Detecting Disaster Recovery Activities via Social Media Communication Topics

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ABSTRACT

Enhancing situational awareness by mining social media has been widely studied, but little work has been done focusing on recovery phases. To provide evidence to support the possibility of harnessing social media as a sensor of recovery activities, we examine the correlations between topic frequencies on Twitter and people's socio-economic recovery activities as reflected in the excess demand for used cars and housing, after the Great East Japan Earthquake and Tsunami of 2011. Our research suggests that people in the disaster-stricken area communicated more about recovery and disaster damages when they needed to purchase used cars, while the non-local population communicated more about going to and supporting the disaster-stricken area. On the other hand, regarding the excess demand for housing, when the local population of the disaster-stricken area started to resettle, they communicated their opinions more than in other periods about disaster-related situations.

Keywords

Social Media, Topic modeling, Socio-economic recovery, Used-car demand, Housing demand.

INTRODUCTION

There have been various efforts to use social media data to detect the situation surrounding disaster-stricken communities. However, few studies focus on detecting recovery. This paper explores the possibilities of detecting socio-economic recovery activities by exploring social media communication topics and market data. To build resilient communities after a large-scale disaster, improving mid-to-long-term situational awareness could enhance recovery efforts. This is because traditional socio-economic recovery indicators (e.g., observing changes in population and consumption, and conducting questionnaire surveys) are not published in a real-time way. Social media data hold the possibility of filling this gap by its timeliness. This study conducts topic analysis on Twitter communication data for the first six months after the Great East Japan Earthquake and Tsunami of 2011, and looks into the relationships between the topic appearance ratios and two types of socio-economic activities, namely, excess demand for used cars and excess demand for housing. The Great East Japan Earthquake and Tsunami occurred on March 11th, 2011. It caused devastating building damage across the coastal areas. According to the Japanese Fire and Disaster Management Agency[1], 19,667 people were killed, and 2,566 people went missing. The disaster destroyed 121,787 buildings.

This study takes these two goods as proxies of people's socio-economic recovery activities to rebuild their daily-lives because related research and reports have demonstrated that both used cars and housing are in higher demand in affected communities when a large-scale water-related disaster hits (the details are explained later). According to Drabek (1986), a disaster involves four phases: (1) preparedness, (2) response, (3) recovery, and (4) mitigation. This study focuses on the recovery phase. We particularly analyze the data collected during the first six months after the disaster.

The rest of the paper is constructed as follows. First, we review related literature and introduce research questions. Secondly, the data are described. Then we conduct topic analysis on social media communication data and topic frequency scores are calculated. To analyze the possibility of using social media data as a sensor of recovery activities, we analyze the correlations between the topic frequency ratios and the proxies of socio-economic

[1] http://www.fdma.go.jp/bn/higaihou_new.html

recovery activities. Lastly, we explain and discuss the results, and conclude with implications for future study.

RELATED LITERATURE

Socio-economic Recovery Activities: The Excess Demand for Used Cars and Housing

When a large-scale water-related disaster (e.g., hurricane, typhoon, tsunami) hits a community, there tends to be an excess demand for used cars and for housing in the local community. For example, after Hurricane Harvey and Irma in 2017, the media reported excess demand for used cars around the flooded areas (Breuninger, 2017; Chee, 2017; Lang, 2017). Likewise, after the Great East Japan Earthquake and Tsunami, newspapers reported a rise in the demand for used cars in the disaster-stricken area to replace water-damaged vehicles. Used cars were preferred over new cars because of their lower prices and quicker registration process (e.g., Nikkei Sangyo Shinbun, 2011, The Tohoku Finance Bureaus, 2017). In addition, Shibuya and Tanaka (2018a) conducted interviews with used-car dealers in disaster-stricken areas and revealed that the affected population needed to buy used cars when they became active in restarting their daily-lives (e.g., restarting working).

Regarding housing, various reports described the excess demand for non-inundated housing after a large-scale disaster. For instance, after Hurricane Sandy which flooded more than 300,000 homes and approximately 23,400 businesses (Bloomberg, 2013, p.13), the media reported increased demand for dry houses near the damaged areas (Kearns, Park and Buhayar, 2012; NBC, 2014; Racioppi, 2014). Another example of increased demand for housing occurred after the Great East Japan Earthquake and Tsunami, which destroyed 121,783 buildings across the coastal areas[2]. The newspapers reported that although the land values declined in the inundation zones, lands located on hills were in higher demand, causing increased land prices (Asahi Shimbun, 2011).

