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Beyond the Flood: Media Coverage of Flood Events and Property Valuation

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Abstract

Svoboda Dominik, Hanousek Jan, Jr., Zahirovic-Herbert Velma: **Beyond the Flood: Media Coverage of Flood Events and Property Valuation**

We use major flood events in Florida as exogenous climate events, we assess the role of news coverage and sentiment on property values. Our analysis draws on a rich panel of Florida property transactions, covering the period from 2000 to 2022, which allows us to control for a wide set of user and property characteristics. We find that properties in flood-affected areas experience significant price discounts. These discounts are amplified in cases of negative sentiment and lack of coverage. Indeed, we observe that coverage of flood events is not reliable, as media tends to focus on certain areas, and the coverage is not purely driven by the extent of the damage. Out-of-state buyers demand larger discounts than in-state buyers, as they are more reliant on those information sources. We employ both difference-in-difference and propensity score matching approaches, which support the causality of our findings.

Key words

Information asymmetry; behavioral finance; real estate markets; peer influence; climate risks

JEL: R30; G54; G40

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Introduction

Information asymmetry has long been a challenge in real estate markets, with buyers and investors relying on fragmented sources to evaluate risks and opportunities. Traditionally, these evaluations were grounded in tangible factors such as historical sales data and geographic risk assessments (Chen, 2010). However, there has been a long-observed differences between in-state and out-of-state buyers (e.g., Kurlat and Stroebel, 2015; Chico and Mayer, 2016), that underlines how important aspect being informed about neighborhood characteristics is to valuation. While locals can observe the area's economic and environmental conditions (Garmaise and Moskowitz, 2004), out-of-state buyers have to rely on media narratives and publicly available information to make investment decisions (Stroebel, 2016; Bailey et al., 2018; Soo, 2018).

While a growing body of literature has documented the influence of climate-related risks—such as sea-level rise, wildfires, and flooding—on property valuations, less is known about the informational mechanisms that mediate these effects. Specifically, how risk information is transmitted, interpreted, and internalized by market participants remains an emerging and underexplored area. This paper addresses that gap by examining how disaster-related media coverage and sentiment influence homebuyer behavior and real estate outcomes following major flooding events. We argue that the impact of climate shocks on property values is not solely driven by physical damage or geographic exposure, but also by the way information about such events is disseminated and perceived.

Using major flood events as plausibly exogenous shocks, we assess the role of news media sentiment and coverage in shaping real estate pricing. Our analysis draws on a rich panel of Florida property transactions (2000–2022) from CoreLogic, which we match with FEMA flood-related insurance claims and media sentiment data from RavenPack. We employ a Difference-in-Differences (DiD) identification strategy to estimate both the immediate and dynamic effects of flooding on home values, while also capturing the moderating influence of media reporting.

We find that properties in flood-affected ZIP codes experience significant price discounts post-disaster, consistent with a repricing of perceived environmental risk. However, the reporting on these damages is not uniform, with many areas that were severely flooded not receiving any coverage. The coverage seems to be determined by other factors, and the distribution of coverage of flooding is not significantly different from coverage of other events. This coverage gap leads to significant information asymmetry, which increases uncertainty and significantly impacts the closing prices. We observe that buyers demand greater discounts in areas with no or negative media coverage. Out-of-state buyers, which are more reliant on media coverage, appear to demand a greater discount in the case of no coverage than local buyers, as they perceive greater risk for which they want to be compensated.

This study adds to the expanding literature on climate risk and asset valuation by foregrounding the informational role of the media. Prior research has shown that climate-related risks are capitalized into housing markets (Baldauf et al., 2020; Bernstein et al., 2019; Ortega et al., 2018; Giglio et al., 2021; Engle et al., 2020; Huynh and Xia, 2021), with flood-prone properties frequently trading at a discount. For instance, Bin and Landry (2013) demonstrate that the largest price declines occur immediately following flood events. Similarly, Zhang and Leonard (2019) find higher discounts in flood-vulnerable regions. In contrast, Zivin et al. (2023) observe price increases in disaster-stricken areas in the short term, attributing this to temporary supply shortages. Giglio et al. (2021) further show that properties near the coast may command a premium due to amenity value, though this premium declines as climate risk awareness grows. Bernstein et al. (2019) and Baldauf et al. (2020) both highlight how beliefs and awareness about future risks influence whether and how these risks are priced in.

Despite growing data availability, discrepancies between climate risk exposure and home prices persist, suggesting that real estate markets do not fully internalize available risk information. Glaeser and Nathanson (2017) point to the role of behavioral narratives in driving real estate demand. Relatedly, buyer characteristics significantly shape outcomes: in-state buyers are generally better informed about local conditions than out-of-state investors (Kurlat & Stroebel, 2015; Chico & Mayer, 2016). These local advantages are often rooted in direct observation and community-based interactions, such as conversations with neighbors or participation in social networks (Garmaise & Moskowitz, 2004; Hong et al., 2004; Brown et al., 2008). In contrast, non-local buyers face informational disadvantages (Ivković & Weisbenner, 2005; Agarwal et al., 2018; Agarwal et al., 2019; Cvijanovic & Spaenjers, 2021) and are more dependent on media reports to assess risk (Stroebel, 2016; Bailey et al., 2018; Soo, 2018).

Moreover, while sellers and real estate agents typically possess more information than buyers, disclosure practices may be strategically limited to preserve transaction prospects (Liberti & Petersen, 2019). This dynamic heightens the importance of third-party information sources—especially the media—in shaping risk perception and valuation. By centering on media coverage, this study sheds light on an overlooked but crucial mechanism of information asymmetry between buyers and sellers, particularly across geographic lines.

In doing so, our research builds on a robust literature at the nexus of media attention, behavioral finance, and real estate (Engelberg & Parsons, 2011; Loughran & McDonald, 2011; Zhou et al., 2016; Nowak & Smith, 2017; Bailey et al., 2018; Soo, 2018; Liu et al., 2020; Nowak et al., 2021). We find that information-poor environments exacerbate asymmetries, allowing more informed and sophisticated buyers—often locals—to negotiate lower prices. These findings underscore the informational inefficiencies that persist in climate-exposed real estate markets and highlight the underappreciated influence of media as a driver of price discovery.

