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Earthquakes and Price Discovery in the Housing Market: Evidence from New Zealand

Michael LaCour-Little*
Ph.D., Professor of Finance. California State University - Fullerton, 5113 Mihaylo Hall, Fullerton, CA 92834-6848. Email: mlacour-little@fullerton.edu

Arsenio Staer
Ph.D., Assistant Professor of Finance. California State University – Fullerton 5159 Mihaylo Hall, Fullerton, CA 92834-6848. Email: astaer@fullerton.edu.

This paper uses hedonic regression to examine prices in the Christchurch housing market before, and after, the recent severe earthquakes. Prices were relatively stable prior to the earthquakes but increased rapidly thereafter, consistent with the contraction of supply and increased demand from displaced households and a net influx of workers involved in the rebuilding effort. In addition, we find that the use of auctions increased after the earthquakes and that auctioned properties command significantly higher prices as compared to other sales methods, helping to explain the increased interest in this form of price discovery. Results are robust after correcting for potential sample selection bias.

Keywords

Housing Prices, Earthquakes, Auctions, Hedonic Regression

* Corresponding author

1. Introduction

Christchurch, the second largest city in New Zealand, was rocked by major earthquakes during 2010 and 2011, resulting in significant loss of both residential and commercial buildings. By some estimates, approximately 70% of the downtown central business district (CBD) was, or will have to be, demolished. Tragically, there were 185 fatalities during the 2011 quake which occurred mid-day during the work week. Moreover, approximately 8,000 residences in the city and nearby suburbs were rendered uninhabitable. In this paper, we examine the effect of these devastating natural disasters on the local housing market. In the process, we extend and update earlier work on residential property auctions in New Zealand by Dotzour, Moorhead, and Winkler (1998). Briefly, we find that house prices were relatively stable prior to the earthquakes, increased sharply following the earthquakes, and that the use of auctions to sell properties increased significantly too.

Studying the Christchurch housing market under such conditions can lead to a number of insights. First, we can see how prices respond to an entirely exogenous shock. Second, we can see how sellers and agents adapt their marketing approach to newly changed circumstances. Third, we can assess whether there are changes among the factors, or the weighting of the factors, that affect house values. Finally, we can gauge whether the findings of Dotzour, Moorhead, and Winkler (1998) persist.

The plan for the balance of the paper is as follows. In the next section, we provide more detail on the earthquakes and their effect on the city and its environs. In the third section, we provide an overview of the New Zealand housing market with a focus on Christchurch. The fourth section reviews the relevant literature on both the effect of natural disasters on housing prices and the use of auctions to sell residential properties. In the fifth section, we describe the data used for the analysis presented. In the sixth section, we sketch out the modeling method, and present and discuss the empirical results. The final section offers conclusions and extensions.

2. Christchurch and the Christchurch Earthquakes

Christchurch is the second most populous city in New Zealand with a population of almost 400,000 in the city and immediate suburbs[1]. Unlike Auckland and Wellington, the two other major population centers in the country both of which are located on North Island, Christchurch is located on the Canterbury Plain of South Island, a large, relatively flat area on the eastern side

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[1] Statistics New Zealand (2012). Before the earthquakes, Christchurch had overtaken Wellington to become the second largest city in the country. http://www.stats.govt.nz/browse_for_stats/population/mythbusters/Chch-overtakes-wellington-population.aspx [accessed March 30, 2014].

of the Southern Alps. The latter extend as a ridge down through the South Island, dividing the less developed West Coast from the more developed East Coast communities. The Canterbury region is a highly productive agricultural region with goods shipped in and out through the Lyttelton Harbour, located about seven miles southeast of Christchurch. Christchurch functions as the primary commercial center for the entire South Island, which is generally less populated than the North Island. Christchurch stretches from the coast of the Pacific Ocean to about ten miles inland with many of its eastern suburbs built on relatively marshy land with a high water table, a geological fact that contributed to the concentration of the worst earthquake damage in those areas.

New Zealand has long been plagued by earthquakes and a particularly strong one measuring 7.1 on the Richter scale struck on September 4, 2010 (the first quake). The epicenter, however, was in a relatively rural area outside of Christchurch and that fact, together with its depth and time of day (4:30 a.m.) limited casualties and damage. Technically an aftershock of the larger quake, the second major earthquake, measuring 6.3 on the Richter scale, struck on February 22, 2011 (the second quake). Due its epicenter center, only slightly southeast of the CBD, its relatively shallow depth, and its timing (12:51 p.m. on a work day), the second quake produced damage labeled "destructive" by the Canterbury Earthquake Recovery Authority (CERA), the government agency charged with managing recovery and rebuilding efforts in the region[2]. The second quake was also rated VIII on the Mercalli scale[3] and its most dramatic effects occurred in older unreinforced masonry buildings in the CBD. In addition, the second quake caused liquefaction in many of the eastern suburbs, causing entire neighborhoods to be rendered uninhabitable. A number of smaller after-shocks followed.

