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Living Like There's No Tomorrow

Saving and Spending Following the Sichuan Earthquake

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ABSTRACT

In addition to human casualties and physical damage to infrastructure, natural disasters affect survivors emotionally and psychologically. Research on such impacts has almost exclusively been confined to the medical field, and focused on severe conditions such as post-traumatic stress disorder. The fact that emotional shocks and increased risk awareness may trigger changes in the preferences and behavior of economic agents has until now largely been ignored, including by economists. Based on panel datasets from China's Sichuan province, which was struck by an earthquake in 2008, and using distance from epicenter as a proxy for earthquake severity, we empirically show that the saving and consumption behavior of households closer to the epicenter changed after the earthquake. They saved less, spent more lavishly on alcohol and cigarettes, and also played *majiang* (a Chinese game) more often. The magnitude of the estimated impact on saving behavior, a drop of 6 percentage points for each degree of earthquake intensity, is economically significant. It appears that the earthquake has induced a shift in people's preferences characterized by a carpe diem attitude toward spending and greater preference for the present.

Keywords: seism, discount rate, carpe diem, Wenchuan, China

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1. INTRODUCTION

Economic studies of natural disasters tend to focus on physical damages, such as the costs of losses and reconstruction (Anderson 1990; Mechler 2004; Toya and Skidmore 2007), or economic consequences, such as the impacts on growth (Hallegatte and Przyluski 2010; Cavallo and Noy 2009; Noy 2009). The psychological literature, on the other hand, places greater weight on emotional damages, such as the prevalence and persistence of depression or post-traumatic stress disorder (PTSD) (Madakasira and O'Brien 1987; Yule et al. 2000). The fact that disasters influence economic systems through consumer preferences is sometimes alluded to in both literatures but seldom explicitly treated. The full economic impact of a disaster cannot be determined without taking into account the resulting changes in the attitudes and behaviors of economic agents. This paper contributes to filling this lacuna.

Identifying such impacts is not straightforward. Natural disasters cannot be randomly allocated to treatment and control groups, so identifying impacts on consumer behaviors requires clever empirical strategies. Luckily (for economists), some types of natural disasters are not predictable and constitute "natural experiments" in themselves. Earthquakes, in particular, are perhaps the least predictable and most sudden type of natural disaster, often causing extensive damage in mere seconds, thus constituting a good natural experiment.

Another complication for estimating behavioral impacts of disasters arises from the fact that it is difficult to measure disaster intensity. Using damages as an intensity variable poses problems of endogeneity, because more damaged areas are not necessarily those where nature struck hardest; they may simply be those least prepared. Since behavior *prior* to the disaster partly determines the extent of damages, the effects of damages on behavior cannot be identified directly. Earthquakes also have an advantage in that respect. Modern seismology provides measurements that can pinpoint the origin and magnitude of tremors with great precision. The distance to the epicenter is a fully exogenous proxy for damages and is also remarkably easy to compute.[1] In this article, we use distance to the epicenter of the highly destructive Sichuan earthquake of 2008 to estimate the impacts of the disaster on consumer preferences.

One of the ways in which an earthquake affects consumer preferences has to do with how agents perceive the future and "discount" future outcomes. Economists commonly consider that discount rates are fixed (Stigler and Becker 1977; Loewenstein and Elster 1992), but it is also understood that these time preferences vary with a range of individual circumstances such as age and income, dependency ratio, habit formation, or as in this case, information about risk (Warner and Pleeter 2001; Samwick 1998; Harrison, Lau, and Williams 2002). The occurrence of an earthquake may lead agents to update their risk priors and to alter their valuation of the future and their time preferences, all of which in turn shape their saving and consumption patterns.

It is generally believed in economic theory that agents act more conservatively in the face of risk (Sandmo 1970). If we believe in that theory, the 2008 disaster should have induced Sichuan villagers to invest in safeguards against the next earthquake or to accumulate more savings to smooth potential negative outcomes. Yet certain observations do not support this model. In conversations with the authors of this article, villagers often stated that the earthquake made them realize that life is short and needs to be enjoyed while it lasts. They claimed to spend more time on leisure activities, such as playing *majiang* (a popular game in China played by four people). A local farmer interviewed by the press after the earthquake stated, "Life is so unpredictable. People can leave us anytime" (Xia 2013). These observations fit an alternative model, under which agents facing disaster risk choose to "live like there is no tomorrow" and turn toward a more epicurean lifestyle.[2] In this paper we find empirical evidence supporting that alternative model.

[1] Earthquake intensity also depends on the geology and topography of an area, such that distance to epicenter is only a proxy for intensity, not a perfect measure of it.

[2] The two models are not necessarily incompatible; they may both be valid under different types of risk, for different personalities, and so on.

Using primary survey data over three years (2007, 2009, and 2011), we analyze how consumer behavior changed following the earthquake, exploiting the panel nature of the data with fixed-effects and random-effects frameworks. Regression analysis reveals that proximity to the earthquake is associated with a decrease in saving rate, higher expenditures on alcohol and cigarettes, and more frequent *majiang* playing. Our models are specified so as to rule out the confounding effects of reconstruction expenditures, income fluctuations, and price inflation, as well as gifts and other transfers. The next section reviews the literature and outlines our empirical strategy. Section 3 describes the background and data. Section 4 presents results as well as discussions on the robustness and the economic significance of those results. Conclusions follow.

2. LITERATURE AND THEORETICAL FRAMEWORK

Several strands of literature provide insights useful to our present question, which is located at the nexus of economics and psychology. The medical field documents the psychological damages of natural disasters. In this body of literature, psychologists are usually concerned with medical conditions such as depression or PTSD. Symptoms of PTSD were documented, for instance, in survivors of a tornado in North Carolina (Madakasira and O'Brien 1987), of the Loma Prieta earthquake in California (Nolen-Hoeksema and Morrow 1991), and indeed of the 2008 Sichuan earthquake (Kun et al. 2013). The focus of our paper is partly related to the psychological disorders documented in the medical field, because PTSD also affects consumption (for example, consumption of alcohol). However, the overlap with our study stops there, first because we focus on more subtle behavioral changes that do not necessarily qualify as medical conditions, and second because we rely on economic data from household surveys rather than medical data and evaluations of mental and emotional health.

How agents act under risky conditions has been widely studied in the economic literature. Economists have shown that households face risks through consumption smoothing (Townsend 1994), income smoothing (Takasaki, Barham, and Coomes 2010), activity diversification (van den Berg 2010; Mueller and Osgood 2009), or saving (Paxson 1992). Udry (1995) documented how households increase their saving when they anticipate a shock (and tap into their savings when a shock strikes). At the macro scale, Skidmore (2001) showed that countries more prone to natural disasters tend to have higher saving rates. These studies have in common that they describe behaviors that can largely be thought of as conservative: households protect themselves against potentially negative outcomes.

A different body of literature documents instances in which agents act *less* conservatively when anticipating negative outcomes. Agents may be overall inclined toward risk taking if they see small chances of ever reaping the benefits of conservative behavior, the "nothing to lose" theory (Harris, Duncan, and Boisjoly 2002; Hill, Ross, and Low 1997). Living in a risky environment has been linked to lower investment in education (Fortson 2011), higher prevalence of unsafe sexual behavior (Oster 2012), and drug use (Gibbons et al. 2004). Agents may also become less conservative in reaction to a recent disaster. Behavioral economists have directly estimated discount rates of disaster survivors and found a prevalence of embracing risk in the wake of natural disasters (Cameron and Shah 2013; Eckel, El-Gamal, and Wilson 2009). Most of these studies unfortunately rely on cross-section data, and usually on small samples. An exception is work by Hanaoka, Shigeoka, and Watanabe (2014), who used an individual-level two-year panel to show that males who experienced a higher intensity of the Great East Japan Earthquake became more risk tolerant, gambled more, and drank more.

Theories and previous results are thus ambiguous as to how agents' behavior may change after an earthquake. On the one hand, they may act conservatively to insure against future outcomes, for instance through increased saving. On the other, they may discount future outcomes, start acting more recklessly, and save less. Our results suggest that the latter effect was dominant following the Sichuan earthquake, and the net effect economically significant.

Empirical Framework and Identification Strategy

Since we have data collected both before and after the earthquake, a straightforward starting point to estimate whether the earthquake affected a given measure of consumer behavior (here, the saving rate), would be a first-difference framework, such as the following:

$$\Delta s_h = \beta + \gamma I_h + \delta X_h + \eta \Delta Z_h \, , \tag{1}$$

where Δs_h is the change in a consumer behavior variable at the household level, I_h is the level of intensity of the earthquake experienced by the household, and X_h and ΔZ_h are relevant control variables, in levels and differences respectively, that can be specific to a household or common to all households in a given village. Two considerations make this specification somewhat impractical.