Our study is organized as follows. We introduce our hypotheses in Section 2. Section 3 covers our data and methodology used. We provide our empirical results in Section 5. Lastly, Section 6 concludes.

1 Hypothesis Development

This study integrates insights from three intersecting literatures—climate risk and asset pricing, information asymmetry in real estate markets, and the behavioral influence of media on financial decision-making—to develop a structured set of hypotheses. Climate-related disasters, such as flooding, have been shown to exert a measurable impact on property values by altering perceptions of risk and utility. Prior research has consistently demonstrated that properties exposed to flood hazards experience significant price discounts, particularly in the aftermath of an event (Bin & Landry, 2013; Zhang & Leonard, 2019; Bernstein et al., 2019). Thus, we begin with the expectation that flooding events serve as negative exogenous shocks to housing demand and asset value. Specifically, we hypothesize that residential properties in flood-affected ZIP codes will experience statistically significant price declines relative to similar properties in unaffected areas.

However, the magnitude and persistence of these price effects are unlikely to be uniform. Media coverage serves as a critical mechanism through which information about disasters is disseminated and interpreted. As the behavioral finance literature suggests, both the volume and tone of media narratives shape investor expectations and influence asset pricing (Tetlock, 2007; Engelberg & Parsons, 2011). In the context of natural disasters, a well-informed public may respond differently to risk signals depending on the framing of media narratives. Accordingly, we posit that the intensity of media coverage may attenuate price discounts by reducing information asymmetry, while negatively framed sentiment may amplify these discounts by exacerbating perceived risk and uncertainty.

The informational role of media is not experienced uniformly across buyer segments. Consider two prospective homebuyers evaluating properties in a recently flooded coastal ZIP code in Florida. The first buyer is a local resident with established social networks, routine familiarity with the region, and direct experience with the event's aftermath. The second is an out-of-state buyer whose perception of risk is shaped predominantly by secondhand information, most notably, news coverage. The local buyer may talk to neighbors, observe cleanup activity, or understand that flood mitigation infrastructure is being improved. The out-of-state buyer, by contrast, is more reliant on the prevailing media narratives, which may understate or exaggerate the true level of risk. This divergence in information sources suggests that the out-of-state buyer is more sensitive to media cues and therefore more likely to adjust offer prices based on sentiment or attention. We hypothesize that the influence of media coverage and sentiment on pricing outcomes is stronger among out-of-state buyers relative to in-state buyers.

Further, we argue that in markets with sparse or inconsistent media reporting, local buyers have a distinct informational advantage. In the absence of detailed public coverage, buyers with local knowledge are better equipped to assess true risk levels and negotiate favorable prices. Consistent with literature emphasizing the role of informal information and social connectedness in investment decision-making (Garmaise & Moskowitz, 2004; Hong et al., 2004), we hypothesize that in ZIP codes with limited flood-related media coverage, in-state buyers will obtain significantly larger price discounts than out-of-state buyers due to their superior situational awareness.

Together, these hypotheses articulate a complex framework in which climate risk, information frictions, and behavioral responses jointly shape real estate pricing. They underscore the media's role as a non-fundamental yet potent moderator of climate risk perception and highlight how geographic proximity shapes buyer behavior in the face of environmental uncertainty. Building on the conceptual framework outlined above, we derive a series of testable hypotheses that guide our empirical investigation. We begin by examining whether flood events lead to significant price discounts in affected ZIP codes, consistent with prior evidence on climate risk repricing. We then test whether the extent and tone of media coverage moderate this effect, either dampening or amplifying price responses. Next, we explore heterogeneity across buyer types, positing that out-of-state buyers—more reliant on media narratives—are more responsive to coverage intensity and sentiment than their in-state counterparts. Finally, we test whether in-state buyers achieve larger discounts in media-scarce environments, leveraging their informational advantage. We now turn to the data and empirical strategy used to evaluate these hypotheses.

2 Data

In this section, we describe the data sources for our analysis and the construction of main measures. This includes identifying affected locations, measuring sentiment and media coverage, and defining buyer and housing characteristics.

2.1 CoreLogic and Listings data

For our empirical analysis, we use a comprehensive listing-level dataset on property transactions collected by CoreLogic, restricted to transactions in Florida over the period from January 2000 to May 2022. Each observation represents a housing transaction with detailed property characteristics, including the listing date, contract date, listing price, closing price, number of bedrooms and bathrooms, cooling system, living area (square footage), age of the property, property address, and buyers' information. The data comes from Multiple Listing Services (MLS) platforms created and maintained by real estate boards. For our analysis is crucial that each transaction in an MLS is given a unique identifier that we can track throughout the sample.

In Table 1, we present basic summary statistics of the key variables used in this study, including dependent variables - closing and listing prices, disaster event indicators, sentiment and media coverage measures, and buyer and housing characteristics. Closing (listing) prices are defined as the natural logarithm of the close (list) price of the property. Bedrooms and bathrooms are the number of units reported on the property. Cooling system indicates whether the cooling system is present. Property age is defined as the difference between the closing date and the year built. The living area represents the total square feet of the living area. Time to contract is the number of days from when the property was listed to when it went under contract (contract date).

In-state buyers are identified based on their mailing address. If the buyer's mailing address is within the state, they are classified as in-state buyers and take a value of 1. Conversely, if their previous address is outside the state, they are categorized as out-of-state buyers and take a value of 0. The data shows that 83% of all transactions involve local buyers.

For disaster event indicators, the variable Affected Counties is defined as a treatment group that takes a value of 1 if the county experienced any flood damage claims at the time of the disaster event, while Non-Affected Counties take a value of 0 as a control group. Similarly, Affected ZIPs take a value of 1 if the ZIP code was within an affected county and had recorded any flood damage (treatment group) and 0 for those without any flood damage (control group). Table 1 shows that during the month of the disaster event, around 22% of transactions occurred in affected counties over the sample period, while 73% of transactions within these counties were in affected ZIP codes.

