The Effect of Flood Insurance on Property Values After a Flood

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1 Introduction

Climate change is expected to contribute to more frequent and more severe extreme weather events and natural disasters (Ornes, 2018; Stott, 2016). The worldwide damage costs of natural disasters have steadily increased from an average of about $23 billion (in 2020 USD) a year between 1980-1989 to $140 billion between 2010-2019 (EMDAT, 2020). In the United States in 2018, total property losses due to natural disasters were $89.1 billion with insured losses accounting for $52.3 billion (III, 2020) of this total. Flooding represents the largest and most financially damaging share of natural disasters in the United States (*NOAA*, 2020). In addition, it is estimated that over $3 trillion worth of US property will be exposed to flood risk due to sea level rise in the future (Gaul, 2019). Not included in these figures are the financial losses resulting from depressed home values in areas affected by natural disasters, which can range from 2-10% of the value of one's home (Atreya et al., 2013; Bakkensen et al., 2019; Beltrán et al., 2018; Bin & Landry, 2013; Boustan et al., 2020; Gibson & Mullins, 2020; Hino & Burke, 2020; Kousky, 2010; Ortega & Taspinar, 2018).

To protect housing values against damage from floods, the United States government started the National Flood Insurance Program (NFIP) in 1968. The program allows homeowners to insure against potential losses from flooding. The maximum building coverage available is $250,000 while the maximum contents coverage is $100,000. In many areas, policies can be purchased at a less than actuarially fair level due to inaccurate flood maps (Pralle, 2018; Xian et al., 2015) or grandfathering (Michel-Kerjan & Kunreuther, 2011). Indeed, buildings built before the drawing of the initial flood maps pay premiums that are far below actuarially fair levels (Michel-Kerjan, 2010). In addition, anyone who takes out a mortgage on a home located in areas designated as 100-year floodplains are obliged to buy flood insurance (Michel-Kerjan & Kunreuther, 2011), although this requirement is sometimes loosely enforced (Kousky, 2016). Despite this, only around 10% of American homeowners have flood insurance, whereas up to 50% of Americans live in flood prone areas (Economist, 2019). There are also large socio-economic discrepancies in take-up (i.e., the percentage of homeowners with a flood insurance policy). Flood insurance take-up is higher among high-income and more educated homeowners (Atreya et al., 2015; Billings et al., 2019; Browne & Hoyt, 2000; Gallagher et al., 2019).

Our research question is: Does flood insurance protect housing values in areas affected by a major flooding event? McCoy and Zhao (2018) find that individuals in Special Flood Hazard Areas, who are more likely to have flood insurance, invest more in repairing damaged properties than homeowners outside such areas. In light of this finding, our hypothesis is that, following a flood, neighbourhoods with higher levels of flood insurance should, all else being equal, be able to build back faster and better. If neighbourhoods that have a higher insurance rate recover faster by being able to rebuild more quickly, they will remain attractive both to current homeowners and prospective buyers. This should be reflected in housing prices which either fall less or recover faster in more insured areas following a storm.

There are a few important mechanisms through which the effect of flood insurance on post-disaster housing prices could operate. First, in less insured neighbourhoods, individuals moving out and/or foreclosures following a flood may increase the supply of housing. In addition, in such neighbourhoods, a more prolonged state of disrepair may result in a more permanent salience effect on risk perceptions. More insured neighbourhoods may spend more on housing repairs in aggregate, due to higher liquidity resulting from insurance payouts, resulting in more physically desirable neighbourhood characteristics. In competitive markets, these effects should be capitalized into housing prices (Rosen, 1974) following a natural disaster.

Thus, in theory, flood insurance should help safeguard housing values. However, this question has not been evaluated empirically in the literature. The contribution of our paper is to address this gap by evaluating the effect of flood insurance take-up on housing prices using the case of Hurricane Harvey. Hurricane Harvey made landfall in the Houston, Texas area in August 2017 and was the second costliest hurricane in American history (*NOAA*, 2020). It provides a good testing ground for study as it flooded a very large geographic area across many different socio-economic groups (Billings et al., 2019). we use three rich data sets. First, we obtain all active flood insurance policies underwritten by the Federal Emergency Management Agency (FEMA) through the National Flood Insurance Program (NFIP) between 2010-2020. Second, we utilise Zillow's ZTRAX database which provides detailed public records and sales data for essentially all properties in the US for the past twenty years (Zillow, 2020). Third, we use US Geological Survey (USGS)/FEMA flood depths to identify the extent of flooding in each area affected by Hurricane Harvey (Federal Emergency Management Administration (FEMA), 2020).

We utilize an instrumental variable difference-in-differences model with heterogeneous treatment effects to identify the effect of zip-code level flood insurance take-up on housing prices after a home is affected by Hurricane Harvey. Treatment is defined as the level of flood insurance take-up in a given zip-code in the period prior to Hurricane Harvey. The use of an instrument is necessary to address the potential endogeneity of housing prices with flood insurance take-up. In order to overcome this problem, we propose instrumenting for own zip-code level take-up with take-up in US zip-codes unaffected by Hurricane Harvey, weighted by the "social connections" between each affected zip-code and unaffected zip-codes. To do so, we use Facebook's Social Connectedness Index (SCI) (Bailey et al., 2018).

Two main findings emerge from this analysis. First, we confirm results from earlier work and find that homes in flooded areas sell for around 5% less than homes in non-flooded areas. Second, we find a significant protective effect of flood insurance. For homes in moderately flooded areas, a 20 percentage point increase in zip-code level flood insurance take-up mitigates 50% of the discount from living in a flooded area. While the average home in a moderately flooded and low insurance take-up area of Houston would see a $22,926 discount in the value of their home following Hurricane Harvey, an identical home in a high take-up area would see that discount cut to $11,133.

2 Related Literature

One strand of the literature related to flood insurance and housing values examines the effect of floods on properties that were directly affected or in the vicinity of affected areas. In general, authors have reported a decline of 2.5-30% in housing prices following a flood (Atreya et al., 2013; Bakkensen et al., 2019; Bin & Landry, 2013; Boustan et al., 2020; Gibson & Mullins, 2020; Kousky, 2010; Ortega & Taspinar, 2018; Smith et al., 2006).[1] However, none of these papers control for the potentially protective impact of flood insurance. Another group of papers looks specifically at the impact of flood zones or flood risk beliefs on housing prices. These papers report that homes in higher flood risk areas, as measured by proximity to coasts or flood zones, tend to sell at a discount relative to similar homes in less risky areas (Bakkensen & Ma, 2020; Bernstein et al., 2019; Bin et al., 2008; Hino & Burke, 2020; Zhang, 2016). In addition, within equally risky areas, homes in neighbourhoods where individuals believe they are more at risk of climate change related damages sell for a discount relative to those in neighbourhoods where individuals are less realistic about their risk (Bakkensen & Barrage, 2017; Baldauf et al., 2020). Taken together, these papers demonstrate that beliefs play a large role in housing markets and that individuals' risk perceptions are rapidly updated following large flooding events.

