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Redrawing of a Housing Market: Insurance Payouts and Housing Market Recovery in the Wake of the Christchurch Earthquake of 2011

Abstract

On the 22nd of February 2011, much of the residential housing stock in the city of Christchurch, New Zealand, was damaged by an unusually destructive earthquake. Almost all of the houses were insured. We ask whether insurance was able to mitigate the damage adequately, or whether the damage from the earthquake, and the associated insurance payments, led to a spatial re-ordering of the housing market in the city. We find a negative correlation between insurance pay-outs and house prices at the local level. We also uncover evidence that suggests that the mechanism behind this result is that in some cases houses were not fixed (i.e., owners having pocketed the payments) - indeed, insurance claims that were actively repaired (rather than paid directly) did not lead to any relative deterioration in prices. We use a genetic machine-learning algorithm which aims to improve on a standard hedonic model, and identify the dynamics of the housing market in the city, and three data sets: All housing market transactions, all earthquake insurance claims submitted to the public insurer, and all of the local authority's building-consents data. Our results are important not only because the utility of catastrophe insurance is often questioned, but also because understanding what happens to property markets after disasters should be part of the overall assessment of the impact of the disaster itself. Without a quantification of these impacts, it is difficult to design policies that will optimally try to prevent or ameliorate disaster impacts.

JEL-Codes: G220, Q540, R110, R310.

Keywords: house price prediction, machine learning, genetic algorithm, spatial aggregation.

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1. Introduction

On 4th September 2010, an M7.1 earthquake occurred south-east of the city of Christchurch, New Zealand's second biggest city. This event was followed by an M6.3 earthquake on 22nd February 2011. This shallower second event resulted in intense ground motions that were directed toward the city center. This sequence of earthquakes and aftershocks ended up as the most devastating disaster in the modern history of New Zealand, costing almost 20 percent of GDP (as a comparator, the 2011 Japanese triple earthquake/tsunami/nuclear disaster led to damages valued at less than 4 percent of Japan's GDP).

The earthquake sequence led to high losses overall and to the insurance industry, about 32 billion USD and 21 billion USD, respectively. Approximately 167,000 dwelling and 73,000 land insurance claims were settled by the public and private insurers. Overall, about 98 percent of residential buildings were insured for earthquakes (this is a much higher insurance penetration than in any other high risk country, see Nguyen and Noy, 2020).

The long-term process of recovery from disasters is the least researched stage of the 'disaster cycle,' yet it is also the most important one for long-term prosperity. Even less examined is the role of insurance as a mitigating factor, enabling better or faster recovery. Here, we ask whether or not insurance payments for damage incurred in this sequence of earthquakes in 2010-2011 had a significant impact on housing market dynamics in the following years. Was insurance able to mitigate the damage adequately, and therefore no significant change to the housing market occurred, or did the earthquake, and the associated insurance payments, lead to a spatial re-ordering of the housing market in the city. The question is an intriguing one, without an obvious answer, as the earthquake created a negative supply shock which in isolation should have led to price appreciation. At the same time, as the most damaged neighborhoods may have been now perceived to be at higher risk for future earthquakes, demand should have declined. In other words, the negative supply shock may have been matched or offset by a negative demand shock.

The question we pose is important not only because catastrophe insurance's utility is often questioned for large scale disasters such as the Christchurch earthquake, but also because understanding what happens to property markets after disasters is part of the overall impact of the disaster itself. Without a quantification of these impacts, it is difficult to design policies that will fully account for disasters' adverse impacts and will try to prevent or ameliorate them.

We find a negative correlation between insurance payouts and house prices at the Area Unit (AU) level. This negative association remains statistically significant when we control for geographic fixed effects like earthquake intensity to account for the level of destruction associated with each AU, and when we include pre-quake demographic measures. The interpretation of this negative association, however, is not straight-forward, as the earthquake damage, and the corresponding insurance claim payments, are likely associated with impacts on the supply and demand for housing.

One possible mechanism for this result is that insurance payouts lead to more houses being put on the market. If true, and payouts shift the supply curve, we should find an association between the number of houses being sold and insurance payouts. We do not find this. For the best models we estimate, with geographic and demographic controls, we find no statistically significant effect of payouts on transaction volumes.

Another possible mechanism behind the result is that some houses are sold "as is" and are actually not fixed (owners having pocketed the insurance payments). In that case, cash payouts, in contrast to managed repair, may not have led to sufficient repairs, with a consequent deterioration in the quality of the housing stock. If so, transaction prices could therefore reflect a lower technical and aesthetic standard in the post-earthquake AU houses. We find supporting evidence for this mechanism. The negative correlation we find between house prices and insurance payouts rests on such an association only for cash payouts. Claims that were managed (i.e., repaired directly by the insurance company) did not lead to any relative deterioration in prices.

To explore this possibility further, we also acquired a data set of all building consents given by the local council for significant alterations to the houses, at the AU level. A standard regression approach finds a one-to-one relationship between the number of managed repairs and building consents, as expected. The corresponding estimates for cash payouts are about two-to-one (two claims for each building consent).

The remainder of the paper is organized as follows. Section 2 provides a literature review and institutional details regarding New Zealand's earthquake insurance market. Section 3 describes the three data sets the analysis here relies on: the full record of all housing market transactions, the full record of all insurance claims submitted to the public insurance post-earthquake, and the building consents data. Section 4 details a standard hedonic approach to estimate the determinants of house prices, where prices are explained by insurance payouts at the AU level, housing characteristics, and a number of geographic and demographic controls. Section 5 considers the ranking of AU housing markets before and after the quakes. For this ranking, we use a novel approach, a genetic machine-learning algorithm, to identify AUs with similar location premiums. These AU premium estimates are used to find the AUs' relative ranking. With these, we estimate the probability of a positive rank jump as explained by insurance payout and a set of covariates. Section 6 assesses several plausible mechanisms that may explain the negative association between payouts and house prices (at the AU level). As these mechanisms have different empirical imprints, we search for these in our data sets. Section 7 concludes.

2. The Literature and the Context

There are quite a few papers that examine recovery of regions and cities in the aftermath of disasters of various types. Especially prolific is a literature that examines recovery of US counties in the aftermath of floods or hurricanes (e.g., Xiao and Feser 2014; Xiao 2011; Boustan et al. 2020; Strobl 2011; Hornbeck and Naidu 2014). Fewer papers have focused on the recovery of urban areas from catastrophic events. This latter group includes several papers on recovery in Kobe after its 1995 earthquake (e.g., duPont et al. 2015; Fujiki and Hsiao 2015; Cole et al. 2019), in New Orleans after Hurricane Katrina in 2005 (e.g.,Deryugina, Kawano, and Levitt 2018), after the Boston fire of 1872 (Hornbeck and Keniston 2017), and after the 1960 tsunami in Hilo, Hawaii (Lynham, Noy, and Page 2017).

