Demographic Shock and Economic Recovery: Evidence from Japan after the 2011 Earthquake

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Abstract

This paper investigates the effect of a sudden demographic shock on intensity of economic activity. Demographics and macroeconomics interact and evolve in complementarity with each other and it is usually very difficult to disentangle the causal effect of demography on the economy. Studying Japan after the earthquake and tsunami in 2011 gives us this opportunity. We use the night light emission data to estimate the region's economic recovery relative to year 2010. Our result suggests that death rate due to the disaster affects the subsequent economic recovery. The result is significant to 0.1% level. Furthermore, we found some evidence that the death rate of the elderly (65+) is insignificant in explaining recovery once we control for the 15-64 age group. Overall, demographic shock appears to only have a very transient effect on recovery.

1 Introduction

How does demography affect the macroeconomy? A difficulty in answering the question empirically is that both macroeconomy and demographic indicators are endogenous variables, determined possibly, by geography, technology, epidemics, and other historical factors. We use the tsunami and earthquake in 2011 in Japan to obtain an exogenous shock to population size and demographic structure, and study the subsequent economic recovery at the regions hit differentially by the disaster. Another difficulty in trying to understand the relationship between demography and macroeconomy is that the effect of a sudden shock to demography is likely to be different from a continually declining population. When a long-term decline in population slowly takes place, individuals can adjust and adapt to the new macroeconomic reality by developing new technology or change existing policy (e.g. extending official retirement age). While our study does not allow us to say anything about the effect of long-term demographic change on the macroeconomy, a sudden shock in demography can change an economy's balanced growth path and an economy can converge to a new equilibrium. It is therefore still worthwhile to study a sudden change in demography and its effect (if any) on the economy.

Japan has one of the lowest fertility rate in the world and more than 20% of Japan's population is older than 65. This makes understanding how an aging population affects the macroeconomy a very important question. Tohoku, the six-prefecture region hit by the tsunami, has been suffering from depopulation and aging population for decades like other rural parts of Japan. With few jobs available, the young leave for the cities to find work. But the old remain. Depopulation and aging population thus leaves the area unattractive for investors, which further drives the young people out for better economic prospects. Does the earthquake exacerbate this downward spiral of decline? Does the regions that suffer from a larger youth loss recover lower relative to other regions? Answers to these questions have large economic implication not only to Japan but other advanced countries which are aging quickly.

This study is related to two main strands of literature. The first strand of literature is on economic geography in which the main objective is to explain the spatial variation in economic activities. This paper is particularly related to Davis and Weinstein (2002). They examined data on regional population density in Japan from the Stone Age to the modern era. In particular they found that temporary shocks, using the Allied bombing of Japanese cities during World War II, appear to have little long-run impact on the spatial structure of the economy. Our study does not allow us to say anything about the long-term impact of a temporary shock because it has only been 3 years since the happening of the disaster. It does, however, provide a new perspective on the short-term effect of temporary shock, which arguably has more policy relevance than the very long-term effect.

The second strand of literature is related to demographic structure and economic performance. There are many studies that study the effect of economic performance on demography (specifically on fertility) but there are fewer studies that tried to study the reverse direction of the linkage. Some of these effects arise partly as accounting identities, such as the effect of population size on GDP, or the effects of population age structure on aggregate labor supply and savings. Some other effects such as the effect of longevity on the incentives to save and to retire are fundamentally behavioral in nature. Bloom and Canning(2004) consider the effect of long-term demographic change on the macroeconomy. They show how Ireland benefited from lower fertility in the form of higher labor supply per capita and how Taiwan benefited through increased savings rates. In the short run, it is unclear how an economy with a larger aged population will fare in comparison to an economy with more youth.

