# THE SOCIOECONOMIC VALUE OF LENDER-PLACED INSURANCE

MARCH 2021

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# EXECUTIVE SUMMARY

We have set out to understand how the existence of lender-placed insurance (LPI) affects the US mortgage market. We also intended to study the relationship between LPI and the socioeconomic consequences of a natural disaster. We have collected evidence and analyzed data across the United States, combining industry statistics from Assurant with socioeconomic data from secondary sources.

### WHAT IS LENDER-PLACED INSURANCE?

LPI is an insurance policy placed by a lender on a home when the property owner's required insurance is cancelled, has lapsed, or is deemed insufficient. This insurance **allows the lender to protect the financial interest in the property,** while at the same time protecting the borrower's asset against damage and destruction.

LPI is available across the US, but our analysis suggests coverage is **most prevalent in areas subject to higher levels of natural disasters risk**. Such high risks could make borrower-purchased coverage difficult to obtain and may result in more widespread placement of LPI.

### BACKGROUND CONTEXT AND STUDY OBJECTIVES

In order to better understand the socioeconomic impact of LPI, Assurant commissioned Oxford Economics to engage in an empirical assessment underpinned by gold-standard methodological techniques. In particular, we have tested the following hypotheses:

(1) does LPI cause borrowers to fall behind on their mortgage payments i.e. become delinquent?
(2) does the existence of LPI impact lenders' willingness to take on the risk involved in providing secured lending and therefore enable a higher number of mortgage approvals?
(3) to what extent does the prevalence of LPI coverage affect the socioeconomic consequences of natural disasters?

### KEY FINDINGS

For this study we first constructed a comprehensive dataset of all US counties over the period 2015-2019.[1] The dataset included over 100 variables, ranging from personal disposable income to the number of natural disaster declarations in each county. We then used this database to statistically test our main research hypotheses. Our key findings are as follows:

[1] We chose to analyze the 5-year period before the Covid-19 pandemic to avoid confounding from that episode, while at the same time having a long enough time dimension to capture changes in behavior over time to ensure robust estimation of the parameters.

(1) We find **no independent association between LPI coverage and the rate of mortgage delinquency**. Therefore, our research does not suggest that the marginally higher price of LPI— in the context of overall housing costs—has led to more delinquencies in the US during the period studied.
(2) We identify a **positive independent association between LPI coverage and mortgage approvals**. In our baseline specification, we estimate that a 10-percentage point hypothetical increase in the growth of LPI policies per household is associated with a 0.7% increase in mortgage approvals per household, after controlling for other factors. This supports the hypothesis that LPI does function as a market maker, **ultimately enabling higher rates of home ownership**.[2]
(3) Following a disaster, LPI is responsible for **lower debt to income ratios**, **fewer mortgage delinquencies,** and **lower federal disaster spend**. This implies that borrowers, lenders, and public finances are all better off with a greater LPI coverage in the aftermath of a disaster.

**RESEARCH EVALUATION**

Overall, therefore, our research paints a relatively positive picture of the socioeconomic contribution of LPI. Of course, the benefits of any insurance system in the context of catastrophic events are fairly self-evident. Nevertheless, given the well-documented and ongoing increase in the risk of natural disasters as a result of climate change, **LPI's *de facto* prominence in covering catastrophic risk makes it an even more important player in the insurance market**.

Our research shows that **LPI plays a small but valuable role as a market maker**, enabling the 'homeownership' dream for individuals who would otherwise not have been able to access mortgage finance. On the other hand, there is **no evidence of the higher costs of LPI policies causing sufficient financial pressure to result in an increased probability of delinquency** and thereby default.

[2] The relationship indicated above could also go the other way, i.e. increased mortgage approvals may lead to greater LPI coverage in the future. If this was the case, our estimate of the impact of LPI coverage on mortgage approval would be unreliable. To address this, we employed lagged values of LPI coverage as instruments, which make our estimates credible and appropriate (mortgage approvals today cannot affect LPI coverage in the past). Therefore, we can interpret the positive association as a casual effect of LPI coverage on mortgage approvals. To ensure accuracy, we tested whether our assumptions hold statistically by using a series of tests, which all indicate that the model is robust and fit for purpose.

# 1. INTRODUCTION

When a residential mortgage is originated, the lender acquires an ownership stake in the house as collateral for the loan. To protect its financial interest in the property, **the lender requires the borrower to maintain insurance** that would cover any damage caused by the hazards to which the house might typically be exposed (e.g., a fire, a hurricane). To meet this requirement, the vast majority of borrowers buy homeowners insurance.

**Lender-placed insurance (LPI) generally comes into play when the primary insurance carrier cancels the policy or when a mortgage borrower stops paying homeowners insurance premiums**. To continue protecting their financial interest in the home, lenders place property insurance with an insurance company that specializes in this form of coverage, charging the premiums to the borrower.

LPI rates are filed with and approved by state regulators. Such rates tend to be higher than rates for borrower-purchased insurance as LPI provides coverage for any property in a servicer's portfolio, without a rigorous underwriting process. The limited information on the properties covered adds an additional layer of risk for the insurer, hence requiring higher rates. In addition, LPI properties tend to have higher risk characteristics, such as higher-risk locations (as demonstrated in Chapter 2) and higher vacancy rates due to foreclosures.

Assurant, the US's largest provider of LPI policies, has commissioned this independent analysis of the economic implications of the use of LPI in the US. We believe the findings of this work can be used to inform policymakers and other selected stakeholders about the topic of LPI.

We divided the research program into three steps (Fig. 1). First, we conducted a **thorough literature review** about a set of variables, including mortgage approvals and delinquency rates. Next, we constructed a **county-level dataset,** which combines Assurant-provided LPI data with demographic and economic characteristics. The dataset covered all US counties over the period 2015-2019 and it included over 100 variables, ranging from personal disposable income to the number of natural disaster declarations in each county. [3] Lastly, we undertook **econometric analysis** to comprehensively test the statistical validity of the following pre-specified research hypotheses:

(1) Whether the higher mortgage cost under LPI could increase financial stress on the borrower, potentially leading to a higher default rate.
(2) Whether LPI fills the gap when the homeowner is unable to maintain his/her coverage and hence can facilitate mortgage approvals and homeownership.