There is no consensus in this literature about the likely longer-term outcomes of a catastrophic event, in either a regional or an urban setting. Some find convergence to the previous trajectory, while others point to a (semi) permanent loss that is statistically identifiable even 15 years or more after the catastrophe. The disagreement might be associated with the specifics of each event, but in some cases, even the same event generates different conclusions in different papers – for example in the Kobe papers.

Few of these research projects, however, focuses on housing markets. One of the exceptions is Hornbeck and Keniston 2017; they use the tax assessments of land values in the decades following the 1872 Boston urban fire to identify long-run positive effects associated with positive externalities generated by the ability to upgrade the destroyed building stock. In their reading of the evidence, reconstruction of individual properties led to benefits to neighboring properties so that, in the aggregate, neighborhoods affected by the fire saw their long-term trajectory improve. A similarly positive picture, identified through examination of land use changes, is provided by Siodla 2017 about the aftermath of the 1906 San Francisco earthquake and Xu and Wang 2019, when they examine population density changes as a consequence of the 1995 Kobe earthquake.

These few papers that do examine housing markets in the aftermath of catastrophic events, however, do not focus on insurance and its role in housing market dynamics after the shock. This is partly because most of these events were not very well insured, as insurance was typically voluntary, and data from commercial insurance firms is almost impossible to obtain for research purposes. We are able to overcome these two challenges as there is a public insurer for earthquakes in New

Zealand, and its insurance policy is mandatory (for anyone who purchases regular fire insurance, which about 95-98 percent of house owners do).

While there are quite a few examples of mandatory (and consequently universal) disaster insurance, globally, that is typically not the case for earthquake insurance (Nguyen and Noy 2020b). The main obstacle to assessing the impact of insurance in places where it is not mandatory is the issue of selection. It is clearly the case that households who have chosen to purchase insurance are different in important respects (e.g., income, risk tolerance, etc.) from households that did not.

The mandatory characteristic of natural hazard insurance in New Zealand allows us to investigate its impact without this selection bias, and indeed a few papers have already examined the role of insurance in economic recovery more broadly in New Zealand (Owen, Noy, et al. 2019 and Nguyen and Noy 2020a) used change in nightlights to measure the economic recovery of households, while Poontirakul et al. 2017 relied on surveyed responses from firm managers to examine how firms fared in the aftermath of the Christchurch earthquake. No paper, as far as we know, has investigated directly the role of insurance (or other forms of compensation/assistance) in post-disaster housing markets, in New Zealand, or elsewhere.

The Earthquake Commission, the public insurer for earthquakes in New Zealand, was established in 1945 following two major earthquakes in 1931 and 1942. It took its current form with the enactment of the 1993 EQC Act. At the time of the earthquakes in 2010-2011, it provided seismic insurance cover for residential buildings that was capped at NZD 100,000 for the building, NZD 20,000 for personal contents, and at the tax-assessed value for the land the building sits on; commercial, industrial, and agricultural properties are not covered by this public scheme. Any damage above the cap is insured by the private insurer for which this public component is amended. The EQC scheme has guaranteed viability, as it buys reinsurance internationally, and also purchases annually a government 'guarantee of last resort'. The set of catastrophic earthquakes in 2010-2011 was enough to deplete the re-insurance (USD 3.15 billion) and the amount that was previously accumulated (USD 4.1 billion). However, the EQC only needed to resort to the government promised guarantee after another destructive earthquake hit in 2016. In the years following the Canterbury earthquakes, the EQC settled more than 450,000 claims for damages (separately for dwellings, content, and land, as these were insured differently by the corresponding private insurers).

3. Data Description

3.1. The housing market transaction data

The housing market data for greater Christchurch consisted of 70,567 observations. The basic data preparation left 59,015 observations (details found in Appendix

Table 12). Table 1 gives the summary statistics of key variables used for the housing market transactions. Figure 1 plots the median transaction price by month (in 1000 NZD) and the number of transactions. We see as expected a significant drop in the number of transactions in the immediate aftermath of the earthquake. Maybe more surprisingly, there is no dramatic change in the median price after the earthquakes. In the analysis that follow the last full prequake year of transactions (2009) and the first full postquake year with transactions (2013) will be of special interest. These will serve as primary data for before and after quake comparisons.

Table 1: Summary statistics for housing market transactions in Christchurch region by dwelling type. Price in 1000 NZD.

Dwelling Type	N	Statistic	Mean	Min	Max
Residence	35,358	construction year	1967	1880	2010
		price	431	120	1,106
		living area	159	17	400
		lot area	743	82	5,000
Townhouse	8,101	construction year	1987	1900	2010
		price	346	121	1,100
		living area	121	40	400
Unit	9,301	construction year	1982	1900	2010
		price	269	123	1,100
		living area	88	30	380
Apartment	6,255	construction year	1990	1910	2010
		price	335	153	1,093
		living area	81	32	341

3.2. The insurance claim data

The EQC keeps records of all individual earthquake insurance claim. The information includes event date, spatial location of the affected property, payment amount and whether it was a cash payout or a managed repair by EQC-managed contractors. In this study, we select insurance claims from the 2010-2011 Canterbury earthquake events. In the dataset, there were 220,000 closed claims for nearly 100,000 properties in Christchurch. On average, homeowners received approximately 45,000 NZD to cover damages to their dwelling. In the paper, we aggregate the insurance payment to the AU level, since we investigate the dynamics of the housing market at that spatial resolution. Table 2 gives summary statistics for the insurance claims at the AU level.

Figure 1: Number of transactions (red) and median price by month (blue). Q1 is the September 2010 earth quake. Q2 is the February 2011 earth quake. No transactions in the data set between September 2011 and September 2013.

Table 2: Summary statistics of distribution of payouts (closed claims) in thousands within administrative units in the Christchurch Region. Insurance payouts. All payouts, cash settlements and managed repairs.