First, an appropriate household-level "intensity" variable is not easy to find. An obvious candidate would be the damage to someone's house, but this raises issues if our outcome of interest has to do with saving or spending. Damages at the household level are endogenous to household consumption behavior, for instance, if lower propensity to save translates into a less earthquake-proof house. Moreover, considering that an agent's preferences are also influenced by the intensity of damage to the village in general (for instance, if a neighbor's house was destroyed or the local school collapsed), a village-level intensity variable is more appropriate. Destruction at the village level poses less of an endogeneity problem (though it does not fully solve it, because people with similar behaviors may tend to live in the same villages). By comparison, distance to epicenter is arguably likely to be exogenous.[3] In this paper, we will rely primarily on distance-to-epicenter variables to capture damage intensity, and also use village damage as a robustness check.

Second, the destruction brought about by the earthquake requires reconstruction expenditures, which by definition shape spending patterns. A drop in the saving rate could likely be due to these incompressible expenditures and thus a rather trivial result. The goal of this paper is to document not the shifts in expenditures that are driven by rebuilding necessity, but rather those attributable to a change in preferences. This is primarily an issue when using the saving rate as a left-hand-side variable. We also estimate impacts on the frequency of playing *majiang* and on alcohol expenditures, which are not so obviously related to the need to rebuild a house. These results bolster the notion that our estimates may indicate a preference shift. Another solution to the issue of incompressible reconstruction expenditures is to restrict our analysis to those households whose homes were *not* destroyed. Such households do not incur reconstruction expenditures but likely observed destruction around them, which could trigger a change in their preferences.

Taking these issues into consideration, our basic specification becomes

$$\Delta s_{h|non-affected} = \beta + \gamma D_v + \delta X_h + \eta \Delta Z_h \,, \qquad (2)$$

where D_v is distance to epicenter, and the sample is restricted to those who did not suffer destruction themselves. We refer to this as a first-difference (FD) specification. The same theoretical model can also be expressed in a fixed-effects (FE) framework. An FE specification is identical to the corresponding FD model when there are only two years of data. However, it can also be run on panel datasets of more than two years (we have three), and in that case may yield in slightly more efficient estimates. The FE specification is

$$s_{h,t|non-affected} = \beta + \zeta T_t + \xi D_v * T_t + \eta\, Z_{h,t} + \lambda H_h \,, \qquad (3)$$

where T_t is a set of year dummies, $Z_{h,t}$ are household- or village-level time-varying control variables, and H_h is a set of household dummies controlling for all time-invariant household characteristics (previously captured in X_h). The key terms in this specification are the distance-year interaction terms D_v*T_t. They capture the same effect as the distance term in the FD model, namely whether distance explains change in the left-hand-side variable in T_t relative to the base year. If this coefficient is nonzero for post-earthquake years, it suggests that the quake had an effect. Note that the noninteracted distance term does not appear in the equation, since distance to epicenter is a time-invariant characteristic, and thus captured by the household dummies. We also run this as a random-effects (RE) specification, in which case the distance term is included and the household dummies disappear.

Most results in this paper will be based on a model such as the one in equation (3), which minimizes endogeneity issues and rids us of the effect of reconstruction expenditures. However, as with any econometric specification, this model is not immune to criticism. In particular, there is some danger

[3] Distance to epicenter would not be exogenous if people chose their living locations according to earthquake risk. However, the region had not experienced a quake since 1930, and in interviews conducted in 2007 residents of Maoxian indicated they thought they were at very low risk of natural disasters, making this unlikely. In addition, the Chinese *hukou* registration system limits household relocation.

that by restricting the sample to nondestroyed households we may introduce some selection bias. Therefore, we also present results of similar models that use the full sample, controlling for the cost of reconstruction, as follows:

$$s_{h,t} = \beta + \zeta T_t + \xi D_v * T_t * R_t + M_t + C_t + \eta Z_{h,t} + \lambda H_h \, , \tag{4}$$

where C_t refers to the cost of rebuilding incurred in year t, M_t refers to the number of months the household was rebuilding its home during year t, and the triple interaction term $D_v*T_t*R_t$ includes a "no rebuilding in year t" dummy (R_t) to capture the effect of distance for those households who either have not needed to rebuild or have completed rebuilding before year t. This specification has the advantage of increasing our sample and limiting selection bias, while still controlling for rebuilding.

In what follows we use variants of both specifications (3) and (4), expressed as ordinary least squares, Poisson, or RE Tobit models, depending on the nature of the left-hand-side variable. In some specifications we will also use distance to aftershock, village-level damage, and estimates on the Modified Mercalli Intensity Scale (MMI) as a proxy for earthquake intensity.

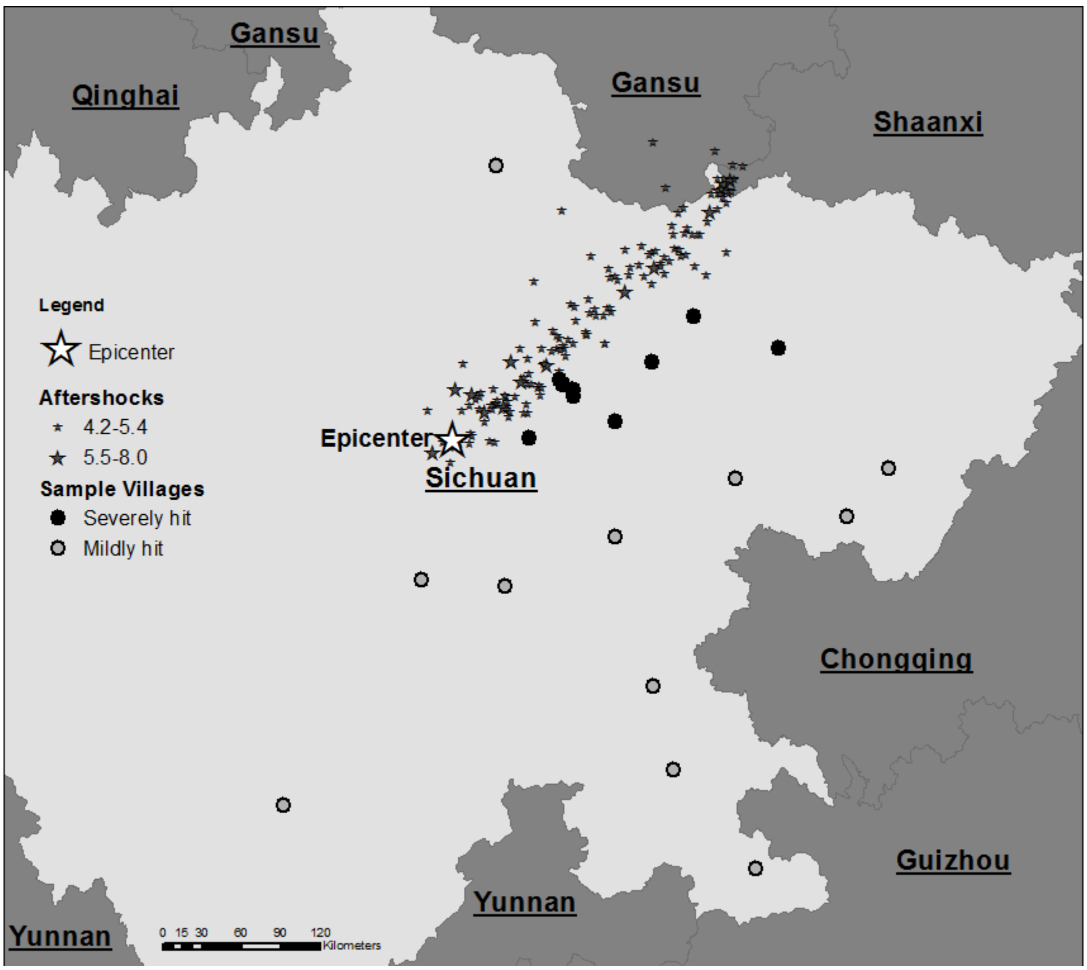
3. BACKGROUND AND DATA

The Wenchuan Earthquake

The province of Sichuan is located in southwestern China. At the point of contact between the Tibetan plateau and the eastern fertile basins, the region's topography is highly uneven. Tectonic tensions between the Indian and Eurasian plates created the Longmenshan Fault, responsible for the seismic activity that resulted in the 2008 disaster.

The 2008 earthquake took place on May 12 with the epicenter in the county of Wenchuan. The location of the epicenter is shown in Figure 3.1. The original seism reached a magnitude of 8 on the Richter scale. It was followed by strong aftershocks spreading toward the northeast along the fault line, many of which were also of considerable magnitude (see Figure 3.1). The damage of the earthquake spread through the entire region and even affected Gansu, the province to the north.

Figure 3.1 Map of villages, earthquake epicenter, and aftershocks



Source: Baidu maps and Wikipedia (coordinates and magnitude); datasets from annual rural panel administered by Chinese Ministry of Agriculture's Research Center for the Rural Economy (2007, 2009, 2010) and Sichuan Rural Household and Migration Survey, Shanghai University of Finance and Economics, and the International Center for Agricultural and Rural Development (2007, 2009, 2010) (damage severity).