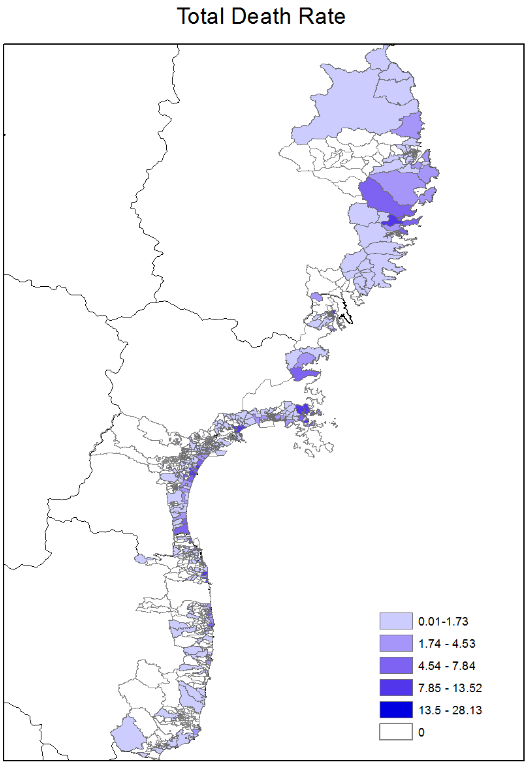
2 Background: the Tohoku Earthquake and Tsunami

The earthquake and tsunami in 2011 was the most powerful earthquake ever recorded to have hit Japan. It claimed over 15,000 lives and injured thousands across the Northeast region of Japan. Death rate across regions varies (See figure 1). A striking feature of the casualty patten is that the death rate of the 65 and over age group has been much higher than the age group between 15 and 64. A main reason is that about one-in-three residents in the areas hit by the disaster are more than 65 years old, a significantly higher ratio than the national average of 22.7 percent. The disaster highlights the vulnerability of Japan's increasingly elderly rural countryside.

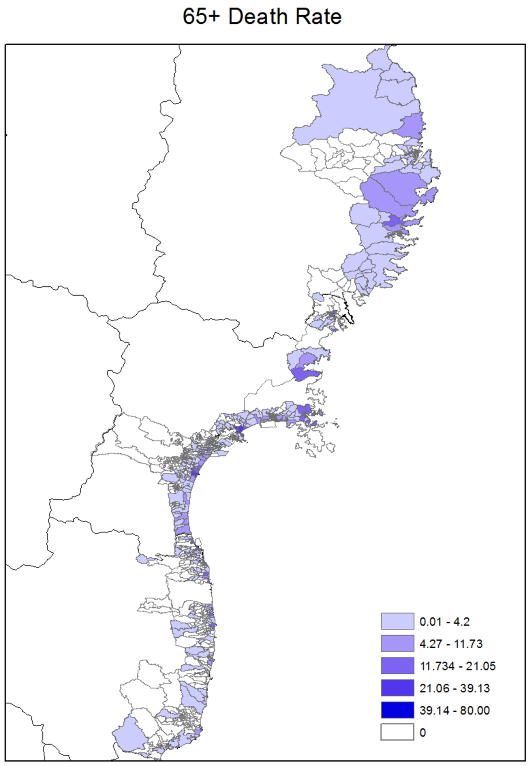
The natural disaster has also triggered the failure of the Fukushima Daiichi nuclear power plant. Residents within 12 mi radius of the Fukushima Daiichi Nuclear Power Plant and a 6.2 mi radius of the Fukushima Daini Nuclear Power Plant were evacuated. This would necessarily reduce the economic activity in the affected region. We therefore exclude Fukushima from our analysis.

3 Hypothesis

The study is motivated by two hypothesis. The first hypothesis is that a larger population shock, i.e. higher death rate, will hinder subsequent economic recovery. Intuitively, when there is less people in a region, the size of economic activity should go down. Our second hypothesis is slightly more controversial. Condition on the size of casualty, we hypothesize that a larger fraction of working force death relative to old-age fraction is going to have a slower economic recovery. The argument is that individuals who are beyond 65 usually are presumably less active relative to an individual between 15 to 64.



(a) Total Death Rate



(b) Death Rate of 65+

Figure 1: Death Rate across regions. Death Rate is considerably higher for the aged population than the average death rate. The thinner grey line outlines the size of the sub-district level that our data is referenced. The thicker grey line represents the subnational admin-1 boundary. *Source*: Tani(2002)

4 Data

We have detailed geographic level of casualty data by age group and gender. There are 450 subdistricts in our casualty dataset. The data comes from a study compiled by Tani (2002). The fineness of the casualty data demands very fine boundary shape file. So instead of using the usual subnational administrative boundary 2 level shape file, I opt for much finer street-level data which is only available in the Japanese government website: http://e-stat.go.jp/SG2/eStatGIS/page/download.html. Unfortunately, the very fine level is not available in a single shape file. Instead, we have to download the individual district one by one and change the projection of each street-level district shape file. The night light imagery comes from NOAA. I used the average visible light file in 2010, 2012 and 2013 as the basics of my analysis.