Other papers examine the spatial dependence of housing valuations more generally. These papers are useful to study as they provide supporting evidence for the potential mechanisms that would drive neighbourhood housing prices to diverge based on flood insurance take-up. This work shows that individuals living near foreclosed properties or homes sold as a

[1]See table 7 in the Appendix for specific estimates.

"forced sale" see the value of their own home decrease by around 1% (Campbell et al., 2011; Harding et al., 2009) and increases their risk of default by 18% (Towe & Lawley, 2013). Similarily, living in a neighbourhood that undergoes significant revitalization significantly increases housing prices (Rossi-Hansberg et al., 2010). The most relevant study in the context of the present study is Fu and Gregory (2019)'s work studying the spillover impacts of a neighbourhood rebuilding program following hurricane Katrina. They find that neighbours of households who qualified for the rebuilding program were 2.4 percentage points more likely to rebuild their own homes, despite not qualifying for the program themselves. These papers highlight the presence of significant neighbourhood spillover effects and support the hypothesis that there could be contagious effects of flood insurance. This is especially true if flood insurance leads individuals to rebuild their homes faster (and/or better) and helps alleviate financial burdens that could otherwise lead to an increase in foreclosures or bankruptcies.

A substantial literature studies the characteristics, effects and determinants of flood insurance coverage through the NFIP. Individuals that purchase flood insurance tend to be better educated, have higher incomes and live in higher risk areas (Atreya et al., 2015; Bradt et al., 2021; Fan & Davlasheridze, 2015; Landry & Jahan-Parvar, 2010). In addition, flood insurance take-up tends to spike immediately after large floods (Gallagher, 2014; Kousky, 2016) or the release of new information about flood risk (Hu, 2021). More generally, individuals seem to systematically underestimate their flood risk (Botzen & van den Bergh, 2012; Wagner, 2020) and are myopic when it comes to incorporating information about flood risk (Pryce et al., 2011).

Finally, this paper is related to the emerging literature on evaluating the effect of government-run disaster relief programs. Davlasheridze et al. (2017) show that FEMA spending is correlated to a decline in property losses after a flood and Gregory (2017) finds that the Louisiana Road Home program increased the share of rebuilt homes in New Orleans. More specifically, for flood insurance, McCoy and Zhao (2018) show that after Hurricane Sandy, individuals more likely to be covered by flood insurance were also more likely to invest in damaged properties. Gallagher and Hartley (2017) and Gallagher et al. (2019) study credit market outcomes (e.g., mortgage delinquencies, mortgage repayment rates, bankruptcies) following Hurricane Katrina and a panel of tornado events. In both cases, they find that credit outcomes actually improve, on average, for individuals most affected due to the availability of cash grants and insurance payouts. Deryugina et al. (2018) use individual tax return data and find a similar result, in that the incomes of those most affected by Hurricane Katrina actually surpass those in similar yet unaffected cities a few years after Katrina. Billings et al. (2019) nuance the above finding by examining Hurricane Harvey victims. They find that individuals who are less likely to have flood insurance are more likely to go bankrupt following the passage of Hurricane Harvey and that while credit outcomes may improve on average, there is a great deal of heterogeneity. Missing in this literature is the effect of flood insurance on housing prices.

3 Empirical Model

In order to estimate the effect of flood insurance on house prices after a flood, we use an instrumental variables difference-in-differences model with varying treatment intensity. Each observation is a housing transaction in a zip-code affected by Hurricane Harvey. The sample spans the period of August 2015 to December 2018. Treatment is defined at the zip-code level as the average take-up, t_{iz}, [2] in zip-code z for the period of August 25th 2016-August 25th 2017 (ie. the year prior to Hurricane Harvey). The identification strategy relies on comparing housing prices before and after Hurricane Harvey, for homes with similar characteristics and similar levels of flooding that were located in zip-codes with different levels of flood insurance take-up. Heterogeneous treatment effects are analyzed by interacting a zip-code level measure of flood depth with flood insurance take-up levels. Note that there

[2](# of single family policies/ # single family households)

are no time-varying effects included in this model, so it is assumed that every sale post-flood has the same marginal impact on housing prices.

The basic structural equation is of the form:

$$\begin{aligned} p_{izt} = \alpha + \beta_1 Post_{izt} + \beta_2 t_{iz} + \sum_{k=1}^{4} \beta_{3k} D^k_{izt} + \beta_4 Post_{izt} \times t_{iz} + \sum_{k=1}^{4} \beta_{5k} D^k_{izt} \times t_{iz} \\ + \sum_{k=1}^{4} \beta_{6k} Post_{izt} \times D^k_{izt} \times t_{iz} + my_t + C + \gamma Z_z + \Psi H_i + \psi Post_{izt} \times h_i + \epsilon_{izt} \end{aligned} \tag{1}$$

In the above equation, z indexes the zip-code, t indexes time (in months) and i indexes individual properties. p_{izt} is the logarithm of the price of home i in zip-code z at time t, $Post_{izt}$ is an indicator variable that is equal to 1 after September 2017, (ie. after Harvey). D^k_{izt} is equal to the flood depth quartile of the zip-code after hurricane Harvey. my_t is a month-year fixed effect, C is a county fixed-effect, Z_z is a vector of zip-code characteristics (e.g., zip-code average housing prices, median household income, education, demographics), H_i is a vector of housing characteristics (e.g., square footage, number of bedrooms, number of bathrooms, property area, distance to the nearest flood zone, distance to the sea shore and distance to the nearest inland body of water), h_i is a subset of housing and zip-code characteristics that is interacted with the post indicator. Specifically, zip-code average housing prices, distance to the nearest flood zone, sea shore and inland body of water. Finally, all standard errors are clustered at the zip-code level.