[Insert Table 1 about here]

2.2 Flood damage data

We combine our real estate data with disaster assistance data from the OpenFema datasets, which provide access to disaster-related datasets. According to FEMA, the Individuals and Households Program (IHP) provides financial aid and assistance to those who are underinsured or uninsured and face significant financial hardship following disaster damage. IHP includes information about disaster-related damages such as real property damage, personal property damage, and flood damage. Since IHP assistance cannot compensate for all losses caused by disaster, there is a potential concern that the data may not fully capture all losses, as not all affected homeowners apply for assistance. To address this concern, we aggregate damages at the county and ZIP code levels for different incident types and months of declaration, ensuring a more robust effect of disaster impact.

Our analysis focuses on properties affected by flood damage and how it influences property values. Prior research shows that flood risk can lead to price discounts (Harrison et al., 2001; Zhang, 2016; Atreya et al., 2013; Zhang & Leonard, 2019). While many studies explore the relationship between flood risk and home prices, there is a lack of evidence incorporating the role of media narratives.

Table 2 reports the summary statistics of mean flood damage and total claims by different types of disasters. For each disaster event, we present the percentage of affected counties and affected ZIPs in affected counties, as well as the number of property transactions during the month of the incident. The table shows that the Sep 2017 Hurricane had a widespread impact on Florida, with 96% of all property transactions occurring in affected counties that month. During this event, the mean flood damage reached $220,000, and the total number of claims exceeded 40,000. Additionally, 97% of ZIPs within affected counties experienced flood damage. A similar pattern is observed across other hurricanes and severe storms, where data suggest that once a county is hit, more than half of the ZIPs within it are impacted.

[Insert Table 2 about here]

2.3 Media sentiment and media coverage

To measure media sentiment and coverage, we utilize the news from RavenPack database, which provides various sentiment and relevance scores. For our research, we focus on the Event Sentiment Score (ESS) due to its high relevance in capturing sentiment from news articles related to climate events and their potential economic impact. To ensure that the sentiment measure aligns with our focus on natural disasters, we specifically consider articles related to flooding disasters. ESS scores range between -1 and 1, with a score above 0 indicating positive news; a score equal to 0, neutral news; and a score below 0, negative news. In our analysis, we aggregate ESS sentiment scores at both Florida state and the county/city level to capture regional variations in sentiment within a month. We first merge media sentiment data at the city level, and if no articles are written at the city level, we use county-level data. The No media coverage County/City variable takes a value of 1 when there is not any disaster-related article at the county or city level. Otherwise, the variable takes a value of 0 if any related article is present. Table 1 shows that more than 85% of all transactions have no articles related to climate risk at the local level. It highlights a significant information gap or lack of awareness.

While flood damage data are available at both the ZIP and county levels, our media coverage variables are defined at the county/city level based on the structure of the RavenPack dataset. To ensure consistency between our treatment definition and the information geography accessible to buyers, we define treatment (affected areas) at the county level. This approach aligns the geographic scale of the physical shock (flooding) with that of the perceived risk (media coverage), which in turn allows for a more accurate assessment of how information asymmetries shape market outcomes.

2.4 Geographic distribution of flood damage and media coverage

We focus on the event date and the six months after to capture both the immediate impact of floods and how the media reacts to them. This allows us to analyze if areas with significant flood damage also receive relevant media attention for the next 6 months. Figures 1 illustrates the geographic distribution of flood damage and media coverage across Florida following major disaster events. The left panel in each figure represents the average flood damage in affected areas, while the right panel shows the disaster-related media coverage at the county level.

[Insert Figure 1 about here]

A comparison of these figures shows that even though some counties had serious flood damage, the affected places did not get appropriate media attention in the six months following the event, highlighting a lack of public awareness. Particularly, media coverage tends to focus more on high-profile areas like Miami, Key West, and other major urban centers instead of regions that have suffered significant flood damage. This suggests that media attention refers to the location's popularity or economic significance rather than the actual impact of the disaster. We estimate that homebuyers are more likely to have prior information about the market conditions in areas with less public reporting, which may influence their investment decisions.

3 Empirical results

To examine the effect of flood damage on property prices, we first employ a static difference-in-differences (DID) model that compares affected and non-affected areas during the disaster and the following six months. In addition, we extend empirical analysis to capture media sentiment and media attention.

The baseline static model that we use in our analysis is given by:

$$p_{i,t} = \alpha_i + \beta_1 \text{AffectedCounty } \times \text{Post} + \gamma Controls_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (1)$$

$$p_{i,t} = \alpha_i + \beta_1 \text{AffectedZIP } \times \text{Post} + \gamma Controls_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (2)$$

where $p_{i,t}$ represents the closing or listing price of property *i* at time *t*. Time *t* indicates the year-month of the listing. *AffectedCounty* (1) and *AffectedZIP* (2) serve as proxies for flood damage; variables take a value of 1 for transactions occurring in a county or in a ZIP code within an affected county with any flood claims and 0 otherwise. *Post* is a dummy variable that takes a value of 1 for all observations during the disaster event and remains 1 for the following six months. Otherwise, it takes a value of 0. *Controls* include the housing characteristics of the property. We also include property fixed effects δ_i and time fixed effects δ_t.

We show the results of Equation (1) and (2) in Table 3. The model is divided into two main groups: closing price and listing price. Columns (1) to (4) report the full sample, while columns (5) to (8) focus on properties in counties or ZIP codes where flood damage was above the median in the event month. The estimated coefficients in Table 3 show that both closing and listing prices are significantly and negatively impacted in the period following hurricanes and severe storms. For example, whereas affected counties only account for a 0.2% discount on all transactions in our database, this number rises to 12% for affected zips within affected counties.

Once we control for properties with higher flood damage, we find that the discount becomes pronounced in affected counties. However, the discount for affected ZIPs remains stable despite the amount of damage. It appears that homebuyers already account for risk factors at the ZIP code level, and the magnitude of flood damage does not lead to further discounts. In contrast, for affected counties with higher flood damage, we observe the opposite effect – the homebuyers demand a larger discount with higher flood damage.