We also collected pre-existing information about the affected areas. In the more elaborated analysis, we included street-level employment information across different sectors in 2010. This includes the size of employment in each of the following 20 industry classifications: agriculture, home farming, fishery, mining, construction, manufacturing ,utilities, information, transportation, retail,finance, real-estate, professional, food service, entertainment, education, medical,other service, public, unclassified.The data is available on the Japanese government website.

4.1 Data Manipulation

We use night light data to measure economic activities. We measure economic recovery by simply dividing the night light intensity in 2012 and 2013 by the night light intensity in 2010.

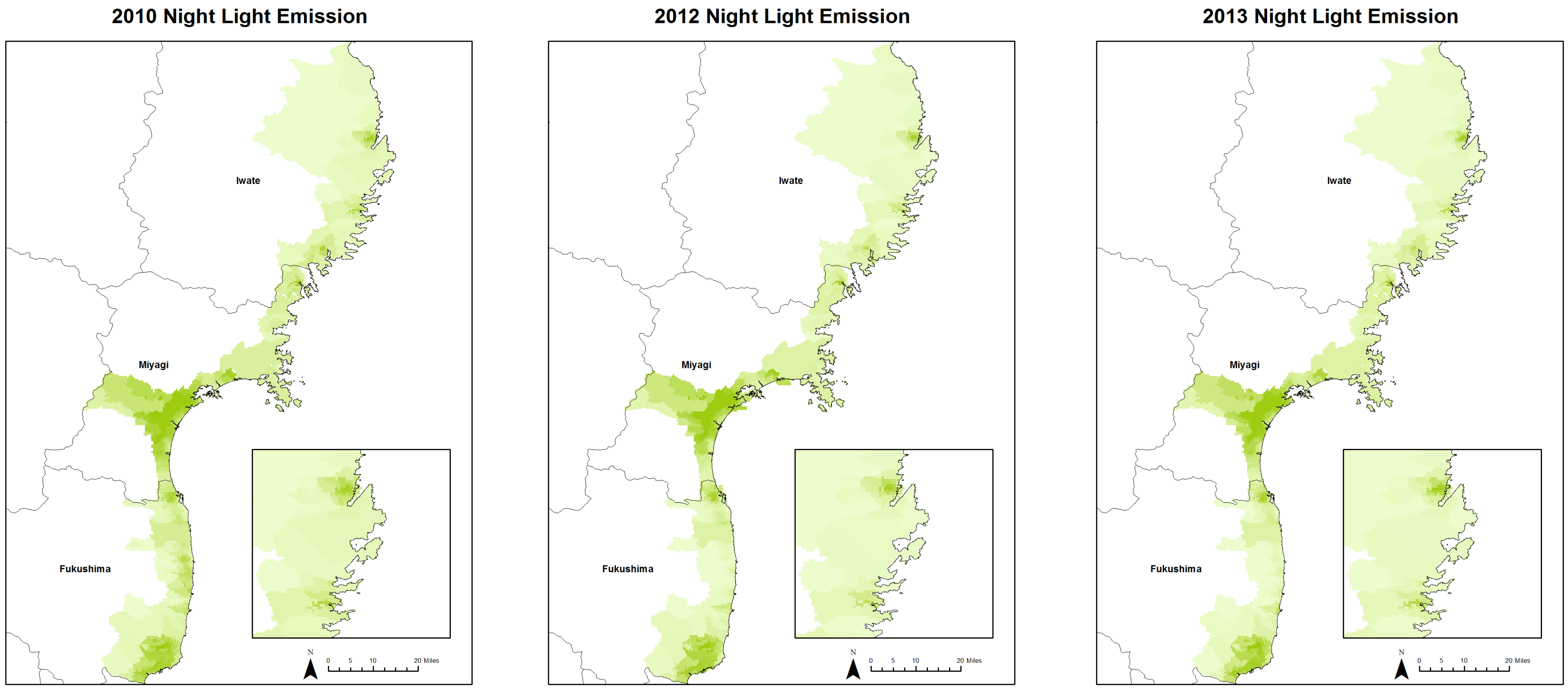
$$rr = \frac{\text{Night Light Intensity in 2012/3}}{\text{Night Light Intensity in 2010}}$$