3. The New Zealand and Christchurch Housing Markets

The homeownership rate in New Zealand is approximately 65%, comparable to that of the United States. Nationally, the median house price was $390,000 NZ$[4] as of April 2013, with higher prices in the major cities of Auckland, Wellington, and Christchurch (Real Estate Institute of New Zealand, 2013). Rental properties (flats) have prices quoted on a weekly basis which, for convenience and comparability to U.S. numbers, we have converted to monthly

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[2] See http://cera.govt.nz/recovery-strategy/overview/read-the-recovery-strategy for further information.

[3] A rating of VIII on the Mercalli scale is characterized by "damage slight in structures of good design, considerable in normal buildings with a possible partial collapse. Damage great in poorly built structures. Brick buildings easily receive moderate to extremely heavy damage. Possible fall of chimneys, factory stacks, columns, monuments, walls, etc. Heavy furniture moved". Source: U.S. Geological Survey www.earthquake.usgs.gov.

[4] The New Zealand dollar (NZ$) has traded at roughly US$0.80 - $0.85 during that period.

equivalents. As of April 2013, the median rent was NZ$1,473 per month. As might be expected, larger cities have higher median rents, including Auckland (NZ$1,820), Wellington (NZ$1,733), and Christchurch (NZ$ 1,538). As the data used in this study are limited to housing prices for properties selling during 2010-2012, the effect of the earthquakes on the Christchurch rental housing market is out of the scope of this paper. Massey University (2013) reports, however, that "As expected Christchurch led the annual rent increase (10.9%) for the period February 2012 to February 2013", corresponding to the one-year growth rate after the second quake.

4. Literature Review

Natural disasters, whether floods, hurricanes, tornados, or earthquakes, provide an exogenous shock to the stock of housing in affected areas and prices generally rise sharply afterwards. Moreover, properties located in hazard-prone areas appear to sell at a discount to otherwise similar properties in less risky locations and the discount associated with a particular risk often is found to increase following an event, as market participants are reminded of the natural hazards they face. A few examples from the literature are illustrative.

Vigdor (2008) reports that the median price of an owner-occupied house in the Orleans Parish increased by 59% as a result of the destruction caused by Hurricane Katrina. Moreover, the median rent rose from $566 to $838, a 48 percent increase in the same two-year time period. Bin and Polasky (2004) examine data from an area of North Carolina affected by Hurricane Floyd. Using hedonic regression, they find that houses located within a floodplain have lower market values than similar houses located outside the floodplain and that the magnitude of floodplain discount increased significantly after Hurricane Floyd. Speyrer and Ragas (1991) also examine the effect of floodplain location on house prices, confirming earlier results that such properties sell at lower prices, with the use of data from the New Orleans area. Naoi, Seko, and Sumita (2009) use nationwide data from Japan to analyze earthquake risk, its effect on house prices, and the magnitude of the earthquake risk discount before, and after, large earthquakes. They find a price discount associated with particularly earthquake prone areas and that the price discount from locating within a quake-prone area is significantly larger soon after earthquake events than previously.

The research on the effect of hazard related price discounts is not entirely consistent, however. For example, Beron et al. (1997) use data from California to examine the pricing of earthquake risk before and after the Loma Prieta earthquake[5]. They find that households over-estimated the risk of earthquake-related property damage prior to the earthquake and that the price discount

[5] The Loma Prieta earthquake, measuring 6.9 on the Richter scale, struck the San Francisco Bay Area in October 1989 causing a collapse of a portion of the San Francisco-Oakland Bay Bridge.

associated with such risks actually decreased following an event. One might characterize such effects as reflecting adaptive learning. Skantz and Strickland (1987), on the other hand, investigate a flood in Houston, Texas in 1979 and find that prices do not decline after the event, but the insurance premiums increase thereafter. It is worth noting that all of the literature mentioned above with the exception of Skantz and Strickland (1987) and Naoi, Seko, and Sumita (2009) limit the sample to the disaster area without using other geographical markets as controls.

Turning to methods of sale, a large literature has focused on auctions and bidding strategies, including sealed bidding, open outcry, and Dutch auctions. Reviews may be found in McAfee and McMillan (1987) and Milgrom (1989). Since our focus is on the empirical side, we will not review these studies here. As a broad characterization, auctions, rather than negotiated sales, tend to be used to sell distressed properties in the U.S. whereas a number of other countries use auctions more broadly, notably Australia and New Zealand. Exactly why these practices differ is unclear.

A number of empirical studies examine house prices when sold by auction often using data from countries outside the U.S. Corder and Reinold (2010) argue that properties sold in the auction market will tend to have lower reservation prices than properties sold otherwise, increasing the probability of a sale and reducing the effect of any inertia inhibiting the reduction of prices in a declining market. Using data from the U.K., Corder and Reinold (2010) find that auction use spiked during the 2008-2009 market downturn and price movements appear to lead other indices by about one quarter. In a study using methods similar to those employed here, Frino et al. (2010) examine the price effect of the auction sales method in five major Australian cities. Using hedonic regression, they find a price premium associated with auction sale across cities. Moreover, this price premium persists after controlling for sample selection bias associated with those properties selected for auction sale.

