originate from a specific city, enabling us to construct a proxy for social connectedness. By measuring the concentration of people living outside their native city but in counties with strong ties to it, we capture the presence of family networks and regional affinity. We use this as a proxy for family ties, which allows us to examine how social connectedness may influence behavioral responses to earthquake risk and salience.

Another component of our study is the Socio-Economic Development Index (SEDI) provided by the Ministry of Industry and Technology. This index integrates various socio-economic variables into eight dimensions: demographics, employment and social security, education, health, finance, competitiveness, innovation, and quality of life, offering a comprehensive view of socio-economic development. We use this index as a proxy for county-level wealth, allowing us to account for regional disparities in economic capacity and resilience when analyzing the effects of earthquake risk and salience.

Lastly, we include election outcome data from the Supreme Election Council from 2019 to 2023. This data helps us to understand migration patterns, as voters are required to declare their residences to vote, providing indirect insights into population movements and their effects.

4. Empirical Strategy

Our empirical strategy addresses two core questions: (1) how do housing markets respond to updated information about natural disaster risk, and (2) how does the realization of a known but previously underweighted risk affect market behavior? We use a monthly county-level panel of listed housing prices from January 2018 to August 2024, matched with official earthquake

risk assessments derived from Türkiye’s national seismic hazard maps. The first setting exploits the March 2018 update to the hazard map, which revised each county’s assessed risk based on new geophysical data. Using this shock, we estimate whether changes in risk levels influenced home values by interacting each county’s percentage change in risk (from the 1996 map to the 2018 version) with a post-update indicator.

In the second setting, we examine market reactions to the realization of seismic risk through the February 2023 earthquakes. Here, we test whether counties with higher baseline risk experienced larger price declines after the disaster by interacting their fixed risk level with a post-earthquake indicator. In both cases, we implement a two-way fixed effects (TWFE) framework with county and time fixed effects, taking advantage of the quasi-experimental variation in timing and cross-sectional exposure. Event-study models further allow us to examine dynamics and test for parallel trends. Our empirical setting is well-suited to this strategy: counties’ baseline earthquake risk is time-invariant, there were no major nationwide policy shocks concurrent with the events we study, and fixed effects help account for persistent differences across counties.

We estimate two-way fixed effects regressions using a balanced monthly panel of 350 counties observed from January 2018 to August 2024. Our baseline outcome is the logarithm of inflation-adjusted home listing prices, although we also consider rent prices, insurance uptake, and mortgage usage as alternative outcomes. The variation we exploit differs between the two empirical settings. For the 2018 hazard map analysis, we examine how changes in officially assessed earthquake risk affected property values by interacting Treatment which is each county’s percentage change in risk—defined as $(\text{NewRisk}_c / \text{OldRisk}_c) - 1$ —with a post-update indicator that equals one for months after March 2018. For the 2023 earthquake analysis, we assess how counties with higher baseline risk responded to the realization of that risk. In this case, we interact each county’s time-invariant seismic risk level with a post-earthquake indicator that equals one for February 2023 and all subsequent months.

Our baseline specification takes the form:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot (\text{Treatment}_c \times \text{Post}_t) + \varepsilon_{ct}, \quad (1)$$

where Y_{ct} denotes the outcome in county c and month t , α_c are county fixed effects, and γ_t are month-year fixed effects. The term Treatment_c represents

either the percentage change in risk classification (for the hazard map analysis) or the level of seismic risk (for the earthquake analysis). The coefficient β captures how market outcomes changed after each shock, differentially by treatment intensity.

County fixed effects account for time-invariant local characteristics (e.g., topography, baseline amenities), and time fixed effects absorb any nationwide trends such as inflation, monetary policy, or seasonal cycles. We cluster standard errors at the province level to allow for spatial correlation in housing outcomes.

The empirical strategy relies on two distinct exogenous shocks: the 2018 earthquake hazard map update and the 2023 earthquake realization. In both settings, we exploit monthly variation in timing and continuous cross-sectional variation in earthquake risk to define treatment exposure. Rather than comparing treated and untreated counties, we assess whether the post-event change in outcomes was larger in counties with higher exposure to earthquake risk or to changes in risk levels.

For the hazard map analysis, we construct a post-treatment indicator that equals one beginning in April 2018, immediately after the official release of the revised map. The key interaction term in this specification is the percentage change in risk for each county between the 1996 and 2018 maps. This allows us to test whether counties whose risk classification increased (or decreased) experienced corresponding changes in housing outcomes after the map update.

For the earthquake analysis, the post-treatment indicator equals one for February 2023 and all subsequent months, reflecting the timing of the twin earthquakes that struck southeastern Türkiye. Here, the treatment intensity is each county’s pre-assigned seismic risk level. The interaction of risk with the post-earthquake period captures whether counties facing higher background risk experienced larger shifts in prices or insurance behavior following the disaster.

To assess the validity of the parallel trends assumption and to trace the dynamic effects of the shock, we estimate event-study specifications that interact seismic risk with a series of time-relative dummies, as shown in Equation 2:

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{k \neq 0} \beta_k \cdot (\text{Risk}_c \times D_{kt}) + \varepsilon_{ct}, \quad (2)$$

where D_{kt} is a dummy indicating that month t is k months relative to the event. The omitted category is the month just prior to the event, so coefficients β_k trace the relative evolution of outcomes across risk levels, centered on the event month.

These dynamic regressions allow us to visualize treatment effects over time and provide a formal test for pre-treatment balance. We observe no significant pre-trend differentials across risk levels before either the 2018 map update or the 2023 earthquake, lending credibility to our identification strategy. In contrast, we observe a sharp divergence in outcomes after the 2023 earthquake, consistent with salience-driven repricing of risk. Figures 24 present the results of these dynamic analyses.

Our identification strategy relies on the assumption that, conditional on fixed effects, no other time-varying shocks differentially affected counties by risk level during the study period. This assumption is plausible for two reasons. First, the 2018 hazard map update was implemented nationally and was not tied to local market conditions or housing policies. Second, the February 2023 earthquakes were unexpected and geographically localized natural disasters, exogenous to county-level economic fundamentals.

We address potential confounders by including county and month-year fixed effects in all specifications, ensuring that our estimates are identified from within-county variation over time. To further support the validity of our design, we conduct formal parallel trends tests using event-study models and find no significant pre-treatment differences across counties with different levels of risk exposure.

We include alternative specifications with controls for education levels, household wealth, construction activity, and distance to the earthquake epicenter. In addition, we explore heterogeneity in treatment effects between counties with varying levels of social connectivity, finding that family ties amplify behavioral responses to disaster events. These checks strengthen confidence in the interpretation of our results as reflecting causal behavioral reactions to shifts in perceived seismic risk.

In addition to fixed effects, we include time-varying county-level controls to account for local housing market conditions and financial dynamics. These controls cover average home and rent sizes, the total number of home sales, and mortgage activity, including the share of mortgage-financed transactions. To capture the housing supply margin, we include both new construction permits—reflecting planned development—and occupancy permits, which indicate completed buildings entering the market. These two measures

allow us to separately account for forward-looking investment intentions and realized supply. We also control for local insurance uptake, including new and renewed earthquake insurance policies, and commercial property prices. Together, these variables help ensure that our estimates are not driven by concurrent changes in demand, supply, or credit conditions that may vary across counties.

5. Results

5.1. Informational Risk and the 2018 Hazard Map Update

We begin by analyzing whether an exogenous update to earthquake risk information affected housing market behavior. In March 2018, AFAD released a new earthquake hazard map that significantly revised prior risk classifications. These scientific revisions were not accessible to the public beforehand and required advanced geological modeling. Therefore, we treat this map update as an exogenous shock to public risk perception.

Our dataset for this analysis spans from January 2018 to March 2019 and includes monthly housing data for 336 counties, covering approximately 70% of Türkiye’s population. Due to data limitations, county-level home price data is not available before 2018. As a robustness check, we replicate key specifications using city-level data—available prior to 2018—and confirm the absence of differential pre-trends in either home or rent prices (see Figure 4 and Figure 5). Figure 1 presents the distribution of counties in the sample according to the percentage change in their seismic risk level. The distribution is approximately normal, indicating that the treatment intensity varies smoothly across space. Figure 2 displays a county-level map of these risk changes, showing that affected areas are geographically dispersed rather than concentrated in a specific region.¹⁰

Table 1 presents descriptive statistics for this sample. As shown in Figure 1 and Figure 2, the percentage change in earthquake risk across counties ranges from -80% to $+110\%$, offering a rich source of variation. During this period, Türkiye’s economy was undergoing a recession. Inflationary pressure was strong due to currency depreciation. While overall housing prices and rents declined, mortgage sales ratios remained relatively stable at 20% —a

¹⁰City-level pre-trend checks suggest that market prices were not responding to prior unobserved changes before the official announcement.

reflection of Türkiye’s housing market structure, where most transactions are conducted in cash rather than financed through mortgages. As a result, price movements are mainly driven by individuals, rather than institutions.

We measure the treatment as the interaction between the percentage change in seismic risk at the county level and a post-update dummy (equal to 1 after March 2018). We then regress log home prices on this variable. Table 2, Column 1, shows that the coefficient is 0.34 and statistically insignificant. If buyers fully priced in the increased seismic risk, we would expect a negative coefficient, as rising risk should reduce willingness to pay. Instead, the effect is null, and adding control variables—including occupancy permits and new construction permits—does not materially alter the result (Columns 2 to 5). We also include the average size of homes sold as a control variable to account for non-linearities in housing price formation. Larger homes do not scale proportionally in price due to diminishing marginal utility of space and common fixed costs, meaning that a 100 m² house typically costs more than half the price of a 200 m² house. However, this relationship may reverse or flatten in markets where larger homes are relatively scarce, as constrained supply can increase their marginal value. Despite heterogeneity in market liquidity, the estimated effect of the hazard map update remains statistically insignificant across low-, moderate-, and high-transaction counties (Columns 1–3 of Table 2.1). Similarly, the null result holds when restricting the sample to counties experiencing any risk change or only those with extreme reclassifications (Columns 4–5). These findings confirm that the lack of market response is not driven by sample composition or differential sensitivity across liquidity strata or risk intensity levels.

To address the possibility that insurance demand may have reacted more immediately or precisely than prices given that insurance decisions might be influenced by insurance companies, we examine new earthquake insurance policy purchases and policy renewals. Columns 6 and 7 of Table 2 show no significant effects on either outcome. This suggests that, even in the insurance market, the updated risk classification failed to trigger behavioral change.

We explore heterogeneity in response by splitting the sample by county-level education. Counties above the median share of college graduates are compared to those below. Table 3 shows that even highly educated counties did not adjust prices in response to the map update. A similar analysis using the SEDI also finds no differential pricing behavior by income level. In fact, counties with lower development scores experienced slightly larger (but

still insignificant) increases in home prices after the risk update, counter to theoretical expectations. The coefficient of 0.502 in low-income counties is only marginally significant at the 10% level, and in the opposite direction.

We also examine whether demand-side dynamics changed. In Table 4, we regress the number of home sales on the ‘Risk $\times$ Post’ interaction. In both specifications, the interaction coefficient remains insignificant. This supports the conclusion that demand volumes were not disrupted by the hazard map revision.

To address the hypothesis that renters may respond more quickly than homeowners due to lower switching costs, we test for price effects in the rental market. Table 5 shows no statistically significant effects on rent prices either, suggesting that even renters were unresponsive to the updated seismic risk.

Finally, Table 6 presents results from a cross-sectional analysis using yearly data from January 2018 to January 2019, conducted to leverage control variables only available annually. These include population size, household count, the ratio of first-hand to total home sales, and the mortgage-to-total-sales ratio. Columns 1–5 confirm that risk change has no significant effect on home prices or mortgage sales. Intriguingly, Columns 6 and 7 show that earthquake insurance policies declined in counties where risk also decreased. Instead of targeting increased coverage in newly high-risk areas, the public appears to have de-escalated coverage in areas where perceived risk fell—highlighting a general inattentiveness to probabilistic information updates.

Taken together, these results suggest that the 2018 hazard map update—although scientifically rigorous and widely publicized—did not affect pricing behavior or insurance decisions. Neither homebuyers, tenants, nor insurers appeared to revalue risk based on the new classification. This finding aligns with predictions from salience theory: when risk is abstract and not personally experienced, markets may underreact, even in settings with relatively frequent seismic activity.

5.2. Realized Risk and the 2023 Earthquake

We next turn to our second main research question: how does the realization of a known but previously underweighted risk affect market behavior? Specifically, we study the impact of the February 6, 2023, earthquakes on housing prices in counties outside the directly affected region.

Although our estimation sample excludes the physically affected provinces, we exploit the psychological salience of the disaster as a national event. This

strategy allows us to isolate behavioral repricing effects—driven not by direct property damage but by the nationwide shift in risk perception. Figure 6 shows the geographic distinction between the earthquake zone and our estimation sample.

The main sample for this analysis spans from April 2019 to August 2024 and includes monthly data across approximately 350 counties. During this period, Türkiye experienced high inflation and a housing boom. However, as this boom was not geographically concentrated, our design is not confounded by region-specific economic shocks.

Table 7 presents descriptive statistics for counties grouped into earthquake risk quartiles. When comparing pre- and post-earthquake periods across quartiles (Panel C), we show that housing prices in low- and moderately low-risk counties increased more than in high-risk counties. Similar trends are observed for rent prices. Insurance uptake, particularly new policy purchases, rose more in lower-risk counties—a finding consistent with salience theory, in which fear may spill over irrationally into relatively safer areas.