For the night light satellite data, I restricted the lights data to Japan for computational ease. To do that, I clip the lights data down to the Japanese border. Because the subdistrict level data is so fine, the size of some of the districts is smaller than the size of the cell in the night light image. We used the resampling tool to resize the of cell of night light raster layer to be 0.000083 X 0.000083 degrees. This is 100 times smaller than the original cell size. Without this operation we would lose a lot of data points. After that I calculated the average light intensity in each of the subdistrict. I used both zonal statistics and zonal statistics for table for this procedure. The first yields the maps in figure 2. I then convert the zonal summary statistics table to excel using the "Table to Excel" tool.

Next we discuss the casualty data treatment. We changed the coordinate system of the street level shape file to WGS 1984. Next, we merged individual street level shape files into one shape file using the Merge tool. In order to georeference the casualty data, we have to join the casualty data with the street level shape file. The casualty data, despite the fineness, are at subdistrict level so we cannot join it with the street level shape file directly. To circumvent that, we dissolved the street level data into subdistrict level such that it matches the casualty data.

5 Preliminary Analysis

We first test the hypothesis that the size of casualty negatively affects the the recovery. We run a simple regression of recovery rate on the total size of casualty, dropping all observations that are in Fukushima. Furthermore, we only use data points with positive death rate in the region. The first two columns of table 1 presents the result for 2012 and 2013. Death rate is very negatively correlated with subsequent recovery rate. Since death rate is exogenous, we can interpret that as higher death rate causes a



(a) 2010 Night Light

(b) 2012 Night Light

(c) 2013 Night Light

Figure 2: Night Light Intensity substntially weakened between 2010 and 2012.The change is not as obvious between 2012 and 2013.

smaller economic recovery. The explanatory power of death rate drops in 2013. The same pattern can be observed in all the subsequent regressions. This seems to suggest that demographic shock only has a transient effect on recovery.

Our second hypothesis relates demographic structure with economic recovery. As before, we first regress recovery rate on the death rate to the 15-64 age group. The result is presented in columns (3) and (4) in table 1. Again, the result is very significant at 0.0001 level. We went on further and regress recovery rate on the death rate to the two other ages group: under 15 and over 65. The results are presented in columns (5), (6), (7) and (8). We found that death rate for the under 15 age group has insignificant effect on subsequent recovery but death rate for the 65 or older age group has a rather significant effect. However, we notice that the sample size of under 15 age group is much smaller than the other age groups. This suggests that the number of regions that suffer from positive children death rate is much smaller than the number of regions. A possible explanation is that adults evacuated children to highland ahead of themselves. Note that the death rate for the 65+ is no longer significant in recovery in 2013. Nevertheless, the significant correlation between death rate for the 65 or older age group and subsequent economic recovery in 2012 suggests that the aged population contributes significantly to economic activity also, though the magnitude is smaller than the 15-65 age group.

Finally, we tested whether death rate by gender affects recovery rate. Both death rates of male and female appear to have significant effect on recovery. However, it appears that death rate of male is more significant for both 2012 and 2013. In 2013, the recovery rate is no longer signifincat with female death rate. In all the simple regressions above, the intercepts are all significant and quite large. If there is omitted-variable bias, even if it’s uncorrelated with the other variables, this could cause a vertical shift which biases your estimate of the intercept. We investigate this possibility in the next section.

	(1) rr_12	(2) rr_13	(3) rr_12	(4) rr_13	(5) rr_12	(6) rr_13	(7) rr_12	(8) rr_13	(9) rr_12	(10) rr_13	(11) rr_12	(12) rr_13
DR_Total	-0.0205***	-0.0103*										
	(0.0044)	(0.0042)										
DR_1564			-0.0371***	-0.0199**								
			(0.0079)	(0.0076)								
DR_Under15					0.0029	-0.0021						
					(0.0049)	(0.0051)						
DR_65o							-0.0079**	-0.0042				
							(0.0025)	(0.0024)				
DR_Male									-0.0212***	-0.0107*		
									(0.0048)	(0.0046)		
DR_Female											-0.0125**	-0.0061
											(0.0044)	(0.0043)
Constant	0.8775***	0.9280***	0.8756***	0.9286***	0.7650***	0.8777***	0.8562***	0.9205***	0.8768***	0.9311***	0.8414***	0.9054***
	(0.0139)	(0.0132)	(0.0161)	(0.0155)	(0.0261)	(0.0270)	(0.0187)	(0.0182)	(0.0156)	(0.0148)	(0.0175)	(0.0171)
Observations	324	324	279	279	87	87	231	231	286	286	250	250