Statistic	N	Mean	St. Dev	Min	Max
All payouts	161,355	18.80	15.8	0.27	120.5
Cash payouts	135,010	19.12	16.5	0.27	124.4
Managed repair payouts	26,345	5.5	3.2	0	21.2

3.3. The building consents data

Building consent is approved by local authority/council in order to carry out specific building work on residential dwellings. This ensures that all construction work is complying with the existing building code at the time it is completed. Building consent statistics are released monthly by Statistics New Zealand. The data contains the monthly count of demolition or repair works by type of property at the AU level. The available statistics only include consents which were valued above 5,000 NZD.

Table 3: Summary statistics of number of building consents at AU level. The 187 AUs in the Christchurch region.

Year	Dwellingtype	Mean	St. Dev	Min	Max
2009	Residence	1,901	711	1,010	3,148
	Townhouse/unit	89	187	0	666
	Apartments	917	356	479	1,713
	All dwellings	2,908	893	1,489	4,581
2013	Residence	3,946	1,048	2,720	5,637
	Townhouse/unit	198	312	0	1,014
	Apartments	1,396	911	246	3,030
	All dwellings	5,540	1,996	3,174	9,413

4. Hedonic approach

First, as a first pass, we estimate the effect of insurance payouts on house prices with a hedonic model where the (log) insurance payouts is included as a regressor. We use the following model:

$$\log P_i = \alpha + \sum_{i=1}^{3} \beta_j \log(X_{ji}) + \sum_{j \in FE-regressors} \gamma_j D_{ji} + \eta \text{payout} + \epsilon_i, \qquad (1)$$

where P_i is the price, X_{1i} is the area (in sqm.), X_{2i} is the age (in years), X_{3i} is the lot area (for residence house type in sqm), D_{ji} are either dummy or dummy-interaction variables $j \in \{$d-type, d-type*area, d-type*bedrooms, month, AU $\}$, and payout is the payout by AU and year[1].

Table 4 and 5 gives the regressions of model 1 in the case where the payout variable is the log of payouts of all closed claims in a given year for a varying number of FE. Table 4 is a classical hedonic approach with dwelling characteristics, time, and location controls. The most refined model gives a small negative effect of

[1]d-type short for dwelling type.

payouts. It must be stressed that this applies even though payouts are measured at the AU level, and we control for the AU level in these specifications.

Table 5 is a slightly different regression approach where we control for geographic variables like earthquake intensity and distance to the city center, but do not have AU fixed effects. These models give a small positive effect of payouts on house prices. The most refined model with demographic controls gives a small positive effect at the 10 percent level.

Table 4: Hedonic Regression 1: Regressing log price on log payout with hedonic covariates and fixed effects (Time and Administrative Unit (AU)). Transactions after 2010. [a]

	Dependent variable: log price		
	(1)	(2)	(3)
log payout	0.025***	0.003**	−0.009***
	(0.001)	(0.001)	(0.002)
log lot area	0.067***	0.056***	0.119***
	(0.005)	(0.005)	(0.004)
log building age	−0.040***	−0.037***	−0.101***
	(0.003)	(0.002)	(0.002)
Dwelling type FE	*Yes*	*Yes*	*Yes*
Dwelling type*LogLiving FE	*Yes*	*Yes*	*Yes*
Bedroom FE	*Yes*	*Yes*	*Yes*
Time FE	*No*	*Yes*	*Yes*
AU FE	*No*	*No*	*Yes*
Observations	33,036	33,036	33,036
R^2	0.572	0.612	0.774
Adjusted R^2	0.572	0.612	0.772
Note:			*p<0.1; **p<0.05; ***p<0.01

[a] Note: Payout measured yearly by value of closed claims by AU. Dwelling types: Residence, townhouse, unit, apartment. Time FE by month.

The first regression approach finds a small negative effect of payouts, whereas the second finds a small positive effect of payouts. Both these regression approaches may be easily challenged, as we are by necessity obliged to compare the local housing markets several years apart, and macroeconomic trends are likely to play a role. The year 2009 was the last full normal year before the earthquake, and 2013 was the first year where the Christchurch housing market had normal transaction volumes again.

Of particular concern is beta or sigma convergence(Wood, D. E. Sommervoll,

Table 5: Hedonic regression 2: Regressing log price on log payout with hedonic covariates, and fixed effects (Geographical, Time, Demographic). Transactions after 2010. Regressions with Geographic and Demographic FE. [a]

	Dependent variable:	
	log price	
	(1)	(2)
log payout	0.027***	0.003*
	(0.002)	(0.002)
log lot area	0.099***	0.104***
	(0.005)	(0.005)
log building age	−0.050***	−0.065***
	(0.002)	(0.002)
Dwelling type FE	*Yes*	*Yes*
Dwelling type*log living area FE	*Yes*	*Yes*
Bedroom FE	*Yes*	*Yes*
Time FE	*Yes*	*Yes*
Geo FE	*Yes*	*Yes*
Demo FE	*No*	*Yes*
Observations	30,041	30,041
R^2	0.680	0.722
Adjusted R^2	0.680	0.721
Residual Std. Error	0.221 (df = 29970)	0.206 (df = 29962)
Note:		*p<0.1; **p<0.05; ***p<0.01

[a] The payout measure is the aggregated dollar amounts at AU-year level. Geographic FE: AU area, distance CBD, Sep 10 earth quake intensity , Feb 11 earth quake intensity. And demographic FE median age, number of kids, European decent, fraction of full time worker, fraction of married, Maori descent, fraction of elderly at AU level. Original dataset 59,015 (see in Table 12), observations 2010-2016: 30,041, 4 observations lost due to missing geographic controls.

and Silva 2016).[2] If we have a general price convergence, and high priced neighborhoods received more payouts (Owen and Noy 2019), we may wrongly attribute the somewhat lower appreciation due to payouts. One way to address this concern is to compare Christchurch with a similar city in New Zealand and try a difference-in-difference approach to control macroeconomic trends. This, however, does not control for idiosyncratic economic trends that are likely to be present in Christchurch. Moreover, there are not many candidates for a "twin city" in New Zealand. An alternative approach is to consider rankings. These are largely unaffected by potential beta or sigma convergence. Since we can estimate the price at AU level, we can infer from that to what extent the inflow of insurance payouts affected the probability of a positive rank jump for each AU.

5. Neighborhood rankings by location premium and insurance payouts

The location premium in a metropolitan housing market has substantial variation. One way to address this variation is to use data with low spatial aggregation. However, low spatial aggregation produces thin data sets and potentially noisy premium estimates. A way to lessen this trade-off is not to aggregate at the whole-market level but to aggregate into larger submarket units with similar price premiums.