[3] We chose to analyze the 5-year period before the Covid-19 pandemic to avoid confounding from that episode, while at the same time having a long enough time dimension to capture changes in behavior over time to ensure robust estimation of the parameters

(3) Whether following a natural disaster, LPI can reduce the need to turn to personal debt and improve the likelihood of on-time mortgage payments. It can also act as a private safety net, requiring less need for the government to provide post-disaster relief.

**Fig. 1. Methodology: a three-step approach**

We first reviewed the **empirical literature** in two areas: 1) analyses of the drivers of outcome variables, such as homeownership and mortgage delinquency rates; 2) assessments of the socioeconomic effects of natural disasters

Next, we **constructed a county-level database**, combining Assurant data with a range of variables resulting from secondary sources (e.g. unemployment, home prices, interest rates…)

Lastly, we developed **econometric models** to better understand the nature of underlying relationships between key variables of interest. We have used various model structures depending on the hypothesis.

This report is the result of this three-step analysis. It begins by introducing LPI concentration in disaster-prone areas (Chapter 2). In Chapter 3, we set out our approach to modeling mortgage delinquency rates and mortgage approvals, based on a panel dataset of all US counties covering the period 2015–19, with the objective of identifying whether LPI is a statistically significant driver of these variables. In Chapter 4, we illustrate the results from our post-event empirical analysis, showing the substantial effects of LPI in the aftermath of a natural disaster. The final section summarizes the key takeaways and conclusions.

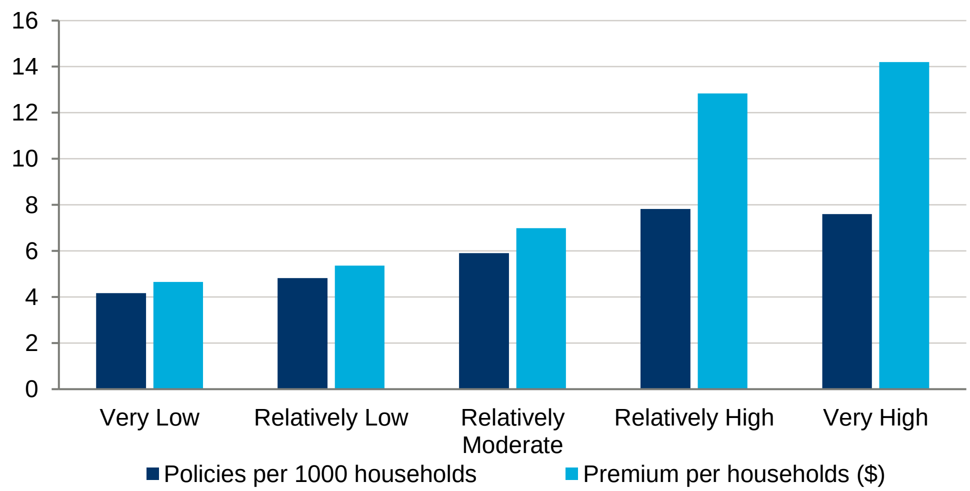
# 2. LPI AND DISASTER RISK

**In the US, LPI coverage is most prevalent in areas that are subject to higher levels of catastrophe risk related to natural disasters**, events which seem set to occur more frequently given climate change. In some extreme disasters, even state residual insurance programs, which are designed to be insurers of last resort, may refuse to insure some high-risk properties, particularly those that are vacant. Such high risks could make borrower-purchased coverage difficult to obtain and may then result in placement of LPI.

While catastrophe risk coverage is a fundamental use of lender-placed insurance, it should be noted that losses from natural disasters account for about 40% of all the losses paid out by Assurant on average. This suggests disaster coverage is not the sole utilization of LPI.

The geographic concentration of LPI is graphically presented in Fig. 2, which shows that LPI coverage is, on average, more prevalent in counties with a higher FEMA National Risk Index for Natural Hazards (NRI) score. Our statistical analysis indicates that this relationship continues to hold, even after controlling for other socioeconomic factors which might influence the likelihood that a household uses LPI, such as GDP, unemployment, and home prices.

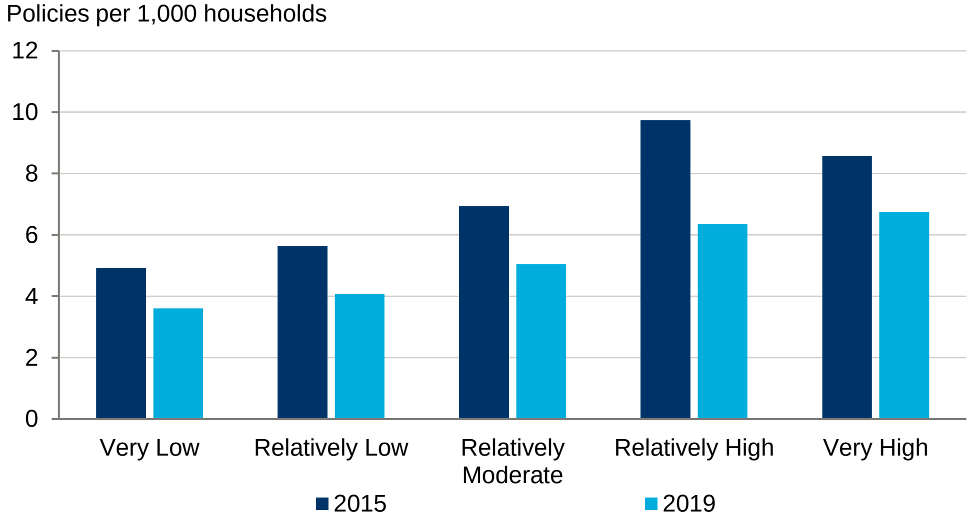
**Fig. 2. LPI concentration and disaster risk**