Standard errors in parentheses

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

Table 1: Simple regression of recovery rate on death rate on age group and gender

A casual observation of the result also suggests that the death rate of the 15-64 age group has a larger effect than the death rate of the 65 or older age group on recovery. We are interested in finding out, once controlled for the death rate of the 15-64 age group, whether the coefficient of death rate of the 65+ age group is still significant. To do that, we regressed recovery rate on death rates of both age group. The result is presented in table 2. The regression result shows that the death rate of the 65+ is no longer significant for recovery in 2012. Neither death rate is significant in 2013. The result from the 2012 regression provides some evidence to our second hypothesis that death rate of the 15-64 age group matters more in short-term recovery rate. One should, however, interpret this result with caution. As this effect seems to be rather transient (reflected by the insignificance in 2013), it does not say anything about age structure to long-term economic performance.

	(1) rr_12	(2) rr_13
DR_1564	-0.0332*	-0.0194
	(0.0167)	(0.0166)
DR_65o	0.0018	0.0016
	(0.0048)	(0.0048)
Constant	0.8439***	0.9151***
	(0.0227)	(0.0225)
Observations	191	191

Standard errors in parentheses

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

Table 2: Regression results by regressing recovery rates on death rates for both 15-64 and 65+ age groups

We also tested whether the observed relationship was specific to a certain prefecture and to our surprise, the relationship appears to only hold in Miyagi but not in Iwate. The results are presented in table 3. Columns (1) and (2) indicate the coefficients of average death rate for Miyagi. Columns (3) and (4) indicate that of Iwate. We have no good explanation as to why Miyagi seems to be more susceptible to population shock at this point.

	Miyagi		Iwate	
	(1)	(2)	(3)	(4)
	rr_12	rr_13	rr_12	rr_13
DR_Total	-0.0274***	-0.0149***	0.0100	0.0101
	(0.0040)	(0.0039)	(0.0127)	(0.0126)
Constant	0.9232***	0.9544***	0.7352***	0.8442***
	(0.0133)	(0.0130)	(0.0348)	(0.0347)
Observations	237	237	87	87

Standard errors in parentheses

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

Table 3: Prefecture specific regression results

5.1 Spatial Autocorrelation

The tsunami affected the coastal regions more than the regions inland. As a result, the death rate should be higher in coastal regions. One might suspect that the relationship between will be different between coastal regions and the regions slightly inland. To verify that, we ran Global Moran I's statistics on all data points with positive death rate and excluding the Fukushima observations. Before doing that, we had to convert the night light raster layer into points. We did that with "Extract to Multi-value" tool. Next we calculated the recovery rate using a simple Phyton script in the fields calculator to deal with the fact that there are many zeros in the data. The Index is 0.096 and the z-score is 16.4. The simple siagnosis suggests that there is no strong evidence for spatial autocorrelation.

6 Empirical Analysis

In this section I consider a slightly more elaborated econometric specification to explore alternative explanations in accounting for differences in recovery rate across regions. Specifically, we include pre-tsunami economic variables as control:

$$\omega = \alpha + DR\beta + X'\gamma + \varepsilon \tag{1}$$

where DR denotes the death rate, and X denotes the control variables. Economic recovery may depend on the types of industry that a region engages in prior to the earthquake. For example, if employment of an affected region was concentrated in the fishing sector prior to the tsunami, the tsunami is likely to have a larger negative affect on the region's recovery than a region with primary employment sector is in service. We tested this hypothesis by using street-level employment information in 2010 at the affected areas. We included the fraction of employment in each sector for each region in our estimating equation.

For this version of the paper, we only consider the data points in Miyagi (We were able to process the industry level data in Miyagi only at this time.). The next version will include all data points in Miyagi and Iwate. We divide the size of employment in each industry by the total to get a fraction of total employment in each industry. The results are presented in table 4.