Note: Villages were classified as severely hit if data gave reports of collapsed houses, mildly hit if not.

The Sichuan earthquake of 2008 was among the most destructive earthquakes in recorded history: it killed tens of thousands, injured hundreds of thousands, and left five million homeless, according to official numbers. The extent of the damage captured national and worldwide attention. The collapse of school buildings and the number of child casualties exacerbated the emotional shock, fueled anger against officials involved in school construction, and triggered a corruption scandal. The severity of the disaster prompted the Chinese government to launch a swift reconstruction effort of unprecedented scale. Reconstruction was fully complete in less than four years (Yang 2012). The full impacts of the earthquake, however, may have been longer lasting.

Data Sources and Variables

Data Sources

Because natural disasters are difficult to predict, it is rare for economists to have the predisaster data necessary for solid econometric estimations. Our work was made possible by constructing a unique dataset merging three separate household surveys: the Sichuan component of the annual rural panel administered by the Chinese Ministry of Agriculture's Research Center for the Rural Economy (RCRE), a supplementary survey administrated jointly by the RCRE and the International Center for Agricultural and Rural Development (ICARD), and the Sichuan Rural Household and Migration Survey (SRHMS) administrated jointly by Shanghai University of Finance and Economics and ICARD. The design of the RCRE and SRHMS surveys has enough in common that merging them presents only minor compatibility concerns. The RCRE dataset is a national rural panel collected annually since 1984, and one of the most widely used data sources on rural China. It includes about 800 household observations in the Sichuan province, collected from 16 villages. While all of those villages experienced the earthquake (it was felt even in Beijing), 5 of them were designated as directly affected by the earthquake according to government classification, and 1 as severely affected. This may limit explanatory power for earthquake-related questions. The SRHMS was started in 2007 and gathered information on about 800 households from 6 villages. The SRHMS focused specifically on Mianzhu County, which was later to become one of the most severely affected counties in the 2008 earthquake. The SRHMS was repeated after the earthquake, in 2009 and 2012. By merging 2007, 2009, and 2011 data from the RCRE, the supplementary RCRE data, and the SRHMS, we obtain a unique panel dataset that spans all of Sichuan, has a considerable number of observations in severely affected areas, and includes a pre-earthquake baseline.[4]

A full description of both datasets exists (L. Jin et al. 2013), and the location of villages is shown in Figure 3.1. Our full sample, constructed by merging data from the RCRE and the SRHMS, contains 1,322 households (each with observations in 2007, 2009, and 2011). The restricted sample of households whose homes were not damaged is 603 for each year.

In addition, we used Global Positioning System (GPS) coordinates to compute distances between villages and the epicenter of the earthquake or the epicenters of its major aftershocks (shown in Figure 3.1). Coordinates for villages were obtained from the online mapping website map.baidu.com. All epicenter coordinates came from the United States Geological Survey (USGS).[5] We also used mapping software to match each village with seismic intensity estimates publically available from the USGS website.[6] We culled consumer price index (CPI) values from the Sichuan Statistical Yearbook (SBSP 2007, 621; SBSP 2009, 525; SBSP 2011, 481) (using the CPI in the nearest county for which data are available).

[4] We had no access to the 2012 RCRE data when writing this paper. The RCRE is collected in December of each year, and SRHMS is collected in August, such that the recall periods of the 2011 RCRE and 2012 SRHMS overlap.

[5] Available from http://en.wikipedia.org/wiki/List_of_2008_Sichuan_earthquake_aftershocks as of September 2014, itself compiled using data retrieved from earthquake.usgs.gov.

[6] Available at http://earthquake.usgs.gov/earthquakes/shakemap/ as of June 2015.

Explained and Explanatory Variables

The household saving behavior was measured as the natural logarithm of the ratio of income over consumption, ln(Y/C). The log income/consumption ratio is thought to be a more accurate estimate of the saving rate than other formulas, and one that limits the power of outliers, particularly when using data from household surveys with incomplete information on savings and investments. Other explained variables we use include the *majiang* frequency (expressed as the summed number of times per month any member of the household played *majiang*), as well as expenditures on alcohol (expressed in Chinese renminbi, or RMB) and consumption of cigarettes (expressed in number of cartons). The data in 2007 reported cigarette expenditures in RMB, so for that year we converted the cash value to number of cartons, assuming a carton costs 40 RMB (10 packs, 4 RMB each).

Our primary proxy measure for earthquake intensity is the distance between a village and the epicenter of the seism. It was computed from GPS coordinates using geographic information systems (GIS) software in the World Geodetic System (WGS) 1984 Universal Transverse Mercator (UTM) Zone 48N coordinate system. This is the intensity proxy we use in almost all specifications, yet we also use other proxies for robustness checks. Because numerous aftershocks were scattered along the fault line, some of the most severely damaged villages are closer to an aftershock than to the original epicenter. We thus introduce a second measure: the distance to the closest aftershock epicenter of magnitude 5.5 or greater that occurred within three months of the original shock (there were 16 such aftershocks, shown in Figure 3.1).

In addition to those two measures of distance, we run specifications with more direct measures of earthquake damage: percentage of population injured at the village level and percentage of houses collapsed in the village. The information was collected only in villages the RCRE classified as hard hit or hardest hit by the earthquake; we assume both values are zero in the 11 lightly affected or nonaffected villages.

Finally, we also run regressions using measures of seismic intensity expressed in the MMI scale, a scale from 1 to 10 describing increasingly intense shaking of the earth (values in our sample range from 4.4 to 8.8). The MMI scale is a nonmathematical scale based on observed effects of an earthquake (movement of furniture, damage to chimneys, collapse of buildings, and so on).[7] The arbitrary nature of the scale ranking makes it an imperfect tool for regression analysis—however, we include it as one of our intensity measures because it is the most widely used and most meaningful to nonscientists. Estimates of the MMI throughout most of Sichuan at the time of the earthquake are available online from the USGS website—they are based on instrumental ground motion recordings of peak acceleration and velocity amplitudes using a conversion method developed from observations of California earthquakes (Wald et al. 1999a, 1999b). We used GIS mapping software to match survey distances to MMI measures. Three villages in our sample fell just outside of the mapped range and were assigned extrapolated values.

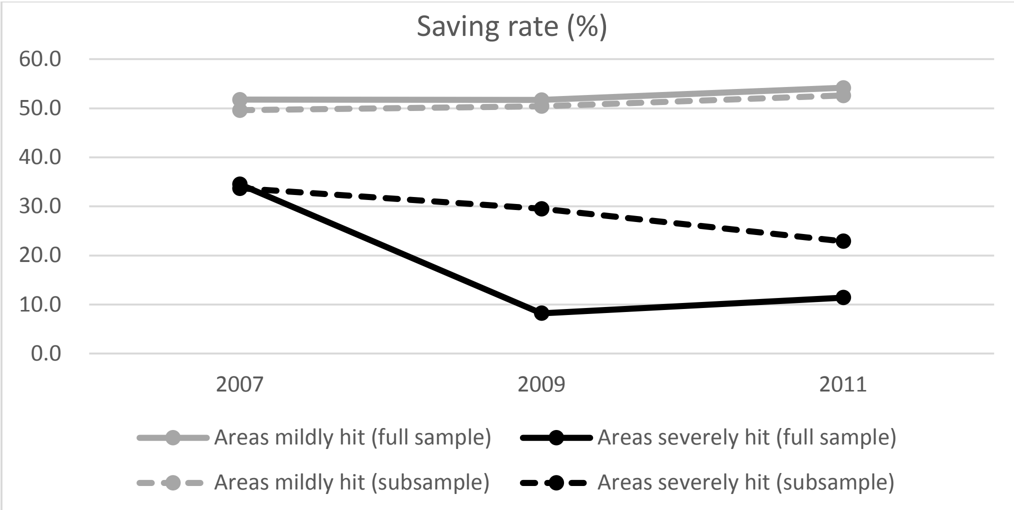
Data overview and Summary Statistics

We chart out the evolution of the savings rate after the earthquake in Figure 3.2, splitting the sample into more and less severely affected areas. While the Wenchuan earthquake was felt throughout all of Sichuan (and indeed, as far as Beijing), damage was severe only in parts of the region. We define villages as “severely hit” if our data reports collapsed houses, and “mildly hit” if not. [8]

[7] See http://earthquake.usgs.gov/learn/topics/mercalli.php for a description of the MMI scale.

[8] The Chinese government classified counties of Sichuan into four categories by earthquake intensity, from disaster zone (category 1) to nonaffected (category 4). The villages we define as severely hit are all in categories 1 and 2, and those we define as mildly hit are in categories 3 and 4, except for one village in category 2. See www.chinanews.com/gn/news/2008/07-12/1310643.shtml (in Chinese).