Source: Oxford Economics

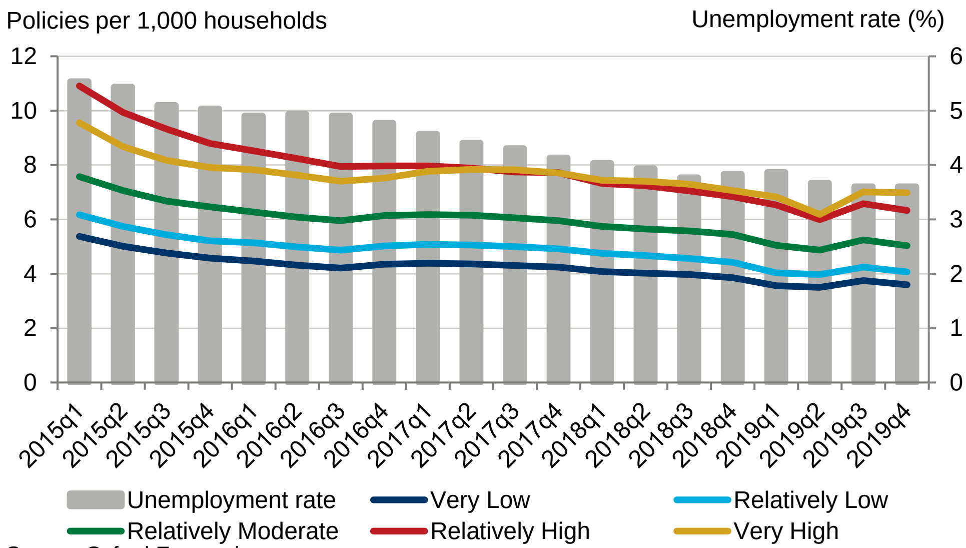
This relationship remained fairly consistent between 2015 and 2019 (Fig. 3), although overall LPI prevalence declined over this period, across all risk bands. This mirrors developments in general economic conditions with a lag (in Fig. 4, economic conditions are proxied by unemployment, and this variable is displayed as a gray bar chart in the background).

**Fig. 3. LPI concentration and disaster risk, 2015 vs 2019**




Source: Oxford Economics

**Fig. 4. LPI concentration, disaster risk and unemployment (grey bars)**




Source: Oxford Economics

# 3. LPI AND THE MORTGAGE MARKET

### 3.1 DELINQUENCY RATES

This report seeks to determine if the presence of LPI causes higher rates of mortgage delinquency. This is in response to critics of lender-placed insurance, who have argued that, for cash-strapped borrowers, the charges associated with LPI can result in mortgage delinquency and even default.

Findings from the **literature review** are presented in the box overleaf. This review **provided some valuable guidance on the drivers for mortgage delinquency**. The ability of borrowers to pay back a mortgage can be affected by economic circumstances, such as unemployment, as well as their personal and aggregate financial condition. We drew on these findings to inform the development of our core model.

In summary, our core model encompasses a set of macroeconomic and financial market conditions that the studies cited in the box have found to be correlated with mortgage delinquency. Fig. 5 lists these key conditions and gives each a directional sign. A positive sign indicates a statistically significant positive relationship, a negative sign indicates a statistically significant negative relationship, and the absence of sign indicates that the relationship is not statistically significant. The model shows a positive relationship between the unemployment rate and mortgage delinquency. Conversely, we find that not only is **LPI prevalence not a significant driver in mortgage delinquency**, but also a causal link between LPI and mortgage delinquency can be ruled out on statistical grounds.

**Fig. 5. Drivers of mortgage delinquency**

| Economic conditions | Financial market conditions | LPI concentration |
|---|---|---|
| • Real GDP (-)<br>• Unemployment rate (+) | • Loan-to-value (+)<br>• Mortgage rate ()<br>• Borrower credit score (-) | • LPI policies per household () |

Our preferred specification is a dynamic model, which is one where delinquency in the previous quarter affects current mortgage delinquency. We chose this model specification because mortgage delinquency shows a lot of persistence and statistical tests suggest a dynamic form is preferable. Additional details about the model specification can be found in the Appendix.

**DRIVERS OF MORTGAGE DELINQUENCY AND DEFAULT**

The following is a summary of some of the most relevant research on the causes of mortgage delinquency and default. Spilbergs (2020) undertook a meta-analysis of mortgage delinquency and default risk drivers and identified both macroeconomic indicators (e.g., unemployment, wage growth, house price index) and micro factors (e.g., the age of the borrower, total debt to income, loan-to-value) as potential explanatory variables.[4]

Among the articles concerning the drivers of **mortgage arrears**, Aron and Muellbauer (2016) used mortgage data over three decades (1983-2014) and found a strong correlation between arrears and aggregate debt-service ratio, the proportion of mortgages in negative equity and the unemployment rate.[5] Similarly, Gerlach-Kristen and Lyons (2018) used national-level panel data to examine mortgage arrears in 15 countries and concluded that unemployment, low income, and high mortgage payments all play a major role in explaining mortgage arrears.[6]

Many scholars have also studied the drivers of **mortgage defaults**. For example, Campbell and Cocco (2015) developed a model to quantify the effects of adjustable versus fixed mortgage rates, loan-to-value (LTV) ratios, and mortgage affordability measures on mortgage default.[7] Similarly, Kelly and O'Toole (2018) found that default increases with loan-to-value and falls with debt-service ratio.[8] Elul et al. (2010) combined loan-level data with credit information about the borrower's balance sheet and found that borrower characteristics, such as initial LTV and credit score, play a significant role in determining mortgage defaults.[9] Lastly, Fuster and Willen (2012) studied the effect of monthly payment size on mortgage default, using a sample of US adjustable-rate loans that experienced large payment reductions thanks to the low interest rate environment.[10] They found that payment size has an economically large effect on repayment behavior; for instance, cutting the required payment in half reduced the delinquency hazard by about 55%.

In addition to this empirical literature, Hott (2015) developed a theoretical model of **mortgage loss rates**.[11] In this model, loss rates are positively influenced by the house price level, the loan-to-value of mortgages, interest rates, and the unemployment rate, while they are negatively influenced by the growth of house prices and the income level.

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[4] Aivars Spilbergs, "Residential Mortgage Loans Delinquencies Analysis and Risk Drivers Assessment", *Emerging Science Journal*, 4(2) (2020).

[5] Janine Aron and John Muellbauer, "Modelling and forecasting mortgage delinquency and foreclosure in the UK", *Journal of Urban Economics*, 94 (2016): 32-53.

[6] Petra Gerlach-Kristen and Seán Lyons, "Determinants of Mortgage Arrears in Europe: Evidence from Household Microdata", *International Journal of Housing Policy*, 18(4) (2018): 545–67.

[7] John Y. Campbell and J.F. Cocco, "A Model of Mortgage Default", *The Journal of Finance*, 70(4) (2015): 1495–554.

[8] Robert Kelly and Conor O'Toole, "Mortgage Default, Lending Conditions and Macroprudential Policy: Loan-Level Evidence from UK Buy-to-Lets", *Journal of Financial Stability*, 36 (2018): 322–35.