Columns (1) and (2) of table 4 show the estimation results by regressing recovery rate at 2012 and 2013 on average death rate and all the employment controls. The coefficient is still significant for 2012 but not 2013. Columns (3) and (4) of table 4 show the estimation results using death rate of the 15-64 age group. As before, the coefficient is significant for 2012 but not 2013. Finally, Columns (3) and (4) of table 4 show the estimation results using death rate of the 15-64 age group. Neither 2012 and 2013 estimate is significant. Overall, the result suggests that death rate of the elderly matters less to subsequent recovery in very short-run. In the longer horizon, sudden change in death rate does not appear to affect recovery at all.

Table 4 also shows the relative importance of pre-tsunami employment across sectors in determining subsequent sectors. It appears that the larger the size of relative employment in the fishing sector prior to the tsunami, the slower the recovery is in 2012 and 2013. The results are very significant in both 2012 and 2013. Size of the construction sector prior to the tsunami appears to have a positive correlation with recovery. All estimates are positive and in particular, the 2012 estimates are all significant to the 5% level. The same is true for the size of real estate employment. Other sectors do not appear to have any effect on recovery.

	(1)	(2)	(3)	(4)	(5)	(6)
	rr_12	rr_13	rr_12	rr_13	rr_12	r r_13
dr_total	-0.0124**	-0.0049				
	(0.0038)	(0.0040)				
dr_1564			-0.0208**	-0.0109		
			(0.0067)	(0.0073)		
dr_65o					-0.0041	-0.0007
					(0.0023)	(0.0024)
f_agriculture	-1.7819	-2.7327	-1.7295	-2.8909	11.3460*	18.7758**
	(2.1830)	(2.3060)	(2.3555)	(2.5511)	(5.7271)	(6.0031)
f_homeagriculture	1.0305	2.1636	0.9212	2.3212	-12.3116*	-19.5388**
	(2.1585)	(2.2801)	(2.3257)	(2.5188)	(5.7482)	(6.0252)
f_fishery	-0.5433***	-0.3851**	-0.4097*	-0.2297	-0.5765***	-0.4619**
	(0.1336)	(0.1412)	(0.1665)	(0.1804)	(0.1576)	(0.1652)
f_mining	-2.2640	-6.1051	0.5638	-8.5358	2.6415	4.0032
	(17.4796)	(18.4650)	(26.6011)	(28.8097)	(21.2507)	(22.2748)
f_construct	0.0473**	0.0042	0.0682**	0.0187	0.0575*	0.0220
	(0.0176)	(0.0186)	(0.0213)	(0.0231)	(0.0234)	(0.0246)
f_manufacturing	-0.1428	0.1607	-0.0439	0.2951	-0.2543	0.0027
	(0.1626)	(0.1718)	(0.1987)	(0.2152)	(0.1969)	(0.2063)
f_gas_heat_pipe	-0.0972	-0.3305	-0.1461	-0.3274	-0.0307	-0.2677
	(0.4153)	(0.4387)	(0.4551)	(0.4929)	(0.4806)	(0.5037)
f_information	-0.3736	-0.4730	-1.0826	-1.4797	0.5611	0.2093
	(1.0573)	(1.1169)	(1.2938)	(1.4012)	(1.5380)	(1.6122)
f_transportation	0.5265	0.7370	0.5176	0.8091	0.5550	0.8060
	(0.3656)	(0.3862)	(0.4515)	(0.4889)	(0.4810)	(0.5042)
f_retail	0.2133	0.3384	0.3029	0.4489	0.1943	0.3375
	(0.1812)	(0.1914)	(0.2469)	(0.2674)	(0.2174)	(0.2279)
f_finance	-0.5027	-0.0624	0.1017	1.2937	-0.7089	-0.1312
	(1.0342)	(1.0925)	(1.3981)	(1.5141)	(1.3048)	(1.3677)
f_realestate	3.2238**	1.5968	3.5334*	1.9562	4.7274**	2.6366
	(1.2354)	(1.3050)	(1.5090)	(1.6343)	(1.7381)	(1.8219)
f_professional	1.2673	0.0542	0.6229	-0.9527	0.7747	-0.2960
	(0.9987)	(1.0550)	(1.1509)	(1.2465)	(1.4448)	(1.5145)
f_foodservice	-0.3555	-0.1085	-0.2155	0.0425	-0.3773	-0.2881
	(0.3288)	(0.3473)	(0.4517)	(0.4893)	(0.4111)	(0.4309)
f_lifeservice_ent	0.0816	-0.0427	0.5419	0.1188	0.0302	0.0630
	(0.7448)	(0.7868)	(0.8983)	(0.9729)	(0.9553)	(1.0013)
f_education	0.3189	0.3465	0.3860	0.3497	0.0944	0.2051
	(0.6321)	(0.6677)	(0.7137)	(0.7730)	(1.0043)	(1.0527)
f_medical	-0.3398	-0.0436	-0.5533	-0.1884	-0.2198	0.1521
	(0.3647)	(0.3853)	(0.4681)	(0.5070)	(0.4670)	(0.4895)
f_service	-0.1351	0.7986	0.3751	1.4025	-0.0007	1.1531
	(1.6015)	(1.6918)	(1.7354)	(1.8795)	(1.9746)	(2.0697)
f_otherservice	0.6123	0.1529	2.1096**	1.5952*	0.3085	-0.0836
	(0.4560)	(0.4817)	(0.6914)	(0.7488)	(0.5814)	(0.6095)
f_public	0.0515	-0.0608	0.2242	0.1667	0.1188	-0.3713
	(0.3400)	(0.3592)	(0.3768)	(0.4081)	(0.7049)	(0.7389)
f_unclassified	0.5897	1.0272	0.7745	1.1353	1.0166	1.3544
	(0.5464)	(0.5772)	(0.5903)	(0.6393)	(0.7240)	(0.7589)
Constant	0.7924***	0.7840***	0.6394***	0.6286***	0.7795***	0.7705***
	(0.0962)	(0.1016)	(0.1344)	(0.1455)	(0.1105)	(0.1158)
Observations	237	237	201	201	166	166