One possible interpretation of this counterintuitive behavior is that households in low-risk counties began to overreact to the event, updating their risk perception far beyond objective exposure. Conversely, in high-risk counties, the price response is driven by a sudden awareness of previously underweighted risk. Figure 7 provides an unadjusted visual correlation, showing that higher-risk counties experienced larger price declines post-earthquake.

In Figure 8, we further investigate this response using a within-city comparison. The x-axis displays a county’s deviation from its city’s median earthquake risk. Counties with below-median risk within a city experienced significantly higher price growth during the ± 2 -month window surrounding the earthquake. This finding underscores the salience of relative risk, even among peers with similar housing and demographic profiles.

The most direct evidence of repricing appears in Figure 9. Prior to the earthquake, housing prices across all four risk quartiles followed a common trend. In the immediate months following the quake, lower-risk counties begin to diverge upwards while high-risk counties stagnate or decline. The gap persists and stabilizes within 3–4 months, consistent with an immediate and durable shift in pricing.

Figure 10 and Figure 11 provide spatial evidence from Istanbul. Counties in the northern part of the city, associated with lower seismic risk, show sharper price increases than their higher-risk southern counterparts during

the ± 2 -month window. This within-city evidence aligns with our county-level findings, showing how risk salience reshapes valuation at a very local level.

Our primary regression result is shown in Table 8, where we regress the log of inflation-adjusted home prices on the interaction of earthquake risk and a post-earthquake dummy (equal to one starting February 2023). The standardized coefficient on ‘Risk $\times$ Post’ is -0.039 , statistically significant at the 10% level. This implies that a one-standard-deviation increase in baseline seismic risk is associated with a 4% decline in home prices after the earthquake. Columns 2–5 introduce controls such as average home size, new occupancy permits (capturing the supply of deliverable housing), and construction permits. The results remain robust.

The salience-driven price decline following the 2023 earthquake is robust across different transaction environments. Columns 7 and 8 of Table 8 show that both low- and high-transaction counties experienced significant price declines in high-risk areas, with a slightly stronger effect in thinner markets. Notably, the response is even more pronounced in Istanbul (Column 9), where a one-standard-deviation increase in risk is associated with an 11.6% decline in prices, underscoring the heightened sensitivity of high-density markets to realized disaster risk.

In Column 5, we substitute city fixed effects for county fixed effects. This allows us to control for city-wide factors, including inner-city migration, local inflation shocks, and coordinated policy responses. When we control for supply, a one-standard-deviation increase in risk is associated with 6% increase in home prices. In Column 6, we test for the effect of distance from the earthquake zone, but the coefficient is statistically insignificant, confirming that it is not physical proximity, but perceived risk that explains the observed price movements.

To ensure the parallel trends assumption holds, we present an event study in Figure 24. Coefficients prior to February 2023 are flat and insignificant, supporting the validity of our design. After the earthquake, we observe a persistent and significant decline in housing prices in high-risk counties. The clean pre-trend and immediate post-shock divergence support a causal interpretation: the earthquake generated a behavioral revaluation of risk in markets that had previously ignored it.

We find no such effect in the rental market (Table 9). This result is consistent with the idea that renters view housing as a temporary arrangement and may be less attuned to long-term risk exposure. Moreover, during this period, the Turkish government imposed rent ceilings to stabilize prices,

reducing turnover and discouraging renegotiation.

Similarly, we observe no significant effect on commercial property prices. Since these properties are often held for business use rather than residential safety, risk salience may be less relevant or diluted through diversified ownership and lower personal attachment.

5.3. Heterogeneity by Education, Income, and Social Connectivity

5.3.1. Insurance Uptake

To assess the effect of heightened salience following the February 2023 earthquake on insurance behavior, we examine three outcome variables: the number of newly issued earthquake insurance contracts, the number of policy renewals, and the total monthly insurance premium paid at the county level. Figure 13 presents an event study of new insurance contracts, showing a modest spike in uptake during the first two months following the disaster. However, when controlling for pre-earthquake trends, the increase becomes more pronounced and persistent (Figure 16), consistent with salience-driven demand.

For policy renewals, the effect is delayed but notable. As shown in Figure 14, the renewal rate rises significantly about 12 months after the earthquake. This lag reflects the natural timing of contract expirations and suggests that individuals who initially responded to the disaster continued to renew coverage. These findings indicate that salience effects are not purely transitory but may shape long-term insurance behavior.

We also analyze total premiums paid. As demand increased, insurers appear to have raised premiums, particularly in low-risk counties. However, regressions of insurance variables on the $\text{Risk} \times \text{Post}$ interaction term reveal no significant differential response across risk levels—except for a 3.4% increase in premiums in low-risk areas per unit increase in seismic risk (Table 12). This pattern implies a potential mispricing by insurers prior to the earthquake and suggests that behavioral factors, rather than objective risk, drive post-disaster insurance adjustments.

The price reaction is more dramatic than the change in insurance uptake, suggesting that homebuyers are more concerned with the immediate physical risks (e.g., loss of life) than with financial safeguards like insurance. This contrasts with markets in developed countries, where housing prices are largely determined by corporate actors or mortgage providers, and not by individual wealth, as is more common in Türkiye.

We now investigate whether the response to the February 2023 earthquake varied across counties with different socio-economic profiles and degrees of social connection to the affected region. These analyses help identify which groups were most sensitive to the salience of disaster risk and whether any segment of the population had already internalized seismic risk in pre-earthquake prices.

5.3.2. Education and Income Levels.

We first examine heterogeneity by educational attainment. Using the share of college graduates in each county as a proxy, we split the sample at the median. In Table 10, Columns 1 and 2 show that counties with low education levels experienced a statistically significant post-earthquake decline in housing prices in high-risk areas, while high-education counties did not. The ‘Risk $\times$ Post’ coefficient remains negative for both subsamples, but only significant in the low-education group.

This pattern suggests that higher-educated populations may have already priced in earthquake risk or were less likely to engage in panic-driven repricing. Conversely, residents of lower-education counties may have responded more strongly due to limited prior awareness or higher salience amplification. These results are consistent with behavioral models in which cognitive capacity or information access moderates reactions to rare events.

Income-based heterogeneity yields a different pattern. Using the SEDI, we again split the sample. Columns 3 and 4 of Table 10 show that both high- and low-income counties experienced significant price responses, but the magnitude was larger in high-income counties.

We interpret this as evidence that higher-income households may face lower switching costs and are more financially flexible, allowing them to exit risky markets more readily. While both groups repriced risk, wealthier areas appear to have responded more decisively. The key insight is that salience-induced repricing was broad-based but amplified by income-driven mobility.

5.3.3. Family Ties and Social Connectivity.

A novel contribution of this paper is our identification of the role of social ties in amplifying salience. Specifically, we measure each county’s “Family Ties” index—defined as the share of residents whose family origins trace back to the earthquake-affected provinces. This index captures the strength

of personal and emotional connections to the disaster zone and reflects deep social bonds often maintained through visits, remittances, and social media.

To test whether salience propagated through these networks, we estimate a triple-difference model that includes ‘Risk $\times$ Post $\times$ FamilyTies’. Table 11, Column 1, shows that ‘FamilyTies $\times$ Post’ is not statistically significant on its own. This is important: it indicates that family linkages did not cause direct price changes unless coupled with underlying seismic risk. This finding helps rule out migration-driven demand effects or family-based housing purchases as primary mechanisms.

In Column 2, the triple interaction term is negative and statistically significant. This means that counties with high baseline risk and strong family ties to the earthquake region experienced amplified price declines following the disaster. In other words, risk salience increased more sharply in socially connected communities. We interpret this as evidence of emotional spillovers: individuals with close social links to affected families became more sensitive to the risks in their own environment.

Further, Columns 3 and 4 show that this amplification is strongest in high-income counties. In low-income regions, the interaction remains negative but is not statistically significant. This pattern reinforces our earlier interpretation—high-income, socially connected households may be particularly prone to salience-driven repricing due to both emotional exposure and greater financial flexibility.

Figure 12 addresses a potential confound: migration. If price effects were driven by people relocating to safer counties with family members, we would expect voter registration changes to reflect this pattern. To test this, we constructed a proxy for temporary population movement by comparing changes in electoral voter registration between June 2018 and May 2023, relative to annual census baselines from 2018–2022. The scatterplot of voter population change against the Family Ties index shows no significant correlation, and we find no evidence of systematic demographic shifts into counties with strong kinship networks. This suggests that the observed price responses are not due to migration or changes in housing demand but instead reflect socially transmitted updates in risk perception.

6. Conclusion

This paper investigates how housing and insurance markets respond to natural disaster risk, distinguishing between reactions to abstract informa-

tional updates and salient disaster events. Using monthly county-level data from Türkiye (2018–2024), we exploit two distinct sources of variation: an official earthquake hazard map revision in March 2018 and the realization of seismic risk via the catastrophic February 2023 earthquake.

Consistent with salience theory, we find that markets underreact to abstract, probabilistic risk information. The 2018 hazard map update produced no significant effect on home prices or earthquake insurance uptake, even in counties where assessed seismic risk changed substantially. In contrast, the 2023 earthquake triggered immediate and persistent repricing of risk: housing prices declined more sharply in high-risk counties, particularly in areas socially connected to the disaster zone through family ties. These behavioral responses were amplified in low-education and high-income counties—populations either more vulnerable to cognitive biases or more able to act on revised perceptions.

Taken together, our findings underscore the central role of attention, salience, and social proximity in shaping economic behavior under risk. Disaster risk may only be priced once it becomes emotionally or socially visible. This has important implications for risk communication, insurance design, and real estate markets in regions exposed to rare but catastrophic hazards.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Table 1: Descriptive Statistics Before and After Earthquake Map Update

	Before Update (N=1,008) Mean (S.D)	After Update (N=4,032) Mean (S.D)	p-value
Home price (m ² , TRY)	2,051 (1,376.0)	1,899 (1,224.1)	<0.001
Rent price (m ² , TRY)	10.57 (9.9)	9.27 (7.6)	<0.001
Avg. sale price of a home (TRY)	264,301 (225k)	242,398 (193k)	0.002
Average home size (m ²)	127 (21.2)	126 (20.5)	0.143
Average rent home size (m ²)	120 (18.7)	116 (22.0)	<0.001
Mortgaged to total sales ratio	0.197 (0.06)	0.208 (0.06)	<0.001
# of home sales (monthly)	246 (276.3)	263 (305.7)	0.137
# of new earthquake policy issuance (monthly)	693 (750.2)	790 (834.1)	0.001
# of policy renewals (monthly)	938 (1,273.4)	977 (1,273.1)	0.393
# of occupancy permit (monthly)	20,187 (27,747.3)	22,324 (31,319.1)	0.052
# of construction permit (monthly)	13,062 (21,369.1)	14,101 (22,369.8)	0.200

Notes: This table compares the means of key housing market, insurance, and construction indicators before and after the March 2018 earthquake hazard map update in Türkiye. The “before” period covers January–March 2018, and the “after” period spans April 2018 through March 2019. The outcome variables include residential sale and rental prices per square meter, average home prices, home sizes, and monthly home sales (from TÜİK, Türkiye’s official statistics agency). All price variables have been adjusted for inflation using monthly consumer price indices. Insurance-related variables—monthly counts of newly issued earthquake policies and renewals—are sourced from DASK (Turkish Catastrophe Insurance Pool). Building activity is measured through monthly occupancy and construction permits. The treatment indicator equals one for months after the hazard map revision, which updated counties’ seismic risk levels using a new probabilistic model. The sample is balanced at the county level. Reported p-values reflect t-tests of equality in means. This descriptive comparison sets the foundation for testing whether abstract risk information, absent a salient event, leads to any systematic behavioral adjustment in housing or insurance markets.

Table 2: Effect of Map Update of Earthquake Risk on Home Prices and Insurance Uptakes by Risk Level

	Home Price	Home Price	Home Price	Home Price
$\Delta Risk \times Post$	0.338 (0.33)	0.399 (0.32)	0.310 (0.38)	0.422 (0.33)
Average home size (m ²)		4.933 (3.64)	5.430 (4.54)	4.594 (3.56)
# of home sales			-0.104 (0.07)	
Occupancy permit				-0.000 (0.00)
Observations	5,040	5,040	4,481	4,846
R-squared	0.979	0.980	0.982	0.980
County FEs	Yes	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes	Yes

	Home Price (5)	New Policy Issuance (6)	Policy Renewals (7)
$\Delta Risk \times Post$	0.293 (0.36)	-0.193 (0.18)	0.007 (0.15)
Average home size (m ²)	4.186 (3.15)		
New home construction	-0.000* (0.00)	0.001**	0.000
Observations	4,594	4,332	4,332
R-squared	0.981	0.941	0.969
County FEs	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes

Notes: This table presents the effect of the 2018 earthquake risk map update on home prices and insurance policy issuance, with risk level changes interacting with the post-update period. All regressions control for county and time fixed effects (Month $\times$ Year). Robust standard errors clustered at the city level are shown in parentheses. Statistical significance is indicated as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.1 Effect of Map Update on Home Prices by Market Activity and Risk Change Status

	Home Price				
	(1)	(2)	(3)	(4)	(5)
$\Delta\text{Risk} \times \text{Post}$	0.603 (0.47)	-0.363 (0.27)	0.549 (0.84)	0.398 (0.31)	0.331 (0.32)
Average home size (m ²)	1.853 (2.33) (300.08)	0.295 (2.01) (258.91)	31.769*** (7.83) (957.27)	2.970 (2.21) (278.46)	5.625** (2.66) (340.92)
Observations	1,665	1,650	1,725	3,975	1,785
R-squared	0.853	0.989	0.989	0.980	0.964
Transaction Level	Low	Moderate	High	-	-
Sample	-	-	-	No Change	Extreme Change

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table extends the 2nd column of Table 2. It reports the effect of the 2018 earthquake risk map update on home prices across counties with varying market activity levels and risk change intensity. Columns (1) – (3) split counties by terciles of average monthly transaction volume: low, moderate, and high. Columns (4) and (5) restrict the sample to counties with any meaningful risk change and only those with extreme changes (greater than 30% in either direction), respectively. The coefficient on $\Delta\text{Risk} \times \text{Post}$ captures the differential response to risk in the post-update period. All regressions include county and time (month $\times$ year) fixed effects. Standard errors are clustered at the city level.