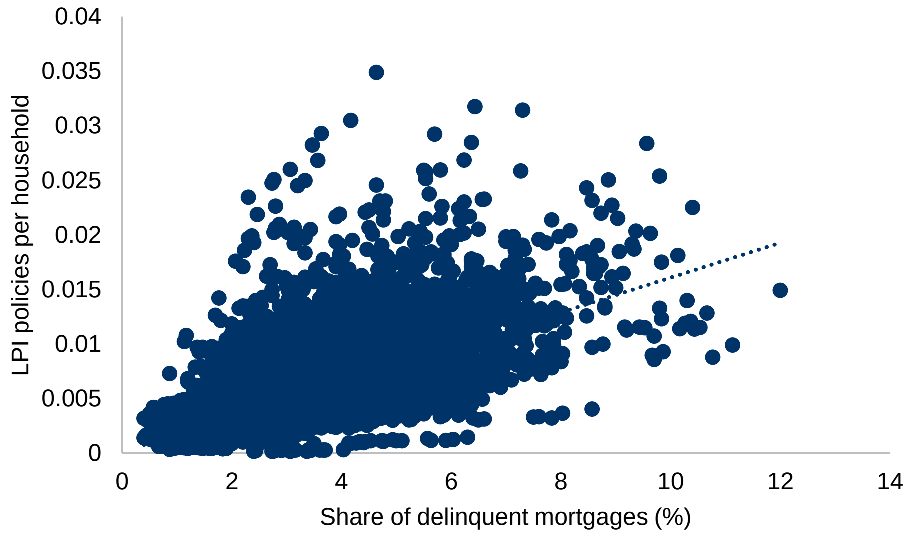
[9] Ronel Elul et al., "What "Triggers" Mortgage Default?", *American Economic Review*, 100(2) (2010): 490-94.

[10] Andreas Fuster and Paul S. Willen, "Payment Size, Negative Equity, and Mortgage Default", *American Economic Journal: Economic Policy*, 9(4) (2017): 167–91.

[11] Christian Hott, "A Model of Mortgage Losses and Its Applications for Macroprudential Instruments", *Journal of Financial Stability*, 16 (2015): 183–94.

As Fig. 6 shows, the prevalence of LPI is positively *correlated* with mortgage delinquency—on average, delinquency rates are higher in counties where LPI is more widespread. What this association does not explain is the nature of the relationship and whether it can be regarded as *causal*.

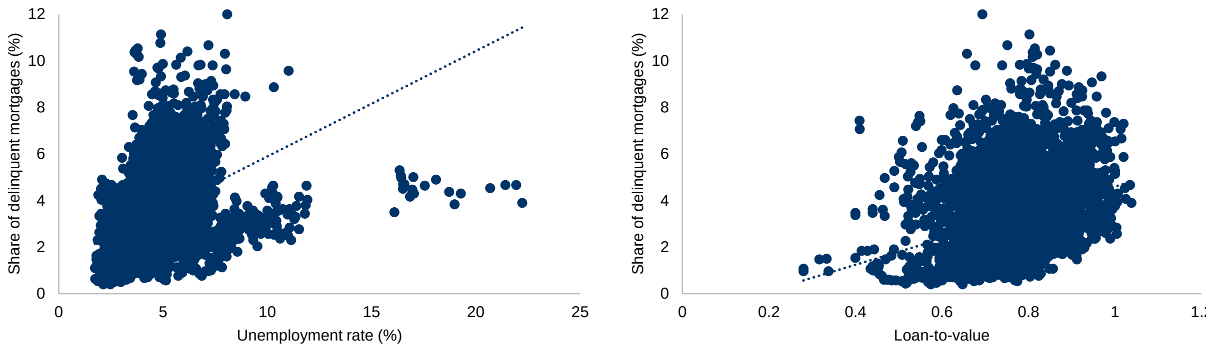
**Fig. 6. Correlation between LPI prevalence and % of delinquent mortgages**



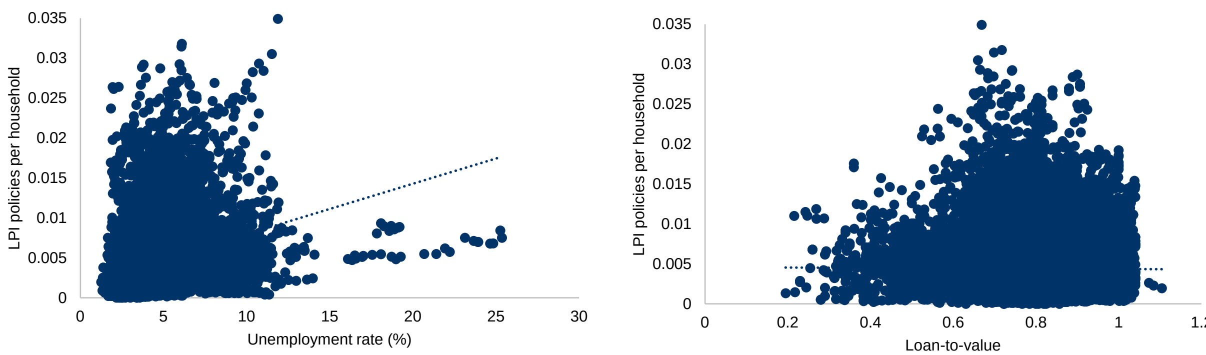

LPI coverage might simply be related to other county characteristics that are the *true* drivers of mortgage delinquency. For example, counties with higher unemployment rates or higher average loan-to-value ratios have higher delinquency rates (see the top panel of Fig. 7)—these factors might plausibly cause both higher delinquency rates and increased LPI coverage (see bottom panel of Fig. 7). Indeed, as we control for these factors in our model, we see the relationship between LPI and delinquency become weaker, to the point where it becomes statistically insignificant. In other words, by omitting unemployment or loan-to value from our regression models, we might erroneously attribute their impact on delinquency to LPI concentration.