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0 > .001$

7 Robustness

One might be concerned that Japan's overall macroeconomic environment has changed in the 2012 and 2013. If the overall macroeconomic condition affects the affected regions uniformly, this will not pose any issue to our estimation. In contrary, if the overall macroeconomic condition has a differential effect across regions, our estimation will be biased. For example, if in 2012 and 2013, the regions with higher death rate also affected more negatively by the overall macroeconomic environment, our result will overestimate the coefficients on death rate. This is however quite unlikely.

A more serious concern is the omitted variable bias since other local factors can affect death rate. One way to mitigate that is to estimate the equation with more controls as we did in the previous section. However, this approach would not address the problem sufficiently if there are unobserved factors that affect death rate. For example, if a region had invested more in disaster prevention measure prior to the tsunami due to higher social capital in that region, death rate should be lower in that region. According to our interpretation, a lower death rate would mask the true cause to faster recovery, which should be because of the level of social capital in the region. However given the finesse of our geographic data, it is hard to imagine that the subregions differ substantially in unobservable ways.

Another concern is that given the finesse of our geographical measure, how good is night light emission in approximating local economic activity? Before resampling our cell size is 0.0083 which is approximately 120 Meters x 120 Meters = 14,400 square meters. We do not have a good sense of how precise is the night light emission data at a level so fine. In the next version of the paper, we plan to run the same regressions using different sizes of subdistrict. This can be achieved by dissolving the street level data to various levels up.

8 Conclusion

This paper investigates the effect of a sudden demographic shock on the intensity of economic activity by studying Japan's night light emission after the earthquake and tsunami in 2011. Overall the result strongly supports Davis and Weinstein (2002) in that population shock seems to have only a transient impact on economic activity. We also found that the death rate of the 65 and over age group is not significant with subsequent recovery after including controls. In many way the result is not particularly surprising. The 65 and over age group is economically less active and is expected to matter less for recovery. To my knowledge, this study is the first study to establish a casual relationship between age structure and economic activity. As emphasized previously, we need to interpret the result with caution as the effect of a long-term decline is likely to be different from a sudden change in population. In the next version of the paper, we will include additional controls to explore reasons for difference in recovery rate.

9 Appendix

Bones, Bombs, and Break Points: The Geography of Economic Activity

Daron Acemogluy Ufuk Akcigitz Murat Alp Celikx. Young, Restless and Creative Openness to Disruption and Creative Innovations

David E. Bloom, David Canning "Global Demographic Change: Dimensions and Economic Significance"