Both used-car and housing market data have been widely analyzed based on the Hedonic model (e.g., Barr et al., 2017; Haan and Boer, 2010; Hallstrom and Smith, 2005; Kooreman and Haan, 2006; McCoy and Zhao, 2018; McKen-zie and Levendis, 2010). The Hedonic model is an economic model that postulates that the price of a product reflects a bundle of embodied characteristics valued by some implicit or shadow prices (Prieto et al., 2015). With the Hedonic model, we can examine used-car/housing prices, which reflect the demand controlled by used-car/housing characteristics. For example, if there is excess demand for housing in a particular area, the prices of housing in the area may rise to re-equilibrate the excess demand. Also, if the amount of supply of goods is the same or more than those of corresponding periods of the previous year, the rises in prices could be explained by the excess demand. Therefore, although analyses focus on prices, the changes in prices controlled by the used-cars/housing characteristics also reflects excess demand for used cars/housing. The previous studies examined the used-car/housing market data by applying the Hedonic model and clarified the excess demand for used cars/housing after large-scale disasters. More specifically, Shibuya and Tanaka (2019) statistically showed that there was an excess demand for used cars, particularly for Light Motor Vehicles[3] in the disaster-stricken area after the Great East Japan Earthquake and Tsunami. Also, Shibuya and Tanaka (2018b) analyzed housing market data of New York City and found there was an excess demand for dry housing in New York City after Hurricane Sandy. Another empirical study (Shibuya and Tanaka, 2018c) analyzed the leased housing market data after the Great East Japan Earthquake and Tsunami, and found there was an excess demand for dry houses located within 3km to the building damage zones. These excess demands for both used cars and housing after the large-scale disasters can be used as proxies of one of the socio-economic disaster recovery activities because people in the disaster area needed these goods and were willing to pay to purchase them. Furthermore, as to used cars, the interviews with used-car dealers showed that people purchased used cars when they started to be active in rebuilding their daily lives, resuming their work and shopping (Shibuya and Tanaka, 2018a). Regarding housing, people from the disaster areas seeking new housing means that people moved their physical locations, for example, from an evacuation shelter to an apartment, and thus, were active in restarting their lives or moving forward to the next stage of recovery. Therefore, in this study, we use used-car and housing market data as proxies of socio-economic recovery activities in the case of the Great East Japan Earthquake and Tsunami.

Social Media for Improving Disaster Situational Awareness

When a disaster hits a community, a massive amount of information that includes individual discussions, and personal experiences and thoughts, is created. Because acquiring useful information about the situations in the disaster-stricken area is critical for relief operations and preventing further losses, social media users have been recognized as "people as sensors" (Laituri and Kodrich, 2008), "citizen sensing" (Castillo, 2016; Sheth, 2009), or " human sensors" (Yuan et al., 2013). Various related works have looked into the potential usefulness of social media as "people as sensors" by investigating the correlations between cyber and real-world activities. For instance, the relationships between chatter on Twitter and donation amounts (Korolov et al., 2015), the proximity

[2] http://www.fdma.go.jp/bn/higaihou_new.html (accessed September 30, 2018, in Japanese)

[3] A Japanese car category whose engine volumes are 660cc or less.

of a hurricane path and social media activities (Kryvasheyeu et al., 2016), and sentiment on social media and actual disaster damage (Guan and Chen, 2014; Kelly and Ahmad, 2014; Nguyen et al., 2014) have been addressed. Also, other researchers argue that social media can be used as earthquake detectors (Kropivnitskaya et al., 2017; Sakaki et al., 2013, 2010), water level sensors (de Albuquerque et al., 2015; Zhang et al., 2016), and sensors of evacuation activities (Kibanov et al., 2017; Martin et al., 2017; Wang et al., 2016; Yuan et al., 2013). These studies suggest that social media data can promote "people as sensor" approaches for disaster management by providing effective and near real-time complement data for detecting or assessing disaster-related incidents (Martin et al., 2017). However, little work has been done on adapting the "people as sensors" approach in recovery. Some of the examples of studies focusing on social media use in recovery are Su et al (2017) and Yan et al. (2017). Yan et al. (2017) analyzed geotagged Flickr (a photo-based social network) photos after the 2013 Earthquake and Typhoon in the Philippines (ranging from April 2004 to July 2016) to identify remaining damage by mining tourist photos. Su et al. (2017) investigated the social media communication patterns after the Great East Japan Earthquake and Tsunami by focusing mainly on nueclear-related topics. In terms of the recovery phase, social media data have the potential to complement traditional socio-economic recovery indicators (e.g., changes in population and consumption, and conducting questionnaire surveys) because such data can provide fine-grained measurements of behavior over time while taking advantage of significant population sample sizes (Gruebner et al., 2017). Detecting recovery activities in a near real-time way may help recovery-related agencies, local public officials and recovery practitioners to obtain a big picture. Furthermore, improving the affected areas' real-time situational awareness may help create an evidence-based and more effective recovery plan.

Local and Non-local to a Disaster

In terms of social media communication data after a large-scale disaster, existing studies have recognized different communication patterns between locals and non-locals during disasters. Starbird et al. (2012) argue that social media contents shared by local citizens in a disaster-stricken area can provide unique and critical information for emergency responders and other diverse stakeholders. Kogan et al. (2015) and Starbird and Palen (2010) found that Twitter users, in general, were more likely to re-tweet the accounts of people local to emergency events. Bica et al. (2017) investigated an imaginary representation of a disaster via images shared on Twitter. They found that locals focus more on the business details of the response and the damage in their cities while a non-local population focus more on the images of people suffering (Bica et al., 2017). In addition, there have been various efforts to make it easier to find communication posted by people local to disaster-stricken areas. For example, Grace et al. (2017) investigate how to effectively discover local populations by using social network ties. Other typical ways to identify local communications are using disaster-related keywords and location-based tweet collections (Olteanu et al., 2014). This study also applies the keyword-based tweet collection and divides local and non-local communication according to whether communication contains disaster-impacted locations' names (details are described in the Data section).

RESEARCH QUESTIONS

Based on the previous studies cited above, this study investigates the following three research questions. First, although only limited research has been done on whether or not we can improve situational awareness during recovery phases and how we can do so, using social media data as a sensor of recovery activities has the potential to improve recovery efforts because social-media generated information may be able to complement existing recovery indicators by its timeliness. Thus, for the first step to explore the possibility of using social media data to detect recovery activities, we analyze whether there were correlations between people's communication in the virtual world and people's activities in the real world.