In equation 1, β_2 is the base effect of flood insurance levels on housing prices prior to hurricane Harvey. β_{3k} is the effect of Harvey flood depths on housing values. β_4 is the effect of flood insurance take-up on post-Harvey housing prices for homes in the least flooded zip-codes. The coefficient of interest is β_{6k}, which represents the effect of flood insurance on housing prices dependent on the level of flood depth in a given zip-code. Calendar month-year fixed effects (my_t) are included to take seasonality and price trends into account. County fixed effects (C) are included in order to control for county-level time-invariant characteristics such as county-specific regulations or flood mitigation measures. Note that zip-code fixed effects would be colinear with the take-up measure and are thus not included. Instead we include zip-code characteristics as controls. Housing characteristics and interactions between the post indicator and distance to a flood zone, distance to the shore, distance to the nearest inland body of water and average house prices in one's own zip-code are also included as controls. This is important because previous studies (Bakkensen & Barrage, 2017; Bin et al., 2008; Hino & Burke, 2020; Zhang, 2016) find there is a differential effect in response to flooding based on flood zone status and proximity to bodies of water. In addition, since it is likely that homes in more expensive zip-codes have higher baseline flood insurance take-up levels (Atreya et al., 2015), it is important to control for differential responses based on average zip-code housing price so as to not confound price and take-up effects.

The main concern with the above specification is the potential endogeneity of zip-code level flood insurance take-up with housing prices. Indeed, flood insurance take-up levels are not randomly assigned. Flood insurance take-up is likely to be highly correlated with unobservable factors affecting one's ability to recover from a natural disaster. In addition, Hino and Burke (2020) and Zhang (2016) both show that properties in high flood insurance take-up areas are discounted relative to similar houses in areas with lower take-up. Thus, it is likely that individuals who purchase flood insurance are more likely to capitalize their flood risk into their housing price valuations. Kahn-Lang and Lang (2020) show that parallel pre-trends are not a sufficient condition for difference-in-differences estimates to be unbiased, the treatment must also be exogenous to the outcome (Cunningham, 2021), hence the need for an instrument.

In order to overcome this problem, we propose instrumenting for zip-code level take-up with take-up in US zip-codes unaffected by Hurricane Harvey, weighted by the "social connections" between each affected zip-code and unaffected zip-codes. To do so, we use Facebook's Social Connectedness Index (SCI) (Bailey et al., 2018). This index measures the degree of connection between two zip-codes based on the number of friends connected through Facebook in each zip-code pair. Thus, the instrument is $tsci_i = \frac{\sum_{j=1}^{N} takeup_j \times SCI_{ij}}{\sum_{j=1}^{N} SCI_{ij}}$, where $takeup_j$ is flood insurance take-up in any zip code that is not affected by Hurricane Harvey and SCI_{ij} is the degree of social connection between a given affected zip-code i and an unaffected zip-code j.

The logic underlying this instrument is that areas that are more connected to each other should have insurance take-up rates that are more similar than less connected areas. Hu (2021) shows that take-up and friends' take-up is highly correlated and Gallagher (2014) shows that flood insurance take-up is highly correlated within media-markets. The rationale is that social networks help shape perceptions and that one's own actions may be instrumented with friends' actions (Bramoullé et al., 2009). One mechanism by which this correlation could exist is simply if friends discuss flood insurance with each other following a large flooding event. Additionally, individuals that are more connected to others in areas more exposed to flood risk may witness images of flood damage on social media more often, or hear about it from their friends. Thus, if individuals are more connected to places in which flooding is frequent they may be more aware of their own risk.

The exclusion restriction is satisfied if housing prices in a given affected zip-code are unrelated to flood insurance take-up in friends' zip-codes. It seems implausible that a friends' flood-insurance take-up in a distant area would affect one's own housing price directly. One potential violation would occur if take-up in other zip-codes is associated with unobserved determinants of housing prices in affected zip-codes. This is partially controlled for using housing and zip-code characteristics. However, heterogeneous risk attitudes or beliefs about flood risk are difficult to control for explicitly. Nevertheless, we control for distance to the nearest flood zone or body of water which are likely to be good proxies for flood risk beliefs

(Fan & Davlasheridze, 2015; Wagner, 2020).

With take-up instrumented for, the first-stage equation is:

$$\begin{aligned} t_{izt} = \alpha + \beta_1 Post_{izt} + \beta_2 tsci_{iz} + \sum_{k=1}^{4} \beta_{3k} D_{izt}^{k} + \beta_4 Post_{izt} \times tsci_{iz} + \sum_{k=1}^{4} \beta_{5k} D_{izt}^{k} \times tsci_{iz} \\ + \sum_{k=1}^{4} \beta_{6k} Post_{izt} \times D_{izt}^{k} \times tsci_{iz} + my_t + C + \gamma Z_z + \Psi H_i + \psi Post_{izt} \times h_i + \epsilon_{izt} \end{aligned} \tag{2}$$

The second stage is:

$$\begin{aligned} p_{izt} = \alpha + \beta_1 Post_{izt} + \beta_2 \hat{t}_{iz} + \sum_{k=1}^{4} \beta_{3k} D_{izt}^{k} + \beta_4 Post_{izt} \times \hat{t}_{iz} + \sum_{k=1}^{4} \beta_{5k} D_{izt}^{k} \times \hat{t}_{iz} \\ + \sum_{k=1}^{4} \beta_{6k} Post_{izt} \times D_{izt}^{k} \times \hat{t}_{iz} + my_t + C + \gamma Z_z + \Psi H_i + \psi Post_{izt} \times h_i + \epsilon_{izt} \end{aligned} \tag{3}$$

The reduced-form is:

$$\begin{aligned} p_{izt} = \alpha + \beta_1 Post_{izt} + \beta_2 tsci_{iz} + \sum_{k=1}^{4} \beta_{3k} D_{izt}^{k} + \beta_4 Post_{izt} \times tsci_{iz} + \sum_{k=1}^{4} \beta_{5k} D_{izt}^{k} \times tsci_{iz} \\ + \sum_{k=1}^{4} \beta_{6k} Post_{izt} \times D_{izt}^{k} \times tsci_{iz} + my_t + C + \gamma Z_z + \Psi H_i + \psi Post_{izt} \times h_i + \epsilon_{izt} \end{aligned} \tag{4}$$

4 Data

4.1 Flood Insurance Policies

In 2019, FEMA released a publicly available dataset of flood insurance policies.[3] This dataset contains information on every flood insurance policy underwritten through FEMA's

[3]https://www.fema.gov/news-release/2019/06/11/fema-publishes-nfip-claims-and-policy-data