[Insert Table 3 about here]

We further investigate the relationship between media sentiment, media coverage, and property prices.

$$p_{i,t} = \alpha_i + \beta_1 \text{Media Sentiment Florida}_t + \beta_2 \text{Media Sentiment County/City}_t$$
$$+\beta_3 \text{No Media Coverage County/City}_t + \gamma Controls_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (3)$$

where $p_{i,t}$ represents the closing or listing price of property *i* at time *t*. *Media Sentiment Florida* measures the overall ESS sentiment at the state level, while *Media Sentiment County/City* reflects sentiment at the local level. *No Media Coverage County/City*, our main variable of interest, indicates the absence of disaster-related news in a given location, taking the value of 1 if the article is missing and 0 otherwise.

The effect of media sentiment and media attention is reported in Table 4. We also divide results into two main groups for closing price and listing price and compare how the media influences affected vs. non-affected areas. We find that sentiment is positively related to higher property prices in both affected and non-affected places. On the other hand, homebuyers tend to demand higher discounts in affected areas with a lack of reporting. This is likely due to information asymmetry that gives them more bargaining power. As shown in Table 4, the coefficients are statistically significant and negative, hovering between 7 and 9% across affected zones. Surprisingly, we observe an even stronger effect in ZIP codes that were not directly affected, where discounts are nearly twice as large compared to affected areas. Our findings suggest that buyers face greater uncertainty about future risks in affected zones, which influences their investment decision-making. As a result, they demand greater discounts to compensate for the unknown risks.

[Insert Table 4 about here]

We include another test that examines the role of in-state and out-of-state buyers in Table 5, which illustrates a clear and statistically significant effect of in-state buyers on property prices. In this test, we do not include listing prices. Listing prices may reflect seller expectations, making it less relevant for comparing in-state and out-of-state buyers. Similar to prior tables, we find that lack of reporting is associated with higher price discounts, but only for local buyers. The effect is not significant for out-of-state buyers. Looking at Table 5, the results show that local buyers demand nearly a 10% discount in the six months following the event when there was no media coverage in affected areas. Based on the results, we assume that local buyers are better informed than out-of-state buyers. They are likely to rely more on different sources, peers, and community networks to evaluate risks and opportunities.

[Insert Table 5 about here]

To address the differences between in-state and out-of-state buyers, we use propensity score matching and the potential outcome framework of the Rubin Casual Model (Holland, 1986) to estimate the Average Treatment Effect on Treated (ATET) model. This model is based on two outcomes, one with and one without treatment:

$$y_{0,i} = \mu_0 + \varepsilon_{0i} \text{ and } y_{1,i} = \mu_1 + \varepsilon_{1,i} \tag{6}$$

Formally, the model can be written as $y_{T,i} = \mu_T + \varepsilon_{T,i}$, where subscript T=1 denotes the treatment, and T=0 represents the control group. We observe only one outcome for each transaction *i*, either $y_{0,i}$ or $y_{1,i}$. The counterfactual outcomes must be estimated. In our study, we restrict the sample on locations that did suffer flooding and use as a treatment whether there has been any reporting on the flooding in the location. In summary, the Rubin Causal Model helps us understand the effects of lack of reporting on flooding damages by comparing what happens to a transaction that receives the treatment to what would have happened if they had not. We estimate the Average Treatment Effect on the Treated (ATET), where $y_{0,i}$ is calculated using the nearest-neighbor approach.[1] We exactly match on number of bedrooms and year, while the approximate coordinate for matching is the square footage of the property.

[1] The treatment effect $E[y_{1i} - y_{0i}]$ is under random assignment equal to $\mu_1 - \mu_0$.

[Insert Table 6 about here]

Our results again show that, in the event of a lack of reporting, buyers demand greater discounts to be compensated for the level of risk. Interestingly, we observe that out-of-state buyers demand far greater discounts than in-state buyers. It may be that the lack of reporting, and the demand for discount, pushes the prices for out-of-state buyers more in line with in-state buyers. Moreover, the matching approach further supports our causality interpretation of how coverage, or lack thereof, of climate events impact the real estate prices.

4 Conclusion

In our study we analyze the impact of climate shocks on property values and how media coverage of these events influences the behavior of buyers. We observe that climate shocks significantly reduce the property closing prices. However, the news coverage of flooding and the resulting damages is unreliable. Many locations severely impacted by climate events are not covered in the media at all, while some areas receive coverage even when virtually unharmed. This lack in reporting significantly increases information asymmetry, especially for out-of-state buyers, who are more reliant on these information sources.

We further see that negative sentiment, or lack of reporting, significantly decreases the closing prices of properties, even while accounting for the damages in the area. Investors appear to rely on these information sources, taking into account negative coverage, and demand discounts when they perceive to be at an information disadvantage. Out-of-state investors appear to demand larger discounts than their in-state counterparts, reducing the differences in the prices among the two groups observed in the literature. Overall, our results show not only how climate risk can impact property prices, but also how the coverage of these events impacts buyers and their behavior. We use both difference in difference (DID) and average treatment effect on treated (ATET) approaches, which support our causality interpretation. Our results contribute to the literature on climate risk in real estate by outlining how information about these events impact property prices. Further analysis of how media coverage impacts property prices is an important avenue for future research.

References

Agarwal, S., J. He, T. F. Sing, and C. Song. (2019b). Do real estate agents have information advantages in housing markets? *Journal of Financial Economics* 134:715–35.

Agarwal, S., Sing, T. F., & Wang, L. (2018). Information asymmetries and learning in commercial real estate markets. Available at SSRN 3022705.

Atreya, A., & Czajkowski, J. (2019). Graduated flood risks and property prices in Galveston County. *Real Estate Economics*, 47(3), 807–844.

Bailey, M., Cao, R., Kuchler, T., & Stroebel, J. (2018). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, 126(6), 2224-2276.

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *Review of Financial Studies*, 33(3), 1256–1295.

Bernstein, A., Billings, S. B., Gustafson, M. T., & Lewis, R. (2022). Partisan residential sorting on climate change risk. *Journal of Financial Economics,* 146(3), 989–1015.

Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, 65(3), 361–376.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science,* 2(1), 1-8.

Brown, J. R., Ivković, Z., Smith, P. A., & Weisbenner, S. (2008). Neighbors matter: Causal community effects and stock market participation. *The Journal of Finance*, 63(3), 1509-1531.

Chen, H.L. (2010). Using Financial and Macroeconomic Indicators to Forecast Sales of Large Development and Construction Firms. *J Real Estate Finan Econ* 40, 310–331.

Chinco, A., & Mayer, C. (2016). Misinformed speculators and mispricing in the housing market. *The Review of Financial Studies*, 29(2), 486–522.

Cvijanović, D., & Spaenjers, C. (2021). "We'll always have Paris": Out-of-country buyers in the housing market. *Management Science*, 67(7), 4120-4138.

Engelberg, J. E., & Parsons, C. A. (2011). The causal impact of media in financial markets*. The Journal of Finance*, 66(1), 67-97.

Engle RF, Giglio S, Kelly B, Lee H, Stroebel J. (2020). Hedging climate change news. *Review of Financial Studies.* 33:31184–216

Garmaise, M., and T. Moskowitz. (2004). Confronting information asymmetries: Evidence from real estate markets. *Review of Financial Studies* 17:405–37.

Giglio S, Maggiori M, Rao K, Stroebel J, Weber A. (2021). Climate change and long-run discount rates: evidence from real estate*. Review of Financial Studies.* 34:83527–71

Glaeser, E.L. and Nathanson, C.G. (2017). An extrapolative model of house price dynamics. *Journal of Financial Economics,* 126(1), pp. 147–170.

Harrison, D., Smersh, G. T., & Schwartz, A. (2001). Environmental determinants of housing prices: The impact of flood zone status. *Journal of Real Estate Research*, 21(1-2), 3–20.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association,* 81(396), 945-960.

Hong, H., Kubik, J.D., Stein, J.C., (2004). Social interaction and stock market participation. *The Journal of Finance* 59, 137–163.

Huynh T, Xia Y. (2021). Climate change news risk and corporate bond returns. *J. Financ. Quant. Anal.* 56:61985–2009

Ivković Z, Weisbenner S. (2005). Local does as local is: Information content of the geography of individual investors' common stock investments. *J. Finance* 60(1):267–306.

Kurlat P, Stroebel J. (2015). Testing for information asymmetries in the real estate market. *Review of Financial Studies*. 28(8):2429–2461.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, 8(1), 1-41.

Liu, C. H., Nowak, A. D., & Smith, P. S. (2020). Asymmetric or incomplete information about asset values?. *The Review of Financial Studies*, 33(7), 2898-2936.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), 35-65.

Nowak, A., & Smith, P. (2017). Textual analysis in real estate. *Journal of Applied Econometrics*, 32(4), 896-918.

Nowak, A.D., Price, B.S. & Smith, P.S. (2021). Real Estate Dictionaries Across Space and Time. *J Real Estate Finan Econ* 62, 139–163

Ortega, F., & Tașpinar, S. (2018). Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics*, 106, 81–100.

Soo CK. (2018). Quantifying sentiment with news media across local housing markets. *Review of Financial Studies.* 31:3689–719

Stroebel, J. (2016). Asymmetric information about collateral values. *The Journal of Finance*, 71(3), 1071–1112.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139-1168

Zhang, L. (2016). Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis. *Regional Science and Urban Economics*, 60, 12–19.

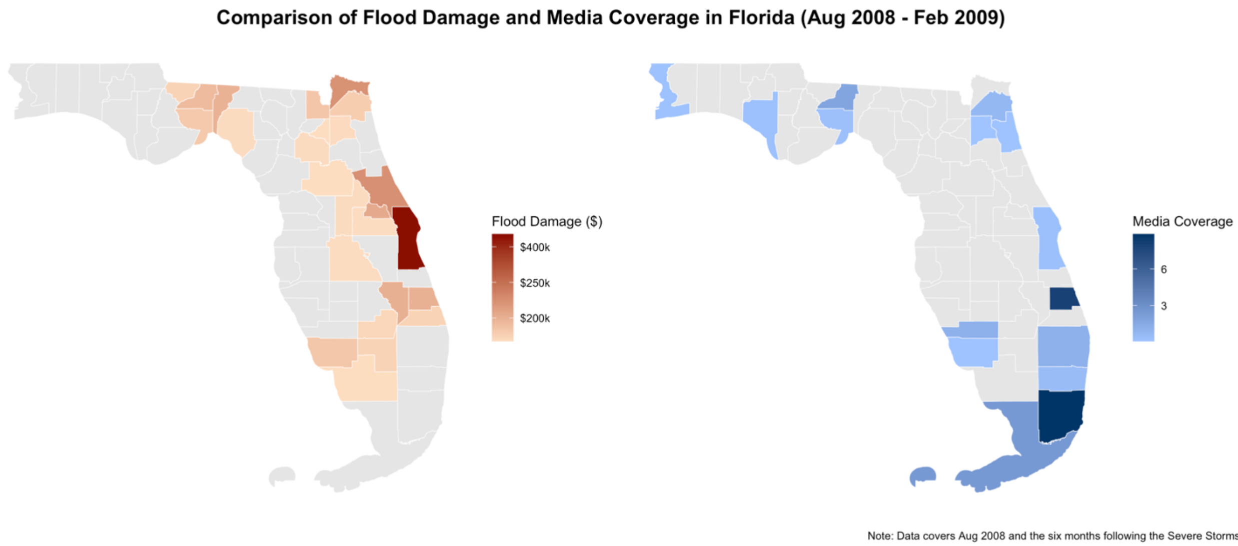
Zhang, L., & Leonard, T. (2019). Flood hazards impact on neighborhood house prices. *Journal of Real Estate Finance and Economics,* 58, 656–674.

Zhou, X., Lei, X., & Li, J. (2016). Do rumors affect house prices? A text mining approach. *Finance Research Letters*, 17, 202-208.