Table 3: Effect of Map Update of Earthquake Risk on Home Prices by Education & Income Level

	Home Price			
	(1)	(2)	(3)	(4)
$\Delta Risk \times Post$	0.446 (0.45)	0.634 (0.45)	0.006 (0.54)	0.502* (0.30)
Average home size (m ²)	15.121 (10.54)	1.679 (2.31)	17.361* (9.58)	1.667 (2.26)
Occupancy permit	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
Observations	2,583	2,263	2,615	2,231
R-squared	0.986	0.919	0.986	0.900
County FEs	Yes	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes	Yes
Education Level	High	Low	-	-
Income Level	-	-	High	Low

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table examines whether the effect of the 2018 earthquake risk map update on home prices varies by education level (columns 1–2) and income level (columns 3–4). High-education areas are defined as counties where the share of the population with a college degree is above the median (10.2%). High-income areas are defined as counties with a county development index above the median (-0.1555). The key variable of interest, Risk $\times$ Post, represents the interaction between earthquake risk level changes and the post-update period (March 2018 onward). All regressions include county and time fixed effects (Month $\times$ Year). Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.***

Table 4: Effect of Map Update on Number of Homes Sold

	(1)	(2)
	# of Houses Sold	# of Houses Sold
$\Delta Risk \times Post$	-0.006 (0.09)	-0.206 (0.42)
Observations	4,481	4,481
R-squared	0.942	0.265
County FEs	Yes	Yes
Month $\times$ Year FEs	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents the impact of the 2018 earthquake risk map update on the number of houses sold. The dependent variable is the total number of monthly home sales in a given county. The key independent variable, $Risk \times Post$, captures the interaction between changes in earthquake risk levels and the post-update period (March 2018 onward). Column (1) includes county fixed effects, while column (2) uses city fixed effects, both controlling for time fixed effects (Month $\times$ Year). Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effect of Map Update on Home Rent Prices by Risk Level

	Home Rent Price				
	(1)	(2)	(3)	(4)	(5)
$\Delta Risk \times Post$	0.008 (0.01)	0.008 (0.01)	0.006 (0.01)	0.008 (0.01)	0.007 (0.01)
Average home rent size (m ²)		-0.022** (0.01)	-0.023* (0.01)	-0.020* (0.01)	-0.019* (0.01)
# of home sales			0.000 (0.00)		
Occupancy permit				0.000 (0.00)	
New house construction					0.000 (0.00)
Observations	8,685	8,685	5,611	7,216	6,887
R-squared	0.880	0.881	0.766	0.867	0.876
County FEs	Yes	Yes	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents the effect of the 2018 earthquake risk map update on home rent prices. The dependent variable is the log of monthly rent price per square meter of residential properties. The key independent variable, $Risk \times Post$, represents the interaction between changes in earthquake risk levels and the post-update period (March 2018 onward). Column (1) estimates the baseline model, while columns (2)–(5) sequentially introduce controls: average size of rented homes in the county (m²), official monthly home sales (rent data is not available since contracts are not recorded officially), occupancy permits, and new house construction. All regressions include county fixed effects and time fixed effects (Month $\times$ Year). Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.***

Table 6: Effect of Earthquake Risk Map Update on Housing Prices, Insurance Uptake, and Mortgage Financing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Change in risk (%)	0.039 (0.03)	0.011 (0.03)	0.039 (0.03)	0.041 (0.03)	0.007 (0.03)	-0.064*** (0.02)	-0.064*** (0.02)	0.000 (0.00)	0.000 (0.00)
Mortgaged sales (%)		35.739* (18.77)			25.159 (19.06)				
Household (%)			-0.000** (0.00)		-0.000** (0.00)		0.000* (0.00)		-0.000*** (0.00)
Population (%)				-0.151 (0.12)	0.082 (0.22)				
First hand (%)									-0.046*** (0.02)
Observations	718	718	480	718	480	718	480	480	470
R-squared	0.006	0.007	0.006	0.014	0.029	0.028	0.032	0.004	0.012
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents cross-sectional regressions estimating the effects of earthquake risk changes from old risk levels to updated risks on home prices, insurance policy uptake, and mortgage financing. The primary explanatory variable is the percentage change in county-level earthquake risk. The dependent variables are the changes between January 2018 and January 2019 in home prices (columns 1–5), insurance policy uptake (columns 6–7), and the ratio of mortgaged to total home sales (columns 8–9). We focus on this one-year change window to capture the impact of the earthquake risk map revision announced in March 2018. Control variables vary by specification and include changes in population, household count, and first-hand sales ratio, as well as the percentage change in mortgaged sales. All regressions include county and year fixed effects, with robust standard errors reported in parentheses.

Table 7: Summary Statistics by Earthquake Risk Category (Before and After Earthquake)

Panel A. Before Earthquake			
	Low Risk	Moderate Risk	High Risk
Home price (m ² ,TRY)	2106.25	3116.88	3208.25
Rent price (m ² ,TRY)	8.59	13.67	13.36
Commercial price (m ² ,TRY)	4173.35	6484.55	5557.75
Commercial rent (m ² ,TRY)	22.49	29.10	24.84
# of policy renewals (monthly)	875.71	1345.91	1339.66
# of new earthquake policy (monthly)	867.46	962.48	824.27
# of home sales (monthly)	314.39	307.75	281.41
Average home size (m ²)	139.10	127.22	129.23

Panel B. After Earthquake			
	Low Risk	Moderate Risk	High Risk
Home price (m ² ,TRY)	3909.86	5450.21	5487.64
Rent price (m ² ,TRY)	19.18	26.73	27.94
Commercial price (m ² ,TRY)	7166.83	9668.00	8613.13
Commercial rent (m ² ,TRY)	42.03	49.54	44.90
# of policy renewals (monthly)	1036.86	1560.60	1561.23
# of new earthquake policy (monthly)	916.54	957.13	804.10
# of home sales (monthly)	271.63	248.24	224.35
Average home size (m ²)	136.86	126.26	130.08

Panel C. Percentage Change (Post vs. Pre)			
	Low Risk	Moderate Risk	High Risk
Home price (m ² ,TRY)	85.6%	74.9%	71.0%
Rent price (m ² ,TRY)	123.3%	95.5%	109.1%
Commercial price (m ² ,TRY)	71.7%	49.1%	55.0%
Commercial rent (m ² ,TRY)	86.9%	70.2%	80.8%
# of policy renewals (monthly)	18.4%	16.0%	16.5%
# of new earthquake policy (monthly)	5.7%	-0.6%	-2.4%
# of home sales (monthly)	-13.6%	-19.4%	-20.3%
Average home size (m ²)	-1.6%	-0.8%	0.7%

Notes: This table presents means of key real estate and insurance variables by earthquake risk category. Risk categories are based on terciles of predicted peak ground acceleration (PGA): Low Risk (bottom third), Moderate Risk (middle third), and High Risk (top third). Panel A reports pre-earthquake values; Panel B shows post-earthquake values; Panel C reports the percentage change from pre- to post-earthquake periods. Reported variables include inflation-adjusted prices and rents for residential and commercial properties, the number of new and renewal insurance policies (DASK), average size of homes sold, and total home sales. Percentage changes are calculated as post-earthquake means relative to pre-earthquake means.

Table 8: Earthquake Impact on Home Sale Prices (Panel A)

Panel A: Baseline Models			
	(1)	(2)	(3)
Risk $\times$ Post	-0.127** (0.05)	-0.129** (0.05)	-0.128** (0.05)
Average home size (m ²)		0.000 (0.00)	0.000 (0.00)
# of home sales			-0.003 (0.00)
Observations	22,399	22,399	22,399
R-squared	0.978	0.978	0.978
County FEs	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Panel A presents baseline panel regression estimates of the February 2023 earthquake's effect on log-transformed home sale prices. The primary variable of interest, **Risk** $\times$ **Post**, is the interaction between earthquake risk (measured by peak ground acceleration, PGA) and a binary post-earthquake indicator. The dependent variable is the log of inflation-adjusted average home prices. The models progressively include controls: average home size and the number of houses sold. All regressions control for county and month-year fixed effects, with standard errors clustered at the city level.

Table 8: Earthquake Impact on Home Sale Prices (Panel B)

Panel B: Extended Models and Standardized Coefficients			
	(4)	(5)	(6)
Risk $\times$ Post	-0.128** (0.05)	-0.177*** (0.06)	
Risk (PGA)		0.259 (0.20)	
Average home size (m ²)	0.000 (0.00)	0.005*** (0.00)	
New construction		0.007* (0.00)	
Occupancy permits	0.001* (0.00)	0.000 (0.00)	
Distance $\times$ Post			-0.000 (0.00)
<i>Standardized Coefficients</i>			
Risk $\times$ Post	-0.039*	-0.059**	
Risk (PGA)		0.072	
Comparable area	0.005	0.177***	
New construction		0.047	
Occupancy permits	0.008	0.002	
Observations	22,399	18,199	22,399
R-squared	0.978	0.787	0.978
County FEs	Yes	No	Yes
City FEs	No	Yes	No
Month $\times$ Year FEs	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Panel B presents panel regression estimates of the effect of the February 2023 earthquake on logarithmic home sale prices. The key independent variable is Risk $\times$ Post, the interaction between a county's earthquake risk (as measured by peak ground acceleration, PGA) and a post-earthquake indicator equal to one for months after February 2023. The dependent variable is the natural logarithm of inflation-adjusted average home sale prices. All models include fixed effects for county or city and calendar time (month $\times$ year). Standard errors are clustered at the city level. Columns (4) and (5) include log-transformed 3-month moving averages of total occupancy permits and newly started residential construction area (m²), capturing local supply dynamics. Column (5) additionally includes the earthquake risk level as a main effect. Column (6) replaces the risk measure with a continuous variable for geographic distance to the epicenter and interacts it with the post-earthquake dummy to capture spatial heterogeneity in price responses. The Panel B reports *standardized coefficients* from models (4) and (5). This is especially helpful when interpreting the relative strength of risk because earthquake risk values are concentrated in a narrow range (approximately 0.08 to 0.73). As a result, unstandardized coefficients may appear numerically large despite representing economically moderate effects. Standardized coefficients reflect the effect of a one-standard-deviation increase in each variable, allowing for meaningful comparisons across covariates.

Table 8: Earthquake Impact on Home Sale Prices (Panel C)

Panel C: Transaction-Level Heterogeneity			
	(7)	(8)	(9)
Risk $\times$ Post	-0.131*** (0.01)	-0.101*** (0.01)	-0.345*** (0.03)
Average home size (m ²)			0.002*** (0.00)
Occupancy permits			-0.000 (0.00)
<i>Standardized Coefficients</i>			
Risk $\times$ Post	-0.044***	-0.031***	-0.116***
Average home size (m ²)			0.069***
Occupancy permits			-0.003
Observations	11,199	11,200	2,496
R-squared	0.972	0.982	0.983
Transaction Level	Low	High	Istanbul
County FEs	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Panel C presents heterogeneity in the housing market's response to the February 2023 earthquake across areas with varying transaction intensity. Columns (7) and (8) split the sample into low- and high-transaction counties based on the median of average monthly home sales. Column (9) focuses exclusively on Istanbul, which accounts for approximately one-fifth of all housing transactions in Türkiye. Istanbul is analyzed separately due to its national market prominence and the wide variation in seismic risk levels across its constituent counties. The main coefficient of interest, **Risk $\times$ Post**, captures the interaction between county-level seismic risk (as measured by PGA) and a post-earthquake indicator. All regressions include county and month-year fixed effects. Standardized coefficients are reported to facilitate magnitude comparisons.

Table 9: Earthquake Impact on Home Rent Prices

	Home Rent Price				
	(1)	(2)	(3)	(4)	(5)
Risk $\times$ Post	-0.121 (0.13)	-0.137 (0.13)	-0.137 (0.13)	-0.128 (0.13)	-0.053 (0.12)
Average home size (m ²)		0.002** (0.00)	0.002** (0.00)	0.002*** (0.00)	0.004*** (0.00)
New houses sold			0.006 (0.01)	0.011 (0.01)	0.108*** (0.02)
Occupancy permits				-0.001 (0.00)	-0.041*** (0.01)
New construction				0.021*** (0.00)	0.015 (0.01)
Observations	16,414	16,414	16,414	14,624	14,624
R-squared	0.934	0.934	0.934	0.937	0.775
County FEs	Yes	Yes	Yes	Yes	No
City FEs	No	No	No	No	Yes
Month $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the effect of the February 2023 earthquake on log home rent prices. The key independent variable is **Risk $\times$ Post**, the interaction of earthquake risk (PGA) and a post-earthquake indicator. All regressions include fixed effects for county or city and month-by-year, with standard errors clustered at the city level. Columns sequentially add controls for average rental size, number of homes sold, and lagged measures of occupancy permits and new construction. The final specification replaces county fixed effects with city-level fixed effects.