- RQ1: Did social media communication topics have relationships with the excess demand for used cars and housing in the disaster-stricken area?

Secondly, although both used cars and housing are likely to be in higher demand after a large-scale water-related disaster, the two goods have different characteristics and thus, when and which people in the disaster-stricken area needed to buy these two goods may be different. In this study, our hypothesis is that the two types of goods had different types of correlations with social media communication.

- RQ2: Did the excess demand for used cars and the excess demand for housing correlate differently with social media communication?

Lastly, related works investigating relatively short-term restoration and response found the different types of communication patterns between people local to a disaster-stricken area and people non-local to the disaster. Our hypothesis in this study is that even during recovery phases, the local and non-local population communicate differently, and thus we consider the following RQ3.

- RQ3: Did social media communication posted by people local and non-local to the disaster-stricken area have different types of correlations with the excess demand for used cars and housing?

DATA

Socio-economic Recovery Activity Data

Used-car market data

As one of the proxies of socio-economic recovery activities, we use the Japanese used-car market data sourced from advertisements posted on one of the most dominant used-car magazines in Japan, "Goo[4]," which is published every two weeks. We used the data posted by dealers in the tsunami-damaged areas for six months after the disaster. For the analysis, we selected a body type named Light Motor Vehicle Cab Van because both quantitative research (Shibuya and Tanaka, 2019) and qualitative reports, such as interviews in the newspaper and in government reports showed that there was an excess demand for the Light Motor Vehicle Cab Van. The data include used-car characteristics such as age, price, and transmission. The real prices of used cars were calculated based on the fiscal 2015 Consumer Price Index[5].

Housing market data

This study uses the leased housing market data from six months after the disaster provided by At Home Co., Ltd[6]. The data include housing characteristics such as the lease price, the size of the building area, the age of a property, and the address. The lease prices were adjusted as real prices with the residential property price index[7]. To exclude outliers, the real sales price per square meters of each property was calculated. Properties whose price per square meter was more than or less than the mean real sales price ± the standard deviation × 4 were excluded. Each property was checked to see if it was in the building damaged zones, and if not, the distance to the building damage zones was calculated based on the survey results of building damages conducted by the Ministry of Land, Infrastructure, Transport, and Tourism[8]. The distance from each property to Sendai station as a proxy of the city center was calculated. The minutes from the nearest station of each property to Sendai station by a train was also added as a feature. The current study only uses the leased houses located in plains and within 3km to the building damage zones because the quantitative research (Shibuya and Tanaka, 2018c) reveals that there was an excess demand for leased properties, particularly those located in plains and within 3km to the building damage zones. Table 1 describes the numbers of used cars and housing for the analysis every two weeks.

Table 1. Observation numbers of used cars and housing every two weeks

	Mar-2	*Apr-1*	*Apr-2*	*May-1*	*May-2*	*Jun-1*	*Jun-2*	*Jly-1*	*Jly-2*	*Aug-1*	*Aug-2*	*Sep-1*
Used Cars	14	118	132	124	129	114	114	104	104	134	106	121
Housing	656	287	436	343	468	389	344	363	349	309	348	266

Note 1: Mar-1 represents the first half of March; Mar-2 represents the second half of March. The same applies hereafter.
Note 2: In this study, we set a one-month time lag for used-car data because our used-car target data are sourced from a paper-based magazine. It took about one month for the magazine to be organized and to publish the data after collecting data from town shops. For example, in this study, used-car data from the second half of April (*Apr-2*) is treated as the second half of March (*Mar-2*). On the other hand, we did not set any time lags for housing market data because they are sourced from an online platform, and they were published in real-time way.

Social Media Communication Data: Twitter Data

Twitter is a platform that allows users to post messages (tweets) to their followers and the public (if a user permits), and to receive posted messages from other users. The target data in this study were collected through an Internet service called "Kuchikomi@kakaricho" (http://kakaricho.jp)[9]. We selected Japanese tweets posted for six months after the disaster (March 11th to September 11th of 2011) that contained at least one of the 16 Japanese keywords deemed to be relevant to our study purposes:[10] "earthquake," "disaster," "affected," "evacuation," "thank you," "temporal," "restart," "recovery," "information," "appreciation," "support," "tsunami," "damaged," "car," "light,"

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[4] The used-car data were provided by "Proto corporation" which publish "Goo."
[5] We used "automobile" deflator sourced from http://www.e-stat.go.jp/SG1/estat/List.do?bid=000001074278&cycode=0 (accessed October 17, 2018).
[6] The study is supported by Joint Research Program No.823 at CSIC, The University of Tokyo ("Real Estate Database 1999-2016" by At Home Co., Ltd.)
[7] Average of 2010 = 100, http://www.mlit.go.jp/totikensangyo/totikensangyo_tk5_000085.html, accessed September 21st, 2018
[8] http://www.mlit.go.jp/toshi/toshi-hukkou-arkaibu.html
[9] Although Twitter API allows collecting public tweets, we cannot collect tweets seven years ago (when the disaster happened). Therefore, we use an internet service Kuchikomi@kakaricho which provides historical tweets.
[10] We applied keywords-based tweets search approach based on related works (e.g., Wendland et al, 2017; Musaey et al., 2017; Alam et al., 2017). Before selecting the 16 keywords, the authors manually checked various types of tweets relevant to the disaster. After discussing the appropriateness of the keywords among authors, we carefully chose 16 Japanese keywords.