**Fig. 7. Correlation matrix: delinquency and LPI vs unemployment and LTV**

Delinquency and unemployment (left side); delinquency and LTV (right side)




LPI and unemployment (left side); LPI and LTV (right side)




Standing back, our findings are not surprising considering the magnitude of LPI monthly premiums in the context of the generalized cost of ownership and the cost of traditional homeowners' insurance. Assurant's calculations suggest that the median annual LPI premium charged in 2019 was $1,329 (~$111 per month). This compares with a median of $83 per month paid on fire/hazard/flood insurance for households whose insurance payment is not included in their mortgage payment, according to the 2019 American Community Survey.[12]

The median monthly cost of homeownership in the US was $1,609 per month, also according to the 2019 American Community Survey. Therefore, a typical LPI premium was roughly equivalent to 6.9% of the monthly cost of homeownership, while a typical fire/hazard/flood insurance was roughly equal to 5.2% of the monthly cost of homeownership. The small entity of this difference suggests that slightly higher LPI premiums are unlikely to meaningfully drive up delinquency rates.

We therefore conclude that, **although the implementation of LPI by lenders adds to mortgage costs faced by borrowers, there is no evidence that this has contributed to an increase in delinquency rates**.

[12] 2019: ACS 1-Year Estimates Data Profiles and Oxford Economics estimates using raw ACS data.

### 3.2 MORTGAGE APPROVALS AND HOMEOWNERSHIP

Beyond the absence of any statistically significant relationship between LPI and mortgage delinquency, does the existence of LPI have any other effects on the US housing market? As described, LPI is designed to allow the lender to protect its financial interest in the property in a worst-case scenario. The existence of LPI therefore fills the gap when a borrower has not been able to maintain his/ her coverage. Plausibly, the *knowledge* that this option exists would make lenders more willing to take on the risk of making a secured loan. If so, the existence of LPI helps to facilitate mortgage approvals and in turn a higher rate of homeownership.

In order to test this theory, we first reviewed the existing literature around the drivers of mortgage approvals. Krištoufek and Pavlicek (2019) provide insights into the dynamics of the mortgage market, specifically the drivers for new mortgage approvals.[13] They include interest rates, unemployment, GDP growth, and the housing price index as explanatory variables.

Some helpful insights can also be drawn from literature studying the drivers of homeownership, a direct by-product of mortgage approvals. For example, a recent OECD report finds that the probability of homeownership increases with age, real household disposable income, and education levels.[14] On the other hand, the probability of homeownership is found to be lower for immigrant households**.** The study also investigates the impact of changes in the down payment constraint on homeownership rates by running an econometric model where homeownership is regressed over the maximum LTV (loan-to-value ratio).

Combining historical data on natural disasters in the United States with household data, Sheldon and Zhan (2019) use a differences-in-differences approach to estimate the effects of natural disasters on home ownership rates.[15] Their results indicate a 3–5-percentage-point decrease in the home ownership rate among households that migrate to areas hit by severe natural disasters.

Drawing from this literature, we built a dynamic model of mortgage approvals, where approvals in the previous year affect current mortgage approvals and a range of explanatory variables are included. To answer our research question, we also include a measure for LPI concentration, measured as the number of LPI policies per 1,000 households. Fig. 8 shows a list of the explanatory variables and the direction of the relationships (when no sign if provided in brackets, the relationship is not statistically significant).

[13] Jaroslav Pavlicek & Ladislav Kristoufek, "Modeling UK Mortgage Demand Using Online Searches", *Working Papers IES 2019/18, Charles University Prague, Faculty of Social Sciences, Institute of Economic Studies*, 2019.
[14] Dan Andrews and Aida Caldera Sánchez, "Drivers of Homeownership rates in Selected OECD Countries", *OECD Economics Department Working Papers No. 849*, 2011.
[15] Tamara Lynn Sheldon and Crystal Zhan, "The Impact of Natural Disasters on US Home Ownership", *Journal of the Association of Environmental and Resource Economists*, 2019.

**Fig. 8. Drivers of mortgage approvals**

| Economic conditions | Housing market conditions | Financial market conditions | Disaster risk | Demographic factors | LPI concentration |
|---|---|---|---|---|---|
| • Real GDP (+)<br>• Unemployment rate (-) | • Home price growth ()<br>• Mortgage applications (+) | • Debt-to-income ()<br>• Mortgage rate (-) | • FEMA county risk score (+) | • Share foreign-born population (-) | • LPI policies per household (+) |

We find that **mortgage approvals increase with LPI coverage**, implying statistical support for the argument that LPI acts as market-maker. According to our model, a 10-percentage point hypothetical increase in the growth of LPI policies per household is associated with a 0.7% increase in mortgage approvals per household.

When investigating the relationship between LPI coverage and mortgage approvals there is a possibility of reverse causality, since increased mortgage approvals may lead to greater LPI coverage in the future. The consequence of this would be to make our estimate of the impact of LPI coverage on mortgage approval unreliable. As a remedy to this issue, we employed the instrumental variable solution, using lagged values of LPI coverage as instruments. This ensured that the resulting coefficient estimates are credible and appropriate. Given that mortgage approvals today cannot affect LPI coverage in the past, the results we detect cannot be driven by reverse causality, so we can interpret the positive association as a casual effect of LPI coverage on mortgage approvals. To ensure accuracy, we tested whether our assumptions hold statistically by using a series of tests. These tests indicated that the model is robust and fit for purpose.

# 4. LPI AND POST-DISASTER OUTCOMES

As detailed in section 2, LPI is concentrated in disaster-prone areas. In this chapter, we investigate the **marginal effect of LPI on a range of outcomes in the aftermath of a disaster**.

We find evidence to suggest that greater LPI coverage is associated with lower debt to income ratios, fewer mortgage delinquencies, and lower federal disaster spend following a natural disaster.[16] This chapter details our econometric findings and explains the underlying mechanisms behind these statistical relationships.

### 4.1 DEBT AND DELINQUENCIES

Natural disasters are known to have a negative effect on most aspects of people's financial lives. A natural disaster can lead to greater debt and delinquencies, thereby increasing financial stress in the near term, but also cause longer-term declines in financial health by deteriorating credit scores.

Articles by Gallagher and Hartley (2017) and Edminston (2017) studied the impacts of disasters on various measures of household finance, including credit scores, debt, and delinquencies. The former article studied the effects after Hurricane Katrina, finding small reductions in credit scores, increases in credit card borrowing and delinquency rates, and evidence that financially vulnerable consumers are less able to access credit in the year following the hurricane.[17] These effects were found to be generally modest in size and short-lived.

Edminston (2017) evaluated the impacts of several major hurricanes in the south eastern United States between 2000 and 2014 on a similar set of outcomes.[18] The author's results linked hurricanes to reductions in credit scores, particularly among people who were more financially vulnerable before the disasters (where vulnerability was measured by unpaid bills and high bank card utilization rates).