National Flood Insurance Program from 2010 onward. Although a small private market for flood insurance exists in the United States, it is estimated that this market represents less than 3% of all flood insurance policies (Gibson & Mullins, 2020), with all other policies underwritten by FEMA. The raw data contains over 50 million observations. Individuals renew their policies either yearly or every three years, meaning policies will show up multiple times in the data. For each policy, around 30 variables are observed, such as the premium, contents and building coverage, deductible, date the policy came into effect, year the building was built and flood zone indicators. We access this data using FEMA's application programming interface (API).[4] We restrict the sample to policy transactions for single-family dwellings and exclude businesses, agricultural structures and houses of worship. We further restrict the sample to policies active within one year of Hurricane Harvey, resulting in a sample of 3,636,719 policies. FEMA does not identify location beyond the census-tract level. Due to the nature of our instrumental variable, we aggregate the policy data to the zip-code level. One disadvantage of this is that zip-codes are less granular than census-tracts.[5]

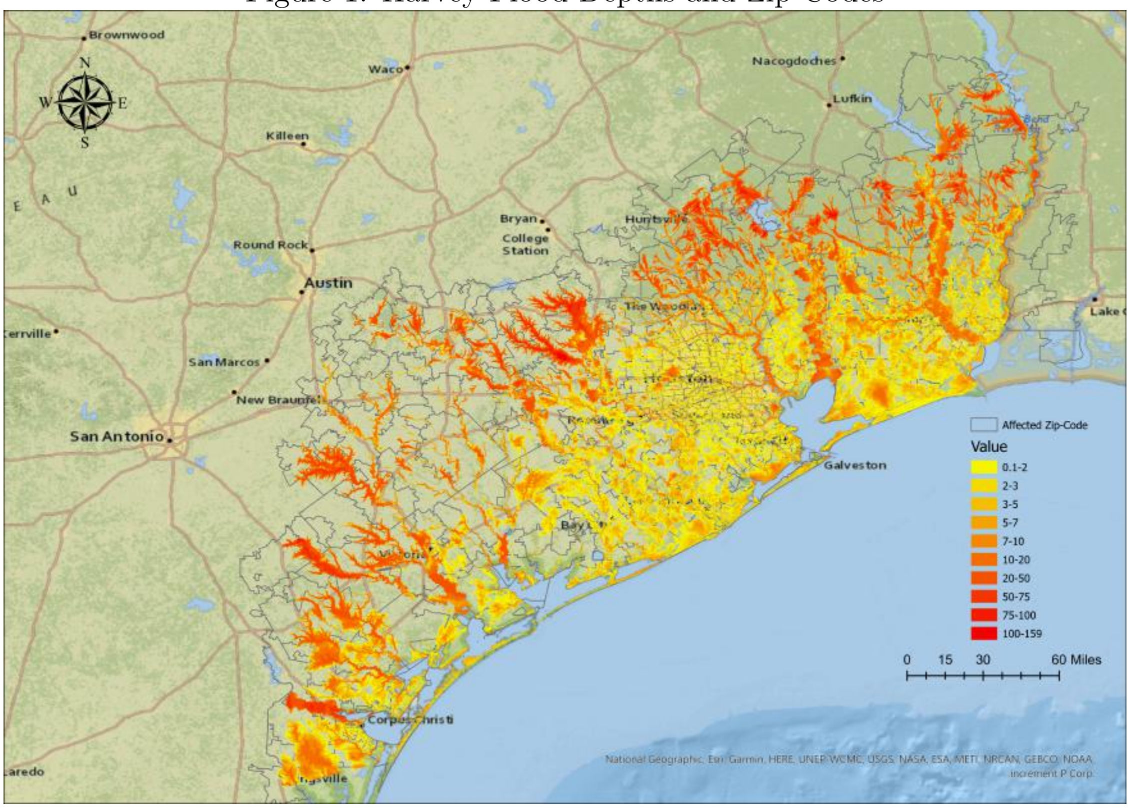
4.2 FEMA flood depths

FEMA, in collaboration with the Harris County Flood Control District (HCFCD) and US Geological Survey (USGS) provides a 3 meter resolution dataset on flooding depths for areas affected by Harvey (Federal Emergency Management Administration (FEMA), 2020). Flood depths range from 0 to 159 feet. We aggregate the flood depths to the zip-code level to produce mean flood depths for each zip code. Figure 1 shows the extent of flooding overlayed onto the zip-codes in the area. The areas in a darker shade of red experienced more severe flooding than those shaded in yellow. In total there are 399 affected zip-codes.

[4]Disclaimer: This product uses the Federal Emergency Management Agency's API, but is not endorsed by FEMA

[5]The average census-tract in the United States has about 4,000 inhabitants while the average zip-code has around 8,000.

Figure 1: Harvey Flood Depths and Zip-Codes



Notes: This figure shows Harvey Flood depths (in feet) based on FEMA/USGS raster files overlaid onto zip-code boundaries using ArcGis.

4.3 Zillow ZTRAX

Zillow's ZTRAX database contains more than 400 million public records across the entirety of the United States (Zillow, 2020), including sales, deed transfers, mortgages, foreclosures, auctions, property tax delinquencies. Property characteristics and precise geographic location are also included for each property. Since property sales are not public record in the state of Texas, we use loan amounts (ie. mortgages) as a proxy for housing prices.[6] We drop transactions that are flagged as "intra-family transfers", observations with missing loan amounts or loan amounts of $0, and outliers.[7] This yields 239,734 transactions for the period between August 1 2015 and August 31 2019 in the 399 zip-codes affected by Hurricane Harvey. Due to reporting lags, there are very few observations in the Zillow data past December 2018. We therefore drop observations from 2019 and restrict our sample to August 1, 2015 to December 31, 2018, yielding a final dataset composed of 236,949 transactions.

4.4 FEMA flood zone

FEMA publishes flood zone information directly on its website.[8] We download flood zone shapefiles for the state of Texas. This serves not only as a potential control variables in the regression but is also useful in highlighting the discrepancies between actual flooding and anticipated flood risk.

[6]Note that we are in the process of obtaining sales price data through CoreLogic in order to confirm the results.

[7]Consistent with McMillen and Singh (2019), we drop observations outside the range $[p_{25}3(p_{75}p_{25}), p_{75} + 3(p_{75}p_{25})]$, where where p_{25} and p_{75} are the 25th and 75th percentile of the loan amount value.