"evacuation" (all keywords are translated by the authors). In total, we collected 11,676,929 tweets.

Selection of disaster-related communication based on machine-learning

To select social media communication that related to the disaster, we classify the originally collected data based on machine learning techniques. First, after removing duplicated and re-tweeted tweets from the initially collected data, we randomly sampled a subset of about 2,000 tweets. After manually annotating the subset of 2,000 tweets based on whether the subset was disaster-related or not, we developed several classifiers including Naive Bayes, Support Vector Machine (SVM), and Logistic Regression along with a 10-fold cross-validation technique to compare the accuracy of these classification models. We found that the Naive Bayes classifier is the best predictor (Accuracy: 0.932, Precision: 0.945, Recall: 0.939)[11]. We then predicted and labeled the rest of the Twitter data with the Naive Bayes classifier. As a result, this study labeled 817,084 tweets as disaster-related. For further research, we only use these disaster-related labeled tweets.

Table 2. The Number of Local and Non-Local Tweets Datasets

	Number of Tweets											
	Mar-2	***Apr-1***	***Apr-2***	***May-1***	***May-2***	***Jun-1***	***Jun-2***	***July-1***	***July-2***	***Aug-1***	***Aug-2***	***Sep-1***
Local	728	549	393	529	401	357	415	385	322	326	307	463
Non-Local	209,346	94,748	60,211	48,653	47,174	49,436	43,040	50,053	42,699	41,301	45,270	79,978

Selection of tweets posted from the local and non-local population

As a means to examine whether a communication posted by the local and non-local population had different types of relationships with the excess demand for used cars and houses (RQ3), we further categorized the data based on tweets with geo-information. We made two datasets; a *Local Tweets dataset* and a *Non-Local Tweets dataset*. The *Local Tweets dataset* consists of tweets either whose tweeters' profile shows that they were in tsunami-stricken cities[12], their profile description contains any of the tsunami-stricken cities' names, or tweets with geo-tagged information that declares that they were in the tsunami-stricken area. The *Non-Local Tweets dataset* are the remainder of the data. Table 2 shows the number of each dataset every two weeks.

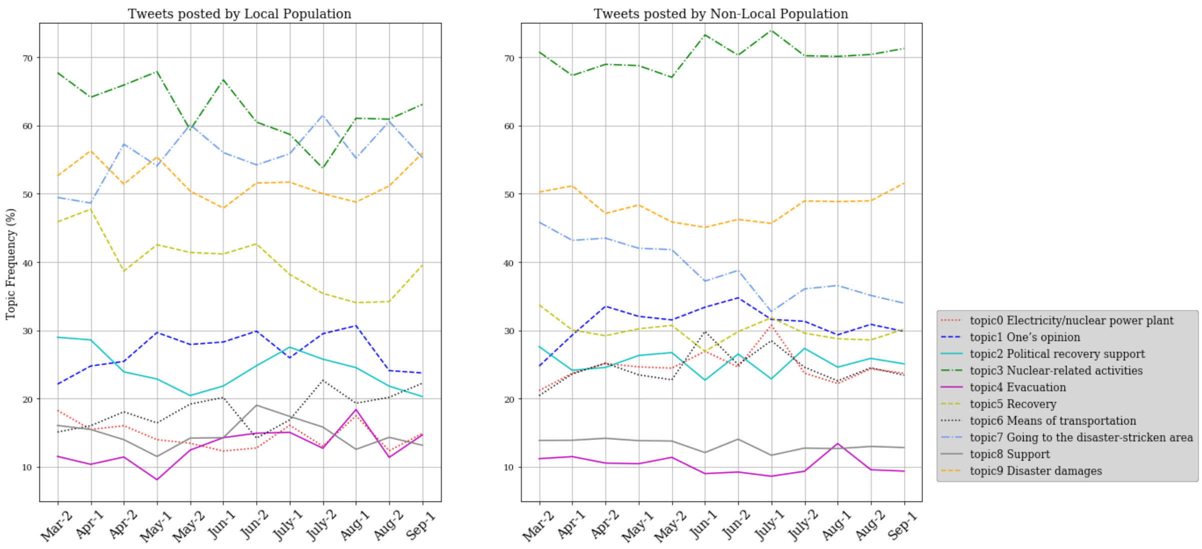

Figure 1. Topic Frequency ratio (T_i^n) of Tweets Posted by Local and Non-Local Populations

[11] SVM: Accuracy: 0.592, Precision: 0.592, Recall: 0.992. Logistic Regression: Accuracy: 0.928, Precision: 0.933, Recall: 0.9458.

[12] This study uses tsunami-stricken cities' names listed on the "Area of inundated area" by the Geospatial Information Authority of Japan (http://www.gsi.go.jp/kikaku/kikaku60004.html). We only used tsunami-stricken cities' names in Miyagi prefecture and Iwate prefecture. Fukushima prefecture was also one of the devastated areas of the disaster, but we did not include cities in Fukushima prefecture because Fukushima prefecture suffered more from the nuclear incident and thus, it should be treated differently.