Ong, Lusht, and Mak (2005) examine the use of auctions using data from Singapore. They find that bidder turnout and market conditions, as well as the choice of auctioning agent, are all important factors in explaining successful auction sales, defined as sales that exceed the reservation price of the seller.

Mayer (1998) examines the use of auctions to sell real estate in the U.S., noting at the outset that auctions are typically used to liquidate distressed properties, rather than for "normal" transactions. Using data from Los Angeles during the 1990s market downturn and Dallas during the 1980s market downturn, he estimates repeat sales indices that houses sold at auction sold at discounts ranging from 0-20% compared to non-auction sales.

Other work related specifically to earthquakes in Wellington, New Zealand, include Clarke (1998) and Prentice (2005). Issues related to the highest and best use analysis performed by appraisers following a natural disaster are discussed in Epley (2010).

The paper most directly related to this work is Dotzour, Moorhead, and Winkler (1998). Like the present study, they use data from Christchurch, although the data employed were from the early 1990s, many years prior to the recent earthquakes, of course. They also use hedonic regression and report that auction sales produce a price premium after controlling for other factors[6], with the premium larger in high prestige neighborhoods than elsewhere. We build on this important early study in the work here and extend it by examining the effect of the Christchurch earthquakes. We hypothesize that auction usage will increase following the earthquakes as the market is rising rapidly, due to reduced supply, and it becomes difficult for agents and appraisers to gauge prices due to greater uncertainty in the market.

5. Data

Data on house sales during 2010-2012 were acquired from the commercial firm, PropertyIQ. The data vendor merges public record data on property sales and other property characteristics maintained by taxing authorities with realtor data to identify mode of sale. Sales between related parties and sales to the crown, i.e., the government, are excluded. While the data are reasonably comprehensive, including property age, size of building and lot, number of bedrooms, total square footage, and building condition (rated GOOD, AVERAGE, or POOR)[7], several variables often used in hedonic regression and related analyses were not available. These included number of bathrooms and listing details sufficient to determine time on market. On the other hand, we do have detailed locational information for each property, including the neighborhood or suburb in which it is located, a ranking of the neighborhood quality on a five point scale[8], and a three point scale rating by the CERA that specifies foundation techniques that must be used in any re-building given soil conditions.

[6] Due to data sources, their hedonic specification is slightly different from the one employed here.
[7] The building quality condition is assigned by the listing agent at his or her discretion. Although the exact criteria for the ranking are not disclosed, it is arguably better than no indication of the property quality condition at all.
[8] This ranking was kindly provided by emeritus faculty Everard Moorhead, one of the authors of the 1998 paper on New Zealand house prices previously cited. In addition to serving as Lecturer at Lincoln University, he was a professional appraiser in the Christchurch market for many years and these rankings represent his expert judgment.

Methods of sale include multiple categories, including negotiations based on an asking price, a stated minimum price, and an invitation to offer without any stated asking price. We group all of these into the negotiation category. Mortgagee auctions and mortgagee sales are combined into a distressed sale category and not included with the standard auctions analyzed. It is possible, of course, that some standard auctions are actually distressed sales by sellers but actual seller motivation is unobserved. If distressed sales tend to occur at discounts, any estimates of premiums identified would be biased downward were such sales included.

Descriptive statistics on the entire dataset appears in Panel A of Table 1. The mean house size is 1,577 square feet and the mean price sold per square foot is $250. For those properties where an asking price was set (about 70% of all observations), the mean asking price is $211,000. The mean sold price, net of any personal property is $379,000. This large difference reflects the fact that it is the higher-priced properties that tend to be marketed without a firm asking price stated. Properties average 3 bedrooms and are 40 years old at time of sale. About 72% of all properties are categorized as in good condition; another 27% are classified as average condition and only about 1% are categorized as poor condition. Over the entire three-year period studied, 11% of the properties are sold at auction and 89% are sold by negotiation. Less than 1% are distressed sales, including mortgagee auctions and post-auction (real estate owned or "REO") sales.

Table 1 Descriptive Statistics

This table shows the descriptive statistics for the variables in the sample. Mean and Std Dev are the means and standard deviations of the variables respectively. N denotes the number of observations. Panel A shows the statistics for the whole sample. Panel B shows the statistics for the 3 subperiods: PreQuake, Quake and PostQuake, as defined in Section 5.