[8]Available at: https://msc.fema.gov/portal/advanceSearch

4.5 American Communities Survey (ACS)

The American Communities Survey is a nationwide, continuous survey that has replaced the long-form census since 2000. It provides social, economic, housing, and demographic data for a representative sample of Americans each year (Census, 2019). We use the 2015-2020 five-year estimates file to obtain detailed socio-economic and demographic information for the inhabitants of the zip-codes in our study. We also use single-family housing units as the denominator in our measure of flood-insurance take-up.

4.6 Facebook Social Connectedness Index

I obtain our measure of social connectedness from the 2018 Facebook Social Connectedness Index (SCI). This index calculates the relative probability of a Facebook friendship link between a given Facebook user in location i and a given user in location j. An easy way of interpreting this measure is that if the SCI is twice as large, a Facebook user in i is twice as likely to be connected with a given Facebook user in j. Facebook calculates the SCI as:

$$SCI_{ij} = \frac{connections_{ij}}{users_i \times users_j}$$

Note that, the SCI is a snapshot of connections at a given point in time. In the case of the 2018 data, the snapshot is taken in mid 2018.

4.7 Other

We use Zillow's publicly available Home Value Index[9] to control for the average price of a home in a given zip-code in the month prior to Hurricane Harvey. We also use NOAA's medium resolution shoreline data[10] to control for a house's distance to the shore. Finally, we use a US waterbodies shapefile[11] to control for a home's distance to an inland body of water.

5 Descriptive Statistics

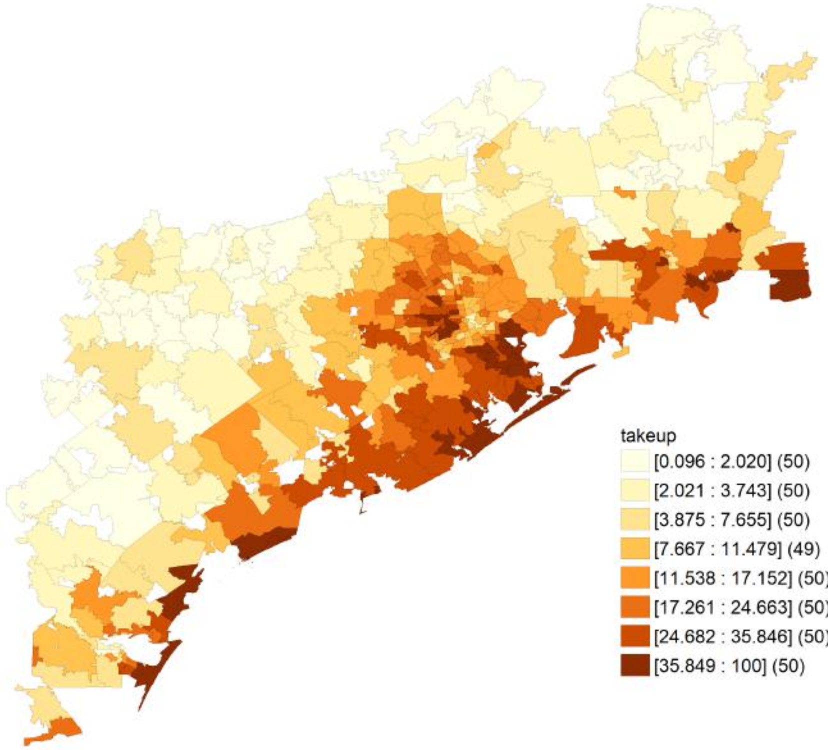
5.1 Flood Insurance

The median take-up in affected zip-codes is 11.5% and the average take-up is 17.9%. Nationally, median zip-code take-up is 1.0% and average take-up is 4.7%. Given that most zip-codes in the United States are not subject to the same level of flood risk as those in areas affected by Harvey, a more useful comparison is with Florida, the state where flood insurance is most prevalent. Median take-up in zip-codes in Florida is 8.7% and average take-up is 18.6%, similar levels to the areas affected by Hurricane Harvey.

Figure 2 presents flood insurance take-up levels by zip-code for the areas affected by Hurricane Harvey. There is a wide distribution of take-up levels in the affected zip-codes, ranging from 0.1% to almost 100%. Take-up is generally higher along the gulf coast, but varies greatly within Harris County, with zip-codes on the west side of the county having higher take-up than those on the east side. When comparing figure 2 to figure 1, we notice that take-up does not necessarily correlate with extent of flooding, as many of the worst hit

[9]https://www.zillow.com/research/zhvi-methodology-2019-highlights-26221/
[10]https://shoreline.noaa.gov/data/datasheets/medres.html
[11]https://www.arcgis.com/home/item.html?id=84e780692f644e2d93cefc80ae1eba3a

Figure 2: Flood Insurance Take-up by Zip-Code in areas affected by Hurricane Harvey



Notes: This map represents average take-up (%) in the year prior to Hurricane Harvey in zip-codes which experienced flooding due to Harvey. The areas are divided into eight quantiles of take-up and shaded accordingly.

areas are far from the high take-up zip-codes near the coast.

5.2 Housing

The median housing price (loan amount) in the affected zip-codes is $181,450 over the period of the study. The median number of transactions per month per zip-code during the period is 10. The average is 19, the minimum is 1 and the maximum is 133. As we can see in table 1, houses in higher take-up zip-codes are generally more expensive, slightly newer and larger. They are also much closer to the shore.

Table 1: Housing Characteristics

	Below Median Take-up	Above Median Take-up
Median House Price	$144,000	$195,000
Average House Price	$149,831	$214,304
Median Year Built	1996	1998
Median sqft	2,032	2,518
Average Number of Bedrooms	2.4	2.5
Average Number of Full Bathrooms	1.5	1.8
Median Distance to Inland Water Body (km)	1.8	1.5
Median Distance to Shore (km)	30.0	18.5
Number of Transactions	53,384	185,496

There was some level of flooding in the locations of 68% of all homes sold in the post-Harvey period.[12] The median level of flooding was 2.5 feet and the average level of flooding was 3 feet. Almost 10% of flooded homes were located in areas with flood depths above 5 feet. Only 9% of the houses in the sample were in a 100-year flood zone, defined by FEMA has having a 1% chance of flooding every year. This is also the zone in which homeowners with new mortgages are obligated to purchase flood insurance. An additional 10% of homes were located in a 500-year flood zone, where yearly flood risk is judged to be 0.2% and homeowners are not obliged to purchase flood insurance. Table 2 shows that while homeowners in above average take-up zip-codes were much more likely to be living in a flood zone, they were about as likely to experience some level of flooding and flooding was more severe in below median

[12] It is not possible to actually know if a given home was flooded, all we know is the flood depth at the location of the home. Presumably not all homes in locations with a flood depth above zero actually experienced flooding.

take-up areas.