Table 3. LDA topics

#	Proposed label	Top 10 most probable words	Tweet examples
0	Electricity/nuclear power plant	restart, power saving, summer, rice, electricity, non-nuclear power, shortage, Kesennuma (city name), Hokkaido (region name), machine	"Now is not the time to criticize the government, but the time to look at the reality and figure out what we have to do. Radioactive substances are detected but we need electricity, and we cannot store it up."
1	One's opinion	think, oneself, thing, myself, say, appreciation, watch, what, now, direction	"I think it is unfair that you need a local government's permission to send relief supplies. I cannot believe that. We have watched affected towns suffering, and I think they have no time to give permission to individuals. "
2	Political recovery support	free, support, person, service, site, governor, consultation, minster, freely, photo	"The Councilors' budget committee will restart the day after tomorrow. I heard that members are preparing to consult about the disaster-stricken area's situations and how to support them."
3	Nuclear-related activities	recovery, nuclear power, Japan, evacuation, country, Fukushima, issue, say, government, China	"I met an elderly person who evacuated from the nuclear-affected area. The lifeline utilities are in need of repair, and we still have family there."
4	Evacuation	evacuation, children, child, shelter, kid, target, need, parent, work, school	"Several people asked us to evacuate to another country.", "Evacuation places are in need of diapers, water, and rice."
5	Recovery	affected-area, affected, recovery, land, use, message, think, smile, Japan, support	"To support recovery efforts, the company bought a boatload of fish."
6	Means of transportation	use, car, vehicle, tax increase, restoration, accident, technology, automobile, ization/ize, need	"We need to send gasoline for cars to the disaster-stricken area." "Timely recognition of priority issues is needed to send relief supplies to the disaster-stricken area." "The train line in the disaster-stricken area is moving towards recovery."
7	Going to the disaster-stricken area	car, go, think, come, inside, time, house, evacuation, go out, myself	"I went back to the disaster-affected area and saw many volunteers who came and helped with the cleaning." "Does anyone know the website informing people how to go or send supplies to the disaster-stricken area?"
8	Support	support, affected area, the Great East Japan Earthquake and Tsunami, recovery, direction, activity, volunteer, participation, recovery support	"If anybody is looking for a place to sleep, please come to Nihonmatsu town. There is a shelter." "We need to support one another." "Photographers are holding an exhibition to support the disaster-affected area."
9	Disaster damages	tsunami, earthquake damage, evacuation, information, occurrence, news, the Great East Japan Earthquake and Tsunami, Mainichi newspaper, Miyagi prefecture	"The height of the first tsunami was over 10 meters. The second one was over five meters." "Teachers and children of the school are still left behind on the third floor of the building in Miyagi prefecture."

Note: All original tweets are in Japanese. All tweets in the table are trasnlated by the authors.

Topic Analysis: Latent Dirichlet Allocation (LDA)

Before conducting the primary analysis, we conducted topic analysis to explore what kinds of topics were on Twitter after the disaster. In doing so, we applied the Latent Dirichlet Allocation (LDA). LDA is a probabilistic topic modeling widely used in natural language processing to summarize and extract topics from documents. The intuition behind LDA is that documents exhibit multiple topics and a topic should be a distribution over a fixed vocabulary (Blei, 2012). When we manually looked into various tweets from the target dataset, we found each tweet could be categorized into several topics (for example, a tweet contains two topics; the disaster's damage and emotional encouragement). Thus, LDA, which assumes that one document contains multiple topics, was chosen for this analysis. By treating one tweet as one document, we conducted LDA with ten topics for the predetermined topic number[13]. The ten topics found by LDA and the most probable terms and proposed labels are shown in Table 3. Next, every tweet in our dataset was automatically labeled with the ten topics based on the results of LDA; If a tweet had more than 10% probability of being categorized as topic n, the tweet was labeled as the topic of n related. Next, the topic frequency ratio (T_t^n) for every two weeks was calculated as follows: $T_t^n = \frac{Topic\ labeled\ Tweet_t^n}{All\ Tweet_t}$ where $All\ Tweet_t$ denotes the number of all tweets in t period and $Topic\ labeled\ Tweet_t^n$ denotes the number of tweets labeled with the topic of n in t period. Figure 1 describes the chronological changes of the topic frequency ratio (T_t^n) of tweets posted by local and non-local populations, respectively.

Table 4. The statistical summary of equation (1) for each body type (six months pooled data)

