DISASTER PREMIUMS IN THE RENTAL HOUSING MARKET:

EXPLORING THE EFFECT OF THE MONTECITO DEBRIS FLOW

28 March 2019

Abstract:

This study evaluates the impact of the 9 January 2018 debris flow in Montecito, California on local long-term rental prices through a difference-in-difference (DID) estimation strategy. Using a proprietary dataset of approximately 191,000 online rental listings, we estimate that, controlling for other observable factors, the debris flow resulted in a 7.6 percent increase in average rent and a 5.6 percent increase in median rent for listings observed in the nine months immediately following the debris flow. We also examine the debris flow's effects at different quantiles of the rent distribution, finding that the debris flow had a larger effect on rents above the median. Our analysis suggests these increases are temporary and dissipating over time.

Robert D. Niehaus, Inc.

RDN Economist Bjorn Kallerud was the lead analyst on this study. He was assisted by Ian Monsma, Dr. Miguel Delgado Helleseter, and Dr. Robert Niehaus.

1. INTRODUCTION

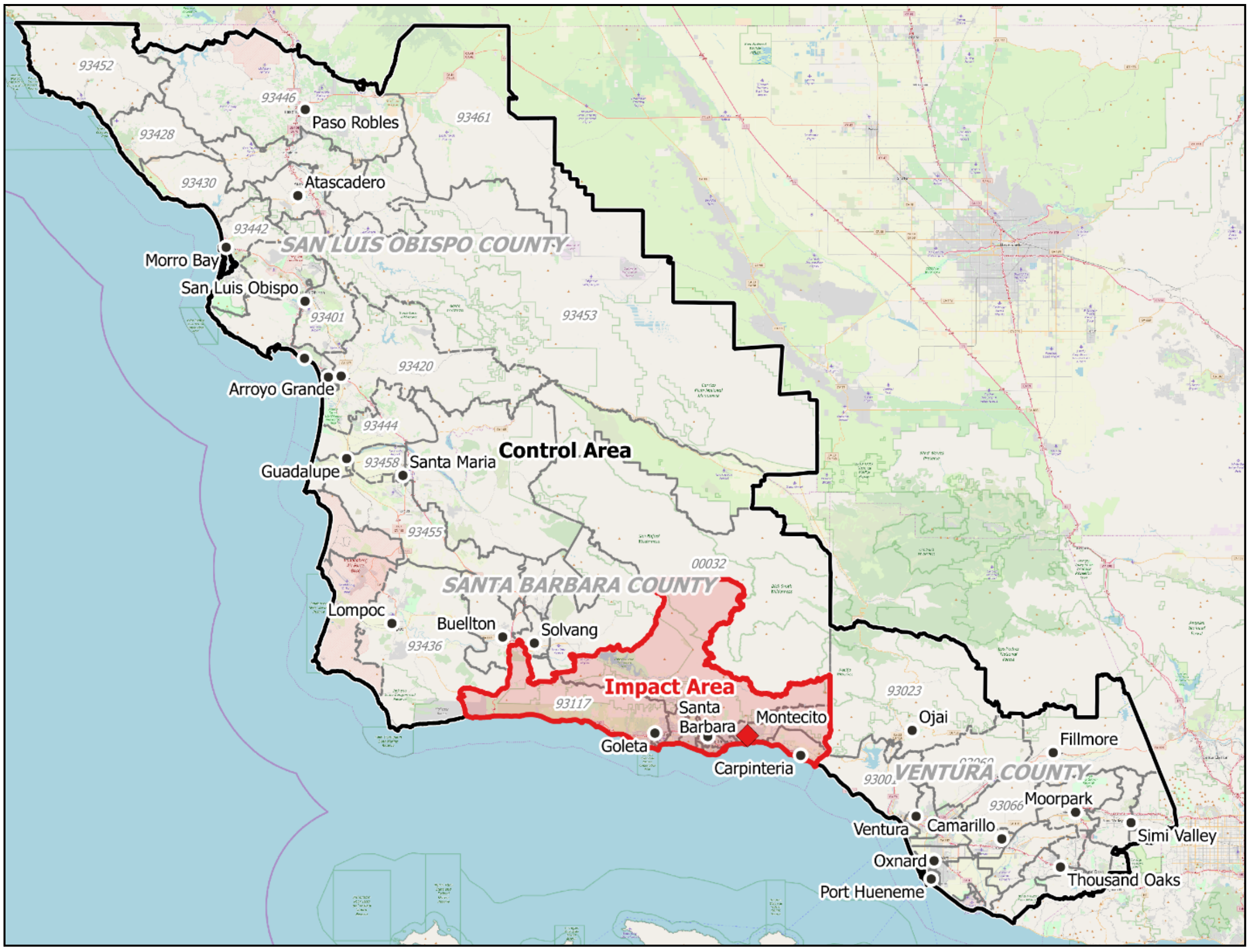
The debris flow that occurred in Montecito, California on 9 January 2018 resulted in a tragic loss of life and intense localized destruction of property. The purpose of this report is to assess the debris flow's effects, if any, on the local area's rental housing prices.