Figure 3.2 Evolution of the saving rate in areas of Sichuan either mildly or severely hit by the earthquake



Source: Annual rural panel, Chinese Ministry of Agriculture's Research Center for the Rural Economy (2007, 2009, 2010); Sichuan Rural Household and Migration Survey, Shanghai University of Finance and Economics and International Center for Agricultural and Rural Development (2007, 2009, 2010).

Notes: Saving rate computed as (r-1)/r, where r is the ratio of income to consumption. The figure reports median values. We defined areas as severely hit by the quake if there were collapsed houses, mildly hit if not. The restricted subsample refers to households who reported no damage to their house and no reconstruction expenditures.

The full lines in the figure correspond to the full sample, and show that the savings rate decreases dramatically in the areas which were severely hit by the earthquake (dark full line), while they are slowly growing in the areas mildly hit (grey full line). This dramatic drop in savings rates is at least partly reflecting incompressible expenditures on reconstruction by households whose home was destroyed. The dashed lines show the same measure of savings rate in severely and mildly hit regions, but restricting the sample to those who reported no damage to their home and no reconstruction expenditures. In mildly hit areas, households in the subsample behave like the full sample (grey dashed line). The dark dashed line shows that in severely affected areas, even households who did not experience damages reduced their savings rate by over ten percentage points, from 33.7 percent to 22.9 percent. Given the way we restricted the sample, this drop in savings rate is not due to household reconstruction expenditures, indicating a possible shift in preferences.

Figure 3.2 is constructed without controlling for any of the possible confounding factors that could explain the differences in saving rate trends. The mildly and severely affected areas need to be reasonably similar prior to the earthquake for the figure to be entirely convincing. In general, severely hit villages are located in more mountainous and less wealthy areas of Sichuan, and Figure 3.2 suggests households there save less on average. The data also show that severely hit villages have slightly smaller families (3.4 versus 4.3 members). Household heads in severely hit villages are slightly less educated—though in both regions more than half of heads have no more than primary schooling (56.0 percent and 60.6 percent in mildly and severely hit areas, respectively). Villagers in severely hit areas own slightly smaller plots on average (3.3 mu versus 4.4 mu[9]), but crop diversity and participation in animal husbandry appear similar. Although wage work is equally common between the groups, nonagricultural self-employment is considerably more common in the mildly hit areas (27 percent of households report operating a business, versus 10 percent in severely hit areas). Per capita annual income is similar in the two areas (just over 5,000 RMB), as is income structure: off-farm labor is the largest income source,

[9] A mu is a Chinese measure of land area equal to 0.066 hectares.

followed by agricultural income. Households in mildly hit areas, however, tend to own more assets, on average 31.6 thousand RMB versus 18.6 thousand RMB. They also spend slightly less, which is consistent with their accumulating more assets by saving more. These statistics, as well as others comparing the mildly and severely affected areas in 2007, are presented in Appendix Table A.1.

The a priori differences between severely and mildly hit villages are not great, but some may be important. This is part of the reason why we cannot simply use a difference-in-difference approach between severely and mildly hit regions to answer our questions about the effects of the earthquake. Instead, we rely on regression analysis in FD, FE, or RE frameworks, which allow us to control for relevant variables and for idiosyncrasies at the household level.

Table 3.1 presents summary statistics for all the variables we use in our regression analysis, using the subsample of households whose homes were not destroyed (Appendix Table A.2 is an identical table for the full sample). We tested means for equality in 2009 and 2011 against the 2007 base, showing the p-values in the last two columns of each panel. The table shows that overall there have been some evolutions during the five years our sample spans. Our main explained variable, the saving rate measure ln(Y/C), dips somewhat in 2009 then rises again in 2011, though these differences are not significant in the subsample. The frequency of *majiang* games decreases on average, also insignificantly. Alcohol spending dips in 2009, while cigarette consumption rises. Only the cigarette result appears significant. Our regression analysis will help reveal the more subtle differences not picked up by means-equality testing and highlight any differential evolutions that are related to distance from epicenter.

Table 3.1 Summary statistics of variables used in regression analysis, subsample of households whose homes were not damaged

Variable	(1)	(2)	(3)	(4)	(5)
				p-value of means equality T-test	
	2007	2009	2011	2007–2009	2007–2011
Explained variable					
Ln(income/consumption)[a]	0.637	0.596	0.641	0.308	0.895
	(0.609)	(0.775)	(0.607)		
Frequency of playing *majiang* (times/month)	3.192	NA	3.048		0.718
	(6.851)	NA	(7.044)		
Expenditure on alcohol (RMB)	66.40	56.80	65.16	0.0889	0.827
	(122.1)	(65.17)	(68.67)		
Expenditure on cigarettes (RMB)[b]	507.0	1108.8	961.8	0.003**	0.000***
	(615.2)	(4932.5)	(2148.4)		
Earthquake intensity variable					
Distance from village to epicenter (km)		235.3			
		(95.27)			
Distance from village to nearest aftershock (km)[c]		196.4			
		(101.5)			
Prevalence of human injuries in village (%)		0.129			
		(0.930)			
Share of houses collapsed in village (%)		4.537			
		(17.99)			
MMI		7.4			
		(1.06)			

Table 3.1 Continued

Variable	(1)	(2)	(3)	(4)	(5)
				p-value of means equality T-test	
	2007	2009	2011	2007–2009	2007–2011
Control variable					
Total net income per capita (ln)	9.688	9.804	9.937	0.042*	0.001**
	(0.990)	(0.981)	(1.565)		
CPI (2011 base village level)	83.39	90.54	100	0.000***	0.000***
	(5.632)	(1.558)	(0)		
Gifts to other households (RMB)	0.0114	0.0117	0.0296	0.971	0.00478**
	(0.0596)	(0.138)	(0.146)		
Loans to other households (RMB)	0.0322	0.0324	0.0460	0.984	0.356
	(0.201)	(0.183)	(0.308)		
Government transfers received (1,000 RMB)	0.290	0.577	0.474	0.000***	0.000***
	(0.485)	(0.752)	(0.656)		
Age of household head	51.84	53.64	55.22	0.006**	0.000***
	(11.43)	(11.36)	(11.34)		
Gender of household head (1: male, 2: female)	1.063	1.073	1.088	0.493	0.102
	(0.243)	(0.260)	(0.283)		
Education of household head#	0.521	0.506	0.514	0.665	0.847
	(0.597)	(0.599)	(0.599)		
Household size	3.847	3.818	3.768	0.727	0.358
	(1.450)	(1.521)	(1.556)		
Number of laborers in the household	2.726	2.687	2.580	0.596	0.0534
	(1.265)	(1.343)	(1.355)		
Landholding (mu)	3.154	3.059	2.702	0.519	0.002**
	(2.441)	(2.637)	(2.660)		
Party member in household (1 = yes, 0 = no)	0.153	0.144	0.141	0.686	0.569
	(0.360)	(0.352)	(0.348)		
Observations	603	603	603	1,206	1,206

Source: Annual rural panel administered by Chinese, MARCRE (2007, 2009, 2010) and Sichuan, Rural Household and Migration Survey, Shanghai University of Finance and Economics, and the International Center for Agricultural and Rural Development (2007, 2009, 2010).

Notes: CPI = consumer price index, MMI = Modified Mercalli Intensity Scale, RMB = Chinese renminbi. [a] Assuming incomes are the sum of consumption and savings, the natural log of income/consumption (λ) is related to the saving rate (s = savings/income) by the formula s = (eλ-1)/ eλ. A saving rate of 50 percent corresponds roughly to λ = 0.7. [b] For 2007, we assumed a cost of 40 RMB per carton (10 packs, 4 RMB each). [c] Computed as the distance to any aftershock of magnitude 5.5 or greater that occurred within three months of the initial shock. # (0: 6 or fewer years, 1: between 7 and 9 years, 2: more than 9 years) *** p < 0.01, ** p < 0.05, * p < 0.1.

The bottom panel of control variables shows that incomes grew somewhat over the period, as did prices. The table shows an expected strong increase in government transfers received (significantly higher than the base year for both 2009 and 2011). The average age of the household head increased (expected for a panel). Landholdings are slightly smaller in 2011 than in 2007. Most other differences in the table, such as the slight decrease in number of laborers per household, are of moderate magnitude and mostly insignificant according to means-equality tests. The same is true for the full sample (see Appendix Table A.2).

4. RESULTS AND DISCUSSION

Impacts on the Saving Rate

Table 4.1 shows the results of various measures of earthquake severity at the village level on the change in the saving rate of households, using the FE framework specified in equation (3).[10] Samples are restricted to households whose houses were not destroyed and who did not report reconstruction expenditures. This ensures that shifts in saving behavior are not driven by rebuilding necessity. All specifications control for the household head's gender, age, age squared, party membership, and education, as well as household size, size squared, and landholdings. Those coefficients are not presented in the table in the interest of space.