	Used Cars (n=1,314)					Housing (n = 4,558)			
	mean	std	min	max		mean	std	min	max
lnP	13.07	0.53	11.00	14.20	*lnP*	10.63	0.31	8.82	11.88
X_1	0.29	0.45	0.00	1.00	X_1	0.68	0.47	0.00	1.00
X_2	0.00	0.06	0.00	1.00	X_2	0.01	0.00	0.00	0.03
X_3	7.37	4.25	0.00	21.00	X_3	0.02	0.04	0.00	0.17
X_4	0.31	0.46	0.00	1.00	X_4	0.02	0.01	0.00	0.12
L0	0.14	0.02	0.12	0.18	X_5	0.02	0.01	0.00	0.07
L1	0.27	0.02	0.22	0.31	X_6	0.03	0.01	0.01	0.17
L2	0.24	0.03	0.2	0.29	X_7	0.00	0.00	0.00	0.02
L3	0.62	0.04	0.54	0.68	*L0*	0.15	0.02	0.12	0.17
L4	0.13	0.03	0.08	0.18	*L1*	0.27	0.02	0.24	0.31
L5	0.4	0.04	0.34	0.48	*L2*	0.24	0.03	0.2	0.29
L6	0.18	0.02	0.14	0.23	*L3*	0.64	0.03	0.59	0.68
L7	0.56	0.04	0.49	0.61	*L4*	0.13	0.03	0.08	0.18
L8	0.15	0.02	0.12	0.19	*L5*	0.4	0.04	0.34	0.48
L9	0.52	0.02	0.48	0.56	*L6*	0.18	0.02	0.16	0.22
NL0	0.25	0.02	0.21	0.31	*L7*	0.54	0.02	0.49	0.56
NL1	0.32	0.02	0.25	0.35	*L8*	0.14	0.02	0.12	0.17
NL2	0.25	0.02	0.23	0.28	*L9*	0.52	0.03	0.48	0.56
NL3	0.7	0.02	0.67	0.74	*NL0*	0.26	0.03	0.22	0.31
NL4	0.1	0.01	0.09	0.13	*NL1*	0.31	0.02	0.29	0.33
NL5	0.3	0.01	0.27	0.34	*NL2*	0.24	0.01	0.23	0.26
NL6	0.25	0.02	0.2	0.3	*NL3*	0.71	0.02	0.67	0.74
NL7	0.39	0.04	0.33	0.46	*NL4*	0.1	0.02	0.09	0.13
NL8	0.13	0.01	0.12	0.14	*NL5*	0.3	0.02	0.27	0.32
NL9	0.48	0.02	0.45	0.51	*NL6*	0.26	0.03	0.23	0.3
					NL7	0.38	0.04	0.33	0.43
					NL8	0.13	0.01	0.12	0.14
					NL9	0.48	0.02	0.45	0.52

Note 1: L_k denotes the topic frequency ratio of topic k within the *Local Tweets dataset*. NL_k in the table denotes the topic frequency ratio of the topic k within the *Non-Local Tweets dataset.*

MODEL

To address how the topic frequency ratio on Twitter correlated with used-car prices, we developed a model below (equation 1) based on the Hedonic model as described in the section on Related Literature. By controlling used-car/housing characteristics, such as age and how many kilometers were driven, the Hedonic model allows us to assess the correlation between the used-car/housing prices, which reflect the demand for used-car/housing, and the topic frequency ratios on Twitter.

$$\ln P_i = \beta_0 + \beta_j X_{ji} + \beta_k T_{ki} + \varepsilon_i \tag{1}$$

where $\ln P_i$ is the natural logarithm of the real price of the i th product, X_{ji} is a vector of j th observable characteristics of the used cars or the houses. T_{ki} is the k th topic frequency ratio (L0 to T9 and NL0 to NL9 in

[13] To decide a suitable number of topics, the author applied LDA with several topic numbers, including 10, 20, 30, 50 and 100. As a result, when the topic number is 10, the results are most convincing and understandable to people although the perplexity is not the best.

Table 4). ε_i is the error term. We apply equation 1 to each topic frequency ratio[14] and used-car and housing market data respectively. For the used-car market data, the following control variables X_i are used:
Transmission:
X_{1i} = Transmission Dummy (Automatic=1, others=0)
Fuel:
X_{2i} = Special types of fuels Dummy (LPG, CNG or FC=1, others = 0)
Age:
X_{3i} = Age (in years)
Kilometers driven:
X_{4i} = 100,000km Dummy (over 100k km driven=1, others=0)

For the housing market data, the following control variables X_i are used:
X_{1i} = Apartment dummy (apartment = 1, others = 0)
X_{2i} = Distance to Sendai station (1/1000 km)
X_{3i} = Time from the nearest station to Sendai station by a train/subway (1/1000 minutes)
X_{4i} = Age (1/1000 year)
X_{5i} = Accessibility to the nearest station by walking (1/1000 min)
X_{6i} = Size of building area (1/1000 m^2)
X_{7i} = Height of a property (the sum of property's levels × 1/1000)

The statistical summary of our model is shown in Table 4.

RESULT

Table 5 shows a summary of the estimated coefficients of the topic frequency ratios (T_{ki}) of equation 1[15]. In the table, if an estimated coefficient of a topic frequency ratio has a significant correlation with the excess demand of used cars or housing at a 5% significance level, the cell is shaded. Other estimated coefficients of our model and adjusted R^2 are presented in Tables 6 and 7.

Regarding the excess demand for used cars, there were significant positive correlations between the used-car demand and the topic frequency ratio of Topic 3 (Nuclear-related activities), Topic 5 (Recovery), and Topic 9 (Disaster damages) within the *Local Tweets dataset*. On the other hand, there were significant negative correlations between the used-car demand and the topic frequency ratio of Topic 4 (Evacuation) within the *Local Tweets dataset*. In contrast, there were significant positive correlations of the topic frequency ratio of Topic 7 (Going to the disaster-stricken area) and Topic 8 (Support) with the prices of used cars within the *Non-local Tweets dataset.*

Regarding excess demand for housing, there were statistically significant positive correlations between the excess demand for housing and the topic frequency ratio of Topic 1 (Electricity/nuclear power plant) and Topic 6 (Means of transportation/ logistics) within the *Local Tweets* dataset. On the other hand, we did not find any significant correlations between the demand for housing and the topic frequency ratios within the *Non-Local Tweets* dataset.