In a pre-and-post analysis of the location premium for the Christchurch earthquakes, this is even harder as the earthquake may have completely redrawn the distribution of the locational premium in nontrivial ways. We estimate before and after price premiums using a machine learning approach, which uses a genetic algorithm to divide the AUs of Christchurch into groups according to their price premium. The main advantage of such an algorithm is its ability to identify (larger) areas with similar location premiums (Å. Sommervoll and D. E. Sommervoll 2019.

The estimation strategy is in three steps:

1. Partition the AUs into 10 location premium groups before the earthquake (in 2009), using the genetic algorithm described in the Section 8.1 in the appendix.

2. Partition the AUs into 10 location premium groups after the earthquake (in 2013), using the same genetic algorithm.

3. Estimate limited dependent variable models for the probability of a positive rank jump with respect to location premium groups, with payouts and a varying number of controls (geographic and demographic).

[2] We have beta convergence if there is a negative correlation between the house price level in an area and the house appreciation. The sigma convergence is related but is the case where the spatial variation of house prices becomes smaller of time.

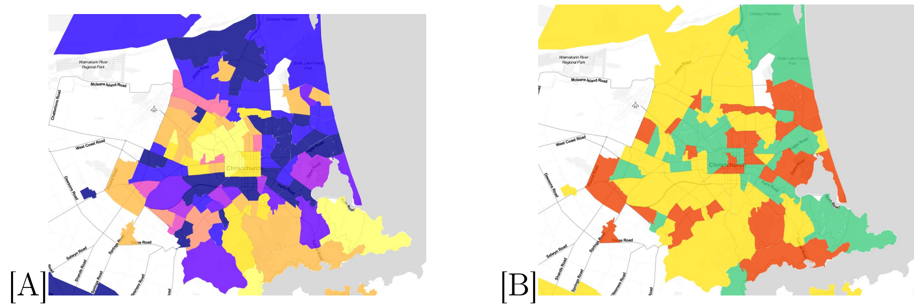

Figure 2: A. The central part of Christchurch Region from high price level (yellow) to low price level (blue) pre quake (2009) B. The central part of Christchurch Region. Yellow higher post quake rank. Green unchanged ranking. Red lower post quake rank.

There are 154 Area Units (AU) in the transaction data we have from Christchurch, so the number of ways to aggregate 154 AUs into 10 groups is the Bell number $B_{174} \approx 1,09 \cdot 10^{78}$. For comparison the number of elementary particles in the universe is believed to be of the order of 10^{80}. A genetic algorithm has shown to be an efficient way to search for spatial aggregations by location premiums Å. Sommervoll and D. E. Sommervoll 2019)[3]. Further details, regarding the genetic algorithm used in this paper are given in Section 8.1. For a more through discussion of spatial aggregation and genetic algorithms see Å. Sommervoll and D. E. Sommervoll 2019.

We use 10 different location premium groups, that divide Christchurch into 10 spatially defined submarkets. We rely on the same hedonic regression model given by 1, apart from the spatial FE terms which we will allow to vary.

In the following, we compare the last year before the earthquake (2009) rankings with the first "normal" year after the earthquake (2013) rankings. It must be stressed that rankings are a zero-sum game. The regression design needs to take this into account. We rely on rank jumps with signs. Moreover, we control for rank in 2009 as high pre-quake rank makes a positive rank jump less likely, all else equal. Another approach is to limit the subset of AU's to a subset where all have an above-average chance to a positive rank jump if post-quake ranks were assigned at random. A way to do this is to consider only the below-median rank pre-quake AUs. We use this alternative approach as a sensitivity check to our main model specification. The corresponding tables for the below-median rank data set are found in the appendix. Table 6 gives the probit estimates for the probability of a positive rank jump by one variable only. We see that the rank jump probability by payout is estimated negative at the 5 percent level. Interestingly, the effect of earthquake intensity is

[3] The key ingredient is random variation and non random selection. A population of regression models all with the same hedonic controls but with different aggregations of AU's into 10 groups, compete in the sense the most fit models (in terms of their explanatory power) gives rise to new models. These new models, which is a recombination of the most fit models (with possible mutations) replace the least fit models and form a new generation. As generations pass models with vhigh explanatory power both in- and out-of-sample tend to arise.

neither statistically significant for the intensity, as it was felt within each AU, in the September quake nor the February more deadly one. Figure 2 shows the central part of the Christchurch region divided into 10 submarkets (A) and the AUs that experienced a positive, unchanged, or negative rank shift (B).

Table 6: Probit models with one explanatory variable and rank 2009 fixed effects. Probability for price level rank increase. Payout at AU level.

	Dependent variable:		
	up		
	(1)	(2)	(3)
Intensity Sep 10 Quake	0.074		
	(0.202)		
Intensity Feb 11 Quake		−0.158	
		(0.113)	
payout			-0.011^{**}
			(0.005)
Rank2009	0.145^{***}	0.140^{***}	0.125^{***}
	(0.034)	(0.033)	(0.035)
Constant	−1.525	0.239	-0.587^{**}
	(1.541)	(0.887)	(0.297)
Observations	142	142	142
Log Likelihood	−88.700	−87.727	−86.115
Akaike Inf. Crit.	183.401	181.454	178.229
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 7 provides the result for the same models, but with a varying number of fixed effects. We see that all specifications have a negative impact of insurance payouts on the probability of a positive rank jump. Furthermore, models 3 and 4 with the most extensive controls give the most considerable negative effect of payouts (-0.019 and -0.015, respectively).

As probit models do not have a uniform marginal effect, it is not easy to assess the impact of payouts on the probability. One way is to represent the probabilities is in a plot. Figure 3 displays the probabilities plotted against the corresponding payouts for model 4. The green line is a smoothing spline that highlights the general tendency of higher payouts to correlate with lower rank jump probability. The red line gives the regression line of an OLS-regression. It must be stressed that this model controls for earthquake intensity as well as a wide array of geographic and

Table 7: Probit models for a positive price level jumps with fixed effects.[a]

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
payout	-0.010^{*}	-0.005	-0.019^{***}	-0.015^{*}
	(0.005)	(0.007)	(0.007)	(0.008)
Rank2009	0.139^{***}	0.223^{***}	0.286^{***}	0.345^{***}
	(0.032)	(0.044)	(0.057)	(0.064)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Constant	-0.767^{***}	15.447^{***}	4.827	15.624^{*}
	(0.272)	(4.568)	(5.328)	(8.744)
Observations	157	142	142	142
Log Likelihood	-94.536	-74.878	-70.971	-65.094
Akaike Inf. Crit.	195.072	163.755	163.943	160.189
Note:				*p<0.1; **p<0.05; ***p<0.01

[a] The payout measure is the aggregated dollar amounts for all years at AU level. Geographic FE: AU area, distance CBD, Sep 10 earth quake intensity , Feb 11 earth quake intensity. And demographic FE median age, number of kids, European decent, fraction of full time worker, fraction of married, Maori descent, fraction of elderly at AU level.