Approximately 7,000 people were placed under mandatory evacuation orders in anticipation of the debris flow, which damaged or destroyed approximately 400 homes (Molina, 2019). Hundreds more were rendered unreachable due to subsequent road closures. Displaced households were forced to find alternative housing. While some residents were able to secure temporary lodging through friends, hotels, shelters, Airbnb, etc., others required more long-term (one month or more) solutions. Displaced renters most likely re-entered the local rental market. We also expect that some displaced homeowners secured long-term rentals while they searched for new homes or repaired/rebuilt their existing homes, a process that may last anywhere from a few months to a couple of years, if not longer. There was also likely an influx of construction workers and emergency management personnel to help with the debris cleanup and subsequent recovery. We hypothesize that these increases in rental demand, combined with the decrease in housing supply, put upward pressure on local long-term rents in the form of a "disaster premium."

The central challenge in testing our hypothesis is that we do not have a counterfactual case for the rental market had the debris flow not occurred. To overcome this obstacle, we employ a "difference-in-difference" (DID) estimation strategy, in which rents in the area that was affected by the debris flow, i.e. the "Impact Area," are compared to rents in a similar area that was not affected by the debris flow, i.e. the "Control Area." Considering the debris flow likely had spillover effects on rental markets in neighboring cities, we define the Impact Area as the ZIP Codes containing Montecito, Santa Barbara, Goleta, Summerland, and Carpinteria, which are all within an approximately 20-minute commute of Montecito. We define the Control Area as all the remaining ZIP Codes in the broader Central Coast region of San Luis Obispo, Santa Barbara, and Ventura Counties.

Figure 1 maps the Impact and Control Areas for reference. Table 4, located in the Appendix, displays a list of the cities and ZIP Codes in the Impact and Control Areas that were included in the analysis. Further discussion regarding the study's methodology and assumptions is included in Section 4.

Figure 1. Map of Impact and Control Areas



2. LITERATURE REVIEW

There is a line of literature that utilizes a DID estimation strategy to assess the effect of natural disasters on housing markets. However, most of these studies have focused on the effect of natural disasters on the sales market. Kiel & Matheson (2018) implement a DID strategy to estimate the effect of a large wildfire in Colorado on home prices. The authors estimate that home prices fell 21.9 percent because of the wildfire, attributing this reduction to updated perceptions of risk. Additionally, Hallstrom & Smith (2004) implement a DID strategy to estimate the effect of 1992's Hurricane Andrew on housing prices in Florida. The authors estimate that sales prices in Lee County, FL fell 19.4 percent following Hurricane Andrew if they were in an area with a one percent or greater annual flood risk.

Atreya et al. (2013) consider the temporal effects of natural disasters on housing prices. Consistent with previous studies, the authors find that, following a flood event, the prices of homes in flood plains decline relative to the price of homes outside the flood plains. But the authors also find that these price decreases are temporary, lasting from four to nine years after a significant flood event.

While most work in the literature addresses only the effects of natural disasters on the sales market, Bouston et al. (2017) addresses both the sales and rental markets. The authors examine a 90-year panel data set at the county level that includes analysis of different types of natural disasters. Their study finds significant impacts on both the sales and rental markets following the most severe natural disasters. Specifically, the authors found that natural disasters which resulted in the deaths of 100 or more people are associated with a 3 percent reduction in local rents over the next decade due to increases in out-migration. The authors do not detect a significant effect on rents following less severe disasters.

Barring Bouston et al. (2017), the topic of the effect of natural disasters on rents is largely unexplored, especially over the short-term. Even though Bouston et al. (2017) explore the effect of natural disasters on rents, their temporal unit of analysis is too long to detect short-term effects. To the best of our knowledge, our study is the first to use a DID framework to examine the effects of a natural disaster over the months immediately following a disaster.

3. DATA

Robert D. Niehaus, Inc. (RDN) has access to a proprietary database containing approximately 70 percent of all online rental listings advertised in the United States between 28 December 2015 and 23 September 2018. (The data vendor discontinued its rental database product in October 2018.) For each rental listing, the database includes variables for the week observed, the location, monthly rent, number of bedrooms, square footage, and other characteristics. This detailed dataset allows us to explore the effects of the Montecito debris flow at various segments of the rental market as well as examine how the effect changes over time.

We begin by extracting all rental listings observed in San Luis Obispo, Santa Barbara, and Ventura counties. This raw dataset includes 319,779 unique observations. However, many observations are out of scope for what is commonly considered the market rate, long-term rental market in which most renter households compete. These observations include rentals that are furnished, age-restricted (i.e. student housing or 55+ communities), income-restricted (i.e. Section 8 or low-income housing), shared housing (i.e. room in a house), or intended for short-term use. RDN has developed an algorithm to filter out such listings. Applying this algorithm to the raw dataset leaves 317,544 observations. Next, we remove any observations missing values for key parameters, such as number of bedrooms, number of bathrooms, housing type, and square footage. Lastly, to account for data entry errors, we only include observations with one or more bathrooms, where the area is between 100 and 10,000 square feet, and where the monthly rent is between \$500 and \$15,000. The final dataset includes 190,877 observations, including 20,073 observations in the Impact Area and 170,804 observations in the Control Area. Table 4, located in the Appendix, breaks out the final number of observations by city/town and ZIP Code.

