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The Real Tokyo Drift: The Effects of the Tohoku Earthquake on Japanese Car Production

Introduction

The Tohoku Earthquake and Tsunami in March 11, 2011 and the destruction of the Fukushima nuclear reactors caused by it had drastic effects for the people of Japan. The earthquake had a magnitude of 9.0-9.1 according to the Richter scale. The effects of this great earthquake were felt around the world, from Norway's fjords to Antarctica's ice sheet, and tsunami debris continued to wash up on North American beaches years later. Many firms in Japan were forced to shut down production due to the amount of damage done by the earthquake and the mass destruction of facilities and infrastructure that it caused throughout northeastern Japan. Hundreds of thousands of people were displaced from their homes, countless buildings were destroyed, and the death toll rose to 22,000. During these next months, Japan saw a steep decline in production of automobiles, which are one of their largest exports.

Research Question

Due to the fact that Japan accounts for 10% of all cars produced, any large-scale disasters that make them unable to produce cars have massive implications for the rest of the world. Since this effect was so large, we have decided to study how the earthquake and the subsequent disasters that came directly from it affected car production in Japan. Since thousands of people were unable to work and certain parts of Japan near the nuclear reactors became unsafe to go near, it is reasonable to assume that part of this relationship is causal.

After careful consideration, we felt that this topic sparked our interest more than other potential topics. Earthquakes are the most unpredictable natural disaster; one cannot predict when they will hit and how strong they will be. When they hit, they can only last for 15 to 20 seconds, yet the ramifications can be truly devastating.

Identification Challenges

The main challenges in identifying the true cause of the earthquake on car production in Japan is the lack of cohesive data on global auto production. Different countries have different standards regarding how often statistics on automobile production must be reported and how specific these reports must be with regard to the type of automobile. Because of this problem, we decided to aggregate data from some of the world's largest car manufacturers: USA, Germany, South Korea, and India. We would have included China, the world's largest automobile producer, but all the available data sets were recorded on a yearly basis, not monthly like the rest.

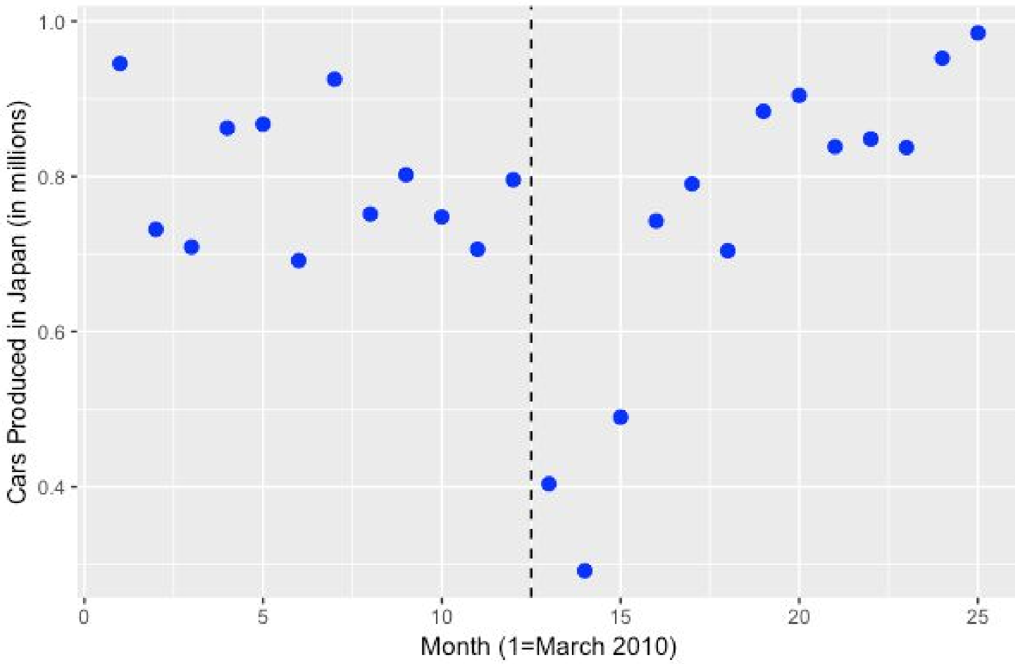
Another major challenge we expect to come across regarding identification is the overall change in car production worldwide. Since the auto industry has consistently experienced an upward trend globally, we expect the omission of this variable to underestimate the effect of the earthquake. The final major identification challenge we expect to encounter is the impact of the deaths not caused directly by the disaster on car production. Since Japan only reports death statistics on a yearly basis every december, a control variable for death rate is not possible in this design which uses monthly data and the discontinuity happens in March.