Panel A Whole Sample

Variable	N	Mean	Std Dev
sqft	17,609	1,577	722
pricesqft	17,609	250	237
Land_Area	12,248	0.069	0.082
Asking Price	12,070	211,602	211,155
Sale Price Net	17,609	379,382	192,181
Bedrooms	17,558	3.047	0.801
age	17,609	40.5	27.3
GOOD	17,609	0.718	0.45
AVERAGE	17,609	0.265	0.441
POOR	17,609	0.011	0.102
AUCTION	17,609	0.111	0.314
FCLR	17,609	0.002	0.04
Negotiated	17,609	0.888	0.316

(Continued…)

(Table 1 Continued)

Panel B Subperiods

Variable	Period=1 (PreQuake)			Period=2 (Quake)			Period=3 (PostQuake)		
	N	Mean	Std Dev	N	Mean	Std Dev	N	Mean	Std Dev
sqft	4,461	1,553	689	6,607	1,600	699	6,541	1,570	764
pricesqft	4,461	241	64.5	6,607	243	63.4	6,541	263	380
Land_Area	4,461	0.072	0.151	4,619	0.067	0.034	4,516	0.067	0.034
Asking Price	4,461	232,340	201,413	4,550	218,559	211,434	4,576	191,344	215,264
Sale Price Net	4,461	360,434	177,216	6,607	379,659	203,530	6,541	392,026	189,139
Bedrooms	4,461	3.017	0.797	6,591	3.061	0.801	6,533	3.054	0.803
Age	4,461	41.1	27.2	6,607	38.5	27.2	6,541	42.1	27.3
GOOD	4,461	0.7	0.458	6,607	0.737	0.44	6,541	0.712	0.453
AVERAGE	4,461	0.277	0.448	6,607	0.247	0.432	6,541	0.274	0.446
POOR	4,461	0.011	0.105	6,607	0.01	0.099	6,541	0.011	0.102
AUCTION	4,461	0.085	0.278	6,607	0.119	0.324	6,541	0.12	0.325
FCLR	4,461	0.001	0.037	6,607	0.002	0.048	6,541	0.001	0.033
Negotiated	4,461	0.914	0.28	6,607	0.879	0.327	6,541	0.879	0.327

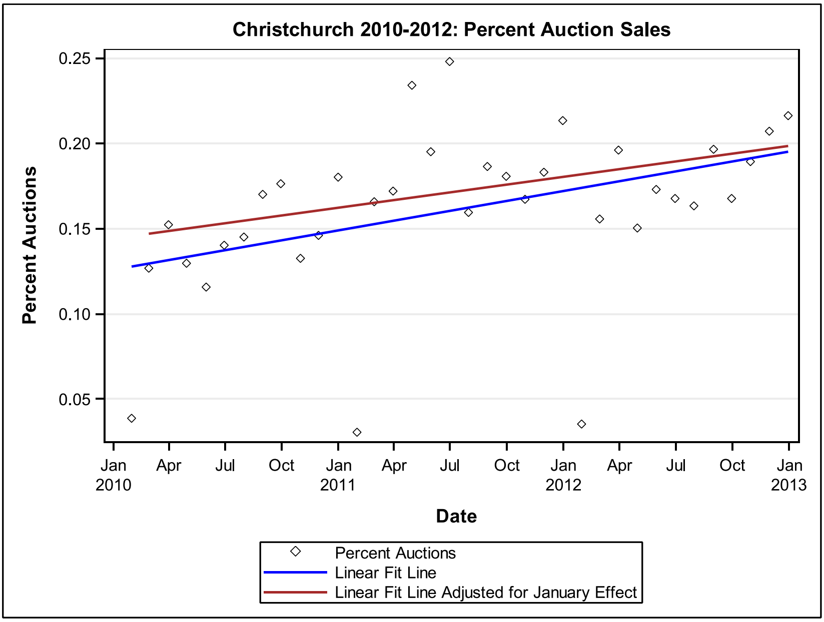
We divide the data into three time periods: the pre-quake period (the first eight months of 2010); the quake-period (September 4, 2010 to February 21, 2011 and the eleven months thereafter, ending in December 2011); and the post-quake period (thereafter, ending in December 2012). The choice of dates and, therefore, time periods is necessarily somewhat subjective but the choices made seemed reasonable and produced adequate size samples of relative sizes of 25%, 37%, and 37%[10]. In Panel B of Table 1, the means of the same variables discussed above are presented by period.

The mean values of most variables are not dramatically different by period. Price per square foot increased from $241 in the pre-quake period to $263 in the post-quake period. The percentage of properties sold via auction increased from 8.5% in the pre-quake period to 12% in the post-quake period. There is no noticeable difference in the distribution of quality rankings, suggesting that seriously damaged properties (which presumably would be rated as "poor" in condition) may have been withheld from the market during the quake and post-quake periods. It is also unclear from the data exactly when these quality rankings were assigned. In any event, as sales to the government resulting from settlement of earthquake insurance claims are excluded from the data set, this is a plausible pattern. As of 2014, a number of households with whom the author spoke were still waiting for insurance claims to be settled.

We calculate the percent auction of all transactions with known sales method monthly and graph the results in Figure 1. An upward trend seems evident with some spiking in the middle of the 36 month time period that would correspond to April-June of 2011, a few months following the second quake. Low values (less than 5% of all transactions) occur consistently during January of each year and we speculate that this is simply a seasonal phenomenon due to the Christmas holiday of the prior month. We fit the ordinary least square (OLS) regression of percent auction of all transactions on the time and draw two fit lines: the first corresponding to the OLS fit line for the whole sample and the second corresponding to the OLS fit line on the sample excluding January observations. Both fit lines exhibit statistically significant positive slopes which seems to confirm our hypothesis about the increased usage of auctions after the earthquakes.