We generate three indicator variables for the DID analysis. The first indicator variable is $ImpactArea$, which equals one for observations located in the Impact Area and zero for observations located in the Control Area (see Figure 1). The indicator variable $DebrisFlow$ equals one for listings observed after the debris flow on 9 January 2018, and zero for all observations observed before the debris flow. The interaction between these two variables, $ImpactArea * DebrisFlow$, equals one if the rental is in the Impact Area and observed after the debris flow, and zero in all other cases.

Table 1 displays descriptive statistics for the final dataset, broken down by Area.

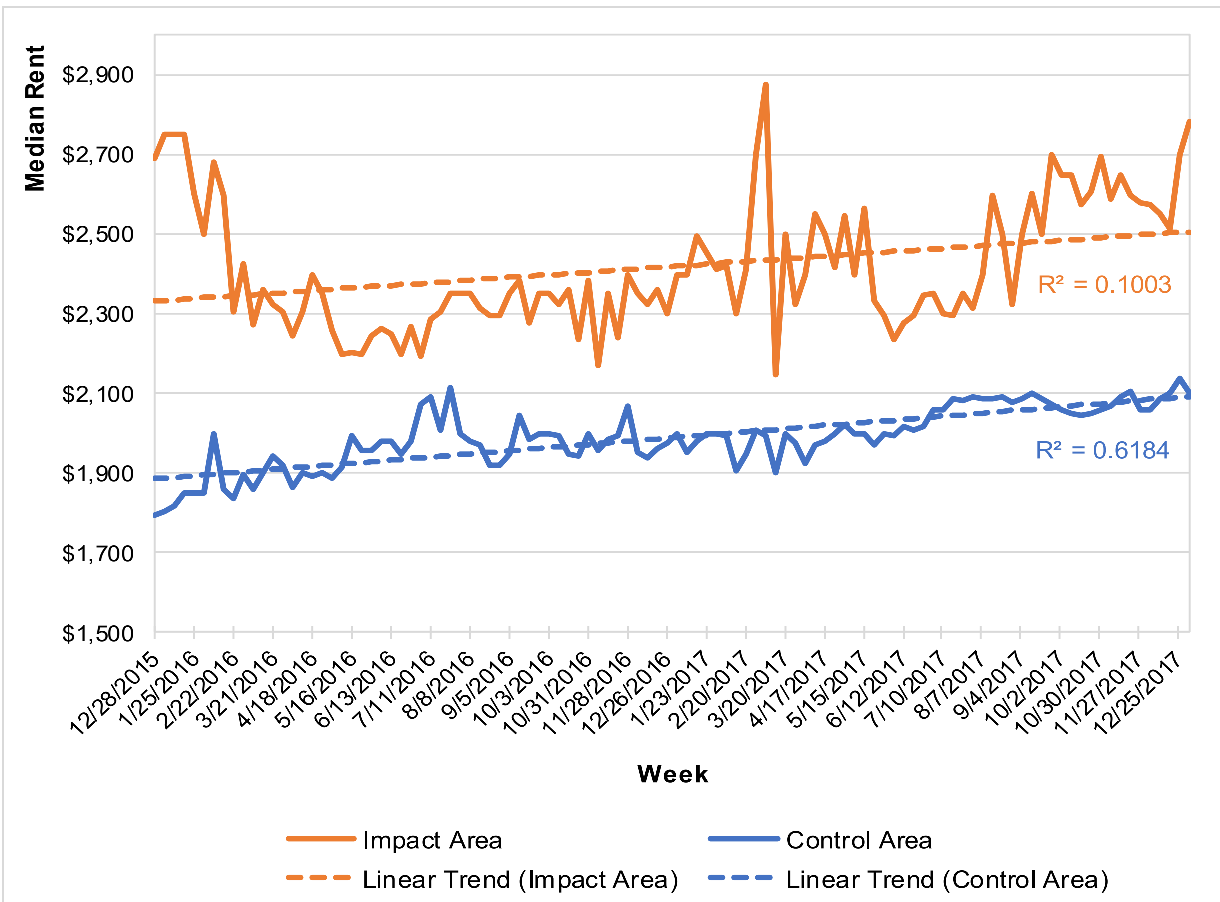
Table 1. Descriptive Statistics

Three-County Region (n= 190,877)					
Statistic	Mean	St. Dev.	Min	Median	Max
Rent	$2,225.99	$911.06	$500.00	$2,060.00	$14,995.00
ln(Rent)	7.64	0.35	6.22	7.63	9.62
Rent/Bedrooms	$1,170.70	$444.60	$149.00	$1,066.70	$7,500.00
ln(Rent)/Bedrooms	7.00	0.37	5.00	6.97	8.92
Rent/SquareFeet	$2.07	$0.68	$0.16	$2.02	$38.76
Bedrooms	2.10	0.89	1	2	8
Bathrooms	1.69	0.69	1	2	6
SquareFeet	1,153.04	574.84	100	1,015	9,600
ImpactArea	0.11	0.31	0	0	1
DebrisFlow	0.22	0.42	0	0	1
ImpactArea*DebrisFlow	0.02	0.15	0	0	1
Impact Area (n = 20,073)					
Statistic	Mean	St. Dev.	Min	Median	Max
Rent	$2,751.94	$1,454.60	$600.00	$2,494.00	$14,950.00
ln(Rent)	7.81	0.47	6.40	7.82	9.61
Rent/Bedrooms	$1,505.47	$557.84	$250.00	$1,465.00	$7,500.00
ln(Rent)/Bedrooms	7.24	0.42	5.52	7.29	8.92
Rent/SquareFeet	$2.85	$1.05	$0.30	$2.76	$25.00
Bedrooms	1.95	0.85	1	2	8
Bathrooms	1.53	0.66	1	1	6
SquareFeet	1,027.79	593.54	100	895	6,615
ImpactArea	1	0	1	1	1
DebrisFlow	0.21	0.40	0	0	1
ImpactArea*DebrisFlow	0.21	0.40	0	0	1
Control Area (n = 170,804)					
Statistic	Mean	St. Dev.	Min	Median	Max
Rent	$2,164.17	$801.62	$500.00	$2,025.00	$14,995.00
ln(Rent)	7.63	0.32	6.22	7.61	9.62
Rent/Bedrooms	$1,131.36	$411.85	$149.00	$1,031.60	$4,167.00
ln(Rent)/Bedrooms	6.97	0.35	5.00	6.94	8.34
Rent/SquareFeet	$1.98	$0.56	$0.16	$1.98	$38.76
Bedrooms	2.11	0.89	1	2	6
Bathrooms	1.71	0.69	1	2	6
SquareFeet	1,167.76	570.80	100	1,025	9,600
ImpactArea	0	0	0	0	0
DebrisFlow	0.23	0.42	0	0	1
ImpactArea*DebrisFlow	0	0	0	0	0

4. ASSUMPTIONS

A critical assumption of the DID analysis is that the trends in the variable of interest (monthly rent) must be similar between the Impact Area and Control Area prior to the debris flow. The first step in validating this assumption is a visual inspection of the two series. Figure 2 displays median weekly rent for two years prior to the debris flow. The solid orange line marks the median rent for the Impact Area and the solid blue line marks the median rent for the Control Area.

Figure 2. Weekly Median Rent Trends Prior to Debris Flow, by Area



Median rents each week are subject to a high degree of variability in both the Impact Area and Control Area. This variability is particularly pronounced in the Impact Area, which has fewer observations each week. To identify their underlying trends, we use the simple linear regression for both series, also shown in Figure 2. The trend lines appear similar, showing average increases of approximately $8.46 per month in the Impact Area and $7.13 per month in the Control Area. To corroborate our conclusion, we also evaluate a t-test for the equality of the slopes of the trend lines. The result confirms that there is no statistically significant difference between their slopes ($t(208)=0.610$; $p=0.544$). Having satisfied the assumption that the rent trends in the Impact Area and Control Area are reasonably similar prior to the debris flow, we proceed to construct an econometric model that isolates the change in rent in each area after the debris flow while controlling for potentially confounding variables.