Table 10: Effect of Education & Income on Home Prices

	Home Price			
	(1)	(2)	(3)	(4)
Risk $\times$ Post	-0.108 (0.08)	-0.106** (0.05)	-0.132* (0.07)	-0.086* (0.05)
Education	High	Low		
Income Level			High	Low
Observations	11,200	11,199	11,200	11,199
R-squared	0.980	0.970	0.982	0.968
County FEs	Yes	Yes	Yes	Yes
Month $\times$ Year FEs	Yes	Yes	Yes	Yes
<i>Robust standard errors in parentheses</i>				
*** p<0.01, ** p<0.05, * p<0.1				

Notes: This table examines the effect of the February 2023 earthquake on log home sale prices based on counties' education and income levels. The key independent variable, **Risk** $\times$ **Post**, captures the interaction between earthquake risk (PGA) and a post-earthquake period indicator.

Counties are classified as *high education* if the share of individuals holding a college degree exceeds the sample median. The *development index* is used as a proxy for county-level income and economic capacity, with high-development counties defined as those above the median of the index distribution. Columns (1) and (2) split the sample by education; columns (3) and (4) split it by development index. All regressions include county and month-by-year fixed effects. Standard errors are clustered at the city level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Family Ties Effect on Home and Commercial Property Prices

VARIABLES	Home Price (1)	Home Price (2)	Home Price (3)	Home Price (4)	Home Rent Price (5)	Comm. Sale Price (6)	Comm. Rent Price (7)
Family Ties $\times$ Post	-0.192 (0.26)	0.574*** (0.20)	0.792*** (0.24)	0.327 (0.37)	0.629 (0.47)	1.649*** (0.41)	0.808* (0.44)
Risk $\times$ Post		0.010 (0.05)	0.071 (0.07)	-0.070 (0.05)	0.214 (0.15)	0.040 (0.28)	0.036 (0.24)
Risk $\times$ Family Ties		0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
Risk $\times$ Family Ties $\times$ Post		-2.733*** (0.63)	-3.331*** (0.62)	-0.420 (1.27)	-6.070*** (1.61)	-3.240 (2.19)	-2.502 (2.18)
Observations	22,399	22,399	11,200	11,199	16,414	1,900	2,705
R-squared	0.978	0.978	0.982	0.968	0.936	0.959	0.924
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month $\times$ Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
Income Level			High	Low			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table investigates how migration-related social connections—measured by **family ties**—influence the effect of the February 2023 earthquake on housing and commercial property prices. The variable **family ties** captures the proportion of a county’s population originally from the earthquake-affected provinces. For example, a value of 0.30 indicates that 30% of residents in a county have hometown origins in the earthquake zone. This measure proxies potential migration flows and relocation demand in the aftermath of the disaster.

The main variable of interest is the interaction **Family Ties $\times$ Post**, where *Post* is a binary indicator for months after the earthquake. A positive and significant coefficient would suggest that counties with stronger kinship ties to the earthquake region experienced higher demand pressure or price growth following the disaster. But we observe the opposite. Subsequent models introduce a three-way interaction: **Risk $\times$ Family Ties $\times$ Post**, allowing the earthquake salience effect to vary jointly by geographic risk exposure and social connectivity. Columns (1)–(4) analyze log home sale prices, with columns (3)–(4) split by county development index (a proxy for income level). Columns (5)–(7) extend the analysis to home rental markets and commercial real estate (sales and rents). All regressions include county and time fixed effects (month $\times$ year), and standard errors are clustered at the city level.

Table 12: Earthquake Impact on Insurance Rates

	(1) Premium	(2) Renewed Pol.	(3) New Ins.	(4) New Ins.	(5) New Ins.
Risk $\times$ Post	-0.297*** (0.06)	-0.054 (0.06)	-0.094 (0.07)	-0.094 (0.07)	0.096 (0.06)
Distance $\times$ Post					-0.000*** (0.00)
Risk				-0.449 (0.46)	
<i>Standardized Coef.</i>					
Risk				-0.064	
Risk $\times$ Post	-0.034***	-0.007	-0.015	-0.015	0.016
Observations	22,400	22,400	22,400	22,400	22,400
R-squared	0.982	0.970	0.965	0.376	0.965
County FEs	Yes	Yes	Yes	No	Yes
City FEs	No	No	No	Yes	No
Month $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table presents panel regression results on the effect of the February 2023 earthquake on insurance uptake across counties. The dependent variables are the natural logs of (1) total earthquake insurance premiums, (2) renewed insurance policy counts, and (3) new insurance policy issuances. The main independent variable, **Risk $\times$ Post**, interacts county-level earthquake risk (PGA) with a post-earthquake period indicator.

Column (4) includes **city-level fixed effects** (instead of county fixed effects), leveraging only within-city variation to estimate the earthquake's impact on new policy uptake. Column (5) explores spatial variation using the interaction of **distance to the earthquake epicenter** with the post-period. All regressions include either county or city fixed effects and month-by-year time fixed effects. Standard errors are clustered at the city level.

The second panel reports *standardized coefficients* for key regressors to improve interpretability across variables with differing scales. This is especially important for risk and distance measures, which vary in narrow ranges.

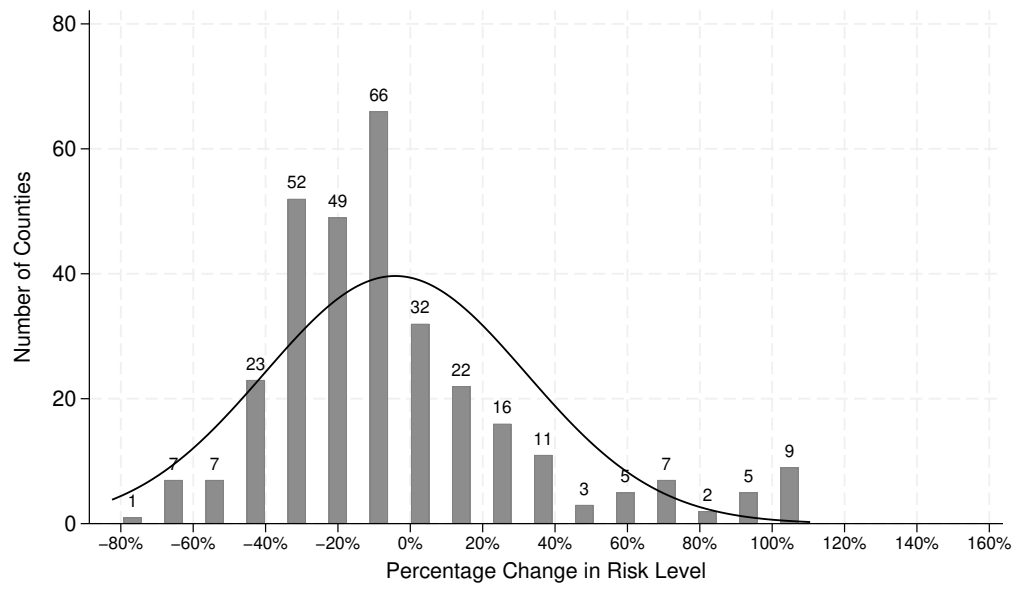


Figure 1: Distribution of counties by the change in their earthquake risk category following the map update

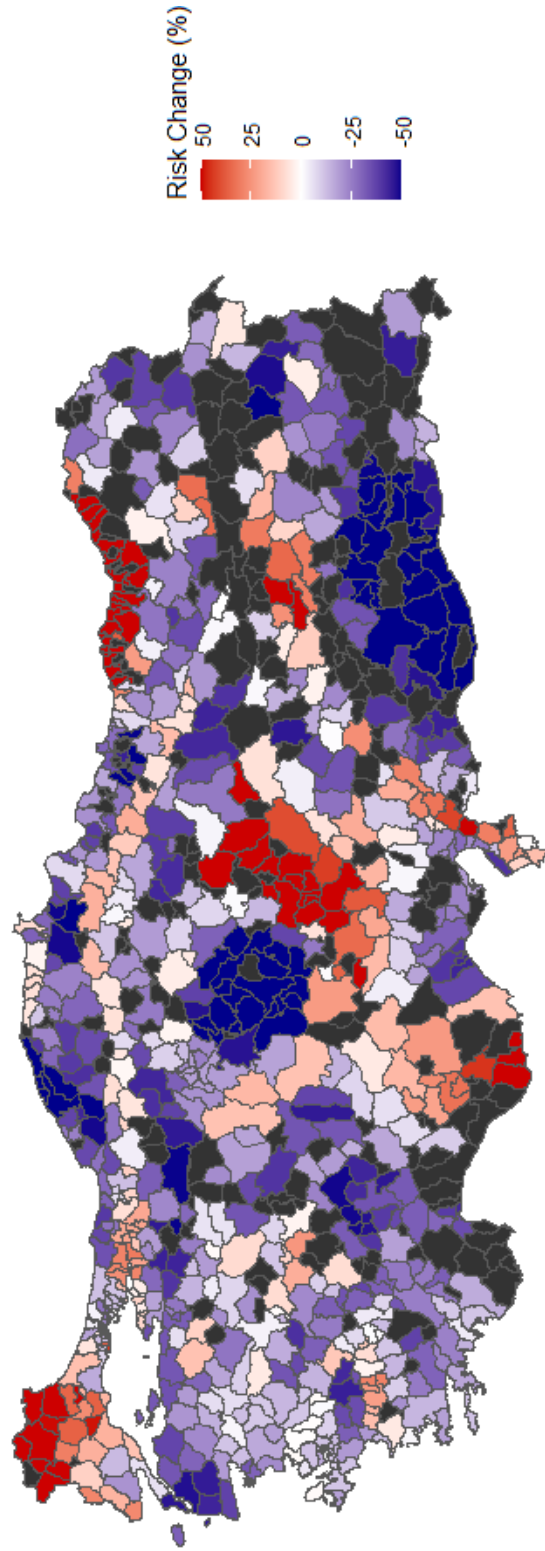


Figure 2: Percentage Change in Earthquake Risk Level (PGA) after the Turkish 2018 Earthquake Map Update

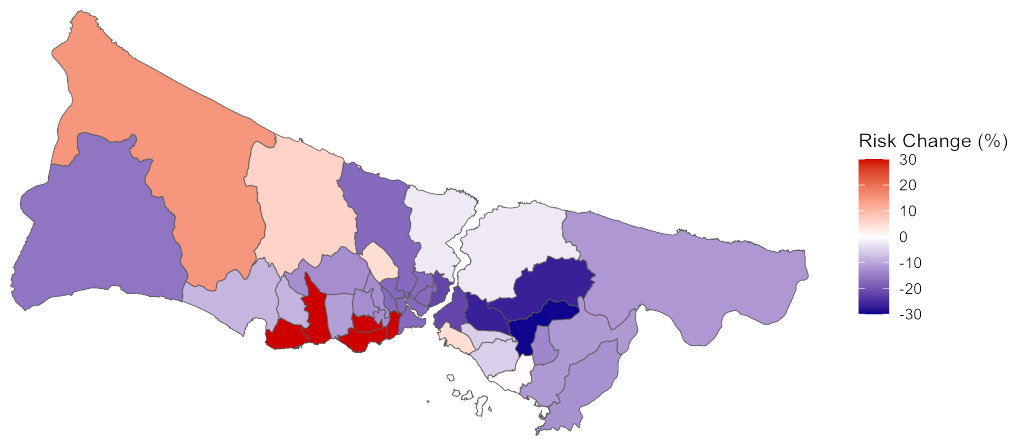


Figure 3: Percentage Change in Earthquake Risk Level (PGA) after the Turkish 2018 Earthquake Map Update - Only Istanbul

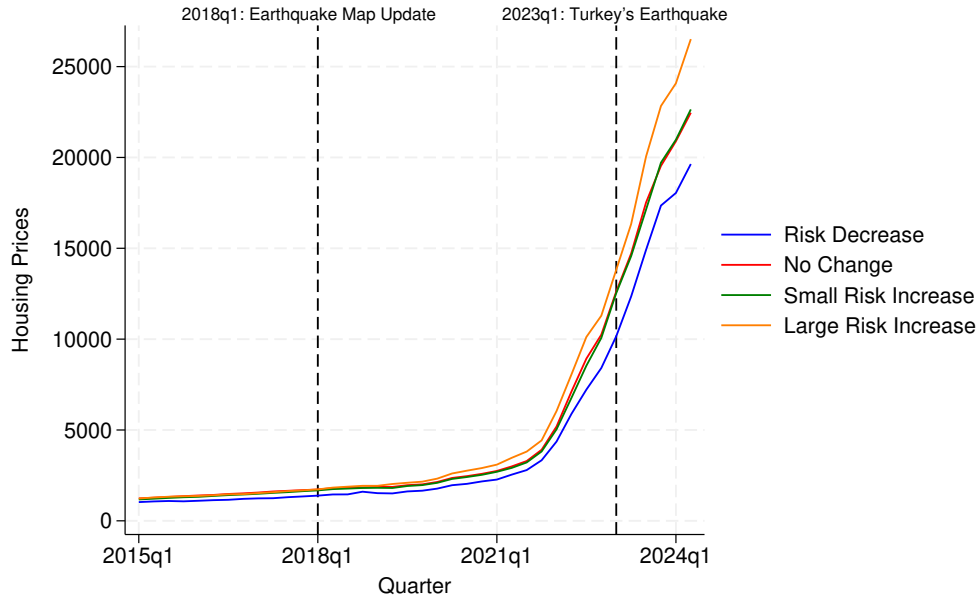


Figure 4: Housing Prices by Different Risk Change Levels at the City Level (To ensure the parallel trends assumption holds)

Notes: This figure plots average housing prices over time by city-level earthquake risk change categories, based on the 2018 hazard map update. Cities are grouped by whether their assigned risk level decreased, remained unchanged, or increased (small or large). Dashed vertical lines mark the timing of the 2018 map revision and the 2023 Turkey earthquake. The figure visually supports the parallel trends assumption prior to the 2018 policy change.