Table 2: Flood-related Housing Characteristics

	Below Median Take-up	Above Median Take-up
% in flood zone	3	11
*% flood depth > 0 **	66	68
*Average Flood Depth (ft.)**	4.1	2.8

** Only for homes sold after August 2017*

5.3 Demographics

As shown in table 3, zip-codes with above median take-up tend to be more populous, wealthier, slightly younger and more educated. Zip-codes do not appear to differ very much along racial lines, except for the fact that there is a much greater proportion of Asian households in above median take-up zip-codes. In a cross-sectional regression of take-up on socioeconomic characteristics, only the proportion of individuals with a bachelor's degree is predictive of take-up.

Table 3: Demographic Characteristics

	Below Median Take-up	Above Median Take-up
Average Population	12,944	29,052
Average Number of Single Family Households	3,540	7,460
Median Household Income	$54,393	$71,090
Median Age	40	37
% White	78	73
% Black	13	13
% Hispanic or Latino	33	31
% Asian	1	6
% Bachelor's Degree	16	30
% Less Than HS	20	15

6 Results

Table 4 presents results from a regression of log housing prices on Harvey zip-code level depth quartiles, month-year fixed effects and post harvey *times* depth interactions. We also control for property[13] and zip-code[14] characteristics. In column 1 we see that prices of homes in areas that were more affected by Hurricane Harvey are not significantly different pre-Harvey. Post Harvey, prices in affected zip-codes drop by around 5% in moderately affected zip-codes compared to less flooded zip codes. In column 2, we replace zip-code characteristics with zip-code fixed effects and find a very similar result. Although we cannot use a zip-code fixed effect in future specifications that incorporate zip-code take-up, it is reassuring that these basic results are similar whether we use a zip-code fixed effect or zip-code characteristics. Using these results, we can conclude that properties in neighbourhoods that experienced more severe flooding have housing valuations that are around 5% lower than those in less-flooded neighbourhoods. The literature (Atreya et al., 2013; Bakkensen et al., 2019; Beltrán et al., 2018; Bin & Landry, 2013; Boustan et al., 2020; Gibson & Mullins, 2020; Hino & Burke, 2020; Kousky, 2010; Ortega & Taspinar, 2018) generally finds effects ranging from 2-10%. These findings are within this same range.

Table 5 presents results from estimating equation 1, using both OLS and IV[15] methods. Homes in flooded areas see their housing prices decline by 8 to 9% relative to non-flooded homes in the OLS specification and 10 to 11% in the IV specification, which is consistent with previous work (Boustan et al., 2020; Gibson & Mullins, 2020; Ortega & Taspinar, 2018). The insignificant coefficient on the takeup term demonstrates that higher take-up

[13]Specifically: square feet, year of construction, # of bedrooms, # of full bathrooms, lot size, distance to the nearest flood zone, distance to the nearest inland body of water, distance to the nearest seashore

[14]Specifically: median household income, average zip-code housing prices based on the Zillow Housing Price Index, % with a bachelor's degree or higher, % with less than a high school degree, % white, % hispanic or latino, % asian, % black, % of households which made a FEMA individual assistance request after Harvey

[15]First-stage estimates are presented in table 8 in the appendix. Note that the first stage F-statistic is above 10 and the relationship between take-up and social connectedness-weighted take-up is strong.

Table 4: Effect of Living in Flooded areas on Housing Prices, Ignoring Flood Insurance

	(1) ZIP Controls	(2) ZIP FE
depth quartile 2	-0.0097	
	(0.0256)	
depth quartile 3	-0.0117	
	(0.0285)	
depth quartile 4	-0.0186	
	(0.0334)	
post $\times$ depth quartile 2	-0.0525**	-0.0476*
	(0.0186)	(0.0195)
post $\times$ depth quartile 3	-0.0467*	-0.0463*
	(0.0196)	(0.0201)
post $\times$ depth quartile 4	-0.0364	-0.0343
	(0.0225)	(0.0222)
N	200148	200148
R^2	0.460	0.478
Month-Year FE	Yes	Yes
County FE	Yes	No
Property Characteristics	Yes	Yes
Zip-Code Characteristics	Yes	No
Zip-Code FE	No	Yes

Robust, clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents estimates for the effect of Hurricane Harvey on housing prices in areas affected by Harvey. In all columns, the dependent variable is the log of housing prices. All standard errors are robust and clustered at the zip-code level. Column 1 presents a regression of log housing prices on a post-Harvey indicator and flood depth quartiles, with the omitted category being non-flooded homes. Month and county fixed effects are included as well as property and zip-code characteristics as described in footnotes 13 and 14. Column 2 replaces zip-code characteristics with a zip-code fixed effect.

Table 5: Effect of Flood Insurance Take-Up on Housing Prices

	(1) OLS	(2) IV
takeup	0.0003	-0.0008
	(0.0015)	(0.0008)
post × takeup	-0.0028**	-0.0040***
	(0.0011)	(0.0005)
depth quartile 2	0.0196	0.0276*
	(0.0382)	(0.0124)
depth quartile 3	-0.0073	-0.0240
	(0.0395)	(0.0147)
depth quartile 4	0.0157	0.0392*
	(0.0356)	(0.0160)
post × depth quartile 2	-0.0922*	-0.1122***
	(0.0399)	(0.0154)
post × depth quartile 3	-0.0822*	-0.1033***
	(0.0413)	(0.0157)
post × depth quartile 4	-0.0833	-0.1030***
	(0.0426)	(0.0229)
takeup × depth quartile 2	-0.0014	-0.0018***
	(0.0016)	(0.0004)
takeup × depth quartile 3	-0.0005	-0.0002
	(0.0013)	(0.0005)
takeup × depth quartile 4	-0.0016	-0.0027***
	(0.0015)	(0.0006)
post × takeup × depth quartile 2	0.0018	0.0026***
	(0.0012)	(0.0006)
post × takeup × depth quartile 3	0.0016	0.0027***
	(0.0012)	(0.0006)
post × takeup × depth quartile 4	0.0019	0.0024**
	(0.0013)	(0.0009)
N	200,149	200,149
R^2	0.461	0.461
Month-Year FE	Yes	Yes
County FE	Yes	Yes
Property Characteristics	Yes	Yes
Zip-Code Characteristics	Yes	Yes

Robust, clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents both OLS and IV estimates for the effect of Hurricane Harvey on housing prices in areas affected by Harvey. In all columns, the dependent variable is the log of housing prices. All standard errors are robust and clustered at the zip-code level. Column 1 presents standard difference-in-differences estimates of the effect of take-up on housing prices corresponding to equation 1. Column 2 presents IV difference-in-differences estimates of equation 1, where zip-code take-up is instrumented with the take-up of one's "social" neighbours.

neighbourhoods do not have significantly different housing prices pre-Harvey than low take-up areas. For homes in the least flooded areas after Harvey (coefficient on post $\times$ takeup), the level of take-up at the zip-code level has a negative impact on post-disaster prices.