Table 4.1 Impacts of earthquake on income/consumption ratio using different proxies for earthquake severity

Variable	(1)	(2)	(3)	(4)	(5)
Model type	**FE**	**FE**	**FE**	**FE**	**FE**
Explained variable	$\ln(\frac{Y}{C})$	$\ln(\frac{Y}{C})$	$\ln(\frac{Y}{C})$	$\ln(\frac{Y}{C})$	$\ln(\frac{Y}{C})$
***Intensity* variable used**	**Ln(Distance to epicenter)**	**Ln(Distance to aftershocks)[a]**	**Prevalence of human injuries in village (%)**	**Share of houses collapsed in village (%)**	**MMI**
*[Intensity]**year09	0.159**	0.111*	-0.065	-0.004	-0.109
	(0.061)	(0.061)	(0.077)	(0.003)	(0.070)
*[Intensity]**year11	0.213*	0.129	-0.059*	-0.000	-0.123*
	(0.111)	(0.081)	(0.033)	(0.004)	(0.070)
Year 2009 dummy	-0.891**	-0.607*	-0.029	-0.020	0.527
	(0.344)	(0.326)	(0.026)	(0.026)	(0.354)
Year 2011 dummy	-1.121*	-0.639	0.032	0.025	0.658*
	(0.621)	(0.439)	(0.053)	(0.050)	(0.338)
Observations	1,809	1,809	1,809	1,809	1,809
R-squared	0.030	0.028	0.025	0.026	0.029
Number of id	603	603	603	603	603
Adjusted R-square	0.203	0.203	0.203	0.203	0.203

Source: Author estimations based on RCRE and SRHMS datasets.

Notes: [a] Computed as the distance to any aftershock of magnitude 5.5 or greater that occurred within three months of the initial shock. All specifications include year dummies and control for 2007 head gender, age, age squared, party membership, and education, and household size, size squared, and landownership. Sample restricted to households with undamaged houses. Robust errors in parentheses clustered at village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. C = consumption, FE = fixed effects, Y = income.

Specifications 1–5 each use a different proxy for earthquake intensity. Column 1 uses logged distance to epicenter, the variable we will use throughout most of the article. Distance to aftershocks is used as a proxy for earthquake intensity in Column 2. Columns 3 and 4 employ village-level measures of damage intensity, respectively the prevalence of human injuries among the village population and the share of collapsed houses in the village, both in percentage terms. For households whose homes were not destroyed, those village-level damage variables can proxy for the severity of the emotional shock

[10] We also ran all of these models using FD specifications in the short (2007–2009) and medium (2007–2011) terms, with practically identical results. This reassures us vis-à-vis endogeneity issues in our specification, since endogeneity would lead to widely differing results between FE and FD models.

resulting from the earthquake. The last column uses intensity on the MMI scale. Note that "distance from" variables are inversely related to earthquake damage, while prevalence of injuries, collapsed houses, and MMI intensity are directly related to earthquake damage, so we would expect the signs in columns 1 and 2 to be opposite to those in columns 3, 4, and 5.

All five columns present the results of ordinary least squares (OLS) regressions with household fixed effects. The explanatory variables of interest are the interaction terms between the distance to epicenter and the year dummies. If the coefficient on one of these variables is different from zero for a given year, it means distance to epicenter mattered for explaining the change in income/consumption ratio relative to the base year, 2007. The intensity*2009 interaction term can be thought of as a short-term impact. The 2011 interaction term reveals medium-term impacts, at a time when much of the reconstruction effort was complete.

Column 1 shows a positive and significant relation between the saving rate and distance from epicenter in both 2009 and 2011. After the quake, saving rates of households further from the epicenter increased more (or decreased less) than those of households closer to it. This suggests that the quake induced lower saving rates. The size of the coefficient (0.15) should be interpreted as an elasticity: a 1 percent increase in distance from epicenter comes with a 0.15 percent greater change in the income/consumption ratio. In other words, the drop in income/consumption ratio in a village 100 km away from epicenter is roughly 1.5 percent larger than in a village 110 km away.[11] The effect seems to persist in the medium run (0.213).

Column 2 uses a different measure of earthquake intensity: distance to aftershocks. In the short run, the coefficient of interest is also positive and significant, but unlike column 1, it loses significance in the medium run. Column 3 shows negative coefficients on both intensity-year interaction terms, which is consistent with columns 1 and 2. After the earthquake, households in villages with a higher prevalence of injuries saved less than those with a lower prevalence. However, only the 2011 interaction term is significant. This result suggests that the earthquake may have impacted consumer behavior in a relatively durable manner, which is somewhat surprising if we imagine that the initial emotional shock of the earthquake gets attenuated over time. Column 4 also displays negative signs on the interaction terms, but both are insignificant. It seems that prevalence of human casualty or injury has left a more vivid impact on people's saving behavior than property damage. Finally, Column 5 also displays negative coefficients on earthquake intensity measured on the MMI scale, significant in 2011 but not 2009.

Overall, Table 4.1 suggests that the earthquake lowered the propensity to save in more affected zones, consistent with our theoretical framework. This result is mostly robust to the use of different measures or proxies for earthquake severity, and relatively persistent in the medium term. Since we restricted the sample, we know that it cannot be due to household expenditures on the reconstruction of the house. However, there are potential alternative impact pathways that could explain this result.

One alternative explanation could have to do with incomes and prices. The literature generally agrees that there exists a relationship between incomes and saving rates, and that richer households tend to save more (Lawrance 1991). Facing a negative shock to income, households may choose to lower their saving rate in order to maintain consumption. Price inflation, which reduces incomes in real terms, may have a similar effect on saving rates. Under this "real income hypothesis," households closer to the epicenter would be saving less because their incomes decreased, because prices increased more than in areas further away, or both.[12] Another possible explanation for nonaffected households' reducing their saving rate is that they may be helping their affected neighbors with loans or gifts—we call this the "altruism hypothesis." Yet another possibility is that households in more affected areas received increased

[11] This is based on the approximation $(1 + p\%)^{0.15} - 1 \approx p*0.15$, which is acceptable for small values of p.

[12] A reviewer pointed out that a variant of this pathway could be the "permanent income" hypothesis. Households anticipating that their discounted future stream of income may be lower than they had previously expected may be saving less for that reason. This hypothesis would be difficult to test directly, because there is no measure of permanent income. The best we can do is to control for proxies of permanent income, as we do when we include income, landownership, family size, and age in the regressions.

government assistance (even if their home was not destroyed). If households treat transfer income differently than earned income, they may be saving less overall (the "nonfungibility" hypothesis).

Finally, the drop in saving rates could be due to a change in preferences, the "live like there is no tomorrow" or "carpe diem" hypothesis. Although we have no reliable data on consumer risk preferences and attitudes toward future outcomes, we can attempt to rule out the real income, altruism, and nonfungibility hypotheses. Results presented in columns (2) through (5) in Table 4.2 control for income levels, CPI at the village level, gifts and loans given out by households, and government transfers received (column 1 repeats the result from the previous table).

Table 4.2 Robustness checks of impacts of earthquake on income/consumption ratio

Explanatory variable	(1) Subsample ln(Y/C)	(2) Subsample ln(Y/C)	(3) Subsample ln(Y/C)	(4) Subsample ln(Y/C)	(5) Subsample ln(Y/C)	(6) Full Sample ln(Y/C)	(7) Full Sample ln(Y/C)
Ln(Distance to epicenter)*year09	0.147**	0.149**	0.146**	0.147**	0.140**	0.182*	
	(0.061)	(0.064)	(0.066)	(0.066)	(0.065)	(0.090)	
Ln(Distance to epicenter)*year11	0.206*	0.100	0.097	0.096	0.095	0.163**	
	(0.110)	(0.093)	(0.096)	(0.097)	(0.097)	(0.078)	
Ln(Distance to epicenter) *year09*not rebuilding							0.053**
							(0.021)
Ln(Distance to epicenter) *year11*not rebuilding							0.083**
							(0.037)
Household incomes (ln)		0.236**	0.236**	0.236**	0.237**	0.662***	0.661***
		(0.097)	(0.097)	(0.097)	(0.096)	(0.184)	(0.183)
Consumer price index			-0.001	-0.001	-0.001	0.002	0.004
			(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Gifts to neighbors				0.049	0.053	-0.165	-0.167
				(0.068)	(0.070)	(0.154)	(0.152)
Loans to neighbors				-0.034	-0.035	0.060*	0.054
				(0.032)	(0.031)	(0.034)	(0.031)
Government transfers					-0.015	-0.031	-0.036*
					(0.026)	(0.019)	(0.020)
Months rebuilding this year						-0.015	0.011
						(0.010)	(0.013)
Cost of rebuilding this year						-0.000	0.000
						(0.001)	(0.001)
Cost financed by loans						-0.002	-0.000
						(0.003)	(0.003)
Observations	1,809	1,809	1,809	1,809	1,809	3,966	3,966
R-squared	0.030	0.233	0.233	0.233	0.234	0.538	0.537
Number of id	603	603	603	603	603	1,322	1,322
Adjusted R-square	0.545	0.545	0.545	0.545	0.545	0.545	0.545

Source: Author estimations.