A 2019 study by the Urban Institute also analyzed how natural disasters affect several financial health outcomes and found evidence of negative impacts on credit card debt, mortgage delinquency and foreclosures.[19] Specifically, the report found that credit card *access* declined for struggling residents (those with poor credit scores before the disaster), while credit card *debt* increased for better-off residents (those with good credit scores pre-disaster). In other words, the effect of natural

[16] We have not found any significant relationship between LPI coverage and population growth and poverty following a disaster.

[17] Justin Gallgher and Daniel Hartley, "Household Finance after a Natural Disaster: The Case of Hurricane Katrina", *American Economic Journal: Economic Policy*, 9(3) (2017): 199–228.

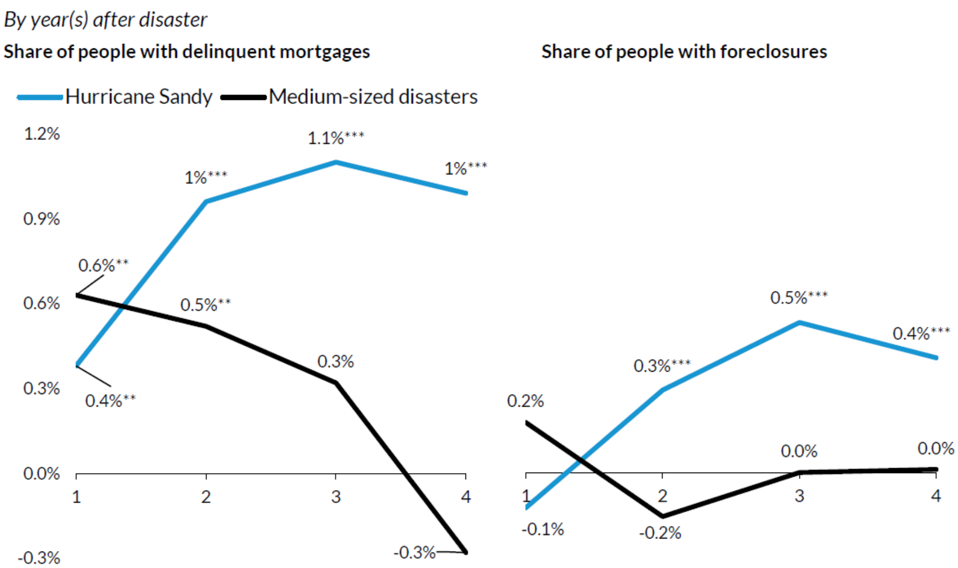
[18] Kelly D. Edmiston, "Financial Vulnerability and Personal Finance Outcomes of Natural Disasters", *Research Working Paper RWP 17-9, Federal Reserve Bank of Kansas City*, 2017.

[19] Urban Institute, "Insult to Injury - Natural Disasters and Residents' Financial Health", April 2019.

disasters on credit card access and debt differed depending on people's pre-disaster financial health.

In addition, following natural disasters, homeowners need to manage mortgage payments along with necessary repairs and any costs associated with temporary housing. In these cases, falling behind on mortgage payments can be an early marker of financial distress for mortgage holders. For example, the Urban Institute found that mortgage delinquency and foreclosures increased in the aftermath of Hurricane Sandy (Fig. 9).

**Fig. 9. Mortgage delinquency and foreclosures, by disaster**




**Source:** Urban Institute calculations based on credit bureau, ACS, and FEMA data
**Notes:** Values represent estimates of average differences in each outcome between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster.
*$p$ < 0.1, **$p$ < 0.05, ***$p$ < 0.01.

It has often been observed that homeowners fail to purchase disaster insurance, even if it could considerably mitigate the risks from catastrophic events, such as floods or earthquakes.[20] Insurance payouts can help homeowners avoid significant deterioration in their personal debt circumstances and their ability to repay their mortgages. To test this theory in the context of lender-placed insurance, we built econometric models that test the marginal effect of LPI over debt-to-income ratios and mortgage delinquency rates in the aftermath of a natural disaster.

In 'normal times' (i.e., in the absence of a disaster) the effect of LPI on debt-to-income ratios is found to be insignificant, suggesting LPI is neutral to indebtedness levels. Most importantly, we find evidence that **greater lender-placed coverage is associated with lower debt to income ratios following a natural disaster**.

[20] Carolyn Kousky and Roger Cooke , "Explaining the Failure to Insure Catastrophic Risks", *The Geneva Papers on Risk and Insurance - Issues and Practice volume*, 37 (2012): 206–27.

Specifically, a 10-percentage point increase in the quarterly growth rate of LPI policies per household corresponds to a 9.5 percentage point fall in the debt-to-income ratio following a disaster.

This statistical relationship can be interpreted as follows; in areas characterized by low insurance penetration, communities tend to turn to personal debt to cover repairs and other costs in the aftermath of a disaster. On the other hand, LPI appears to marginally improve indebtedness levels following a disaster, providing coverage for necessary repairs and expenses, thereby reducing the need to accumulate more debt.

Our models also provide evidence that **greater LPI coverage is associated with fewer mortgage delinquencies following a natural disaster**. By protecting all the parties involved (i.e., the lender and the borrower) against damage or destruction of the property, LPI reduces the incentive for the borrower to walk away from the mortgage in case of property damage or destruction.

This is not simply a positive outcome for the affected lending institution, but also for the financial ecosystem more widely. By avoiding some mortgage delinquencies, the natural life of the mortgage is preserved, with positive effects on the secondary market as well. In other words, after a disaster, the presence of LPI helps preserve the expected performance of mortgages over time, by keeping continuous payment streams and allowing for gradual fall in loan-to-value ratios as mortgages are repaid.

It should be noted that it is typical for a foreclosure moratorium to kick in for 90 days after a natural disaster. This usually requires lenders to temporarily halt foreclosure starts for defaulted loans or stop activity for foreclosures already in progress. Our model allows to distinguish between the effect of a natural disaster (and the associated moratorium) and the effect of LPI on delinquency rates post disaster, so the coefficient associated with LPI measures the marginal effect of LPI concentration on delinquency, over and above any disaster-related moratorium.

### 4.2 FEDERAL SPEND

From wildfires to hurricanes, natural disasters are becoming more frequent and severe throughout the US. Ensuring that public funding is available to respond to, recover from, mitigate against, and prepare for these events has become increasingly important. The rising cost and frequency of disasters is also putting pressure on budgets at all levels of government, stressing the need for robust analyses of the fiscal impact of natural disasters.