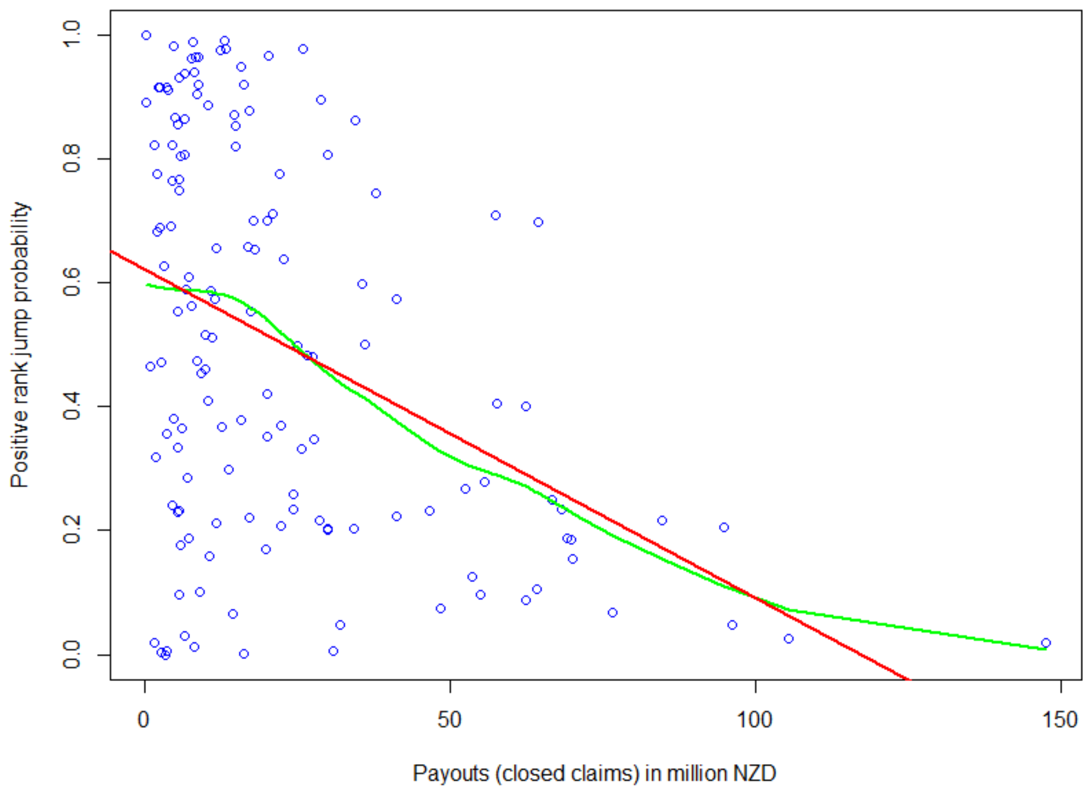

Figure 3: Predicted positive price level rank jump probability for a AU plotted agains payouts in million. Green is a smoothed spline to highlight the nonlinear relationship. The red is the linear regression line. The regression estimates are given in Table 15 in the appendix.

demographic variables.

Moreover, we may use the linear regression (Table 15 and red line in 3) to estimate an average effect of an extra million NZD on rank jump probability. This average effect is 1 million NZD is associated with a 0.5 percent less probability of a positive rank jump. In other words, an insurance payout increase of 20 million NZD, translates to an average 10 percent less chance of a positive rank jump.[4]

6. Possible mechanisms behind the result and looking for their economic imprint

6.1. Insurance payouts give a supply shock

One theory is that payouts cause more dwellings to be put on the market. In other words, they generate a positive supply-side shock that is not fully met by increased demand. This phenomenon, more houses put on the market, is likely to correlate both with lower prices and higher transaction volumes. We adopt the same identification strategy as in the previous section, since the finding an association between payouts and transaction volumes involves the same challenges as in the previous payouts and house prices case. In other words, we rank AUs by the number of transactions before and after the quakes and see if there is a correlation between payouts and the probability of a positive rank jump. It must be noted that the correlation between a positive rank jump in transaction prices and positive rank jump in volume is 0.148. In other words, a small positive correlation. So, the question is whether or not controlling for pre-quake transaction volume rank, geography, and demography affects the probability estimates sufficiently to give a positive effect of payouts on transaction volumes. Table 8 shows that allowing for a wide array of fixed effects does diminish the negative effect of payouts, but not enough to shift the sign. In other words, we do not find support for an increase in transactions driven by payouts.

6.2. Managed repair versus cash payouts

The results of the previous section cast doubt on the supply-side shock explanation for our findings. The negative association between insurance payouts and house price ranks may be driven by houses sold "as is" after the owner received a cash insurance payment. In other words, the negative impact on the housing market by insurance payouts rests on transactions of houses of overall lower quality – houses whose damages were not fixed as the owners pocketed the insurance compensation.

[4] These numbers are to give an economic perspective to the estimated effects. Linear regression for a bounded dependent variable like a probability should be interpreted with caution. Details regarding this OLS-regression is found in Table 15 in the appendix.

Table 8: Probit models for rank volume jumps with prequake volum rank fixed effects.

	Dependent variable:			
	volume rank jump			
	(1)	(2)	(3)	(4)
Payout	-0.029^{***}	-0.020^{**}	-0.025^{***}	-0.011
	(0.007)	(0.009)	(0.010)	(0.011)
Volume rank 2009	0.020^{***}	0.021^{***}	0.025^{***}	0.027^{***}
	(0.006)	(0.008)	(0.009)	(0.009)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Constant	-0.170	-7.078	6.053	9.118
	(0.342)	(5.008)	(5.630)	(9.729)
Observations	159	140	140	140
Log Likelihood	-80.644	-71.533	-70.450	-65.779
Akaike Inf. Crit.	167.288	157.065	162.900	161.557
Note:				*p<0.1; **p<0.05; ***p<0.01

If true, we would expect that this negative impact rests only with cash payouts rather than repairs that were managed by the insurance company. It is interesting to note that cash payouts are on average larger than managed repairs (Table 2), so in general cash was not favored for small payouts only.