Notes: All specifications include year dummies and control for household head gender, age, age squared, party membership, and education, as well as household size, squared size, and landownership. Subsample = restricted to households with undamaged houses. Robust errors in parentheses clustered at village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. C = consumption, Y = income.

Distance to epicenter remains positively and significantly related to the ln(Y/C) ratio in 2009 in all columns (2) to (5), with barely any variation in the size and significance of the coefficient (0.151 to 0.160). For 2011, however, the coefficient on distance remains positive but loses its significance in subsample specifications controlling for income (columns 2 to 5). While incomes appear significant in explaining some of the variation in ln(Y/C), neither CPI nor gifts or loans nor government transfers appear significant. These results bolster the case for the drop in the saving rate to be preference driven, at least in the short run. It is consistent with a shift in time preferences in favor of present consumption, the "live like there is no tomorrow" hypothesis. We continue controlling for incomes, CPI, gifts, loans, and transfers in all following specifications, so as to rule out alternative hypotheses.

The last two columns (6 and 7) of Table 4.2 present models we ran with the full sample, which triples the amount of households in the sample and may yield tighter estimates. With a full sample, we are not worried about selection bias, but we still want to exclude the effect of reconstruction expenditures.[13] In both columns 6 and 7, we control for the cost of rebuilding in a given year and the number of months of the year that the house was in reconstruction. In the last column, we use the specification in equation (4), where the issue of reconstruction expenditures is addressed by interacting a "not rebuilding" dummy with the distance-year terms. The triple interaction term captures the effect of the quake among those who did not rebuild during a given year (either because they never had to rebuild, or because they had already finished rebuilding).[14] We also control for the amount borrowed for house reconstruction, which could influence expenditure patterns. Unfortunately, we are not able to control for whether the loan is still being repaid or not. However, L. Jin and Chen (2014) found that less than a third of rebuilding costs were financed with loans, minimizing the extent of this issue.

Results in both columns 6 and 7 indicate a strong positive relationship between distance to epicenter and saving rate, consistent with our carpe diem hypothesis. Those are significant in both 2009 and 2011, even when we control for incomes. Overall the tables document a very robust short-term effect of distance to epicenter on saving rate, and a somewhat less robust medium-term effect. It is likely that the quake's effect on preferences dissipates over time. Eventually it may be reversed, which would reconcile our results with the overall higher propensity to save in disaster-prone regions documented in the literature (Skidmore 2001).

In the next section we estimate impact on other behavioral variables: the frequency of playing *majiang*, alcohol expenditures, and smoking. Since these behaviors are not straightforwardly related to house rebuilding, the results can serve as a robustness check supporting that the change in saving rates we are estimating is not driven simply by the necessity to rebuild, but rather reflects a change in preferences.

Impacts on Playing *Majiang*

The game of *majiang* (or mah-jongg) is a popular pastime throughout Sichuan, as in much of eastern Asia. While the game usually involves some financial stakes, in the region we are studying those stakes are usually small enough to be considered symbolic, such that playing *majiang* is a form of entertainment rather than gambling. The 2007 and 2011 surveys asked how frequently household members played *majiang*. This part of the questionnaire was not administered in 2009, which limits us to estimating the medium-term effects, three years after the earthquake.

Table 4.3 presents the results of OLS, Poisson, and Tobit regressions of *majiang* frequency on the distance from epicenter, with all previously introduced controls to rule out hypotheses other than a change in preferences. Column (1) uses an OLS model with fixed effects. It shows a significant negative relationship between *majiang* frequency and 2011-interacted distance from epicenter, suggesting the earthquake triggered an increase in *majiang* frequency.

[13] Note that failing to exclude the effect of reconstruction expenditures does not bias the results. It just renders them less interesting. We want to isolate the part of the impact that is due to a preference shift.

[14] It is also possible to run these regressions only on the "not rebuilding" subsample. Results do not differ significantly from the full-sample specification. We do not discuss these results in the interest of space.

Majiang frequency is expressed as the average number of times someone in the household played *majiang* in a month, summed over all members, which can reach several dozen times. This can be thought of as a count variable, and therefore may be better represented by a Poisson distribution rather than a normal. We thus rerun the same specification using a Poisson count model, also with fixed effects. We obtain a negative and highly significant coefficient on the interaction term. We can also think of *majiang* frequency as a continuous variable (monthly averages need not be integers), but one that is truncated at zero. The third column uses a Tobit model left-censored at zero with random effects, and also shows a negative and significant coefficient on interacted distance.[15]

Table 4.3 Impact of earthquake on frequency playing majiang at the household level

Variable	(1) Subsample OLS, FE	(2) Subsample Poisson, FE [a]	(3) Subsample Tobit, RE	(4) Full Sample Tobit, RE	(5) Full Sample Tobit, RE
Ln(Distance to epicenter) *year11	-0.928*	-0.424***	-3.784***	-1.300*	
	(0.484)	(0.155)	(1.230)	(0.664)	
Ln(Distance to epicenter) *year11*not rebuilding					-1.152*
					(0.646)
Ln(Distance to epicenter)			2.425	-6.255***	-6.323***
			(1.638)	(0.980)	(0.978)
Months rebuilding this year				0.378	-0.391
				(1.190)	(1.273)
Cost of rebuilding this year (1,000 RMB)				-1.834	-1.972
				(190.718)	(184.921)
				-3.373	-3.368
				(767.264)	(520.654)
Observations	1,206	504	1,206	2,644	2,644
R-squared	0.020				
Number of id	603	252 [a]	603	1,322	1,322

Source: Author estimations

Notes: FE = fixed effects, OLS = ordinary least squares, RE = random effects, RMB = Chinese renminbi. [a] The Poisson model with fixed effects drops time-invariant households, but we obtain similar results with random effects or standard Poisson models and all 603 households. Majiang data not available for 2009. All specifications include year dummies and control for logged income; village consumer price index; loans and gifts to neighbors; transfer income; head gender, age, age squared, party membership, and education; and household size, size squared, and landownership. Subsample = restricted to households with undamaged houses. Robust errors in parentheses clustered at village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impacts on Alcohol Expenditures and Smoking

Preference for the present can be characterized by risky behavior, particularly engaging in behaviors that cause delayed harm. Agents with a high discount rate would be more likely to engage in such behaviors, since they place lower value on future outcomes (in this case, negative ones). Our data contain information on two such behaviors: purchases of alcohol and cigarettes. Both of those behaviors have been proven detrimental to health, but with symptoms that tend to develop over the long run. Under our "living like there

[15] Using a Tobit accounts for the fact that the explained variable is truncated at zero. Tobit is incompatible with fixed effects, so we used random effects. We do not run double-hurdle or zero-inflated Poisson models because of the challenges that arise when using such models in a panel setting.

is no tomorrow" hypothesis, agents closer to the earthquake would be more likely to engage in such behaviors. The same would happen if depression were aggravated by the earthquake, because it is often linked to drinking, smoking, and risk-taking behavior in general. More benignly, agents may rationally choose to increase their intake of ethanol or nicotine to relieve stress. Either way, this would be a manifestation of earthquake-induced changes in consumer preferences. Table 4.4 presents the results of regressions of the logged monthly expenditures on alcohol (columns 1 to 4) and on cigarettes (column 5).

Table 4.4 Impact of earthquake on expenditures on cigarettes and alcohol

	(1)	(2)	(3)	(4)	(5)
Explained variable			Expenditures on alcohol		Cigarette consumption
	Subsample	Subsample	Full Sample	Full Sample	Full Sample
Model type	OLS, FE	Tobit, RE	Tobit, RE	Tobit, RE	Tobit, RE
Explanatory variable					
Ln(Distance to epicenter) *year09	-18.172*	-19.976*	-5.914		
	(10.605)	(10.560)	(10.211)		
Ln(Distance to epicenter) *year11	-21.649*	-26.303**	14.041		
	(11.223)	(10.686)	(9.759)		
Ln(Distance to epicenter) *year09*not rebuilding				-5.361*	-4.768***
				(2.882)	(1.800)
Ln(Distance to epicenter) *year11*not rebuilding				7.741	-10.577**
				(6.826)	(4.356)
Ln(Distance to epicenter)		14.924*	-19.615**	-16.002**	37.882***
		(8.845)	(8.362)	(6.960)	(4.274)
Months rebuilding this year			3.096	0.511	-1.110
			(2.314)	(2.816)	(1.719)
Cost of rebuilding this year (1,000 RMB)			0.010	-0.007	-0.078
			(0.199)	(0.201)	(0.120)
Cost financed with loans			-0.042	-0.269	-0.112
			(0.523)	(0.535)	(0.321)
Observations	1,809	1,809	3,966	3,966	3,966
R-squared	0.036				
Number of id	603	603	1,322	1,322	1,322

Source: Author estimations.