Both the OLS and IV results suggest that flood insurance take-up has a mitigating effect on the home value losses incurred in neighbourhoods that suffered a higher level of flooding. The coefficients on the depth quartile $\times$ take-up interactions are all positive in both the OLS and IV specifications and are significant at the 0.001% level in the IV specification. The IV coefficients imply that a 1 percentage point increase in zip-code level take-up yields a 0.26% increase in housing values in the second depth quartile, a 0.27% increase in housing values in the third depth quartile and a 0.24% increase in the fourth depth quartile.

The average price of a home in depth quartile 2 is $208,417. Using the results from the IV estimates, a 0.26% increase in home prices for the average homeowner in the first flood depth quartile is only $542. However, this is for a very marginal increase (1 percentage point) in flood insurance take-up. Another way to contextualize the results is to assume a larger increase in flood insurance take-up. For example, the 25th percentile of flood insurance take-up in depth quartile 2 is 15.1%, while the 75th percentile is 35.7%. Going from the 25th to the 75th percentile of take-up would cause an increase in post-Harvey housing values of $\$11,162.81$[16] for the median homeowner in depth quartile 1. Considering the average loss in housing values due to flooding is 11%, or $22,926, for the average home in this category of flooding, going from the 25th to the 75th percentile of zip-code flood insurance take-up would cut this loss by 49%.[17] Thus, the effect of zip-code level flood insurance take-up is sizeable. To further put these results into perspective, consider that the average annual premium for insured houses in the affected zip-codes is approximately $500. From an individual perspective, purchasing flood insurance may not seem worthwhile just for the neighbourhood effects. However, from a neighbourhood perspective, the gains from a

[16] $(35.7 - 15.1) \times \$208,417 \times 0.0026 = \$11,162.81$

[17] $\frac{11163}{22926} \times 100 = 48.7\%$

substantial increase in take-up are large. This situation could lead to a collective action problem, where only individuals who believe they will suffer flooding buy flood insurance and those who do not free-ride on those who have more pessimistic beliefs.

Although there are no previous estimates of the effect of flood insurance on housing prices in the literature, we do find significant positive impacts of post-disaster aid on housing prices. This is consistent with Billings et al. (2019), Davlasheridze et al. (2017), Gallagher and Hartley (2017), and Gallagher et al. (2019), who all show that aid after natural disasters has substantial positive financial impacts on recipients.

6.1 Potential Bias

A possible concern for the robustness of these estimates is related to the use of loan amounts instead of housing prices as the dependent variable. If we interpret loan amounts as a noisy measure of housing prices, the situation is analogous to one where there is measurement error in the dependent variable. In this case the measurement error is only a concern if it is related to the explanatory variables of interest (Wooldridge, 2015). This would mean that the down-payments (the difference between loan amount and sales price) would have to differ systematically by flood depth and/or by level of flood insurance. To explore this possibility, we take advantage of the fact that beginning in 2018, Home Mortgage Disclosure Act (HMDA) data includes loan-to-value ratios. we match homes sold in 2018 in our sample with those in the HMDA data using a procedure outlined in Bayer et al. (2017). While we am only able to match around 30% of the data, we find no statistical differences in the loan-to-value ratios by level of flooding. We do find some evidence of lower loan-to-value ratios among higher take-up groups, yet these differences disappear once average zip-code housing prices are controlled for.

Another source of potential concern is omitted variable bias, specifically in regards to risk perceptions. While objective risk is controlled for using FEMA flood zones, subjective risk perceptions of individual home-buyers cannot be controlled for with this data. All else being equal, individuals living in high take-up areas would be expected to perceive flood risk more acutely than in lower take-up areas. If this is capitalized into local house prices, then house prices in such areas should be lower, causing estimates to be downward biased. This is confirmed as we see the magnitude of coefficients increase slightly once take-up is instrumented. However, if risk perceptions in a social neighbour's zip-code is associated to one's own risk perceptions and thus housing price in a similar way, then the estimates again will be biased toward zero, despite the instrument. While risk perceptions are available at the county level through the Yale Climate Opinions Survey (Howe et al., 2015), we have not found similar data at the zip-code level.

Another concern is the level of aggregation. In this study, flood-insurance take-up is aggregated at the zip-code level. While this is convenient for our instrument, zip-codes are much larger than a neighbourhood as typically conceived. The average take-up in one's zip-code may not be a true representation of take-up in a given neighbourhood. Most studies of neighbourhood externalities study much smaller areas, such as city blocks or immediate neighbours (Campbell et al., 2011; Fu & Gregory, 2019; Harding et al., 2009; Towe & Lawley, 2013). The treatment's scale of aggregation in this study is likely to bias estimates downward as externalities are usually experienced most acutely at smaller aggregates.

Finally, it is important to note that Hurricane Harvey was an exceptional event. This makes it easier to study, but also less representative than most flooding in the US, which generally occurs at a smaller scale. A possible next step in this literature would be to study a more representative panel of flooding events.

6.2 Potential Mechanisms

There are several mechanisms through which higher flood insurance take-up could affect housing prices. First, there could be supply effects from homeowners that sell their home due to a lack of liquidity to repair it. Some of these could conceivably default on their mortgage payments or simply move away. This would cause an increase in the supply of housing in less insured areas, and all else equal drive prices down. On the demand side, individuals who are thinking of purchasing a home may think twice about buying a home in a heavily flooded area, especially if these homes seem to be in disrepair. Thus, flooded but less insured areas could also be less attractive to buyers, while flooded and better insured areas could see faster rebuilding after a flood and thus remain attractive to buyers. This is especially the case since individuals who receive disaster assistance often undertake extensive renovations of their homes (Gallagher & Hartley, 2017), thus making properties in areas which received more aid more attractive to future buyers. While subjective expectations or impressions are difficult to measure, the Zillow data does allow for the study of transaction patterns over time and space. A measure of the total number of transactions confounds supply and demand effects,[18] but may be informative nonetheless in indicating large supply or demand shifts. As we can see in table 6, there does not seem to be a large shift in the number of transactions following hurricane Harvey. While overall, there is about half a transaction less in each zip-code, transactions do not differ substantially by level of flooding or take-up level post Harvey.