Table 9: Probit models for price level rank jump driven by cash payout and managed repair payouts. All models have prequake rank fixed effect.

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
repair payout	−0.181	0.121	−0.266	0.004
	(0.140)	(0.183)	(0.182)	(0.225)
cash payout	-0.012^{**}	−0.005	-0.020^{***}	-0.017^{*}
	(0.006)	(0.007)	(0.007)	(0.009)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Observations	142	142	142	142
Log Likelihood repair	−87.857	−74.917	−74.402	−66.904
Log Likelihood cash	−86.016	−74.817	−70.743	−64.857
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 9 points towards that the effect of insurance claims on house prices is associated with cash settlements rather than repairs. Intriguingly the point estimate for cash settlement is estimated close to (and not significantly different from) the point estimate for closed insurance claims (-0.015 versus -0.017). It is also interesting to note that there is a strong correlation between cash settlement and managed repair (0.88). In other words, we could risk that the covariation between cash and managed repair could potentially make it hard to cleanly estimate cash as the sole driver of the adverse effect on house prices. The statistically significant estmates of model 3 and 4 for the cash payout coefficient (and not for the repair payout coefficient) shows that there is enough independent variation to separate the effect of cash payout from the effect of managed repair.

Our regression results are consistent with a quality dip in AUs that receive a considerable amount of cash payouts in contrast to managed repairs. One way to shed some light on this possibility is to look for differences between managed repairs and cash payouts with respect to building consents issued by the local council for building work. This data is available at the AU level. In the next subsection, we combine our housing market data, and insurance claim data with the building consents data set to explore this further.

6.3. Cash payouts and building consents

As a first pass an investigation of consents is to see whether or not insurance payouts did boost the number of building consents given by council. We apply the same methodology looking at pre and post ranks as before. In other words, we rank AUs by pre-quake building consent rank (2009) and consider the probability of a positive rank jump with a varying number of controls.

Table 10 shows that indeed both insurance payouts in general, as well as cash payouts, lead to more consents even after controlling for a wide array of fixed effects. A challenge for this approach is the high correlation between payouts to managed repairs and cash payout. Managed repair is necessarily associated with a consent, whereas a cash payment is not. In other words, the almost same effect of payouts, both managed repair and cash, and cash alone may be due to this the correlation between repair and cash.

Another approach is to run a regression of the number of consents explained by the number of payouts while controlling for the pre-quake consent level. Table 11 provides these regression results. Model 1 estimates that, on average, a managed repair is associated with 1.02 building consents. This is intuitively expected, as we know that almost every managed repair will require a building consent, at the property level. Model 2 estimates, however, that a cash payout is associated, on average, with only 0.375 building consents. In other words, only 4 out of 10 cash payouts resulted in a building consent being issued by council to undertake work. This strongly provides suggestive evidence that supports our contention that indeed our central result, that cash insurance payments are associated with a housing market decline, is due to the decline in housing quality associated with repairs that are not being completed, or completed thoroughly with sufficient quality assurance. Even though cash payouts were not only used for smaller claims, we cannot rule out that, partly, this regression result may be due to cash payouts aimed at smaller repairs that did not require a building consent.

One way to provide more detail with respect to this possibility is to partition the AUs into below and above median cash payouts and run the same models on these two subsamples separately. Model 3 (below median) and Model 4 (above median) in Table 11 provide these regression results. Intriguingly, for the below-median sample there is no significant effect on consents at all, whereas, for the above-median sample, the effect is stronger than in the full sample case (0.581 versus 0.375). At a higher level, the rather modest improvement from 4 to 6 out of 10 payouts when only looking at AUs with above-median average payouts, is still consistent with the scenario in which owners pocket the insurance money rather than *fully spend it on* *fixing whatever was damaged.*

Table 10: Probit models for positive jump in consent ranking with total payouts and total cash payout respectively. Both models have prequake consent rank fixed effects.

	Dependent variable:			
	consent jump			
	(1)	(2)	(3)	(4)
payouts	0.018***	0.020***	0.027***	0.026***
	(0.006)	(0.007)	(0.008)	(0.009)
cash payouts	0.018***	0.019***	0.026***	0.025***
	(0.006)	(0.007)	(0.008)	(0.009)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Observations	110	110	110	110
Log Likelihood cbsum	−63.516	−61.347	−59.159	−58.703
Log Likelihood cashsum	−66.441	−61.347	−59.159	−58.703
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 11: OLS regressions with dependent variable consents and prequake fixed effects. Model 3 (4) estimated on the below (above) median AUs with respect to cash payouts.

	Dependent variable:			
	consents			
	(1)	(2)	(3)	(4)
number of repair payouts	1.019***			
	(0.351)			
number of cash payouts		0.375***	0.146	0.581***
		(0.109)	(0.238)	(0.128)
consents 2009	0.699***	0.657***		
	(0.146)	(0.146)		
Constant	86.602	−34.083	297.146	−13.132
	(92.176)	(110.892)	(210.770)	(145.585)
Observations	117	117	58	58
R^2	0.238	0.259	0.007	0.269
Adjusted R^2	0.225	0.246	−0.011	0.256
Note:		*p<0.1; **p<0.05; ***p<0.01		

7. Conclusion

We investigated the impact of insurance payments for seismic damage on the housing market in Christchurch, New Zealand, following its 2011 destructive earthquake. We combine three separate datasets – a comprehensive house transaction data, a full record of all insurance claim payments, and building consents record – to analyse the housing market dynamics in the years following this destructive earthquake, the most damaging in New Zealand's modern history. Identifying the impact of insurance on housing markets is important not only because it constitutes part of what happens to the economy after disasters more generally. This quantification should also help us quantify the benefit from disaster risk reduction, mitigation, or resilience-building activities, and in particular the potential re-design of insurance arrangements.

It is also important as the details we uncover, in particular the differences between cash payments and managed repairs, can help design catastrophic insurance systems that will be more effective post-disaster. The primary role of insurance is to transfer the financial component of the risk, but a well-designed insurance system can do more, including incentivise a build-back-better recovery. For example, our findings suggest that it might be better, in terms of the likely impact on housing markets, to make sure that payments are followed by actual repairs, so that affected neighbourhoods do not experience longer-term decline resulting from these unrepaired properties.

We also contribute by developing a new methodology to examine the impact of one-off shocks on housing markets, using a machine-learning genetic algorithm which has a better explanatory power than the traditional hedonic pricing models. It is possible to extend this methodology to the analysis of other types of asset markets, and other types of shocks, but we leave those possibilities for our future research.