Notes: FE = fixed effects, OLS = ordinary least squares, RE = random effects, RMB = Chinese renminbi. All specifications include year dummies and control for logged income; village consumer price index; loans and gifts to neighbors; transfer income; head gender, age, age squared, party membership, and education; and household size, size squared, and landownership. Subsample = restricted to households with undamaged houses. Robust errors in parentheses clustered at village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) uses the restricted sample with an OLS model, and shows a negative and significant sign on the distance interaction term. Given the large number of nondrinkers in the sample, we use a Tobit specification left-censored at zero in column (2), with the same result. We lose significance when we use the full sample (column 3) with the simple interaction term, but obtain a significantly negative coefficient on the triple-interaction term in column (4). Households closer to the epicenter increased their alcohol consumption more, relative to those further away. Column (5) suggests that the same is true for cigarettes, with a specification identical to that of column (4). We also ran specifications of columns (1), (2), and (3) with cigarette expenditures on the left-hand side, with insignificant results (not in table). As Hanaoka, Shigeoka, and Watanabe (2014) found, the earthquake appears to have led to more smoking and drinking, consistent with higher discount rates, symptoms of post-traumatic stress, or both. Note that in most columns these effects persist and are reinforced in the medium term (2011), which may be due to addictive substances contained in alcohol and cigarettes.

Ruling Out Price Transmission

Prices influence consumer behavior, which is why our regressions control for price levels by including the CPI as an explanatory variable. However, we may still worry that CPI is too coarse a measure of local price fluctuations. Unfortunately, we do not have local panel data that would allow us to include specific price levels (say, of cigarettes) in the regressions we present. What we can do is to test whether, in general, rural markets throughout Sichuan are well integrated. If they are, then we should be reassured that geographic differences in price fluctuations are likely not what explains the changes in consumer behavior that we document.

If markets in two different locations are integrated, then any difference in prices between those two locations should reflect only the differential costs of getting the goods to market (for example, transportation). This is sometimes called the "law of one price," illustrated by the equation $P_{m,t} = \alpha + P_{n,t}$, where $P_{m,t}$ and $P_{n,t}$ are the prices of that good at time *t* at markets *m* and *n*, respectively, and α captures transaction costs. Variants of this equation can be tested in a regression framework, and we do so using a panel of price data from the *Sichuan Statistical Yearbook*.[16] We use rural retail price data on 17 expenditure categories from 10 counties in Sichuan, including one (Maoxian county) that was severely affected by the earthquake (see Table 4.5). The data for Maoxian are available for 2004–2008.[17] We regress the normalized change in price in Maoxian county on the change in price in each of the other counties and category-specific dummies:

$$\tilde{P}_{Maoxian,i,t} = \beta \tilde{P}_{Other\ County,i,t} + \sum_i \alpha_i + u_{i,t}, \tag{5}$$

where *i* is a category subscript, α_i captures category-specific cost fluctuations, $u_{i,t}$ is an error term, and a tilde indicates the year-over-year change in price. We run one such regression for each of the counties in the dataset and test whether the beta parameter is equal to 1. Results appear in Table 4.5. Coefficients range from 0.952 to 1.044 and are highly significant (different from zero). Coefficients are all close to 1, suggesting market integration. Post-estimation tests reveal that for only one county can we reject the null hypothesis that β is equal to 1 (Shifang county, β = 1.044). Local inflation is thus not a likely explanation for our results.

[16] When high-frequency data are available, there exist more sophisticated ways to test for market integration, for instance with an Engle-Granger procedure (Alexander and Wyeth 1994; Engle and Granger 1987; Fackler and Goodwin 2001; Ravallion 1986). Although we do not have the luxury of high-frequency data, testing the law of one price in a regression framework is preferred to the default method of simply computing a correlation matrix.

[17] Maoxian is the most relevant county because it was severely struck by the earthquake. Data for a longer period (2004–2013) are available for only five counties, none of them in the disaster zone. Nevertheless, we did verify that prices between those five counties largely conformed to the law of one price over the whole period.

Table 4.5 Testing the law of one price between Maoxian and other counties in Sichuan

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
County	**Shifang**	**Shehong**	**Nanxi**	**Nanbu**	**Wenjiang**	**Hanyuan**	**Pingchang**	**Emeishan**	**Xuyong**
Beta	1.044***	1.017***	1.006***	0.999***	1.029***	0.952***	0.991***	1.023***	1.004***
Standard error	(0.022)	(0.026)	(0.019)	(0.024)	(0.022)	(0.030)	(0.019)	(0.022)	(0.020)
P-value for null beta = 1	0.0486**	0.515	0.764	0.967	0.186	0.118	0.653	0.295	0.827
Observations	68	68	68	68	68	68	68	68	68

Source: Author estimations. Based on a 2004–2008 panel of yearly average rural retail price data for 17 categories (food, beverages, garments, textiles, appliances, cultural and office goods, consumables, sports goods, transportation and communication, furniture, cosmetics, precious metals and jewelry, medicine, healthcare articles, newspapers and magazines, fuels, and building materials).

Notes: Each column refers to the regression of year-on-year change in price in Maoxian on the change in price in each of nine other counties, with item fixed effects and no constant term. Save for the first column (Shifang), we cannot reject the null that the coefficient on other-county-price is equal to 1, suggesting price integration. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Economic Significance

Assessing the economic significance of a shift in *majiang* playing behavior or alcohol consumption is not straightforward. However, we can use our saving rate results to provide some insight into the size of the impacts we measure. The log-log specification coefficients in Table 4.2 are elasticities: the drop in income/consumption ratio between 2007 and 2009 is 1.5 percent larger in a village 100 km away from epicenter than in a village 110 km away. This interpretation is still somewhat cryptic: in order to provide a more illustrative estimation, we reran the saving rate regressions with MMI as an intensity variable, and with income/consumption ratios (not logged) on the left-hand side. The MMI scale is the most commonly used measure to discuss earthquake intensity, making such a specification more meaningful. We run the same specifications as in Table 4.2 and report the results in Appendix Table A.3.

Regression results indicate that an increase of 1 level on the MMI scale was associated, in 2009, with an income/consumption ratio lower by 0.20 (including all controls). In 2011, that coefficient is -0.22. If we use a 0.20 decrease to make back-of-the-envelope calculations, this means that for households starting off with a Y/C ratio of 2 (saving half of their income, about the mean of our sample), one additional degree of earthquake magnitude lowers the Y/C ratio to about 1.80 (a 44 percent saving rate, 6 percentage points lower). If we are willing to extrapolate this linearly to the difference between the least-hit village (MMI = 4.4) and the most-hit village (MMI = 8.8), the difference in saving rate would be about 26 percentage points.[18] Since the scale is not based on a mathematical formula and represents highly nonlinear processes, such extrapolations should be taken with caution, and we do not make this figure the cornerstone of our analysis. However, the result does suggest that the effects of the earthquake on saving rates are far from trivial in magnitude, and have the potential to significantly alter the growth path of affected areas.

[18] A difference of 4.4 MMI times 6 percentage points.

5. CONCLUSIONS

Even when their home was not affected by the tremors, households who live closer to the 2008 earthquake reduced their saving rate, increased their purchases of alcohol and cigarettes, and played *majiang* more often after the disaster. Our estimates are significant in 2009, and persist into 2011 in some specifications. Results are not explained by incomes, prices, altruism, or government transfers, suggesting that the earthquake triggered a shift in the underlying preferences of consumers. This shift carries high economic significance: it potentially cuts the saving rate by several percentage points with each level of earthquake intensity.

Explaining the preference shift may be complicated and needs to draw on knowledge from psychology. At one extreme, a number of villagers may be suffering from PTSD, which is associated with (extreme) shifts in behavior. If that is the case, our results are reflecting severe emotional stress on a scale widespread enough that we pick it up in economic data. On the other hand, consumers may simply have updated their risk priors upward and increased their discount rate accordingly, as any rational agent would. In that case, our results would be reflective of a shift toward carpe diem consumer attitudes, placing higher value on present enjoyment. The two explanations are not mutually exclusive, but our conversations with Sichuan farmers pointed toward the latter. Many other explanations can exist, more or less associated with one of those extremes: Agents could have become more optimistic about their future income prospects and decided they did not need to save up. Conversely, they could have become more pessimistic about those prospects and decided there was no point in saving up (somewhat like the above carpe diem*,* but with a decrease in levels rather than an increase in the discount rate). The exact mental pathways that led to our results may differ between agents in the sample, and properly identifying them is not possible without psychological evaluations of the respondents.