LPI policies protect federal taxpayers, by covering losses that would otherwise require government relief *ex post*.[21] This is especially important in an era where catastrophe risk is increasing rapidly. Moreover, while the federal rates offered through the National Flood Insurance Program (for example) are generally

[21] LPI also protects states taxpayers by keeping substantial numbers of policies out of state-run property insurance residual market plans. This analysis is however out of the current scope of this report.

subsidized by taxpayers, LPI includes flood coverage at unsubsidized actuarially sound rates, thereby saving taxpayers money *ex ante*.

Our econometric model provides evidence to suggest that **greater LPI coverage is associated with lower federal disaster spend following a disaster**. In other words, in the aftermath of a disaster, LPI helps create a private safety net, thereby reducing the need for government relief.

To give a sense of scale, we evaluated the model-predicted effects of LPI in the aftermath of the Thomas fire, a large wildfire that affected Ventura County in southern California in December 2017. The Federal Emergency Management Agency (FEMA) declared a disaster during the first quarter of 2018 and in the same period it committed around $22.2 million in federal relief. Using our model, we estimated that had LPI coverage in Ventura County been 10% lower prior to the disaster, federal relief spending would have needed to be $1.4 million, or 6.3%, higher to compensate.

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# 5. CONCLUSION

The aim of this study was to understand how the existence of lender-placed insurance affects the US mortgage market. We also studied the relationship between LPI and the socioeconomic consequences of a natural disaster. We have found that **mortgage delinquency rates are not substantially driven by the presence of LPI**. We estimate that LPI is not only an insignificant determinant, but we also do not find evidence of a *causal* relationship between LPI and mortgage delinquency rates.

Second, this study has found that **LPI has a meaningful association with mortgage approvals and in turn homeownership**. It is estimated that a 10-percentage point hypothetical increase in the growth of LPI policies per household is associated with a 0.7% increase in mortgage approvals per household.

Finally, our analysis has pointed to the fact that **LPI is associated with positive outcomes in the aftermath of a natural disaster**. We have evidence that greater LPI coverage is associated with lower debt to income ratios, fewer mortgage delinquencies, and lower federal disaster spend following a natural disaster.

In conclusion, this study points to the fact that lender-placed insurance:

- Is not causally associated with mortgage delinquencies;
- Significantly supports mortgage approvals, thereby facilitating homeownership; and
- Brings about positive outcomes following disasters, reducing the burden on public finances and the financial system altogether.

# METHODOLOGICAL APPENDIX

## DYNAMIC PANEL MODELS

### Introduction to System GMM

Many of the dependent variables we are modeling, such as mortgage approvals, may be affected by their own past trends in addition to mortgage market indicators, general economic conditions, and LPI coverage. In such cases, dynamic panel methods, such as the Arellano Bond estimator (also known as Difference GMM) and Blundell Bond estimator (System GMM), allow us to account for the presence of such "dynamic effects." This work employs System GMM, which estimates the equation in levels as well as differences, using lagged variables as instruments.

Dynamic panel models have become increasingly popular in many areas of economic research, and their use has provided new insights. Using dynamic panel models allows us to find overall (long-run) coefficients for the explanatory variables as well as the contemporaneous (or short-run) ones.

The advantages of dynamic models include:

- controlling for the impact of past mortgage approvals on current mortgage approvals, and
- use of past values of explanatory variables as instrumental variables to mitigate the bias due to two-way causality between mortgage approvals and mortgage market conditions; omitted variable bias; and measurement error.

### The need for a dynamic model: Wooldridge test for serial correlation

The Wooldridge test allows us to test whether the errors are serially correlated; if these are found to be autocorrelated, we may infer that there is a need for a dynamic model.[22] The disadvantage of a dynamic panel model, however, is that it can add considerable complexity to the modeling process. A simpler static model might therefore be a preferable approach if the Wooldridge test does not suggest a dynamic panel is necessary.

### Use of instruments

Instruments are used to control for potential endogeneity in a regression. In particular, we find that LPI coverage is endogenous in many of the specifications we tested, and so we instrument this variable with lags of its own value in order to mitigate any bias.

### System GMM model results

The results of the System GMM estimates are given in Fig. 10. Dynamic models allow for the calculation of both short-run (instantaneous) and long-run effects; the coefficients reported here are those pertaining to the short-run effects.

[22] Strictly speaking, the Wooldridge test is a test for autocorrelation and not a definitive test to choose between static and dynamic panel methods. However, it is commonly applied to inform choices between static and dynamic panels.

**Fig. 10. System GMM model results**

| **Mortgage delinquency model**[23] <br> ***Dep var: Share of mortgages which are delinquent*** | **Short-run coefficients** |
|---|---|
| Lagged share of mortgages which are delinquent | 0.465*** |
| **Growth in LPI policies per household** | **-0.444** |
| Real GDP growth | -5.755** |
| Mortgage loan-to-value ratio | 1.073*** |
| Mortgage interest rate (minus fed funds rate) | 0.030 |
| Unemployment | 0.100*** |
| Borrower credit score | -0.099*** |

| **Mortgage approval model**[24] <br> ***Dep var: Log mortgage approvals per household*** | **Short-run coefficients** |
|---|---|
| Lagged log mortgage approvals per household | 0.956*** |
| **Growth in LPI policies per household** | **0.073**** |
| Real GDP growth | 0.154** |
| Log house price index | -0.136 |
| Mortgage interest rate | -2.506* |
| Foreign-born population growth | -0.193*** |
| Mortgage application growth | 0.915*** |
| Unemployment | -0.011** |
| FEMA county risk score | 0.004** |
| Debt-to-income ratio | 0.020 |
| Constant | -0.054 |

legend: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

### Differences-in-differences modeling with an interaction term

When assessing the effect of a treatment—an intervention or occurrence which occurs in some but not all counties—a common estimation strategy is to use a differences-in-differences model. Differences between treated and untreated counties are observed before and after treatment, and any difference in

[23] Model fit using quarterly data observed at the US county level. Quarter fixed effects not reported.
[24] Model fit using annual data observed at the US county-level.

those differences is considered to be the effect of treatment. In this case, we wish to understand the effect of LPI on county outcomes following a natural disaster, so treatment is the occurrence of a disaster. A baseline specification[25] for county $i$ in quarter $t$ might be:

$$outcome_{i,t} = \alpha * disaster_{it} + \beta * any\_disaster_i + \gamma * X_{it} + \delta * outcome_{i,t-1},$$

where $disaster_{it}$ is equal to one after a disaster has happened and equal to zero otherwise, $any\_disaster_i$ is equal to one if a county ever suffers a disaster and equal to zero otherwise, and $X_{it}$ is a vector of control variables.[26] In this specification, the coefficient $\alpha$ is the effect of a disaster on the outcome variable.