Research Design

To answer our research question, we have decided to use a regression discontinuity design with time (t) as the running variable and a binary treatment variable (D) which is equal to 0 for before the earthquake and 1 for after the earthquake, which happened on March 11, 2011. We feel this design is best because we noticed a clear discontinuity when we plotted the data initially and also noticed a linear trend before the discontinuity and a quadratic trend after the discontinuity (see Figure 1). To correct for this change in trends, we included both linear and quadratic interaction terms. In order to more closely identify the effect of the treatment on the number of cars produced in Japan in that month (Y). We decided to add a control variable for the industrial production index of Japan (*I*) in order to isolate the effect on specifically the Japanese auto industry. In addition to this, we have also added a control variable for worldwide car production (w). We decided to convert all car production data to millions in order to more easily measure the effects. Since there was not data readily available on monthly worldwide car production we decided to combine United States, Germany, Korea, and India car production data. This gives us the regression design:

$$\mathrm{Y} = \alpha + p\,\mathrm{D} + \beta t + \gamma(D * t) + \phi(D * t^2) + \delta I + \theta w + e$$

Figure 1



Data

We obtained all of our data from CEIC Data. They are a company that collects detailed global economic data, indicators, charts and forecasts. Since most the of the data is accurate to the month it was not free, so we had to split a basic $40 account to download the excel files. We ended up downloading six data frames. Five of which entailed monthly motor vehicle production for Japan, the USA, Germany, South Korea, and India. We also downloaded a dataset detailing the monthly change in Japanese industry production index. We used Japanese motor vehicle production data to measure the outcome variable. We then compiled all the the other motor vehicle data listed above into one dataframe to control for world car production since they are considered some of the world's largest car manufacturing companies.

We decided to look at data only from March 2010 to March 2012 to capture the effect the Tohoku Earthquake had on Japan's car production in the short term. That left us with 25 observations. To better visualize the effect we referred to each month as a numerical value starting with then counting up until we hit March 2012. We decided to place our discontinuity at point 12.5 since this makes our scatter plot more visually appealing (see Figure 1). Using this as the discontinuity better captures the effect of the earthquake since all the monthly data is reported on the last day of each month.

Results

For the first regression, we decided to run a simple OLS without a dummy variable indicating for before and after the Tohoku Earthquake (see Figure 2). Our main reason for including this specification was to show how a simple OLS is not good enough to capture the effect of the earthquake on the car industry. It is apparent from our stargazer table that we did not stop there. The second regression was a linear RDD. We included the treatment variable which specified 0 for before the earthquake and 1 for after. We used the linear RDD to show how it underestimated the impact the earthquake had on Japanese car production. This is due to the data following a non-linear trend (see figure 1).

The third regression was another RDD that allowed for quadratic slopes, which we thought would best fit the data since the points after the discontinuity do not appear linear in figure 1. This design showed us that the treatment had a much causal larger effect. The fourth regression is the same design but with the control variables. The two treatment (p) results from these regressions are both around the same value of -2.90, which means the earthquake caused 2.9 million less cars to be produced in Japan (-2.9*1,000,000).

Conclusion

Although we noticed a slight causal trend between the Tohoku Earthquake and the decline in Japanese car productions throughout the following months, our identification problems hindered our ability to effectively isolate the perceived causal effect. More specifically, the lack in availability of accurate monthly data really limited our ability to provide substantial evidence in proving a causal effect. A lot of the available data was extremely detailed economic data that was very expensive. Though we were not able to perfectly identify the causal effect of the earthquake, this RDD pointed us towards a causal trend that we would not have found if we had regressed time on cars produced in Japan or regressed earthquakes on car production.

Figure 2

	Dependent variable:			
	Cars_Japan			
	Simple OLS	Linear RDD	Quadratic RDD	Quadratic RDD w/ Controls
	(1)	(2)	(3)	(4)
time	0.003	-0.007	-0.011	0.027
	(0.005)	(0.008)	(0.033)	(0.033)
Treatment		-1.014***	-2.866***	-2.907***
		(0.158)	(0.726)	(0.727)
I(time2)			0.0003	-0.001
			(0.002)	(0.002)
Cars_world				0.334**
				(0.144)
Ind_growth				0.009*
				(0.005)
time:Treatment		0.055***	0.261***	0.272***
		(0.011)	(0.085)	(0.080)
Treatment:I(time2)			-0.006*	-0.006*
			(0.003)	(0.003)
Constant	0.730***	0.841***	0.851***	-0.278
	(0.069)	(0.062)	(0.094)	(0.400)
Observations	25	25	25	25
R2	0.017	0.675	0.761	0.846
Adjusted R2	-0.026	0.629	0.698	0.782
Residual Std. Error	0.168	0.101	0.091	0.077
F Statistic	0.398	14.571***	12.091***	13.333***
Note:				*p<0.1; **p<0.05; ***p<0.01