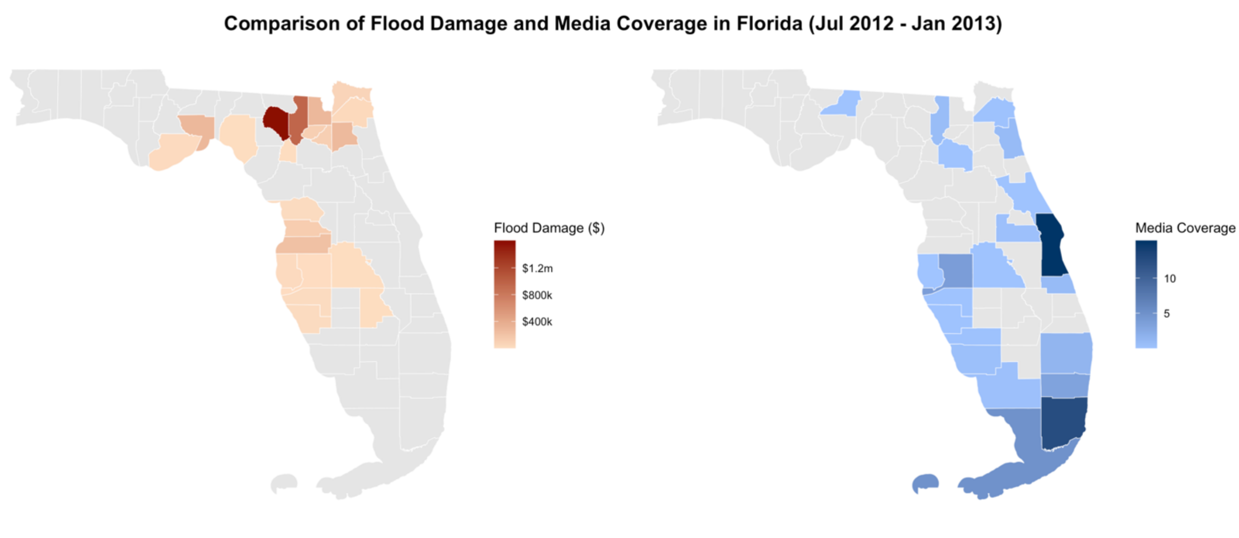
Zivin, J. G., Liao, Y., & Panassie, Y. (2023). How hurricanes sweep up housing markets: Evidence from Florida. *Journal of Environmental Economics and Management*, 118, 102770.

Figure 1.

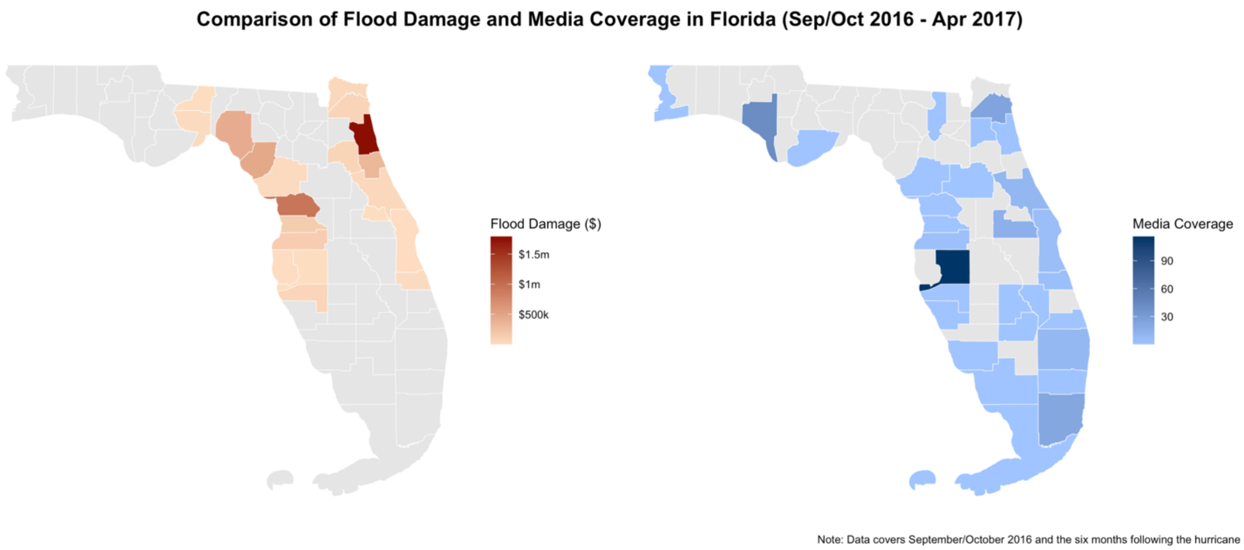
The figure shows the comparison of flood damage and media coverage in the month of the event and the six months following the hurricane. The left panel in each figure represents the average flood damage in affected areas, while the right panel shows the disaster-related media coverage at the county level.