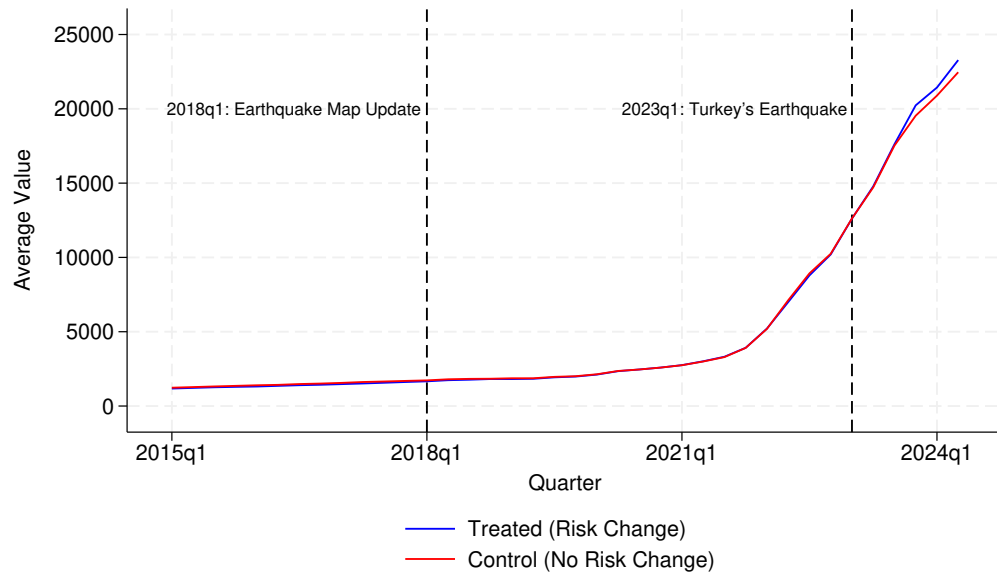


Figure 5: Average Home Prices Over Time by Earthquake Risk Change (Treated vs. Control) at the City Level

Notes: This figure compares average housing prices between treated cities—those that experienced a change in earthquake risk level in the 2018 map update—and control cities, where risk remained unchanged. The two vertical dashed lines indicate the timing of the 2018 earthquake hazard map revision and the February 2023 Turkey earthquake. The close alignment of price trends before 2018 supports the parallel trends assumption for the identification strategy.

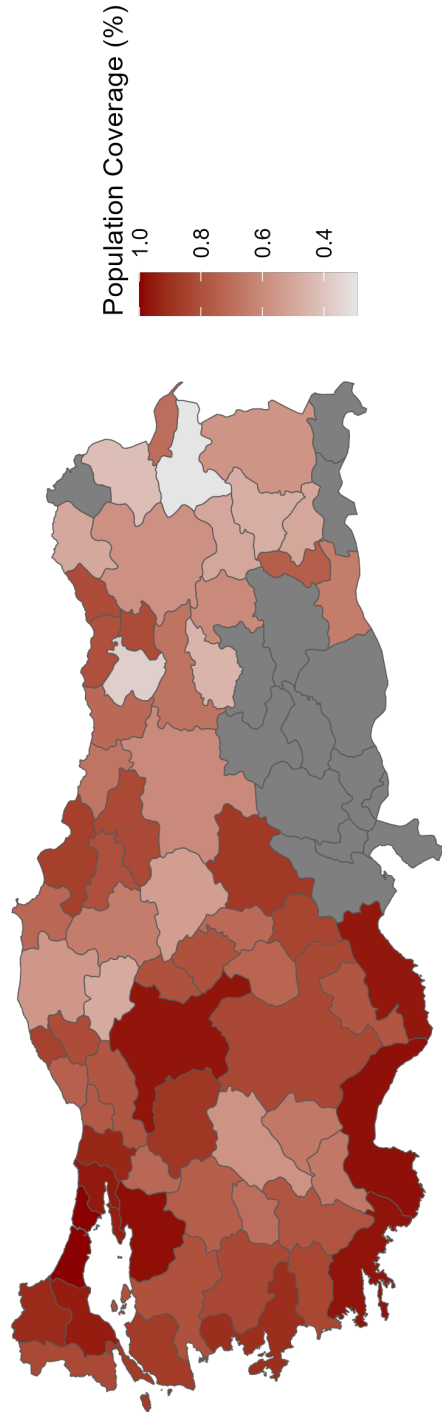


Figure 6: Population Coverage of the Sample by Cities

Notes: This map shows the population coverage of the housing price dataset across cities. Darker regions represent higher population coverage within each province. Earthquake-affected cities are excluded from the analysis to avoid direct disaster zone effects, which are outside the scope of this study (grey-colored cities). The sample covers counties with available housing data and represents over 80% of Turkey's total population. Counties without data (shown in gray) are typically rural or sparsely populated areas with limited market activity.

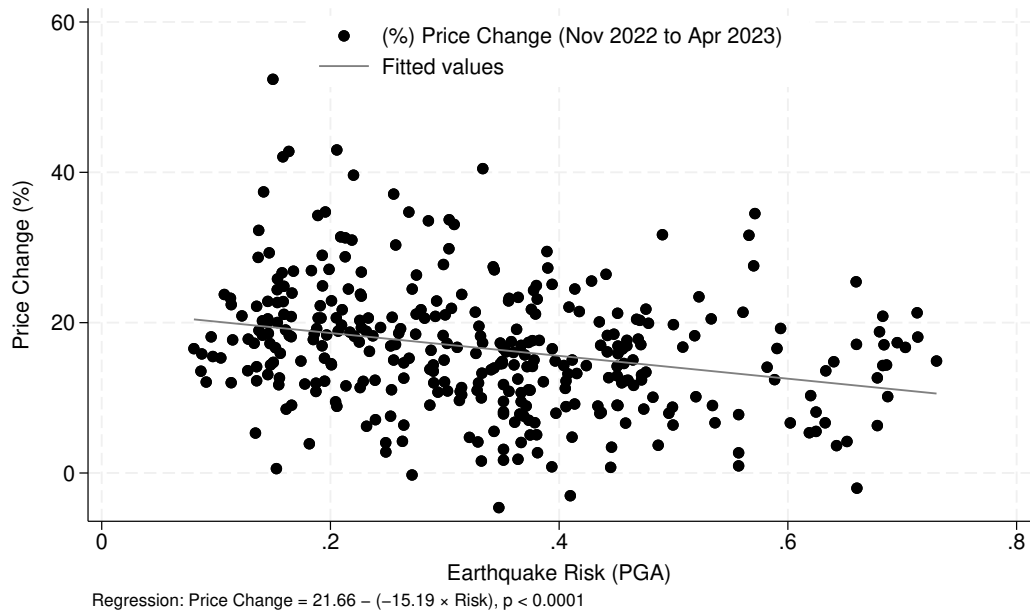


Figure 7: Relationship between Home Price Change and Earthquake Risk

Notes: This figure plots the relationship between county-level earthquake risk (PGA) and housing price changes around the February 6, 2023 earthquake. The y-axis shows percentage changes in home prices between November 2022 and April 2023 (i.e., two months before and after the earthquake). The x-axis reflects each county's earthquake risk level based on predicted peak ground acceleration. The fitted regression line suggests a negative association, indicating that price increases were relatively smaller in higher-risk areas during this period.

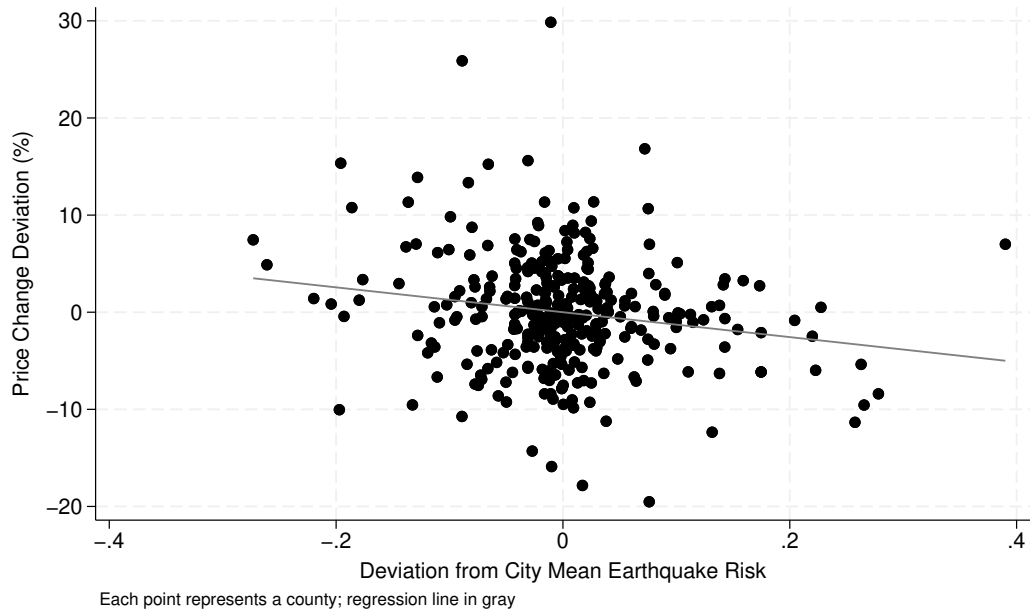


Figure 8: Within-City Relationship Between Earthquake Risk and Housing Price Deviations

Notes: This figure illustrates the relationship between county-level deviations in earthquake risk and deviations in home price changes relative to city averages. The x-axis shows the percentage deviation of each county's earthquake risk from its city's mean risk level. A value of -0.2 indicates that the county has 20% lower risk than the average within its city. The y-axis displays the deviation in price change for each county during the two months before and after the February 6, 2023 earthquake, relative to the average price change observed in the same city. Each dot represents a county.

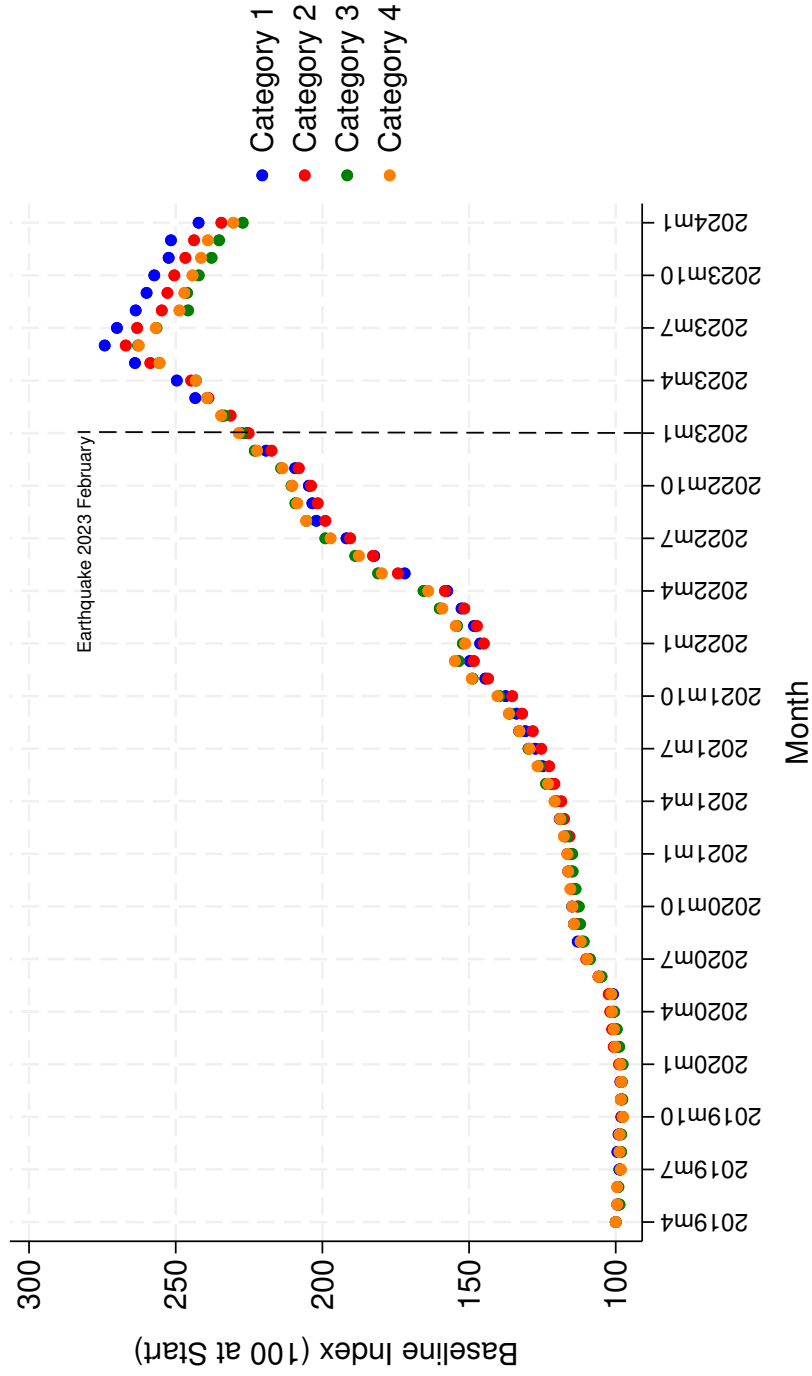


Figure 9: Home Price Index by Earthquake Risk Quartiles (Baseline = 100 in 2019m4)

Notes: This figure displays the relative evolution of housing prices across counties grouped into earthquake risk quartiles. The index is constructed by normalizing average housing prices in each group to 100 in April 2019. Counties are grouped as follows: **Category 1 (blue)** – lowest earthquake risk (bottom 25% of PGA distribution), **Category 2 (red)** – lower-middle risk (25th–50th percentile), **Category 3 (green)** – upper-middle risk (50th–75th percentile), **Category 4 (orange)** – highest risk (top 25%). All groups exhibit similar price trends before the February 2023 earthquake (dashed line). Following the earthquake, lower-risk counties (particularly Category 1) show a clear divergence, indicating increased relative demand in safer areas.