5. ECONOMETRIC MODEL

To estimate the effect of the debris flow, we construct the following econometric model where each observation *i* is a rental listing:

$$Rent_i = \beta_0 + \beta_1 ImpactArea_i + \beta_2 DebrisFlow_i + \delta[ImpactArea_i * DebrisFlow_i] + \sum_1^c \alpha_{c,i} C_{c,i} + \sum_2^w \mu_{w,i} W_{w,i} + \sum_2^z \gamma_{z,i} Z_{z,i} + \epsilon_i$$

Where:

- $Rent$ is the nominal monthly rent in dollars
- $ImpactArea$ is an indicator variable that equals one if the observation is in the Impact Area and zero if it is in the Control Area. The corresponding coefficient β_1 captures the effect of an observation being in the Impact Area. We expect this coefficient to be positive because rents tend to be higher in the Impact Area than the Control Area, as demonstrated in the descriptive statistics.
- $DebrisFlow$ is an indicator variable that equals one if the observation is from after the debris flow and zero if it is from before the debris flow. The corresponding coefficient β_2 captures the effect of a rental listing being observed after the debris flow.
- $ImpactArea * DebrisFlow$ is the interaction between $ImpactArea$ and $DebrisFlow$, and equals one if the observation is in the Impact Area after the debris flow and zero in all other cases. The corresponding coefficient δ is the coefficient of interest for the DID analysis because it captures the isolated effect of the debris flow in the Impact Area. The DID coefficient δ is equivalent to the disaster premium. It is our hypothesis that δ will be positive and statistically significant.
- $C_1 \ldots C_c$ is a vector of control variables for the physical characteristics of the rental, with corresponding coefficients $\alpha_1 \ldots \alpha_c$. These variables include number of bedrooms, number of bathrooms, square footage, and indicator variables for housing type (excludes base case of apartments).
- $W_2 \ldots W_w$ is a vector of indicator variables for each week w (excludes base case W_1), with corresponding coefficients $\mu_1 \ldots \mu_w$. These indicators are included to control for the inflationary trend in rent over time.
- $Z_2 \ldots Z_z$ is a vector of indicator variables for each ZIP code (excludes base case Z_1), with corresponding coefficients $\gamma_2 \ldots \gamma_z$. The comparison between the Impact and Control Areas relies on the assumption that macroeconomic indicators do not differ between them, such as inflation, population growth, and the unemployment rate, as well as local housing regulations. Indicator variables for each ZIP code mitigate the confounding effect of such differences by controlling for time-invariant heterogeneity among geographic areas.
- $\beta_0$is a constant term and ϵ is an error term

6. RESULTS

Table 2 presents the results from the ordinary least squares (OLS) regressions. Control variables have been added one at a time in columns (1) - (4). Column (5) is the same model as column (4) except we use the log transformation of *Rent* and *SquareFeet*. The log transformation of the dependent variable permits interpretation of the coefficients as approximately percentage changes in rent given a one-unit change in the corresponding independent variables.