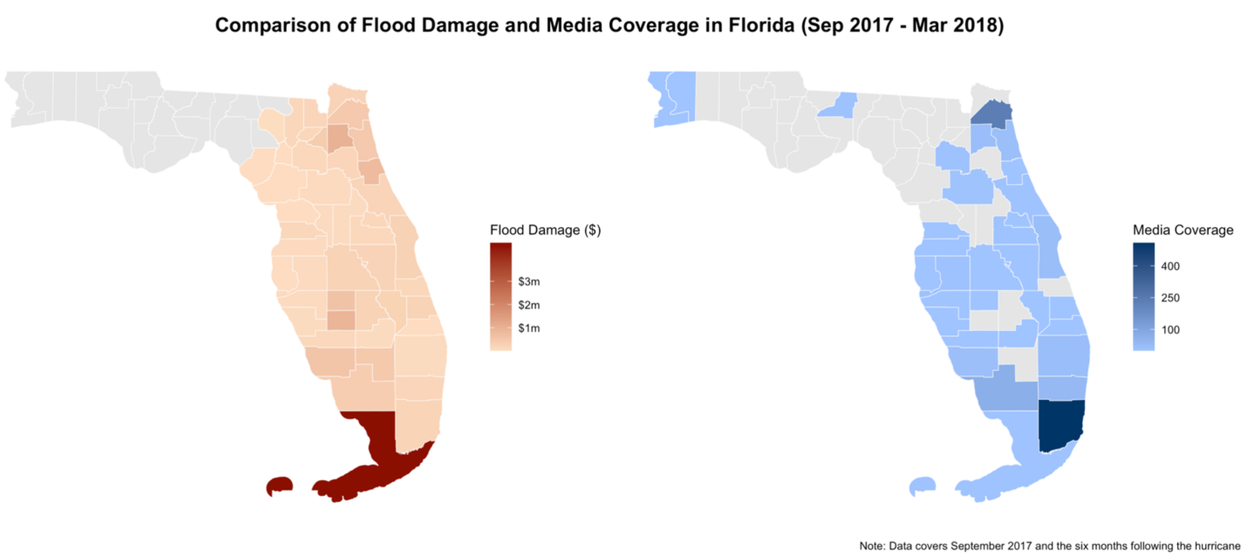
a) Comparison of Flood Damage and Media Coverage in Florida (Aug 2008 – Feb 2018)
Note: In August 2008, a major tropical storm Fay caused extreme flooding and spawned 19 tornadoes, resulting in $390 million in damages across Florida, with Brevard County being one of the hardest-hit areas.



b) Comparison of Flood Damage and Media Coverage in Florida (Jul 2012 – Jan 2013)
Note: In July 2012, Florida was impacted by tropical storm Debby, which brought widespread flooding and spawned 13 tornados throughout Central Florida. In total, damages in Florida were estimated at $250 million.



c) Comparison of Flood Damage and Media Coverage in Florida (Sep/Oct 2016 – Apr 2018)
Note: In late September - early October 2016, Florida was hit by a powerful tropical hurricane Matthew. The storm brought intense winds, extreme flooding, and widespread damage. Over one million people in Florida lost power, and the estimated damage across the state reached $2.8 billion.



d) Comparison of Flood Damage and Media Coverage in Florida (Sep 2017 – Mar 2018)
Note: In September 2017, Hurricane Irma was the strongest observed hurricane since Wilma in 2005. More than 6 million Floridians have been evacuated due to extreme winds that left more than 7.5 million homes without electricity. Irma's damage was estimated at $50 billion.

Table 1. Summary statistics

This table reports the summary statistics of the main variables used in this study. The main variables include log closing price and log listing price. To capture the impact of the Disaster Event, we consider data at the county and ZIP code levels (Affected Counties and Affected ZIPs in Affected Counties) at the time (month) of the event. For sentiment measures, we incorporate ESS sentiment at the state level (Florida) and the County/City level. Additionally, we include a No media coverage indicator at the county/city level to capture whether the article was published (1) or not (0). We also account for buyer characteristics, including an In-State Buyers indicator. For housing characteristics, we include variables such as the number of bedrooms, bathrooms, cooling system, property age, living area, and time to contract. The table includes the number of observations (*N*), mean, standard deviation (*SD*), median, and quartiles (*P25* and *P75*). Data is sourced from CoreLogic, RavenPack, and OpenFEMA, covering the period from January 2000 to May 2022.

	N	Mean	SD	P25	Median	P75
Dependent variables						
Closing price (log)	4,922,590	12.187	0.818	11.731	12.216	12.676
Listing price (log)	8,894,613	11.996	1.503	11.678	12.278	12.779
Disaster Event						
Affected Counties	474,006	0.219	0.413	0	0	0
Affected ZIPs in Affected Counties	103,639	0.725	0.447	0	1	1
Sentiment & Media Coverage						
ESS sentiment Florida	8,897,719	-0.498	0.095	-0.543	-0.514	-0.476
ESS sentiment County/City	8,897,719	-0.067	0.175	0	0	0
No media coverage County/City	8,897,719	0.866	0.341	1	1	1
Buyer Characteristics						
In-State Buyers	4,922,590	0.834	0.372	1	1	1
Housing Characteristics						
Bedrooms	8,565,728	2.912	1.136	2	3	3
Bathrooms	8,897,697	2.249	1.307	2	2	3
Cooling System	8,897,719	0.931	0.253	1	1	1
Property Age	8,450,198	27.916	19.984	12	25	40
Living Area (ft^2)	8,496,718	1,807	12,876	1,199	1,580	2,111
Time to contract	4,797,146	64	175	12	38	92

Table 2. Summary statistics of flood damage and claims by disaster event

This table reports a comparison of different disaster events, including hurricanes and severe storms, across various time periods. It represents the mean Flood Damage in the month of the event and the total number of Flood Damage Claims. The table also shows the mean proportion of Affected Counties, the total number of transactions at the county level, the mean proportion of Affected ZIPs in Affected Counties, and the total number of transactions at the ZIP code level. Data is sourced from CoreLogic, and OpenFEMA, covering the period from January 2000 to May 2022.

Date	Disaster Event	Flood Damage ($)	Flood Damage Claims	Affected Counties	N	Affected ZIPs in Affected Counties	N
2004-08	Hurricane	26,084	1,525	0.495	22,420	0.554	11,103
2004-09	Hurricane	102,317	10,224	0.943	17,147	0.772	16,171
2005-07	Hurricane	213,308	449	0.023	30,741	0.985	715
2005-10	Hurricane	35,037	1,520	0.271	36,986	0.598	10,026
2008-08	Severe Storm	87,303	3,609	0.451	35,044	0.518	15,793
2009-04	Severe Storm	42,376	230	0.017	29,166	0.742	496
2009-05	Severe Storm	337,507	1,385	0.016	27,790	0.984	435
2012-07	Severe Storm	100,584	4,633	0.289	30,687	0.750	8,880
2014-05	Severe Storm	232,658	853	0.001	44,492	0.885	52
2016-09	Hurricane	114,568	1,801	0.185	41,480	0.521	7,656
2016-10	Hurricane	211,642	3,219	0.112	39,590	0.705	4,428
2017-09	Hurricane	220,978	40,327	0.962	28,003	0.975	26,940
2018-10	Hurricane	312,864	1,099	0.012	48,205	0.642	576
2020-09	Hurricane	188,710	322	0.009	42,255	0.986	368

Table 3. The price effect of disaster events, DiD approach

This table reports the estimates from Equation (1) and (2). The model compares affected and non-affected areas during the disaster and the following six months. The dependent variable is either the log closing price or the log listing price. Housing characteristics represent the number of bedrooms and bathrooms, presence of a cooling system, living area (ft^2), age of property, and time to contract. Property fixed, year and month fixed effects are included. Columns (1) to (4) show the full sample, while columns (5) to (8) focus on areas where flood damage was above the median in the event month. The standard errors are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively. Data is sourced from CoreLogic, RavenPack, and OpenFEMA, covering the period from January 2000 to May 2022.