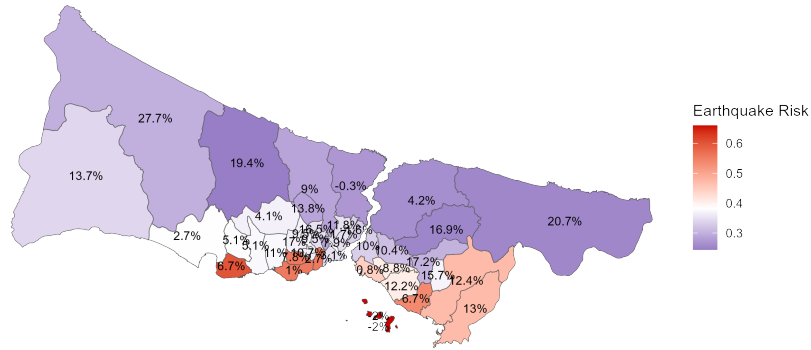


Figure 10: Home Price Changes Before and After the February 2023 Earthquake by County-Level Earthquake Risk in Istanbul

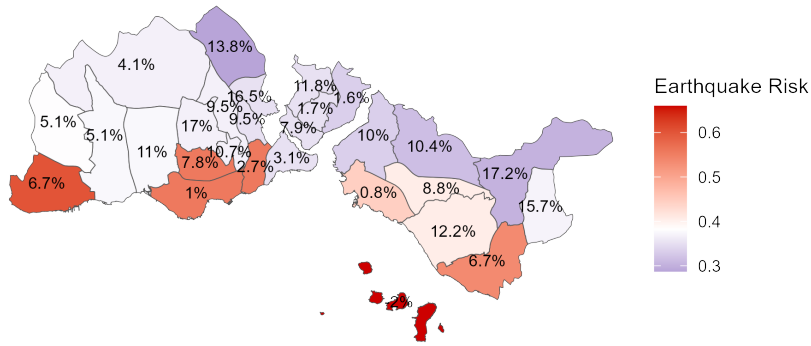


Figure 11: Home Price Changes Before and After the February 2023 Earthquake by County-Level Earthquake Risk in Istanbul -Zoomed View

Notes: These maps illustrate the relationship between home price changes and earthquake risk across Istanbul counties following the February 2023 earthquake. Counties are shaded based on their earthquake risk level, measured by peak ground acceleration (PGA): lighter purple indicates lower risk, while darker red indicates higher risk. The percentage labels reflect the change in average home prices between the two-month periods before and after the earthquake. According to our hypothesis, price growth is expected to be lower in high-risk counties. Istanbul accounts for roughly 20% of Turkey's population and 30% of its housing market, making it a central focus for understanding spatial market responses to earthquake risk. Figure 11 (bottom) provides a zoomed-in view of densely populated central districts where labels may overlap in the full-city map.

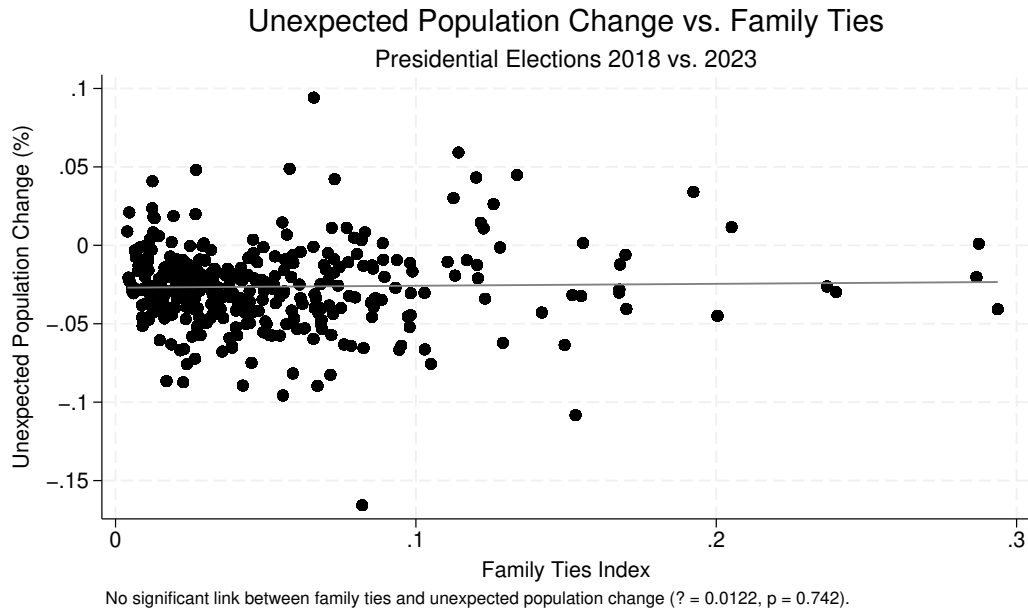


Figure 12: Unexpected Changes in Voter Population Due to the Earthquake

Notes: This figure examines whether counties with stronger family ties to earthquake-affected regions experienced greater short-term population inflows. The x-axis shows the Family Ties Index, calculated as the share of residents in each county whose registered hometown is in an earthquake-affected province. The y-axis represents the “unexpected population change,” measured as the difference between (1) the percentage change in total registered voters from the 2018 to 2023 presidential elections and (2) the percentage change in general population between January 2018 and January 2023. The regression line indicates no statistically significant relationship between family ties and unexpected voter inflows in early 2023 ($\beta = 0.0122$, $p = 0.742$), suggesting limited large-scale migration patterns during this short period.

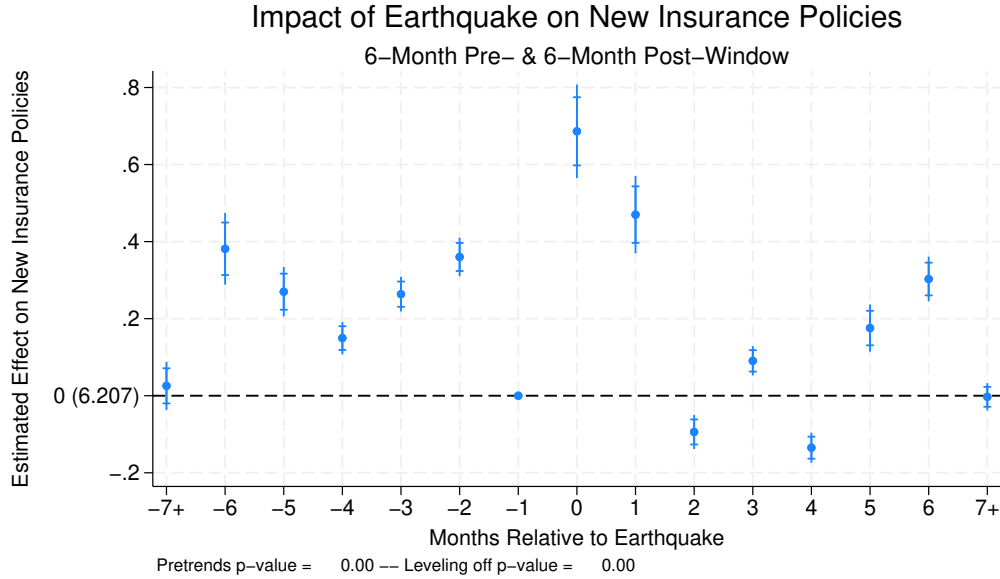


Figure 13: Impact of Earthquake on New Insurance Policies

Notes: This figure presents results from an event study that examines the effect of the February 2023 earthquake on the number of new earthquake insurance policies issued. The vertical axis shows the estimated change in log new policy counts, centered around the month of the earthquake (month 0). Each point represents the estimated coefficient for a given month relative to the earthquake, controlling for county and time fixed effects, with 95% confidence intervals clustered at the city level.

The estimation uses the *xtevent* command with a symmetric window of 6 months before and after the earthquake. The dashed horizontal line indicates the reference period mean (month -1), which is normalized to zero. The pre-trend p-value (0.00) tests the joint significance of coefficients prior to the earthquake and rejects the null of parallel trends, while the leveling-off p-value (0.00) indicates persistent post-treatment effects. The reference mean of 6.207 (in logs) is also noted.

The results reveal a sharp and statistically significant increase in new policy issuance immediately following the earthquake, suggesting heightened insurance demand in response to the disaster.

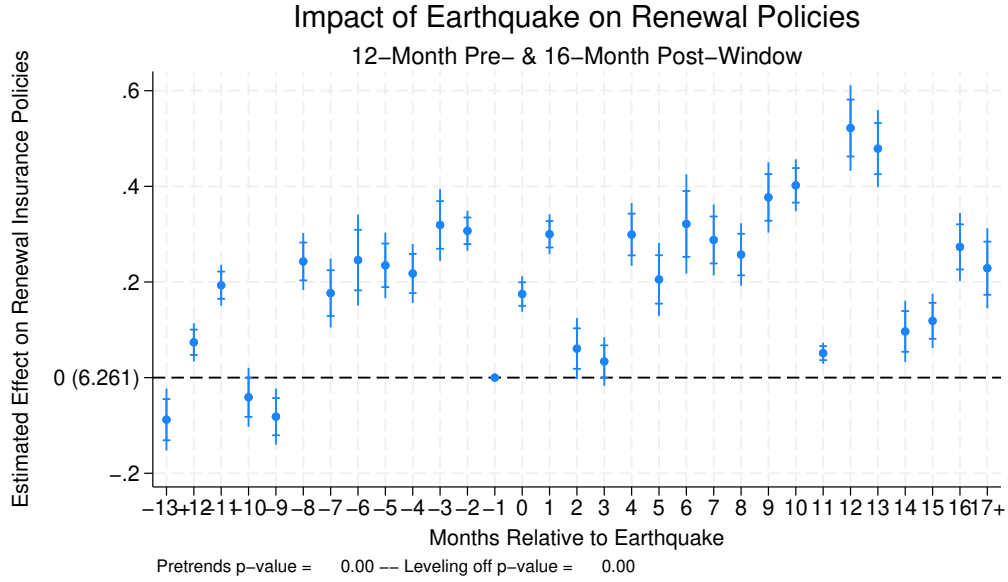


Figure 14: Impact of Earthquake on Renewal Policies

Notes: This event study plot estimates the dynamic impact of the February 2023 earthquake on the number of renewed earthquake insurance policies. The y-axis shows the estimated effect on the log number of renewals relative to the month just before the earthquake (normalized to zero). The x-axis represents months relative to the earthquake, spanning 12 months prior to 16 months after the event. Each point shows a coefficient estimate with a 95% confidence interval. County and time fixed effects are included, and standard errors are clustered at the city level.

The mean of the dependent variable is 6.261 in logs. The significant pretrend p-value ($p = 0.00$) suggests non-parallel trends prior to the earthquake, warranting caution in interpreting causal effects. However, the consistently positive and significant post-earthquake estimates—confirmed by a leveling-off p-value of 0.00—indicate a persistent rise in policy renewals.

Since existing policyholders can only renew their contracts upon expiration, the gradual increase in the following months suggests a behavioral shift: not only did new demand rise immediately after the earthquake, but retention and repurchasing behavior also strengthened in the long run.

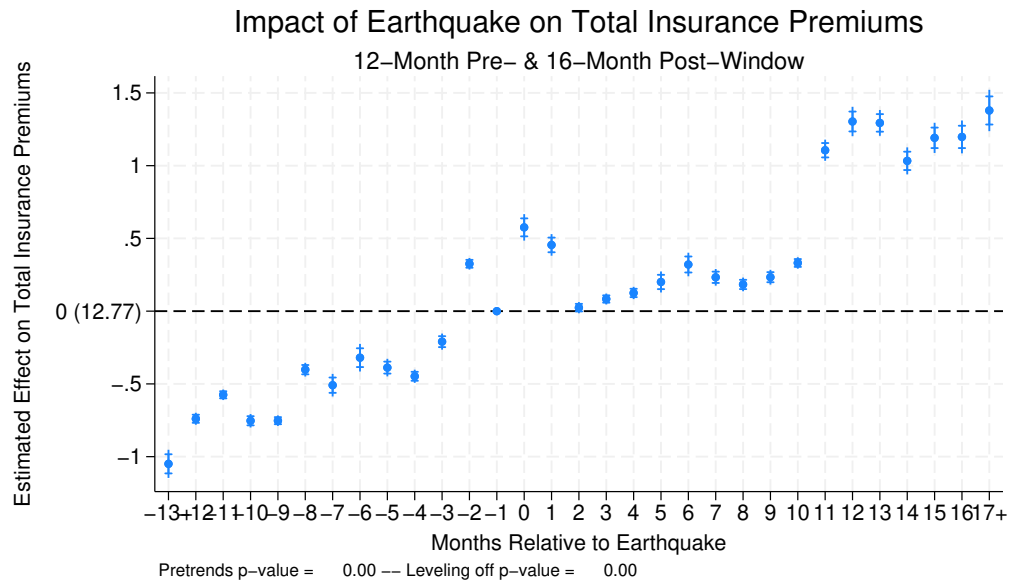


Figure 15: Impact of Earthquake on Total Insurance Premiums

Notes: This figure presents estimates from a dynamic event study evaluating the effect of the February 2023 earthquake on total earthquake insurance premiums (in logs). The outcome variable includes both new and renewal policy payments. The model includes county and time fixed effects, and standard errors are clustered at the city level. The y-axis shows monthly deviations in log premiums relative to the baseline (month before the earthquake, normalized to zero). The reference mean is 12.77 in logs.