The DID coefficients for the interaction term $ImpactArea * DebrisFlow$ are equivalent to the disaster premium. They are positive and statistically significant in all model specifications. This provides support for the hypothesis that the debris flow caused rents to increase in the Impact Area. The coefficients in columns (1) – (4) may be interpreted as the average dollar change in rent attributable to the debris flow, holding all other variables in the model constant.

Under the full specification in column (4), the debris flow raised rents by an average of $235.70, which represents a 10.6 percent increase relative to the nominal rent predicted at the means of the independent variables. In the log specification in column (5), the DID coefficient implies that rents in the Impact Area in the nine months following the debris flow were on average approximately 7.6 percent higher than they would have been had the debris flow not occurred.

It is important to consider that the impact of the debris flow may not have been felt equally by all segments of the rental market. Using the same nominal and log model specifications (columns (4) and (5) in Table 2), we run quantile regressions to examine the disaster premium at different points in the distribution of monthly rent and the natural log of rent, respectively. Unlike OLS regression, in which coefficients represent the marginal effect of a one-unit shift in the independent variable at the conditional mean of the dependent variable, a quantile regression's coefficients represent the effect at a conditional quantile of the dependent variable, such as the median (50^{th} percentile).

Table 3 displays the results of quantile regressions at the 25th, 50th, and 75th percentiles of the nominal rent specification (columns (1)-(3)) and log-transformed rent specification (columns (4)-(6)). For both the nominal and log-transformed specifications, we control for time periods grouped by month instead of by week and for geography grouped by City/Town instead of by ZIP Code. These changes reduce the number of independent variables in the model and thus the inherent computational complexity of the quantile regression. (The quantile regression model does not converge when using the week and ZIP code controls used in the OLS model.) We argue that this should not significantly bias the results because the coefficients from the main OLS regressions with and without the controls for week and ZIP (columns (2) and (4) in Table 2) are reasonably similar for the DID coefficient.

The results of the quantile regressions suggest that the debris flow had a stronger positive effect on rents in the Impact Area for rentals priced above the median. The coefficient of interest for the interaction term $ImpactArea * DebrisFlow$ is positive and significant at the 50th and 75th percentiles in both the nominal rent and natural log of rent specifications. The natural log specification of the model implies that median rent rose 5.6 percent in the nine months following the debris flow whereas the rent at the upper quartile (75^{th} percentile) rose 8.1 percent. In contrast, rent at the lower quartile (25^{th} percentile) only rose 3.3 percent.

Table 2. OLS Regression Results

Variable	(1) Rent	(2) Rent	(3) Rent	(4) Rent	(5) ln(Rent)
ImpactArea	716.8***	715.2***	716.7***	191.4***	0.00514
	(7.730)	(7.676)	(7.675)	(49.56)	(0.0231)
DebrisFlow	145.7***	135.9***	303.2***	222.9***	0.109***
	(2.960)	(2.960)	(22.35)	(20.43)	(0.00821)
ImpactArea*DebrisFlow	260.1***	261.6***	266.3***	235.7***	0.0762***
	(19.32)	(19.17)	(19.13)	(18.23)	(0.00498)
Bedrooms	1.908	6.914	9.118	67.29***	0.0308***
	(5.672)	(5.504)	(5.499)	(5.151)	(0.00140)
Bathrooms	287.9***	292.6***	289.6***	229.6***	0.0857***
	(6.760)	(6.967)	(6.933)	(6.236)	(0.00148)
SquareFeet	0.913***	0.910***	0.909***	0.830***	
	(0.0174)	(0.0175)	(0.0175)	(0.0163)	
ln(SquareFeet)					0.424***
					(0.00458)
Constant	568.1***	571.1***	487.1***	827.0***	4.537***
	(5.277)	(5.390)	(12.79)	(15.16)	(0.0289)
Other Indicator Variables					
Housing Type	NO	YES	YES	YES	YES
Time (Week)	NO	NO	YES	YES	YES
Geography (ZIP Code)	NO	NO	NO	YES	YES
Observations	190,877	190,877	190,877	190,877	190,877

Note: Robust standard errors in parentheses. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Quantile Regression Results