Our results bear economic and social significance regardless of the underlying psychological mechanisms. The saving rate among nonaffected households dropped by one-third (Figure 3.2). A population that starts saving less, consuming more, taking on risks, and generally tending toward "living like there is no tomorrow" is likely to substantially alter its economic path. Attitudes toward the future permeate almost every aspect of life, from investment and employment to health and family planning. Through them, the consequences of natural disasters may continue shaping life and economic growth in affected areas long after reconstruction has been completed.[19]

The carpe diem attitudes we document pose somewhat of a conundrum when confronted by the widely held belief that agents act conservatively in the face of risk. Economists have documented higher saving rates in more disaster-prone areas, which does not square with our result. If the drop in saving rates after the earthquake we document were to become permanent, we would be hard pressed to explain how risk-prone regions end up with higher saving rates on average. One credible explanation is that this relationship depends on the level and type of risk: agents may self-insure in the face of hardship risk, but seize the day in the face of unpredictable sudden death. Another explanation could be that the effect we document is nonlinear: preferences may shift toward risk taking in the short to medium run but ultimately be reversed in favor of risk prevention. This could be the case if there exists a difference between *anticipating* a future disaster and *reacting* to a recent one: agents may be prone to acting recklessly immediately after a disaster, then gradually become more conservative as the trauma of the recent event morphs into anticipation of the next one. Indeed, our estimated drop in the saving rate tapers off in 2011 in some specifications, though we do not observe any sign reversal. On the other hand, the significant increases in spending on alcohol and cigarettes, as well as in *majiang* frequency, persist into the medium term (2011), perhaps due to habit formation. A follow-up to this study could assess the longevity of those impacts. Further research is needed to understand the short-, medium-, and long-term impacts of living under the threat of disaster.

[19] The literature on consumer demand and its resilience after a scandal or food safety scare raises a related question. Some studies have suggested that food scares lead to durable drops in the demand or price of the commodities concerned (Carter and Smith 2007; H. Jin and Koo 2003).

APPENDIX: SUPPLEMENTARY TABLES

Table A.1 Household characteristics in the severely and mildly hit areas prior to the earthquake (2007)

	Mildly hit villages			Severely hit villages	
Variable	**Mean**	**SD**		**Mean**	**SD**
A. Household (hh) characteristics					
Age of the head	51.1	11.8		51.6	11.6
HH size	4.3	1.7		3.4	1.2
Number of working-age workers	3.0	1.4		2.5	1.2
Percent hh heads without secondary schooling	56.0	-		60.6	-
Head is female (%)	5.9	-		6.8	-
Acreage of arable land per hh (mu)	4.2	4.1		3.3	1.7
Number of agricultural laborers in hh	2.1	1.4		1.7	0.9
Diversity of crops at hh level (entropy index)	1.167	0.629		0.993	0.404
Proportion of hh operating husbandry, fishery, or both	78.9	-		80.9	-
B. Household Income					
Percentage of hhs operating nonagricultural self-employment (%)	27.4	-		10.9	-
Per capita annual net income (RMB), of which:	5,004	3,945		5,225	5,148
Agricultural production	*1,867*	*2,876*		*1,691*	*3,779*
Nonagricultural self-employment	*587*	*2,710*		*189*	*936*
Off-farm labor supply	*2,601*	*2,909*		*3,005*	*3,378*
Other income	*764*	*1,756*		*615*	*1,790*
Total value of assets (RMB)	31,684	51,934		18,602	35,169
Per capita monthly consumption (RMB)	2,652	1,476	0	3,816	4,536
Observations	541			781	

Source: Annual rural panel administered by Chinese Ministry of Agriculture's Research Center for the Rural Economy (2007, 2009, 2010); Sichuan Rural Household and Migration Survey, Shanghai University of Finance and Economics and the International Center for Agricultural and Rural Development (2007, 2009, 2010).

Note: RMB = Chinese renminbi.

Table A.2 Summary statistics of variables used in regression analysis—full sample

Variable	(1) 2007	(2) 2009	(3) 2011	(4) p-value of means equality T-test 2007–2009	(5) 2007–2011
Explained variable					
Ln(income/consumption)	0.391	0.211	0.251	0.000***	0.003**
	(1.301)	(1.242)	(1.133)		
Frequency playing *majiang* (times/month)	4.231	NA	4.136		0.761
	(7.969)	NA	(8.176)		
Expenditures on alcohol (RMB)	83.90	79.53	72.27	0.425	0.0301*
	(171.9)	(100.5)	(91.54)		
Expenditure on cigarettes (RMB)	299.6	902.0	803.6	0.000***	0.000***
	(557.9)	(4036.7)	(2582.4)		
Earthquake intensity variable					
Distance from village to epicenter (km)		168.6			
		(94.29)			
Distance from village to nearest aftershock (km)		109.2			
		(107.6)			
Prevalence of human injuries in village (%)		0.980			
		(2.347)			
Share of houses collapsed in village (%)		44.41			
		(49.61)			
MMI		6.4			
		(1.46)			
Control variable					
Total net income per capita (ln)	9.462	9.539	9.686	0.132	0.000***
	(1.364)	(1.256)	(1.474)		
CPI (2011 base village level)	85.72	91.05	100	0.000***	0.000***
	(4.393)	(1.191)	(0)		
Gifts to other households (RMB)	0.0105	0.0119	0.0269	0.638	0.000***
	(0.0428)	(0.0953)	(0.108)		
Loans to other households (RMB)	0.0249	0.189	0.0258	0.000***	0.916
	(0.221)	(0.708)	(0.227)		
Government transfers received (1,000 RMB)	0.224	0.520	0.376	0.000***	0.000***
	(0.478)	(1.167)	(0.718)		
Age of household head	51.50	53.24	55.35	0.000***	0.000***
	(11.55)	(11.48)	(11.41)		
Gender of household head (1: male, 2: female)	1.064	1.073	1.079	0.357	0.132
	(0.245)	(0.261)	(0.271)		
Education of household head*	0.467	0.461	0.471	0.793	0.846
	(0.597)	(0.591)	(0.601)		
Household size	3.722	3.675	3.702	0.431	0.742
	(1.480)	(1.535)	(1.594)		
Number of laborers in the household	2.701	2.650	2.597	0.323	0.0495*
	(1.305)	(1.372)	(1.423)		
Landholding (mu)	3.646	3.432	3.137	0.064	0.000***
	(2.989)	(2.944)	(2.636)		
Party member in household (1 = yes, 0 = no)	0.120	0.128	0.138	0.555	0.164
	(0.325)	(0.334)	(0.345)		
Observations	1322	1322	1322	2644	2644

Source: Author estimations.

Notes: CPI = consumer price index, MMI = Modified Mercalli Intensity Scale, RMB = Chinese renminbi.* 0: 6 or fewer years, 1: between 7 and 9 years, 2: more than 9 years)

Table A.3 Impact of earthquake magnitude (Modified Mercalli Intensity Scale) on income/consumption ratio

Explained variable:	(1) Subsample Y/C	(2) Subsample Y/C	(3) Subsample Y/C	(4) Subsample Y/C	(5) Subsample Y/C	(6) Full sample Y/C	(7) Full sample Y/C
Explanatory variable:							
Ln(Distance to epicenter)*year09	-0.225**	-0.226**	-0.253**	-0.256**	-0.249**	-0.200***	
	(0.102)	(0.104)	(0.115)	(0.114)	(0.111)	(0.068)	
Ln(Distance to epicenter)*year11	-0.295**	-0.182*	-0.216*	-0.214*	-0.213*	-0.224***	
	(0.136)	(0.096)	(0.109)	(0.109)	(0.110)	(0.061)	
Ln(Distance to epicenter) *year09*not rebuilding							0.037
							(0.028)
Ln(Distance to epicenter) *year11*not rebuilding							-0.125***
							(0.039)
Household incomes (ln)		0.411**	0.413**	0.413**	0.415**	0.615***	0.612***
		(0.166)	(0.166)	(0.166)	(0.165)	(0.144)	(0.146)
Consumer price index			-0.022	-0.021	-0.020	-0.008	0.013
			(0.015)	(0.014)	(0.014)	(0.015)	(0.018)
Gifts to neighbors				0.286*	0.298**	0.015	0.006
				(0.139)	(0.136)	(0.195)	(0.194)
Loans to neighbors				-0.238**	-0.241**	-0.151*	-0.153*
				(0.090)	(0.090)	(0.078)	(0.075)
Government transfers					-0.039	-0.002	-0.003
					(0.046)	(0.057)	(0.049)
Months rebuilding this year						-0.026	-0.032
						(0.034)	(0.042)
Cost of rebuilding this year						-0.008**	-0.008**
						(0.003)	(0.003)
Cost financed by loans						0.015**	0.014**
						(0.007)	(0.006)
Observations	1,809	1,809	1,809	1,809	1,809	3,966	3,966
R-squared	0.031	0.138	0.140	0.143	0.143	0.138	0.135
Number of id	603	603	603	603	603	1,322	1,322
Adjusted R-square	0.158	0.158	0.158	0.158	0.158	0.158	0.158

Source: Author estimations.
Note: C = consumption, Y = income.

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