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8. Appendix

Table 12: Housing Market Data Preparation.

Data operation	N. of transactions
Raw data	70,567
Transactions with AU code	70,017
Transactions of Residence, Unit, Townhouse, and Apartment	69,539
Transactions with construction year	67,680
Transactions with living area greater than 15	67,636
Transactions with living area less than 400 sqm.	67,301
Excluding transactions with no bedrooms and larger than 35 sqm.	67,015
Transactions with less than 9 bedrooms	66,985
Transactions where house type "residence" has positive lot size	60,532
Transactions where house type "residence" has lot size less than 5001 sqm.	60,265
Excluding transactions where living area greater than lot area	60,248
Transactions after removing 1 percent highest and lowest trans. prices	59,015
Transactions in AUs that have transactions both before and after 2011	59,102
Transactions in AUs with transaction in each year 07,08,09,13,14,15	58,462

8.1. The genetic algorithm

In this section, we use a genetic algorithm (GA) to find spatial aggregations of the 154 AUs into 10 submarkets. We aim to find aggregations that give high R^2's when used as spatial controls in the regression model 1. Before we go into specifics regarding the genetic algorithm we use here, let us highlight the mathematical intuition behind genetic algorithms. The search for maxima for a function (here R^2) relies on gradient ascent.[5] A genetic algorithm is a variant of gradient ascent, where we keep (and let reproduce) the models with the highest R^2s. We can picture it as a herd of points corresponding to regression models. The models/points highest up the hill is used to create new models by random variation. These replace the points/models with the lowest R^2s. The result is a drift towards higher altitudes, higher R^2s as generations pass.

A genetic algorithm mimics natural selection. The key is random variation and non-random selection. We consider a population of hedonic models that differ only in their spatial aggregation.

An aggregation of 154 AUs to 10 submarkets is naturally represented by a 154-dimensional vector $(1, 10, 3, 3, \dots)$, where a submarket is identified by an integer. We refer to this vector of integers as the genome or genotype of a given model.

[5] In the literature, it is more common to use the notion of gradient descent, as the objective is usually to minimize a loss function Marsland 2009.

Every generation consists of 60 models, and the first generation is 60 random draws of 10 submarkets. The fitness of a model is defined to be R^2 of the hedonic regression model (1) with the spatial controls defined by the model's genotype (the 154-dimensional vector coding for the submarket aggregation). This means that the first generation average fitness is likely to be close to the average random fitness (64.3) given in 14.

The next generation is created in the following way. The population is ranked according to R^2. The 30 highest ranked models are divided into two according to rank. Parent pairs are formed by pairing according to rank. That is, the highest-ranked model is paired with the 16th rank (since it is the highest-ranked in the second group), the second with the 17th, et cetera. Each parent pair gives rise to one offspring. These 15 offspring replace the lowest-ranked models without offspring in this generation.[6]

The offspring is formed by genetic crossover. Let us illustrate genetic crossover by a genome only 6 integers long and only four groups[7]:

Parent one: (1,2,1,3,3,4)

Parent two: (1,3,3,3,4,4)

Offspring: (1,2,1,3,4,4)

It is customary to allow for mutations in order to preserve genetic diversity. A mutation tends to be just a random draw of a place in the genome and a random replacement of the integer by another integer. In this example, say a random draw gave position 5, and group 1, then the resulting offspring would be:

Offspring: (1,2,1,3,1,4)

We have 154 different AUs, so the genome allows for an even split of genetic inheritance between parents. We choose the first 77 elements of the DNA-strain from the fittest parent and the rest from the least fit parent. The offspring are also mutated on three randomly drawn places of the genome.[8]

Table 13 summarize the genetic algorithm.

The global in-sample R^2 maximum for aggregation into 10 submarkets is unknown, but it is lower by construction than the in-sample R^2 for the full model with 154 submarkets ($R^2 = 82.8$).

[6] As the 30 first models beget offspring, the offspring will replace ranks 46 to 60.

[7] Example taken from Å. Sommervoll and D. E. Sommervoll 2019.

[8] A GA tends not to be sensitive to the details of recombination or mutation rates. In other words, we have some leeway in the choice of these parameters. The important thing is to strike a balance between R^2 reward and genetic diversity. The probability of getting stuck on some potentially low local maximum decreases with genetic diversity.

Table 13: Specification of the GA

population size (N)	Crossover	Mutations	Number of generations
60	Yes	20	2,000

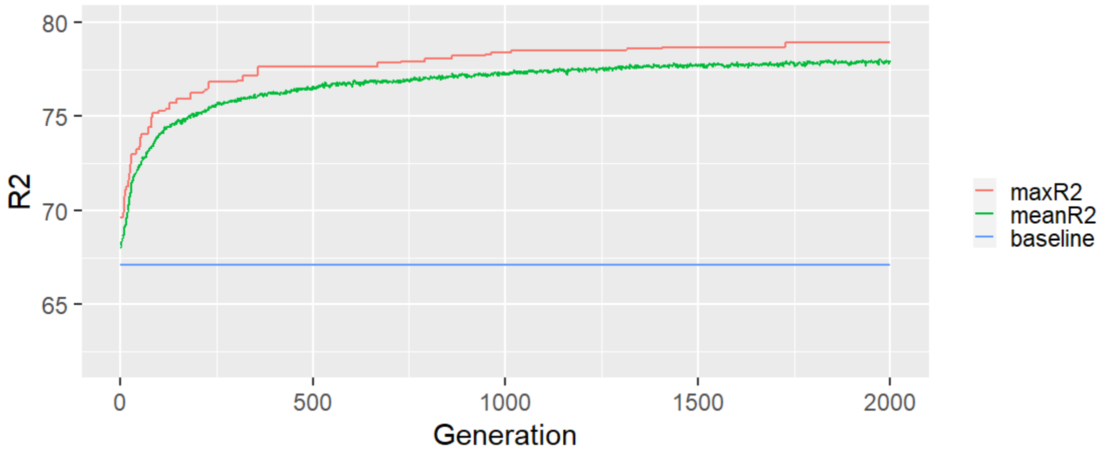

Figure 4: The explanatory power (R^2) by generation number. Data set housing market transactions in 2009 (8418 observations). The baseline is the hedonic model 1 without spatial dummies ($R^2 = 67.1$). Max R^2 in final generation is 78.9

Figure 4 displays a typical run of the GA presented in table 13. We see that both the R^2, rise sharply for the 1000 generations and then level off. We also note that evolutionary pressure does indeed give models with high R^2s. These are naturally a bit from the full model with AU fixed effects (78.9 versus 82.8) as we compare a model with just 9 spatial dummies with a model with 153 spatial dummies (17 times more dummies).