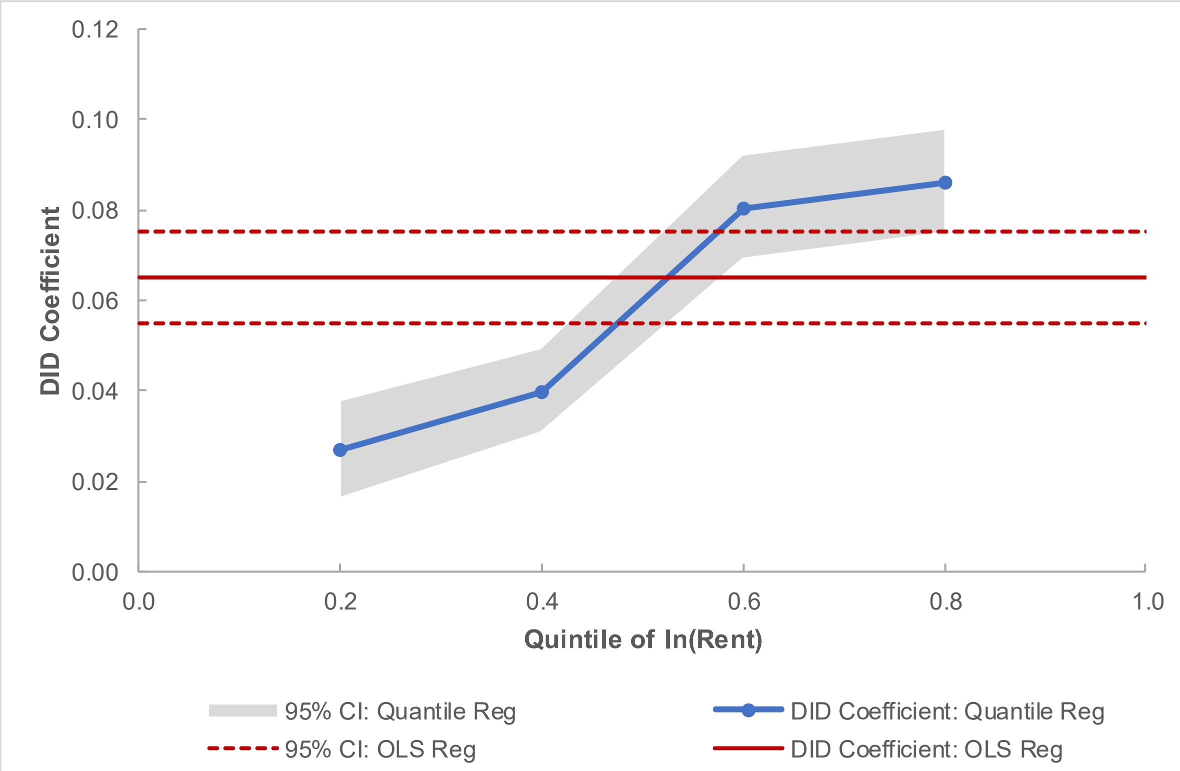
Variable	(1) Rent	(2) Rent	(3) Rent	(4) ln(Rent)	(5) ln(Rent)	(6) ln(Rent)
ImpactArea	999.9***	901.3***	1111.3***	0.444***	0.408***	0.561***
	(14.54)	(7.825)	(19.95)	(0.00540)	(0.00146)	(0.0158)
DebrisFlow	110.1***	113.0***	113.0***	0.0551***	0.0539***	0.0537***
	(1.802)	(1.741)	(2.350)	(0.000991)	(0.000862)	(0.00102)
ImpactArea*DebrisFlow	24.04*	193.6***	369.8***	0.0326***	0.0556***	0.0812***
	(10.49)	(22.98)	(22.28)	(0.00294)	(0.00544)	(0.00709)
Bedrooms	82.76***	65.24***	26.32***	0.0255***	0.0161***	0.0101***
	(1.815)	(1.703)	(1.704)	(0.000794)	(0.000738)	(0.000837)
Bathrooms	153.4***	153.2***	137.4***	0.0646***	0.0677***	0.0577***
	(2.137)	(1.990)	(2.064)	(0.000924)	(0.000868)	(0.000971)
SquareFeet	0.652***	0.813***	1.058***			
	(0.00443)	(0.00443)	(0.00554)			
ln(SquareFeet)				0.449***	0.468***	0.507***
				(0.00186)	(0.00173)	(0.00207)
Constant	566.8***	553.6***	507.2***	4.152***	4.086***	3.897***
	(13.77)	(6.448)	(8.853)	(0.0126)	(0.0104)	(0.0137)
Other Indicator Variables						
Housing Type	YES	YES	YES	YES	YES	YES
Time (Month)	YES	YES	YES	YES	YES	YES
Geography (City/Town)	YES	YES	YES	YES	YES	YES
Percentile	25th	50th	75th	25th	50th	75th
Observations	190,877	190,877	190,877	190,877	190,877	190,877

Note: Robust standard errors in parentheses. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3 charts the DID coefficient (blue line) and 95 percent confidence interval (gray bands) for each quintile of the distribution of the natural log of rent. The results are based on the quantile regression model with the log transformation of the dependent variable *Rent* and the independent variable *SquareFeet*. For comparison, the red solid and dotted lines reflect the point estimate and 95 percent confidence interval for the debris flow's average effect on nominal rents as estimated in the OLS model. The DID coefficients from the quantile regressions are smaller at quintiles below the median as compared to those above the median.

Incomes and housing expenditures tend to be higher in Montecito than those of neighboring cities/towns. According to the U.S. Bureau of the Census's American Community Survey, the median household income in Montecito over the 2013-2017 period was $146,250 (2017 constant dollars). The median household income for Santa Barbara, the next most affluent community in the Impact Area, was $87,068 over the same period. Because those with higher incomes tend to spend more on housing, the Montecito households that were displaced by the debris flow may have disproportionately increased the demand for high-priced rentals (as compared to lower-priced rentals). This dynamic may explain the debris flow's asymmetric effects on the rent distribution in the Impact Area.