[10] We initially started the post-quake period immediately following the second quake, producing approximately equal size samples by period. Overall results are qualitatively similar and accounting for some recovery period following the second quake and a series of smaller aftershocks seemed appropriate.

Figure 1 Auction Use over Time



Notes: The figure above shows the percentage of transactions with reported method of sale that were auctions over the sample period from January 2010 to December 2013. *Linear Fit Line* represents an OLS regression ($\beta = 0.000063$, $t - stat = 2.71$) of a monthly percentage of auctions on the *time* variable which is a month counter. *Linear Fit Line Adjusted for January Effect* represents an OLS regression ($\beta = 0.000049$, $t - stat = 3.41$) of a monthly percentage of auctions on the *time* variable excluding the January observations to account for the holidays effect.

6. Regression Analyses

6.1 Overview

We estimate simple hedonic regressions by period, including time to see how house price appreciation rates changed after the earthquakes occurred. The time variable is coded as $time = 1, 2, \ldots, 36$ starting on January 2010 and ending on December 2012. We choose this specification instead of monthly dummies because we are interested in the average estimate of the price appreciation trend in each period instead of the estimates of the individual monthly shocks to the price in each period. Sales method is then added to the specification to assess its effect on prices during each of the three time periods defined. We also include foreclosure auctions to investigate their effect on the auctioned property prices. Neighborhood quality is measured by prestige ratings described in Dotzour, Moorhead, and Winkler (1998). We adjust for heteroscedasticity by employing monthly clustered standard errors as in Petersen (2009).

6.2 The Effect of the Earthquakes on Prices

Panels A, B, and C of Table 2 present the simple regression results for the three periods. While the results are generally quite stable in terms of the signs and magnitudes of coefficients, some notable differences are apparent.

First, the coefficient on *time* switches from a small, and modestly significant, negative value in the pre-quake period to large, positive and highly significant values in the two following periods.

Second, the coefficient on property *age*, positive in the first two periods, switches to negative in the post-quake period. Normally, the *age* variable should be negative in a hedonic regression. Exceptions to this rule occur occasionally, however, when urban areas have older higher quality neighborhoods surrounded by lower-quality (but newer) suburbs. We speculate that the change in sign noted here reflects buyer awareness of the downsides to older construction following the earthquakes.

In Panel A of Table 5, we present the *p*-values of the Wald χ^2 tests of differences in the *time* and *age* coefficients across periods using pooled observations with neighborhood ranking from Table 2. The null hypothesis is specified as $H_0 : \beta_{i,period=j} - \beta_{i,period=k} = 0$ and the alternative as $H_a : \beta_{i,period=j} - \beta_{i,period=k} \neq 0$ for the *i*th coefficient estimate. The differences in the *age* and *time* coefficients across periods are significant with *p*-values below 0.05.

Third, the discount for a quality rating of "POOR" increases and the premium associated with a quality ranking of "GOOD" increases in the post-quake period, as measured by the size of the negative and positive coefficients, respectively. All of these results seem consistent with prices increasing sharply after the quakes and buyers becoming relatively more sensitive to property *age* and condition following the quakes. A counterfactual for this explanation would be that the increased price discount for "POOR" was caused by the change in the supply of the low quality properties after an earthquake; however, the relative proportion of the "POOR" and "GOOD" properties does not significantly change across periods as observed in Table 1. In unreported analysis, there are also no significant changes in the property characteristics such as square footage or age of the "GOOD" and "POOR" properties across periods which supports the hypothesis of the shift in the hedonic pricing of the property attributes and not the shift in the relative supply of properties *per se*.

Table 2 Sale Price without Controls for Sales Method

This table shows the estimates, standard errors and t-values of a regression of the price in logs on the set of regressors including the neighborhood prestige ranking control variables as described in Dotzour, Moorhead, and Winkler (1998). We adjust for heteroscedasticity by employing monthly clustered standard errors as in Petersen (2009).