The GA is overt data mining in-sample and thus may suffer from overfitting. At the same time, our dataset broken down into AUs, and single years are a thin for some years and some AUs. In other words, overfitting may be a concern. The results of the similar GA in Å. Sommervoll and D. E. Sommervoll 2019, show that such spatial GAs tends to give little overfitting. A division of the dataset into the customary triple of train, test, and validation set, would give us thin data sets. We view thin datasets as a more significant concern than overfitting. The model will just be used to assess AU rankings and not out-of-sample predictions. We run the GA on the whole (yearly) sample in all specifications.

Table 14 in the appendix gives the base model with and without spatial controls for the year balanced sample (154 AUs)[9].

[9]The AUs have transactions in all the years 2007, 2008, 2009, 2013, 2014, and 2015.

Table 14: The hedonic regression model used in the GA with and without AU fixed effects

	Dependent variable:	
	logsaleprice	
	(1)	(2)
apartment	0.624***	0.361***
unit	0.360***	0.235***
townhouse	0.304***	0.404***
logLiving_apartment	0.586***	0.495***
logLiving_unit	0.572***	0.497***
logLiving_townhouse	0.590***	0.453***
logLiving_residence	0.599***	0.429***
bedrooms_apartment	0.005	0.042***
bedrooms_unit	0.030***	0.035***
bedrooms_townhouse	0.046***	0.063***
bedrooms_residence	0.019***	0.021***
logLand	0.055***	0.118***
logAge	−0.028***	−0.077***
Month FE	YES	YES
AU FE	NO	YES
Observations	58,462	58,462
R^2	0.641	0.779
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 15: Regressing rank jump probability on insurance payouts. The corresponding regression in the case of looking at below median prequake ranked AUs are found in Table 18.

	Dependent variable:
	Prob. jump
payout	-0.005^{***}
	(0.001)
Constant	0.622^{***}
	(0.033)
Observations	142
R^2	0.173
Adjusted R^2	0.167
Residual Std. Error	0.290 (df = 140)
F Statistic	29.226^{***} (df = 1; 140)
Note:	*p<0.1; **p<0.05; ***p<0.01

8.2. Sensitivity to rank jump specification

The probability of a positive rank jump is trivially linked to the initial rank. The first rank has, by definition, a zero probability. If the ranking is completely random, the probability of a positive rank jump is correlated with the initial rank. In the main analysis of the paper, we attempt to control for this by introducing the initial rank as a regressor to control for this. Another way to do this is to limit the sample by looking at below-median AUs only. In the following, we present the probit regressions this specification as a sensitivity check to the probit regression in the main body of the paper.

Table 16: The probit models with one explanatory variable. Data set: Below medium rank AUs. Corresponding to Table 6.

	Dependent variable:		
	up		
	(1)	(2)	(3)
Intensity Sep 10 Quake	0.009		
	(0.237)		
Intensity Feb 11 Quake		−0.143	
		(0.111)	
Aggregate closed claims			−0.030***
			(0.009)
Constant	0.229	1.338	0.813***
	(1.742)	(0.819)	(0.200)
Observations	94	94	94
Log Likelihood	−62.557	−61.660	−55.713
Akaike Inf. Crit.	129.113	127.319	115.425
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Probit models for a positive jumps with fixed effects.Data set: Below medium rank AUs. Corresponding to Table 7.

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
cb_sum	−0.030***	−0.033***	−0.049***	−0.051***
	(0.009)	(0.013)	(0.013)	(0.018)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Constant	0.813***	16.412***	17.778*	22.426*
	(0.200)	(4.992)	(10.126)	(12.619)
Observations	94	88	88	88
Log Likelihood	−55.713	−41.471	−38.222	−34.389
Akaike Inf. Crit.	115.425	94.942	96.444	96.778
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Regressing rank jump probability on insurance payout. Sensitivity. Data set: Below medium rank AUs. Corresponding to Table 15.

	Dependent variable:
	Positive rank jump
Insurance payout	-0.011^{***}
	(0.002)
Constant	0.824^{***}
	(0.040)
Observations	88
R^2	0.365
Adjusted R^2	0.358
Residual Std. Error	0.268 (df = 86)
F Statistic	49.519^{***} (df = 1; 86)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 19: Probit for volume ranking. Sensitivity. Data set: Below medium rank AUs. Corresponding to Table 8.

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
cb_sum	-0.022^{***}	-0.017^{*}	-0.027^{**}	-0.021
	(0.008)	(0.010)	(0.012)	(0.013)
Constant	0.170	-10.782	46.837^{***}	50.858^{**}
	(0.258)	(9.315)	(16.902)	(23.736)
Observations	69	69	69	69
Log Likelihood	-39.073	-37.892	-31.714	-28.687
Akaike Inf. Crit.	82.146	87.785	83.427	85.374
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 20: Probit for cash sum. Sensitivity. Data set: Below medium rank AUs. Corresponding to cash models in 9.

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
cash_sum	-0.034^{***}	-0.035^{***}	-0.051^{***}	-0.054^{***}
	(0.010)	(0.013)	(0.014)	(0.018)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Constant	0.914^{***}	16.447^{***}	17.944^{*}	22.768^{*}
	(0.215)	(4.997)	(10.126)	(12.635)
Observations	88	88	88	88
Log Likelihood	−50.453	−41.374	−38.072	−34.158
Akaike Inf. Crit.	104.905	94.749	96.143	96.316
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: Probit model repair. Sensitivity. Data set: Below medium rank AUs. Corresponding to repair models in 9.

	Dependent variable:			
	up			
	(1)	(2)	(3)	(4)
repair_sum	-0.692^{***}	−0.458	-0.942^{***}	−0.522
	(0.228)	(0.328)	(0.330)	(0.405)
Geographic FE	No	Yes	No	Yes
Demographic FE	No	No	Yes	Yes
Constant	0.862^{***}	16.228^{***}	13.937	23.658^{**}
	(0.228)	(4.908)	(9.016)	(11.336)
Observations	88	88	88	88
Log Likelihood	−53.315	−44.622	−43.457	−39.278
Akaike Inf. Crit.	110.631	101.244	106.913	106.557
Note:				*p<0.1; **p<0.05; ***p<0.01