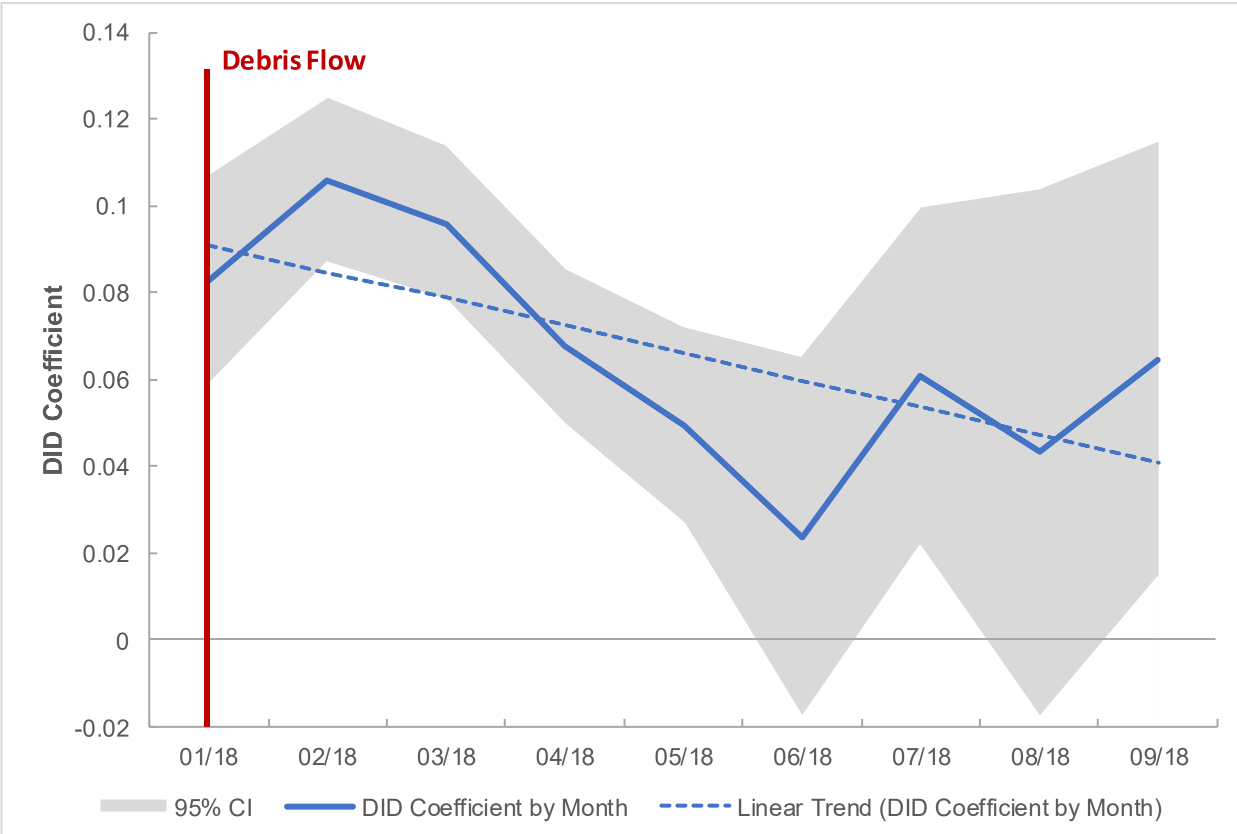
Figure 3. Difference-in-Difference Coefficients by Quintile of Nominal Rent



In addition to having asymmetric distributional effects on local rents, the debris flow may also have different impacts over time. Previous studies of natural disasters' impacts on housing markets generally find that deviations in sales prices are temporary (see Section 2). We explore the temporal effect of the debris flow on rents in Figure 4. In this figure, we have run the main regression with all controls from column (5) of Table 2 with one change: we interact the month and DID indicators such that there is a separate DID variable for each month following the debris flow. Figure 4 plots these coefficients and the 95 percent confidence interval for each of the nine months post-debris flow for which we have data. In the first three months following the debris flow, the disaster premium ranges from 8.3 percent to 10.6 percent. However, the effect diminishes over the next few months and is not significantly different from zero in June 2018. The point estimate of the DID coefficient averages 5.6 percent between July and September 2018, but the confidence intervals are also wider than preceding periods.

The trend line in Figure 4 shows that the debris flow's impact on rents is decreasing over time. Extrapolating this trend forward, we expect the disaster premium to reach zero by March 2019. These results suggest that anyone displaced by a natural disaster or moving to/around an area recently afflicted by a natural disaster would be better off avoiding signing a long-term lease in the first few months following the disaster. All else equal, households that signed a long-term lease in the first three months following the debris flow paid 4.1 percent higher rent on average than households that signed a long-term lease over the next six months. This difference could accrue to hundreds or thousands of dollars over the course of a long-term lease agreement.

Figure 4. Difference-in-Difference Coefficients Over Time



7. CONCLUSION

In this study we have attempted to make a causal claim about the effect of the Montecito debris flow on the local area's long-term rental market. We estimate that the debris flow caused rents in the Impact Area to increase by an average of 7.6 percent in the nine months following the debris flow. We also find that the debris flow disproportionately raised rents for higher-cost rentals as compared to lower-cost rentals.