Variable	Panel A: Period=1 (PreQuake)			Panel B: Period=2 (Quake)			Panel C: Period=3 (PostQuake)		
	Param	**SE**	**t Value**	**Param**	**SE**	**t Value**	**Param**	**SE**	**t Value**
Intercept	11.85	0.0233	509	11.79	0.026	455	11.85	0.0854	139
time	-0.0032	0.0019	-1.68	0.0028	0.0004	7.62	0.0075	0.0008	9.89
sqft	0.0004	0.0	53.68	0.0004	0.0	56.48	0.0002	0.0001	3.62
Land_Area	0.0036	0.0387	0.09	0.9164	0.1324	6.92	1.3944	0.5201	2.68
age	0.0009	0.0002	4.37	0.0004	0.0002	2.18	-0.001	0.0006	-1.59
GOOD	0.0389	0.0128	3.04	0.0339	0.0086	3.95	0.0544	0.0118	4.62
POOR	-0.0636	0.0551	-1.15	-0.0783	0.0311	-2.52	-0.1006	0.0329	-3.06
RANKING	0.0839	0.0024	34.27	0.0754	0.0032	23.65	0.1016	0.0092	11.04
Obs	3,113			4,619			4,516		
R^2	0.7358			0.7338			0.6086		

We also note the coefficients on land size substantially increase and are statistically significant during the quake and post-quake periods, whereas they are not significant in the pre-quake period. Model fit is reasonable given our limited set of covariates with adjusted R^2 values in the 0.60-0.80 range.

6.3 The Effect of Sales Method on Prices over the Three Periods

Next, we expand the simple specification to include mode of sale, including the two auction categories (a standard auction "AUCTION" versus a foreclosure auction "FCLR") with a hold-out category of negotiated sale. The results appear in Panels A, B, and C of Table 3. All of the results described in the previous paragraph continue to hold with the addition of sales method. Foreclosure is statistically significant in the quake and modestly significant in the post-quake periods, but not in the pre-quake period. Coefficients suggest a discount for such distressed sales of 16-23%[1]. Though not our focus here, these values are similar to those obtained by other researchers discussed earlier. For non-distressed auctions, on the other hand, the coefficients are consistently positive and statistically significant, with premiums of 9%, 7%, and 12%, during each of the three periods.

7. Robustness Tests

In this section, we apply various robustness checks to the hedonic regression results in Section 6. First, we re-estimate the regressions by substituting the neighborhood prestige rankings with dummy variables for the 87 city neighborhoods and suburbs. This improves model fit as measured by the adjusted R^2 and probably reduces the spatial correlation as compared to using the neighborhood rankings.

Second, we adjust our regression results for potential sample selection bias by using the well-established two-stage Heckman procedure with two sets of neighborhood control variables: prestige rankings as in Dotzour, Moorhead, and Winkler (1998) from Table 3 and suburb dummies from Table 4.

7.1 Robustness Test on the Effect of Auctions on Prices

As a robustness test, we replace the neighborhood ranking variable with 87 dummy variables for the neighborhood/suburb name. In addition, we add the CERA's designation of soil stability, represented by dummy variables TC2 and TC3, with TC1 (the best category) as the reference group. The results appear in Panels A, B, and C of Table 4.

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[1] Given the *log*-dependent variable specification, the actual effects are calculated as . $(\exp(\beta) - 1) \times 100\%$.

Table 3 Effect of Sales Method on Price with Neighborhood Controls

This table shows the estimates, standard errors and *t*-values of a regression of the price in logs on the set of regressors from Table 2 but adding the action method of sale, distinguishing between distressed sales (FCLR) and standard sales (AUCTION). Neighborhood prestige ranking control variables are specified as in Dotzour, Moorhead, and Winkler (1998). We adjust for heteroscedasticity by employing monthly clustered standard errors as in Petersen (2009).

Variable	**Panel A: Period=1 (PreQuake)**			**Panel B: Period=2 (Quake)**			**Panel C: Period=3 (PostQuake)**		
	Param	**SE**	**t Value**	**Param**	**SE**	**t Value**	**Param**	**SE**	**t Value**
Intercept	11.86	0.0211	563	11.8	0.0262	451	11.89	0.09	133
time	-0.004	0.002	-2.01	0.0028	0.0003	7.91	0.0066	0.0006	10.16
sqft	0.0004	0.0	54.49	0.0004	0.0	59.93	0.0002	0.0001	3.57
Land_Area	0.0044	0.0386	0.11	0.9054	0.1248	7.26	1.3431	0.4914	2.73
age	0.0008	0.0002	3.84	0.0003	0.0002	1.62	-0.0011	0.0006	-1.78
GOOD	0.037	0.0127	2.92	0.0333	0.0087	3.81	0.054	0.0117	4.6
POOR	-0.0679	0.0517	-1.31	-0.0731	0.0308	-2.38	-0.0908	0.0328	-2.77
RANKING	0.0823	0.0022	36.98	0.0735	0.0031	23.37	0.0972	0.0083	11.65
FCLR	0.0369	0.0729	0.51	-0.1787	0.0463	-3.86	-0.2626	0.1606	-1.64
AUCTION	0.0873	0.0141	6.21	0.0656	0.0074	8.92	0.1112	0.0206	5.41
Obs	3,113			4,619			4,516		
R^2	0.741			0.7379			0.6201		

Table 4 Robustness Test: Neighborhood Dummies Replace Neighborhood Prestige Rankings

This table shows the effect of replacing the neighborhood ranking variable used in Table 3 with dummy variables for each of the suburbs included. There are a total of 83 suburbs and 82 suburb dummies in the regression. The parameter estimates for the suburb dummies are not reported. Observations denote total number of observations used in the regression. We adjust for heteroscedasticity by employing monthly clustered standard errors as in Petersen (2009).