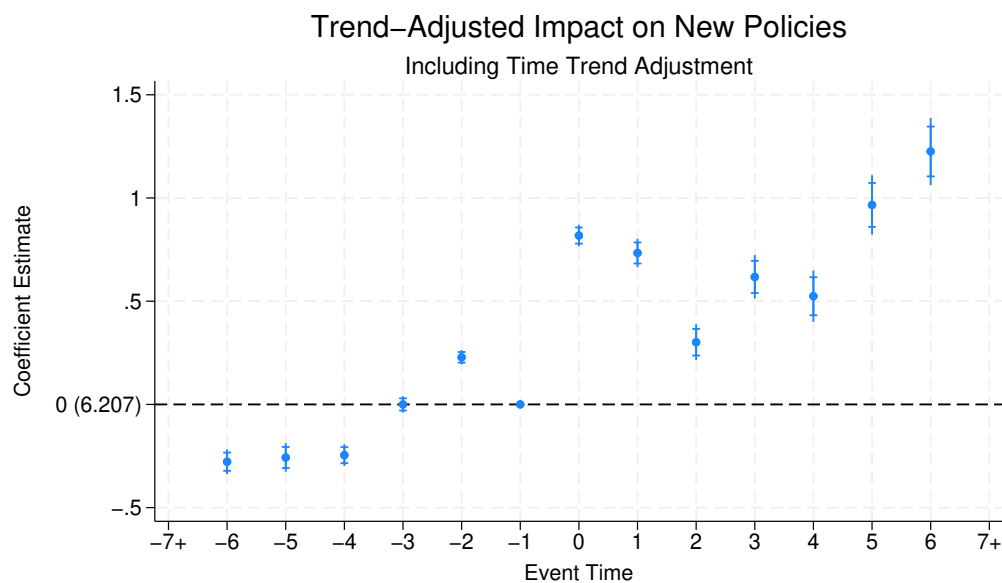


Figure 16: Trend-Adjusted Impact on New Policies

Notes: This figure shows the dynamic effect of the February 2023 earthquake on new insurance policy purchases, adjusted for pre-earthquake time trends. The analysis uses a generalized method of moments (GMM) approach to correct for systematic upward movement in the outcome variable that predates the earthquake.

The vertical axis plots the estimated coefficients (in logs), while the horizontal axis represents time relative to the earthquake. The baseline mean is 6.207. All coefficients before the event are trend-adjusted to reflect deviations from the underlying trajectory.

This approach isolates the earthquake's unexpected impact by accounting for anticipated patterns in new policy uptake. Results confirm that new policy purchases sharply diverge from the predicted trend after the earthquake.

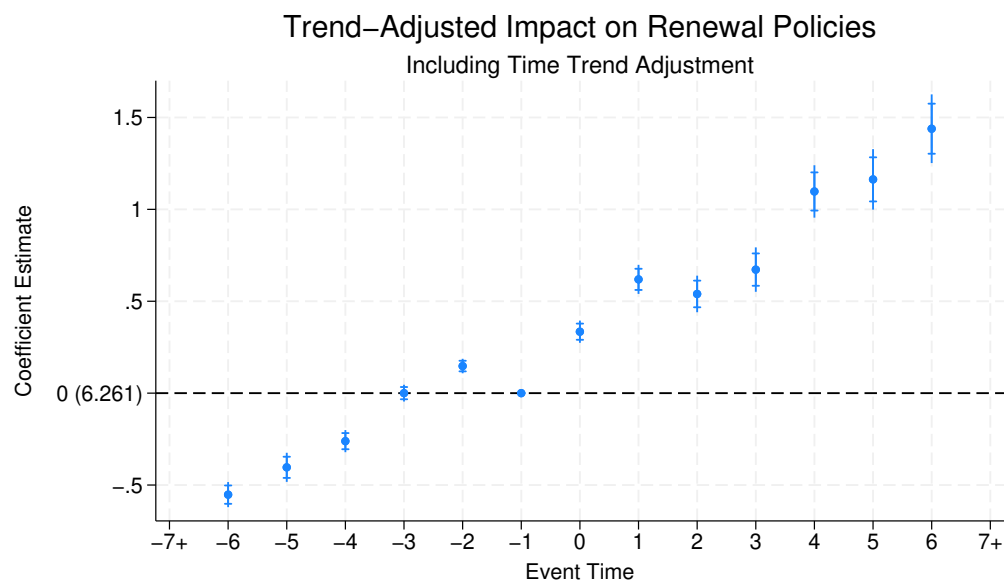


Figure 17: Trend-Adjusted Impact on Renewal Policies

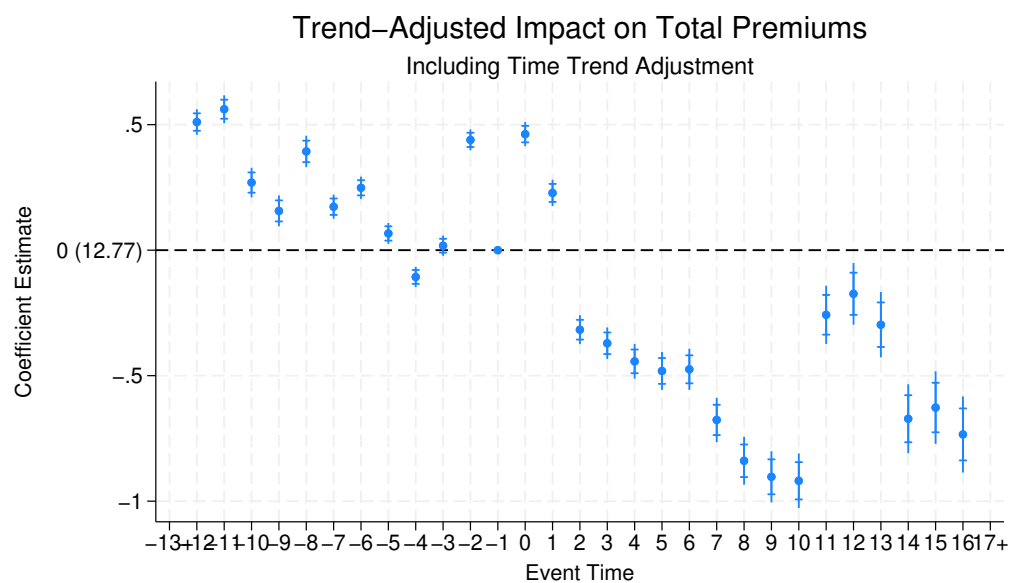


Figure 18: Trend-Adjusted Impact on Total Premiums

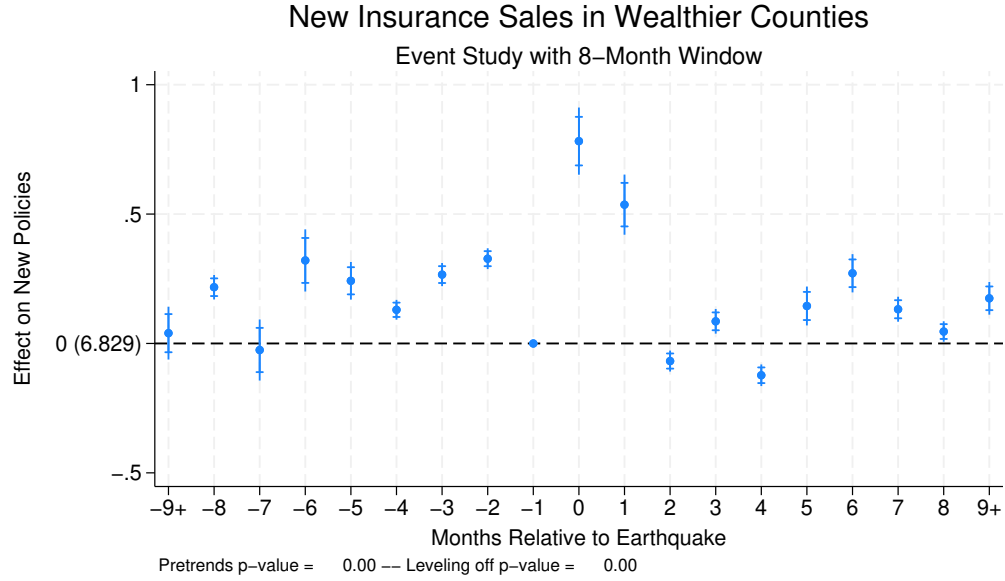


Figure 19: New Insurance Sales in High-Wealth Counties

Notes: This event study illustrates the effect of the February 2023 earthquake on new insurance policy uptake in counties with above-median development index scores, used as a proxy for local economic wealth. The vertical axis represents the estimated change in the log number of new insurance policies, while the horizontal axis tracks time relative to the earthquake month.

The model includes county and time fixed effects and clusters standard errors at the city level. The dashed horizontal line at 6.829 represents the mean of the dependent variable during the pre-treatment period.

Pre-treatment dynamics are statistically significant (pretends $p = 0.00$), suggesting differential pre-trends. However, the post-earthquake coefficients indicate a sizable increase in new policy issuance, particularly during the first three months after the earthquake, suggesting stronger responsiveness in higher-income areas.

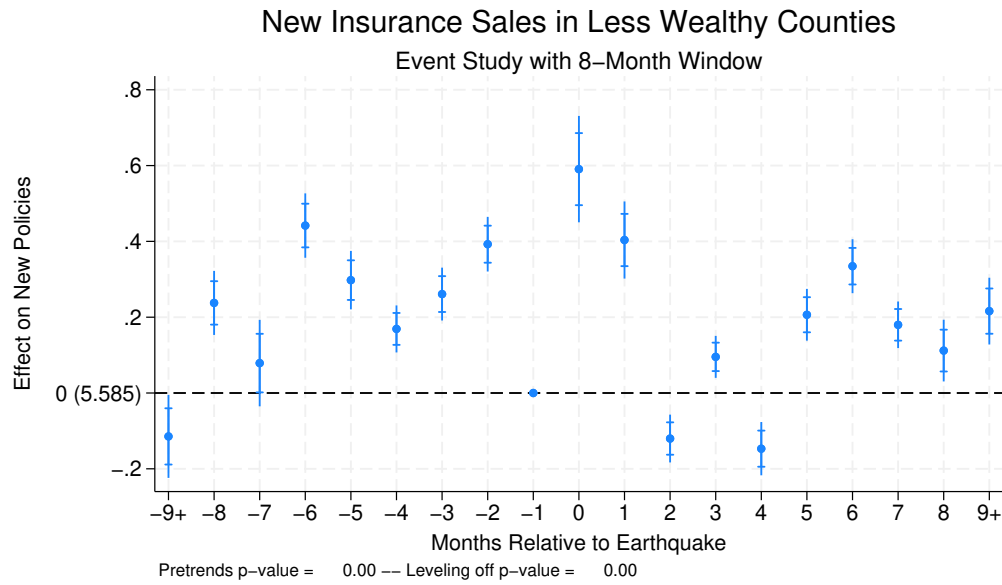


Figure 20: New Insurance Sales in Low-Wealth Counties

Notes: This event study illustrates the effect of the February 2023 earthquake on new insurance policy uptake in counties with below-median development index scores, used as a proxy for lower local economic wealth. The vertical axis represents the estimated change in the log number of new insurance policies, while the horizontal axis tracks time relative to the earthquake month.

The model includes county and time fixed effects and clusters standard errors at the city level. The dashed horizontal line at 5.585 represents the mean of the dependent variable during the pre-treatment period. Pre-treatment dynamics are statistically significant (pretends $p = 0.00$), indicating the presence of differential trends prior to the earthquake. Although new policy uptake increases modestly after the event, the post-treatment effect is a bit weaker compared to wealthier counties. This suggests that lower-income areas may face financial, informational, or logistical barriers that dampen their responsiveness to heightened perceived earthquake risk.