Finally, we explored the change in the debris flow's impact on rents over time. We find that the debris flow's effect on rents in the Impact Area was largest in the first three months after the debris flow and is trending downwards over time. If the trend continues, we project that the disaster premium will fully disappear by March 2019.

8. REFERENCES

Atreya, A., Ferreira, S., & Kriesel, W. (2013) "Forgetting the Flood?: An Analysis of the Flood Risk Discount Over Time." Land Economics (89-4: 577-596).

Boustan, L., Kahn, M., Rhode, P., & Yanguas, M. (2017). "The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data." National Bureau of Economic Research Working Paper 23410.

Hallstrom, D. & Smith, V. (2004) "Market Responses to Hurricanes." Journal of Environmental Economics and Management (50-3: 541-561).

Kiel, K. & Matheson, V. (2018) "The Effect of Natural Disasters on Housing Prices: An Examination of the Fourmile Canyon Fire" Journal of Forest Economics (33: 1-7).

Molina, J. (2019, January 9). A year ago, debris flows brought 'unfathomable destruction' to Montecito. The San Luis Obispo Tribune. Retrieved March 11, 2019, from https://www.sanluisobispo.com/news/local/article224213780.html.

9. APPENDIX

Table 4. Number of Observations by County, City/Town, and ZIP Code

County	City/Town	Zip Code	Observations
San Luis Obispo	Arroyo Grande	93420	590
San Luis Obispo	Atascadero	93422	1,174
San Luis Obispo	Avila Beach	93424	48
San Luis Obispo	Cambria	93428	175
San Luis Obispo	Cayucos	93430	302
San Luis Obispo	Creston	93432	10
San Luis Obispo	Grover Beach	93433	573
San Luis Obispo	Los Osos	93402	423
San Luis Obispo	Morro Bay	93442	919
San Luis Obispo	Nipomo	93444	413
San Luis Obispo	Oceano	93445	173
San Luis Obispo	Paso Robles	93446	1,278
San Luis Obispo	Pismo Beach	93449	542
San Luis Obispo	San Luis Obispo	93401	2,578
San Luis Obispo	San Luis Obispo	93405	1,192
San Luis Obispo	San Miguel	93451	195
San Luis Obispo	Santa Margarita	93453	58
San Luis Obispo	Templeton	93465	153
Santa Barbara	Buellton	93427	353
Santa Barbara	Carpinteria*	93013	1,075
Santa Barbara	Goleta*	93117	6,958
Santa Barbara	Goleta*	93116	60

County	City/Town	Zip Code	Observations
Santa Barbara	Goleta*	93111	24
Santa Barbara	Guadalupe	93434	308
Santa Barbara	Isla Vista	93117	16
Santa Barbara	Lompoc	93436	5,565
Santa Barbara	Lompoc	93437	17
Santa Barbara	Los Alamos	93440	38
Santa Barbara	Los Olivos	93441	12
Santa Barbara	Montecito*	93108	25
Santa Barbara	Orcutt	93455	11
Santa Barbara	Santa Barbara*	93110	1,664
Santa Barbara	Santa Barbara*	93105	2,396
Santa Barbara	Santa Barbara*	93109	1,001
Santa Barbara	Santa Barbara*	93101	3,239
Santa Barbara	Santa Barbara*	93111	1,275
Santa Barbara	Santa Barbara*	93103	1,155
Santa Barbara	Santa Barbara*	93108	865
Santa Barbara	Santa Barbara*	93107	61
Santa Barbara	Santa Maria	93455	4,103
Santa Barbara	Santa Maria	93454	2,151
Santa Barbara	Santa Maria	93458	3,515
Santa Barbara	Santa Ynez	93460	91
Santa Barbara	Solvang	93463	453
Santa Barbara	Summerland*	93067	261
Ventura	Camarillo	93010	11,935
Ventura	Camarillo	93012	7,536
Ventura	Fillmore	93015	173
Ventura	Moorpark	93021	2,990
Ventura	Newbury Park	91320	7,308
Ventura	Oak Park	91377	7,210
Ventura	Oak View	93022	88
Ventura	Ojai	93023	1,206
Ventura	Oxnard	93036	12,550
Ventura	Oxnard	93035	8,649
Ventura	Oxnard	93030	6,157
Ventura	Oxnard	93033	3,638
Ventura	Piru	93040	20
Ventura	Port Hueneme	93041	3,708
Ventura	Santa Paula	93060	701
Ventura	Simi Valley	93065	10,272
Ventura	Simi Valley	93063	5,816

County	City/Town	Zip Code	Observations
Ventura	Somis	93066	134
Ventura	Thousand Oaks	91360	9,437
Ventura	Thousand Oaks	91320	2,038
Ventura	Thousand Oaks	91362	9,721
Ventura	Thousand Oaks	91361	164
Ventura	Thousand Oaks	91319	13
Ventura	Ventura	93004	7,322
Ventura	Ventura	93003	10,795
Ventura	Ventura	93001	4,308
Ventura	Westlake Village	91361	9,384
Ventura	Westlake Village	91362	79

Note: *Indicates observations located in Impact Area. All other observations are in Control Area. Table suppresses ZIP Codes with ten or fewer observations.