Variable	**Panel A: Period=1 (PreQuake)**			**Panel B: Period=2 (Quake)**			**Panel C: Period=3 (PostQuake)**		
	Param	**SE**	**t Value**	**Param**	**SE**	**t Value**	**Param**	**SE**	**t Value**
Intercept	12.23	0.0159	772	12.15	0.0139	876	12.25	0.0953	129
TC2	-0.0178	0.0095	-1.87	0.0273	0.0125	2.18	-0.0053	0.0134	-0.39
TC3	0.0008	0.0136	0.06	0.0309	0.0189	1.64	-0.0638	0.0191	-3.35
time	-0.0029	0.0015	-2.01	0.0041	0.0002	17.68	0.0067	0.0008	8.8
sqft	0.0003	0.0	36.44	0.0003	0.0	56.6	0.0002	0.0001	3.24
Land_Area	0.028	0.0442	0.63	1.3588	0.2626	5.17	1.6534	0.5624	2.94
age	-0.0008	0.0003	-2.81	-0.0014	0.0002	-7.73	-0.0023	0.0006	-4.08
GOOD	0.0274	0.0082	3.32	0.026	0.0062	4.16	0.0505	0.0117	4.32
POOR	-0.0635	0.0366	-1.74	-0.0629	0.0308	-2.04	-0.0279	0.0264	-1.06
FCLR	-0.0327	0.0565	-0.58	-0.1584	0.062	-2.56	-0.2558	0.1492	-1.72
AUCTION	0.0345	0.0127	2.72	0.0195	0.0073	2.67	0.0745	0.0204	3.66
SUBURB	Not reported			Not reported			Not reported		
Obs	3,113			4,619			4,516		
R^2	0.8385			0.7379			0.7359		

In general, all of the results described in the previous paragraph persist when location controls, rather than neighborhood quality rankings, are applied. Land area is low in magnitude with a parameter estimate of 0.028 and insignificant (t-value of 0.63) in the pre-quake period, and becomes highly significant with an average parameter estimate of 1.5 for the quake and post-quake periods. As with property age, this effect may be related to the correlation between older, well-established neighborhoods and lot size, as newer development employs smaller size lots.

The results for auction premiums continue to be statistically significant though magnitudes are attenuated. Non-distressed auctions now appear to produce price premiums of 3.5%, 2%, and 7.7% during the pre-quake, quake, and post-quake periods, respectively. Distressed property discounts exhibit similar magnitudes and *t*-values as in Table 3 with the neighborhood ranking specification. The variable on soil quality (TC2 and TC3) performs less consistently, with changes in sign and significance level dependent on time period, although during the post-quake period a property with a TC3 rating (the worst rating), the discount is 6.2%. As it is unclear exactly when these ratings became known to the market, perhaps this weak performance is to be expected.

Age is now negative and statistically significant in the pre-quake period, when it had not been in previous specifications. This could be because of a correlation between neighborhood prestige ranking and housing stock age. High prestige neighborhoods are generally well-established and have earned their reputation over time, so the housing stock is older. To formally test the changes in coefficient estimates for *time* and *age* across periods, we pool observations and perform a Wald χ^2 test of difference across periods (Cameron and Trivedi 2005) by using the neighborhood dummy model from this section with the results reported in Panel B of Table 5 [1]. The null hypothesis is specified as $H_0 : \beta_{i,period=j} - \beta_{i,period=k} = 0$ and the alternative as $H_a : \beta_{i,period=j} - \beta_{i,period=k} \neq 0$ for the *i*th coefficient estimate. The discount for older properties is significantly larger in the PostQuake period than in the PreQuake period in both specifications, again confirming our hypothesis that the earthquake is associated with changes in the hedonic pricing of older properties. The positive change in the house prices across periods remains highly statistically significant as indicated by very low *p*-values for the difference of *time* estimates.

[1] In untabulated results, as a robustness check, we do not pool the observations and estimate models for each periods jointly using simultaneous equations model (Cameron and Trivedi 2005) which allows us to use the Wald test to compare coefficients for *time* and *age* across periods with different sets of estimated coefficients for other variables in each period. We test differences in coefficients across periods using models from both Tables 2 and 4. The *p*-values obtained that way are qualitatively similar to the ones obtained in the Wald tests for the pooled observations.

Table 5 Tests of Differences between Coefficient Estimates for Each Period

This table shows the Wald χ^2 tests of differences between coefficient estimates for the variables *Time* and *Age* for each period. The tests are performed by using models from Tables 2 and 4. The hypotheses are stated as $H_0 : \beta_{i, period=j} - \beta_{i, period=k} = 0$ and $H_a : \beta_{i, period=j} - \beta_{i, period=k} \neq 0$ for the *i*th coefficient estimate. Periods 1, 2, and 3 are defined as PreQuake, Quake and PostQuake respectively. The results are reported as *p*-values which means that a *p*-value lower than 0.05 is considered to be statistically significant at the $\alpha = 0.05$ significance level. The models are fitted using OLS with monthly clustered standard errors following Petersen (2009).