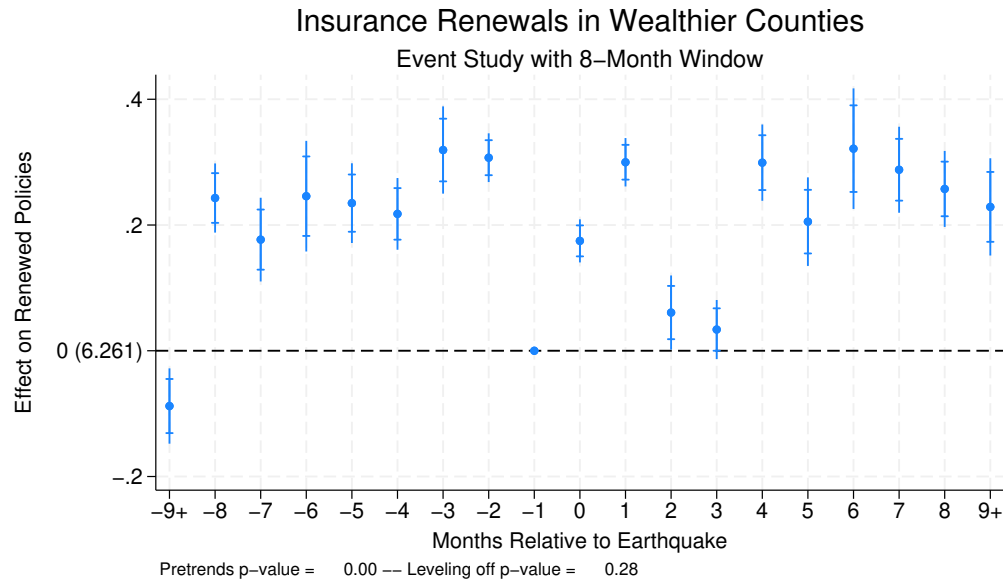


Figure 21: Insurance Renewals in High-Wealth Counties

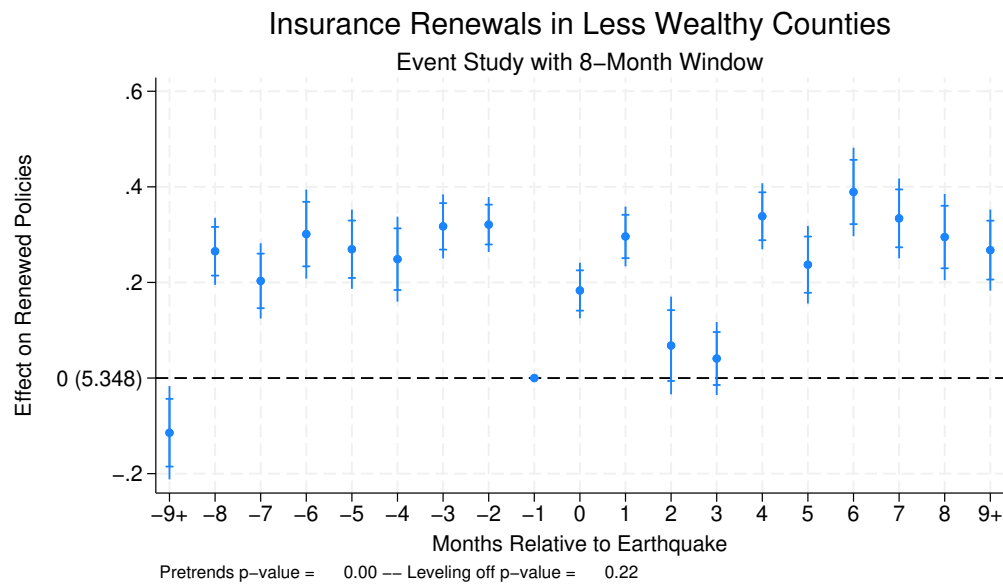


Figure 22: Insurance Renewals in Low-Wealth Counties

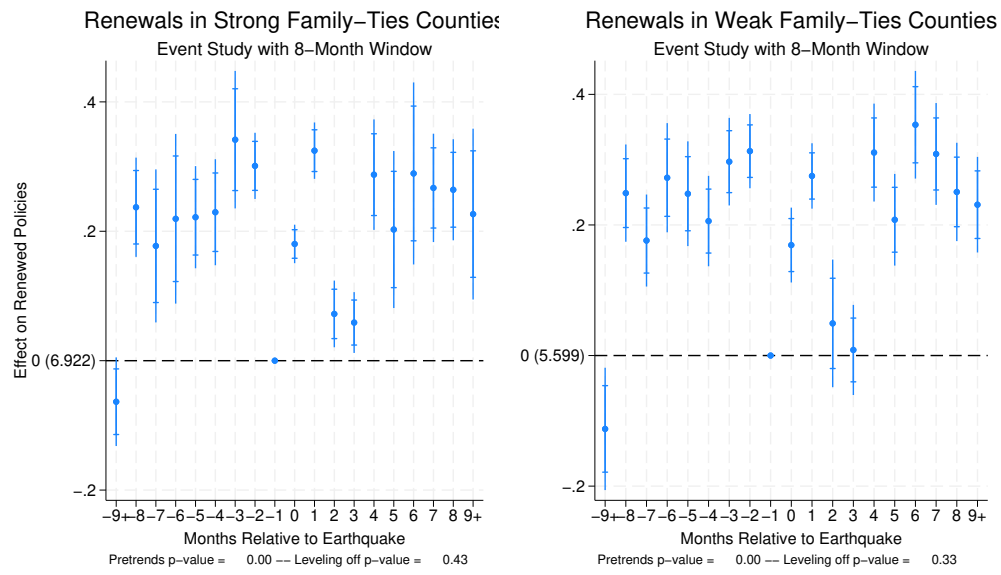


Figure 23: Insurance Renewals in Strong vs. Weak Family-Ties Counties

Event-Study: Earthquake on Home Prices by Risk

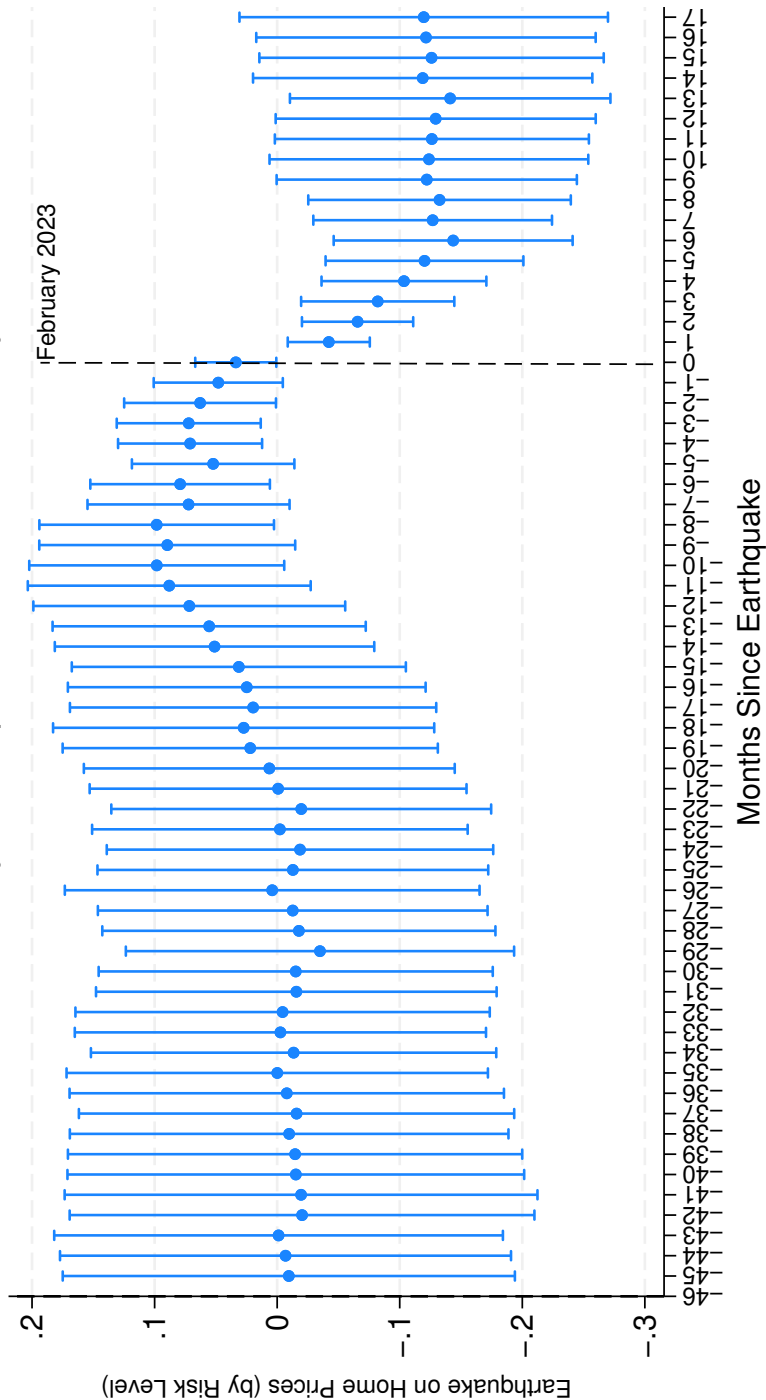


Figure 24: Event-Study: Earthquake on Home Prices by Risk

Notes: This figure plots the dynamic effects of the February 2023 earthquake on home prices across regions with varying levels of seismic risk. The y-axis shows the interaction coefficients from a two-way fixed effects regression of log home prices on `event_time` $\times$ `risk`, where `event_time` denotes months relative to the earthquake (0 = February 2023) and `risk` is the continuous pre-earthquake seismic risk (PGA). All models include county and month fixed effects, and standard errors are clustered at the city level. Pre-earthquake coefficients are statistically indistinguishable from zero, supporting the parallel trends assumption. After the earthquake, high-risk areas experience a significant and persistent decline in home prices relative to low-risk areas. This pattern is consistent for some months with salience-driven repricing of risk following the realization of the disaster.

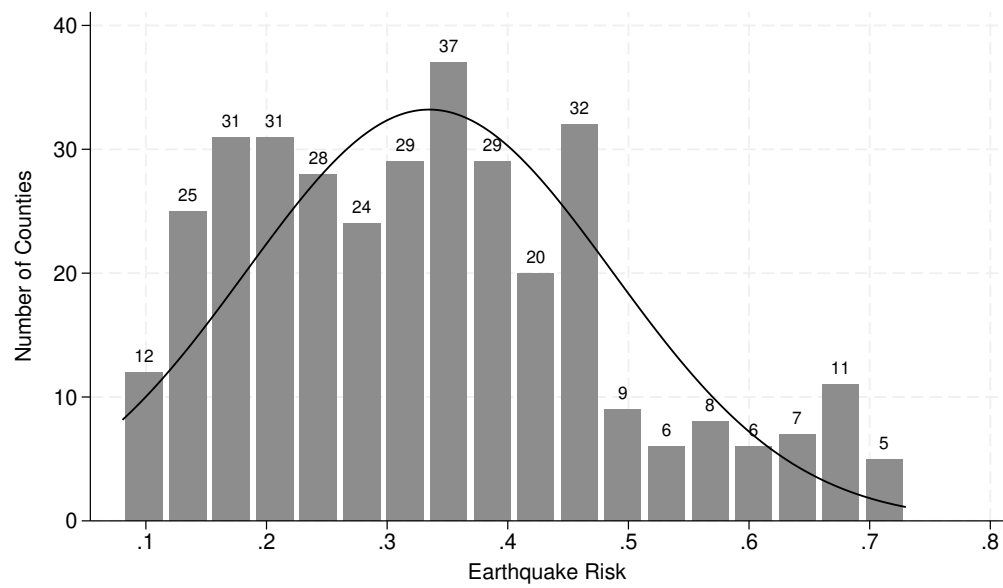


Figure 25: Distribution of counties by their earthquake risk

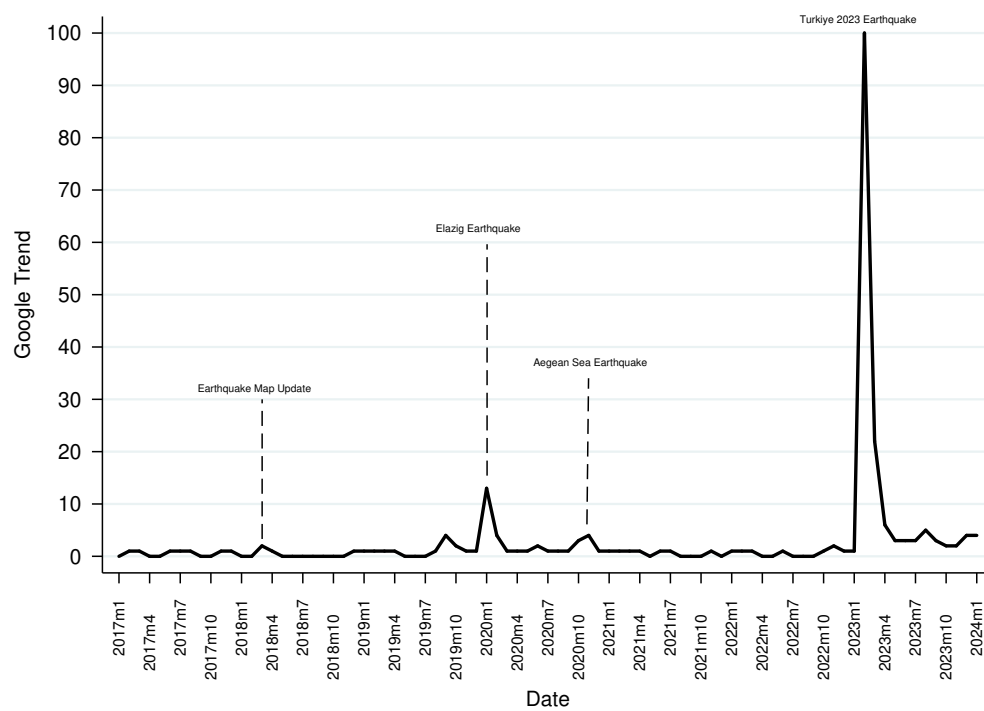


Figure 26: Google Trends on Earthquake Risk Map Update