Since we are hypothesizing that the effect of the disaster changes depending on the degree of LPI provision, we must introduce an interaction term. This allows us to assess the difference in the effect of a disaster when LPI coverage increases or decreases. The specification then becomes:

$$outcome_{i,t} = \alpha_1 * disaster_{it} + \alpha_2 * disaster_{it} * coverage_{it} + \alpha_3 * coverage_{it} + \beta * any\_disaster_i + \gamma * X_{it} + \delta * outcome_{i,t-1},$$

where $coverage_{it}$ is some measure of LPI coverage. In this expanded specification, the coefficient $\alpha_1$ is the effect of a disaster on the outcome variable regardless of LPI coverage, the coefficient $\alpha_2$ tells us whether the effect of a disaster changes with LPI coverage, and the coefficient $\alpha_3$ is the effect of LPI coverage on the outcome variable whether the county suffers a disaster or not. Of particular interest is the coefficient $\alpha_2$ on the interaction term.

**Post-disaster System GMM model results**

System GMM estimates of the effect of LPI coverage on county outcomes following a natural disaster are reported in Fig. 11.

**Fig. 11. Post-disaster System GMM model results**

| **Post-disaster mortgage delinquency model[27]**<br>***Dep var: Share of mortgages which are delinquent*** | **Short-run coefficients** |
|---|---|
| Lagged share of mortgages which are delinquent | 0.448** |
| Disaster | -0.038 |
| **Disaster*Growth in LPI policies per household** | **-0.950**** |
| Growth in LPI policies per household | 0.541 |

[25] Since we are including a vector of controls and the lagged outcome variable as an explanator, this dynamic model is not strictly a differences-in-differences specification. Rather, it is motivated by the difference-in-differences estimator, while taking account of the fact that many of our outcome variables are sensitive to their previous values and other regressors.
[26] Counties that ever experienced a disaster may be systematically different from others in the outcome variable. For this reason, we included $any\_disaster$ in our regression analysis, which is a more parsimonious model than one with individual county fixed effects.
[27] Model fit using quarterly data observed at the US county level. Quarter fixed effects not reported. Data restricted to counties in which at most a single disaster occurred during the time period covered by the data (2015-2019).

| | |
|---|---|
| Any disaster county | 0.011 |
| Mortgage loan-to-value ratio | 1.063*** |
| Mortgage interest rate | 8.327 |
| Unemployment | 0.094*** |
| Borrower credit score | -0.097* |

| **Post-disaster debt-to-income ratio model[28]** ***Dep var: Debt-to-income ratio*** | **Short-run coefficients** |
|---|---|
| Lagged debt-to-income ratio | 0.511** |
| Disaster | 0.010 |
| **Disaster*Growth in LPI policies per household** | **-0.954*** ** |
| Growth in LPI policies per household | 0.138 |
| Any disaster county | 0.046 |
| Damaged per household | 0.129 |
| Destroyed per household | 0.578 |
| Log house price index | 0.430** |
| Unemployment | 0.033** |
| Foreign-born share of population | -0.438* |
| Borrower credit score | -0.030** |
| Homeownership share | 0.020** |
| Disabled share of population | 0.015* |

legend: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

## INSTRUMENTAL VARIABLES CROSS-SECTIONAL MODEL

### Cross-sectional approach

A different approach is required in order to model the effect of LPI coverage on federal disaster spend. Federal funds are released in large infrequent bursts around the time of a disaster, so most counties in

[28] Model fit using quarterly data observed at the US county level. Quarter fixed effects not reported. For increased statistical power, 'Disaster' is not a dummy variable but rather a count of disasters in that county to that point, and counties with more than one disaster are kept in the dataset. 'Damaged per household' and 'Destroyed per household' are numbers of properties reported to FEMA's IHP program as damaged or destroyed, expressed as a share of all households in the county, and are proxies for disaster severity. As with 'Disaster', in this specification the severity proxies are cumulative.

most quarters receive no federal funding. Such a 'lumpy' dataset does not lend itself neatly to panel models such as those described previously.

Instead we isolate the first quarter in each county where there was only a single disaster (if any such quarter exists) and conduct a cross-sectional regression of determinants of the federal spend associated with that disaster.

**Instrumenting LPI coverage**

Since we are not fitting a dynamic model and cannot follow LPI coverage trends with our modeling approach, we take as our LPI coverage variable the share of households in each county that are covered with an LPI policy. However, there are reasons to believe that this variable is endogenous: in the quarter of a natural disaster, there is likely to be significant upheaval in the LPI market as policies pay out claims, and as non-LPI insurance policies also exhibit significant activity.

To address these potential sources of bias, we employ an instrumental variables approach. The national region in which the county lies (the Northeast, Midwest, South or West of the United States) and the number of disasters observed in each county prior to the disaster we are studying are used as instruments, as they might plausibly influence the level of LPI coverage through climatic or regulatory effects but cannot be affected by LPI coverage. Statistical tests confirm that these are good instruments for LPI coverage.

**Model results**

Instrumental variables cross-sectional estimates of the effect of LPI coverage on federal spend following a natural disaster are reported in Fig. 12.

**Fig. 12. Instrumental variables cross-sectional model results**

| **Post-disaster federal spend model[29]**<br><br>***Dep var: Post-disaster federal spend*** | **Coefficients** |
|---|---|
| **LPI policies per household** | **-14,786.37*** ** |
| Damaged per household | -362.67 |
| Destroyed per household | 116,837.10* |
| Unemployment | 13.468** |
| Log house price index | -13.355 |

legend: * p < 0.1; ** p < 0.05; *** p < 0.01

[29] Model fit using quarterly data observed at the US county level. Quarter fixed effects not reported. 'Damaged per household' and 'Destroyed per household' are numbers of properties reported to FEMA's IHP program as damaged or destroyed, expressed as a share of all households in the county, and are proxies for disaster severity.

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