Panel A: Tests of differences between estimates for each period using Model from Table 2 Sale Price without Controls for Sales Method

Model: logprice = time sqft Land_Area age GOOD POOR RANKING		
	Variable	
	Time	**Age**
Difference between Period 1 and Period 2	0.0011	0.0384
Difference between Period 2 and Period 3	0.0000	0.0293
Difference between Period 1 and Period 3	0.0000	0.0026

Panel B: Tests of differences between estimates for each period using Model from Table 4 Robustness Test: Neighborhood Dummies Replace Neighborhood Prestige Rankings

Model: logprice =suburb TC2 TC3 time sqft Land_Area age GOOD POOR FCLR AUCTION		
	Variable	
	Time	**Age**
Difference between Period 1 and Period 2	0.0000	0.0550
Difference between Period 2 and Period 3	0.0009	0.1144
Difference between Period 1 and Period 3	0.0000	0.0124

7.2 Selection Bias Issues

Our study thus far is subject to possible sample selection bias issues. Not all of our original dataset contained information on the mode of sale. If properties with that variable omitted are systematically different from others, there may be a problem. We address this issue using the well-known Heckman correction method.

Briefly, we estimate a probit model for the probability that mode of sale is not reported. A transformation is then used to create the well-known Mills ratio and include that variable as a control variable in our hedonic pricing models. In the interest of brevity, we do not present the probit model, nor the entire regression output with the Mills ratio included in the specification. Rather, in Table 6, we simply show the coefficient on the variable of interest (AUCTION) before and after the Heckman correction accomplished by including the Mills ratio in the model for every subperiod in the sample with two different neighborhood control variables.

Table 6 Effect of Heckman Correction on AUCTION Coefficient Estimate

This table shows the coefficients and their respective *t*-values for the variable AUCTION before and after a Heckman correction for sample selection bias for the regressions using Rankings from Table 3 and Suburbs control variables from Table 4.

Panel A: Heckman Adjustment for Price on Sales Method Regression with Rankings Controls

	Period=1 (PreQuake)			Period=2 (Quake)		Period=3 (PostQuake)	
	Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Heckman = NO	AUCTION	0.087	7.89	0.066	7.89	0.111	11.29
Heckman = YES	AUCTION	0.095	6.05	0.076	8.29	0.082	3.32

Panel B: Heckman Adjustment for Price on Sales Method Regression with Suburbs Controls

	Period=1 (PreQuake)			Period=2 (Quake)		Period=3 (PostQuake)	
	Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Heckman = NO	AUCTION	0.034	3.77	0.019	2.89	0.075	8.82
Heckman = YES	AUCTION	0.039	2.8	0.024	3.31	0.046	1.77

Changes are relatively slight after the Heckman correction. In the specification utilizing neighborhood ranking after the Heckman correction, the coefficient on AUCTION increases by 0.008, 0.01, and decreases by 0.029 in the pre-quake, quake, and post-quake periods, respectively. Yet in all cases, the coefficient is still positive and statistically significant. In the second specification that utilizes neighborhood dummy variables rather than neighborhood rankings, the coefficient on AUCTION increases by 0.05 on average in the pre-quake and quake periods and decreases in the post-quake period by 0.029 from 0.075 to 0.046. Overall, the coefficient on AUCTION sale is positive in all cases with magnitudes ranging from a low of about 2% to a high of about 9.5%, depending on the specification used.

8. Conclusions

In this paper, we have built on the work of Dotzour, Moorhead, and Winkler (1998) to examine the effect of the recent Christchurch earthquakes on the local for-sale housing market. Housing prices were relatively stable prior to the earthquake but increased rapidly thereafter, consistent with the basic principles of supply and demand. The use of auctions to sell properties increased in the quake and post-quake periods as well, probably because in a rapidly increasing market, sellers (or their agents) believe that auctions would reduce the risk of underpricing.

Using hedonic regression, we estimate that use of the auction sales method adds between 2-11% to the sales price after controlling for other factors. The results are qualitatively robust to a number of robustness checks. First, using a different set of fixed effects, suburb dummies, as control variables, does not substantially affect our inferences. Second, given that the mode of sale is not uniformly reported for all transactions in the data, we apply a Heckman correction for the possible sample selection bias with our results holding up consistently well. The coefficients on the auction variable in the regressions remain positive and significant. There is also some evidence that it may be the higher quality properties selected for the auction sale method, a result consistent with Dotzour, Moorhead, and Winkler (1998).

Future research might usefully apply the methods developed here to examine the effect of other sorts of natural disasters and other modes of sale in international markets. Internet based auction sales of real estate are beginning to take hold in the U.S. and this phenomenon deserves study, too. In the data set used here, we also have more detailed marketing information about the properties that were sold through negotiated sales, rather than by auction, and we are currently initiating a research project to examine other questions that arise.

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