[18] In future versions of this paper, we hope to use CoreLogic MLS data to disentangle supply and demand effects by looking at variables such as time on market, and listings which were posted but did not sell.

Table 6: Effect of Harvey on transactions

	(1)	(2)	(3)
post	-0.4520**	-0.3272	-0.0558
	(0.1522)	(0.3006)	(0.6990)
post x depth quartile 2		-0.1291	
		(0.4285)	
post x depth quartile 3		-0.3342	
		(0.4282)	
post x depth quartile 4		-0.0385	
		(0.4297)	
takeup			0.1594***
			(0.0149)
post x takeup			-0.0002
			(0.0239)
N	12303	12296	12281
R^2	0.908	0.908	0.015
Zip-code FE	Yes	Yes	No

Robust, clustered errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents estimates of the effect of hurricane Harvey on housing transactions at the zip-code level. The dependent variable is the number of monthly transactions per zip-code. The first column regresses monthly transactions on a post-Harvey indicator and zip-code fixed effects. The second column regresses monthly transactions on interactions of post, depth quartiles and zip-code fixed effects. The third column regresses transactions on interactions of the post-Harvey indicator and average zip-code flood insurance take-up before Hurricane Harvey. Zip-code depth quartiles are calculated by averaging Harvey flood depths over the area of each zip-code.

7 Conclusion

This paper investigates whether insurance provided by the National Flood Insurance Program protects housing values. To our knowledge, this is the first study explicitly linking flood insurance take-up and housing prices after a flood.

Using an instrumental variable difference-in-differences design, we find that, for homes in moderately flooded areas, a 20 percentage point increase in zip-code level flood insurance take-up mitigates 50% of the discount from living in a flooded area. While the average home in a moderately flooded and low insurance take-up area of Houston would see a \$22,926 loss in the value of their home following Hurricane Harvey, an identical home in a high take-up area would see that loss cut to \$11,133. Thus, for many homeowners, a high level of neighbourhood flood insurance take-up mitigates the losses in housing value resulting from flooding.

These results have important policy implications. First, a high level of flood insurance take-up in one's zip-code helps protect housing values. With more neighbourhoods becoming exposed to flood risk as climate change accelerates, it is important to promote the purchase of flood insurance. Second, accurate flood maps are crucial to helping increase take-up. Homeowners in flood zones are much more likely to own flood insurance. However, incomplete or inaccurate flood maps lead individuals to believe they are safe from flooding. Most households affected by Hurricane Harvey did not have flood insurance because they were located outside flood plains. Third, these results have distributional implications. While it is not possible to know the specific characteristics of flood insurance buyers in our sample, we observe that higher take-up zip-codes are generally wealthier and more educated. Thus, much of the benefit from higher insurance take-up flows to more affluent zip-codes. Given that the NFIP is not self-sufficient and must borrow around \$1 billion annually from the US government (PGPF, 2020), this implies that federal funds are being used to protect housing values in wealthier and more educated areas. Making flood insurance more accessible for the less well-off should be a priority for policymakers.

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Appendix

Table 7: Effect of Floods on Property Values

Paper	**Housing Price Decrease after a Flood**
Atreya et al. (2013)	25-44%
Bakkensen et al. (2019)	8%
Bin and Landry (2013)	6-9%
Boustan et al. (2020)	2.5-5%
Gibson and Mullins (2020)	5-7%
Kousky (2010)	2-11%
Ortega and Taspinar (2018)	9%
Smith et al. (2006)	34%
Zivin et al. (2020)	5-10% increase

Table 8: First-Stage Regression

	(1) Clustered	(2) Not Clustered
takeup_sci	0.4250	0.4250***
	(2.6307)	(0.1158)
post × takeup_sci	-1.0785	-1.0785***
	(0.8683)	(0.1564)
depth quartile 2	-16.0442	-16.0442***
	(17.7380)	(0.7465)
depth quartile 3	-54.2471**	-54.2471***
	(19.4365)	(0.8176)
depth quartile 4	-11.0806	-11.0806***
	(20.6836)	(0.9212)
post × depth quartile 2	3.8031	3.8031***
	(6.6042)	(1.0466)
post × depth quartile 3	3.2058	3.2058**
	(5.8678)	(1.1725)
post × depth quartile 4	0.0422	0.0422
	(4.5973)	(1.3114)
takeup_sci × depth quartile 2	2.6091	2.6091***
	(3.0153)	(0.1312)
takeup_sci × depth quartile 3	9.0135*	9.0135***
	(3.6930)	(0.1480)
takeup_sci × depth quartile 4	1.3451	1.3451***
	(3.4957)	(0.1606)
post × takeup_sci × depth quartile 2	-0.7060	-0.7060***
	(1.2137)	(0.1850)
post × takeup_sci × depth quartile 3	-0.6105	-0.6105**
	(1.0741)	(0.2120)
post × takeup_sci × depth quartile 4	-0.0884	-0.0884
	(0.8090)	(0.2286)
N	200,149	200,149
R^2	0.616	0.616
F-Statistic	10.80	9,424.70
Month-Year FE	Yes	Yes
County FE	Yes	Yes
Property Characteristics	Yes	Yes
Zip-Code Characteristics	Yes	Yes
Clustered at Zip-Code Level	Yes	No

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents estimates of equation 2, which regresses the endogenous take-up variable on the instrument (takeup_sci) as well as the interactions of the instrument with the post indicator and depth quartiles. Also included in this regression are month and county fixed effects as well as property and zip-code characteristics. Column 1 is estimated with standard errors clustered at the zip-code level while column 2 is not clustered. In practice, column 1 is the first-stage in the 2SLS specification, however the F-statistic for clustered regressions uses only 165 degrees of freedom, while the F-statistic without clustering is calculated using the total amount of observations. This is why there is a large discrepancy in the F-statistics in either column. Nevertheless, both F-statistics are above 10.