Table 5. Estimated Coefficients of Topic Frequency Ratio

		Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9
		Electricity/ nuclear power plant	One's opinion	Political recovery support	Nuclear-related activities	Evacuation	Recovery	Means of transportation	Going to the disaster-stricken area	Support	Disaster damages
Used cars	Local	0.19	-0.49	0.06	**0.56****	**-1.08*****	**0.64****	-0.62	-0.41	-0.48	**0.96****
	Non-Local	-0.37	-0.06	0.41	-1.05	0.42	0.74	-0.51	**0.94*****	**3.22****	0.48
Housing	Local	-0.14	**0.25*****	-0.11	**-0.16****	0.07	-0.07	**0.24****	0.13	-0.12	-0.05
	Non-Local	-0.08	0.08	0.23	-0.2	0.1	-0.07	-0.06	-0.04	-0.01	0.01

Note1: **: p < 0.05, ***: p < 0.01. The same applies hereafter.

[14] We apply equation (1) to each topic frequency ratio respectively because the correlations between each topic are from 0.08 to 0.8 and several topic frequency ratios would cause multicollinearity.
[15] We note that this study uses relatively large numbers of observations, and statistical significances (p-values) do not directly estimate the strength of related variables. Among the statistically significant topic frequency ratios (*Tk*), the largest effect size (Cohen's f^2) is 0.01. Future studies need to analyze how to improve accuracy of estimating disaster recovery activities with social media related variables by, for example, applying other social media related variables and by applying different models.

Note2: We found that both heteroskedasticity and serial correlation exist (Breusch-Pagan statistics' p-value are all less than 0.01. Durbin-Watson statistics' p-values are less than 0.01). Therefore, the standard errors are corrected for serial correlation and heteroscedasticity by using the Newey-West procedure.

Note3: The Variance Inflation Factor (VIF) of each regression for the housing datasets is from 1.00 to 2.08. The VIF of each regression for used cars is from 1.00 to 1.18. These VIF scores suggest there are no multicollinearity problems.

Table 6. The results of equation (1) within the *Local Tweets dataset*

Used cars	*Adj.R²*		*Intercept*	X_1	X_2	X_3	X_4	*Topic3*			
	0.70	Estimate	13.42***	0.04**	0.05	-0.08***	-0.35***	**0.56****			
		Std. Error	0.17	0.02	0.19	0.00	0.02	0.26			
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	*Topic4*			
	0.70	Estimate	13.91***	0.04*	0.07	-0.08***	-0.36***	**-1.08*****			
		Std. Error	0.05	0.02	0.17	0.00	0.02	0.40			
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	*Topic5*			
	0.70	Estimate	13.52***	0.04**	0.08	-0.08***	-0.35***	**0.64****			
		Std. Error	0.11	0.02	0.18	0.00	0.02	0.27			
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	*Topic9*			
	0.70	Estimate	13.28***	0.04**	0.06	-0.08***	-0.35***	**0.96****			
		Std. Error	0.19	0.02	0.18	0.00	0.02	0.38			
Housing	*Adj.R²*		*Intercept*	X_1	X_2	X_3	X_4	X_5	X_6	X_7	*Topic1*
	0.71	Estimate	10.43***	-0.07***	-4.49***	-0.33***	-14.45***	-2.07***	14.89***	10.72***	**0.25*****
		Std. Error	0.03	0.01	0.72	0.09	0.61	0.23	0.45	1.99	0.09
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	X_5	X_6	X_7	*Topic3*
	0.71	Estimate	10.60***	-0.07***	-4.47***	-0.34***	-14.47***	-2.07***	14.87***	10.83***	**-0.16****
		Std. Error	0.04	0.01	0.72	0.09	0.61	0.23	0.45	1.99	0.06
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	X_5	X_6	X_7	*Topic6*
	0.71	Estimate	10.46***	-0.07***	-4.44***	-0.33***	-14.45***	-2.05***	14.86***	10.89***	**0.24****
		Std. Error	0.03	0.01	0.72	0.09	0.61	0.23	0.45	1.98	0.11

Table 7. The results of equation (1) within the *Non-Local Tweets dataset*

Used cars	*Adj.R²*		*Intercept*	X_1	X_2	X_3	X_4	*Topic7*
	0.70	Estimate	13.41***	0.03*	0.07	-0.08***	-0.35***	**0.94*****
		Std. Error	0.14	0.02	0.19	0.00	0.02	0.34
	Adj.R²		*Intercept*	X_1	X_2	X_3	X_4	*Topic8*
	0.70	Estimate	13.35***	0.04*	0.05	-0.08***	-0.35***	**3.22****
		Std. Error	0.20	0.02	0.18	0.00	0.02	1.48

DISCUSSION

By applying the Hedonic model, this study observed whether there were correlations between social media communication topics and the excess demand for used cars and housing as proxies of socio-economic recovery activities in the disaster-stricken area (RQ1). Also, we analyzed whether the excess demand for used cars and housing correlated differently with communication topics (RQ2) and whether there were any differences in social media communication posted by people local and non-local to the disaster-stricken area (RQ3). We present our discussion according to these research questions.

Regarding RQ1, by applying equation 1, we found that several topic frequency ratios had statistically significant correlations with the excess demand for used cars and housing. These results imply that the topic appearance ratios on Twitter might be useful in detecting people's socio-economic recovery activities in the real world.