	Closing price (log)		Listing price (log)		Closing price (log)		Listing price (log)	
	Full sample				High Flood Damage (Above Median)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Affected Counties	-0.002*		-0.001		-0.029***		-0.031***	
	(0.001)		(0.002)		(0.002)		(0.002)	
Affected ZIPs in Affected Counties		-0.120***		-0.114***		-0.099***		-0.099***
		(0.005)		(0.005)		(0.004)		(0.004)
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Month X FIPS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,512,900	422,179	1,528,201	426,909	1,512,900	422,179	1,528,201	426,909
R-squared	0.476	0.504	0.401	0.434	0.476	0.504	0.401	0.435

Table 4. Media Sentiment and Coverage

This table reports the estimates from Equation (3). The model tests the effect of media sentiment and media attention by comparing affected and non-affected areas during the disaster and the following six months. The dependent variable is either the log closing price or the log listing price. Housing characteristics represent the number of bedrooms and bathrooms, presence of a cooling system, living area (ft^2), age of property, and time to contract. Property fixed, year and month fixed effects are included. The standard errors are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively. Data is sourced from CoreLogic, RavenPack, and OpenFEMA, covering the period from January 2000 to May 2022.

	Closing price (log)				Listing price (log)			
	Affected Counties	Non-Affected Counties	Affected ZIPs	Non-Affected ZIPs	Affected Counties	Non-Affected Counties	Affected ZIPs	Non-Affected ZIPs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESS sentiment Florida	0.253***	-0.002	0.148***	0.480***	0.300***	0.032	0.198***	0.513***
	(0.042)	(0.019)	(0.049)	(0.071)	(0.045)	(0.021)	(0.052)	(0.082)
ESS sentiment County/City	0.247***	0.050***	0.250***	0.226***	0.262***	0.045***	0.260***	0.248***
	(0.027)	(0.013)	(0.028)	(0.064)	(0.031)	(0.014)	(0.032)	(0.082)
No media coverage County/City	-0.081***	0.024***	-0.076***	-0.160***	-0.088***	0.028***	-0.080***	-0.170***
	(0.014)	(0.006)	(0.015)	(0.036)	(0.016)	(0.006)	(0.017)	(0.045)
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Month X FIPS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,039	1,088,861	344,034	78,145	428,808	1,099,393	347,017	79,892
R-squared	0.501	0.479	0.502	0.665	0.432	0.405	0.435	0.571

Table 5. In-State vs. Out-of-State buyers

This table reports the estimates from Equation (3). The model tests the effect of media sentiment and media attention by comparing affected and non-affected areas during the disaster and the following six months. Additionally, it examines between in-state and out-of-state buyers. The dependent variable is the log closing price. Housing characteristics represent the number of bedrooms and bathrooms, presence of a cooling system, living area (ft^2), age of property, and time to contract. Property fixed, year and month fixed effects are included. The standard errors are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively. Data is sourced from CoreLogic, RavenPack, and OpenFEMA, covering the period from January 2000 to May 2022.

	Closing price (log)							
	Affected Counties		Non-Affected Counties		Affected ZIPs		Non-Affected ZIPs	
	In-State Buyers	Out-of-State Buyers	In-State Buyers	Out-of-State Buyers	In-State Buyers	Out-of-State Buyers	In-State Buyers	Out-of-State Buyers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESS sentiment Florida	0.265***	0.194*	-0.010	0.031	0.160***	0.172	0.466***	0.352*
	(0.044)	(0.105)	(0.018)	(0.053)	(0.052)	(0.124)	(0.074)	(0.185)
ESS sentiment County/City	0.256***	0.137	0.030***	0.064*	0.241***	0.246**	0.297***	-0.141
	(0.027)	(0.105)	(0.010)	(0.036)	(0.028)	(0.121)	(0.067)	(0.205)
No media coverage County/City	-0.098***	0.016	0.011**	0.028	-0.083***	-0.031	-0.208***	0.085
	(0.014)	(0.057)	(0.005)	(0.018)	(0.015)	(0.065)	(0.038)	(0.115)
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Month X FIPS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	357,457	66,582	915,093	173,768	295,219	48,815	60,621	17,524
R-squared	0.516	0.598	0.612	0.470	0.511	0.598	0.690	0.641

Table 6. In-State vs Out-of-State buyers reaction to a lack of reporting, ATET approach

This table reports the Average Treatment Effect on Treated (ATET), measuring the impact when there was flood damage and no news reported on the damage (==1) compared to when there was reporting done on the flood damage (==0).
The standard errors of the ATET (in parentheses) are computed with the robust option (at least two suitable matches for each treated). We require exact matching on number of bedrooms and year, while the approximate coordinate for matching is the square footage of the property. Below is the balance summary of the mean difference and variance ratio between the corresponding treated and control groups. ***, **, and * denote statistical significance on 1, 5, and 10% significance levels.

	Closing price (log)	
	In-State Buyers	Out-of-State Buyers
	(1)	(2)
Damage occurred; No news covering damage (==1) vs There is news covering the damage (==0) (ATET)	-0.038***	-0.054***
	(0.001)	(0.004)
p-value	0	0
Number of treated	323,282	63,984
Number of observations	1160644	235,745
Balance summary		
mean difference (Square footage log)	0	0
variance ratio (Square footage log)	1.016	1.02