Regarding RQ2, the results suggest that the different types of the two goods correlated to different topic frequency ratios. To be specific, regarding used cars, we found that the excess demand for used cars correlated to the frequency ratios of topics related to nuclear-related activities (Topic 3), evacuation (Topic 4), recovery (Topics 5) and damage (Topic 9) within the Local Tweets dataset. Also, the frequency ratios of topics related to going to (Topic 7) and supporting (Topic 8) the disaster-stricken area within the *Non-Local Tweets dataset* correlated with the excess demand for used cars. On the other hand, regarding housing, we found that the excess demand for housing correlated to frequency ratios of topics related to people's opinion (Topic1), nuclear activities (Topic3) and means of transportation/logistics (Topic 6) within the *Local Tweets dataset*. It is interesting to focus on topics related to nuclear activities (Topic 3) because the excess demand for both goods, used cars and housing, correlated with the topics (Topic3), but they correlated in different ways: The excess demand for used cars had positive correlations with nuclear activities while the excess demand for housing had negative correlations with the topic. This implies that because nuclear-related issues caused anxiety among people in the disaster-stricken area, they started to rent new places to resettle when uncertainty about nuclear-related issues gradually diminished. On the other hand, locals might have started to purchase used cars even while there were concerns related to nuclear-related issues.

Regarding RQ3, the analysis implies that communication posted by locals and non-locals correlated differently with the excess demand for used cars. This study found that there were negative correlations between the used cars and the frequency ratios of topics related to evacuation (Topic 4). This implies that when people in the disaster-stricken area were still in evacuation shelters, there was less need to obtain or replace vehicles. Moreover, we found positive correlations between the excess demand for used cars and the frequency ratios of topics related to nuclear-related activities (Topics 3), recovery (Table 5) and damage (Topic 9) within the *Local Tweets dataset,* and topics related to going to and supporting the disaster-stricken area (Topics 7&8) within the *Non-Local Tweets dataset*. This implies that the local population might have communicated more about nuclear-related activities (Topic 3), recovery (Topics 5) and damage (Topic 9) while people became active in recovery efforts and restarted their daily lives as observed in the excess demand for used cars. Meanwhile, people outside of the disaster-stricken area tended to communicate more about going to and supporting the affected area (Topics 7&8). These results are similar to the findings of the previous study that found local people tended to share images of response, recovery and damages while the non-local population tended to share images of people suffering (Bica et al., 2017). This is because local residents needed to face realities and be strong in order to return back to normal routines while people from the outside may have tried to support the disaster-stricken area because they knew of local people's continuous struggles to recover. Our results imply that, for recovery phases, it is also important to distinguish communications posted by locals and non-locals.

In addition, regarding housing demand, we found positive correlations between the excess demand for housing and the frequency ratios of topics related to people's opinions (Topic1) and the means of transportation/logistics (Topic 6) within the *Local Tweets dataset* while there were no correlations between topic frequency ratios within the *Non-Local Tweets dataset* and the excess demand for housing. These results imply that people in the disaster-stricken area started to express their opinions about the situations surrounding them, such as recovery progress while people in the disaster-stricken area started to resettle as observed in the excess demand for housing. Although it is difficult to interpret the correlations between the excess demand for housing and the topic frequency ratios of topics related to transportation means (Topic6), this result might be reflected in the contents of tweets labeled as Topic 6. The tweets categorized as Topic 6 include less communication about car scarcity and the need to buy cars while Topic 6 tweets include more communication about a lack of gas, which might have tended to occur after people purchased used cars, and more communication about public transportation system recovery updates (e.g., tweets sharing the information about train service status).

CONCLUSION

The object of this study was to address how social media data could be used for detecting recovery in disaster-stricken communities. We empirically analyzed the correlations between topic frequency variations in disaster-related tweets after the Great East Japan Earthquake and Tsunami of 2011 and two types of proxies of socio-economic recovery activities, namely the excess demand for used cars and the excess demand for housing. The results showed several statistically significant correlations between social media communication topic frequency ratios and the excess demand for both used cars and housing. These results provide evidence to support the possibility of using social media communication for detecting socio-economic recovery activities in a disaster-stricken area. Furthermore, the excess demands for two different types of goods (used cars and housing) had different types of correlations with socio-economic recovery activities. More specifically, our study implies that people in the disaster-stricken area started to be active in recovering and restarting their daily-lives as observed in the excess demand for used cars when there were more communications related to recovery and disaster damage among them. Also, during those periods, there tended to be more communication related to going to and supporting the affected area among the non-local population. In contrast, when the local population started to resettle, they might have communicated more opinions about their situations. Furthermore, our results imply that tweets posted by people local and non-local to the disaster-stricken area might have had different types of correlations with the socio-economic recovery activities.

The academic contribution of this study is that we were able to show the potential usefulness of social media for detecting socio-economic recovery activities, which has not been adequately studied among previous related studies. Furthermore, we were able to demonstrate that communication posted by local and non-local populations had different types of correlations with people's activities in the real world. This indicates that when we study social media communication for recovery, different communication patterns among local and non-local populations should be considered.

However, the authors acknowledge that this work is the first of its kind to examine the possibility of using social media data for detecting recovery activities. There are several limitations. This study collected tweets that contained specific words related to the disaster and disaster recovery activities as explained in the Data section and thus, the keywords might have affected the overall findings. In addition, we note that there is a likelihood of there being other intervening variables for topic frequency ratios. Further research is needed to analyze causality and direct relationships between topic frequency ratios and recovery activities. There is a need to expand the current study by, for example, analyzing the relationships between social media data and other types of recovery activities in the real world, as well as investigating recent large-scale disasters to understand general baselines of disaster recovery activities. Extracting variable communication topics which are beneficial for disaster responders and managers is another important study topic to demonstrate how social media could be used in all the stages of disaster management. Future studies also need to find effective way to distinguish between posts by locals from those by non-locals.

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