Travel and Tourism Research Association: Advancing Tourism Research Globally

Explore the Spatial Relationship between Airbnb Rental and Crime

Yu-Hua XU
University of Florida

Jin-won KIM
University of Florida

Lori Pennington-Gray
University of Florida

Explore the Spatial Relationship Between

Airbnb Rental and Crime

1 Introduction

The sharing economy, defined as "the sharing of access to goods and services from peer-to-peer/private-to-private coordinated through community-based online services" (UNWTO, 2017) has become a large contributor to many top-ranking destinations.[1] One of the leading sharing lodging service provider, Airbnb, has an expected global market share of 10% out of the lodging industry in the next five years (Winkler, & MacMillan, 2015). Along with this rapid expansion is a wide concern of the security issues in Airbnb. The tourism and hospitality industry is extremely sensitive to criminal activities, frequent guests have a relatively high risk of victimization (Berger, 1992). Recent media attention has shown that guests of the Airbnb rentals have (1) been targets of crime, (2) had valuables stolen while staying at these properties and (3) may in fact be more exposed to a greater range of crimes due to not being in a tourist location.[2][3][4] Previous studies also proved that the crime rate in the tourist destination shows a significantly negative effect on the tourist industry. (Marshall, 1994; Ryan, 1993; Wagstaff, Lague, & McBeth, 2003). Moreover, despite the extent of crime against lodging sites, data from interviews has demonstrated that hoteliers do not perceive crime as a problem (Jones & Mawby, 2005). While the Airbnb wins the market with its lower cost and flexible operations, criminal activities can easily destruct the reputation due to a lack of safeguard awareness and pertinent crime prevention measures. The need for greater information on the relationship between crime and the sharing economy is unprecedented.

In recent years, Airbnb providers are taking endeavors to adjust safety related regulations, various governments are also grappling with how to merge Airbnb into with regard to regulations (Gibbs, 2016). However, the current safety measures only prevent the harm from third parties, actions like setting registration requirements, implementing host protection insurance plays weak in preventing lodging safety from crime risks. Lately, broad discussions focused on topics like whether Airbnb has become the hotbed of danger, and how can different stakeholders take prevention measures, but few grounded researched were taken to explain the detailed relationships. Also, as the lodging sites and crime data carry spatial features, the relationships would vary by locations. Methods failed to consider in the spatial factors could result in biased conclusion. Therefore, it is timely and imperative to take an overall inspection on the spatial relationship between Airbnb and criminal activities.

[1] "The rise of the sharing economy", EY website, http://www.ey.com/Publication/vwLUAssets/ey-the-rise-of-the-sharing-economy/$FILE/ey-the-rise-of-the-sharing-economy.pdf, October 2017.

[2] "10 incredible Airbnb horror stories", Fox News websit, http://www.foxnews.com/travel/2014/05/08/10-incredible-airbnb-horror-stories.html, May 08, 2014

[3] Mike McPadden, AIRBN-BAD BEHAVIOR: 5 SEX CRIMES COMMITTED BY AIRBNB USERS, http://crimefeed.com/2016/09/airbn-bad-behavior-5-sex-transgressions-by-users-of-the-popular-travel-service/. September 28, 2016

[4] Kristen V. Brown, How criminals use Uber, Tinder and Airbnb, http://fusion.net/story/241225/crime-in-the-era-of-sharing/, December 7,2015

This study firstly explores spatial relationships between Airbnb facilities and crimes, explains the general correlations and relationships varied by facility/crime subcategory. Then spatially varying relationships within the state of Florida were analyzed. The purpose of the study is to find out 1) the alternative relationships between crime type and lodging type 2) the spatial patterns of crimes impact on Airbnb industry, hoping to provide security suggestions to protect the safety of sharing lodging guests, hosts, and the property from being victims of crime.

1 Literature Review

1.1 Hospitality and Crime

Relationships between hospitality industry and crime activity has been explored with traditional research methods before. Huang et al. (1998) discussed different external settings of hotels generate different extent of exposure to crimes, finding that levels of crimes were directly related to size of the hotel, target market of business travelers, access to public transportation, and an unsafe image of the environment surrounding the hotel. Zhao et al. (2004) examined the relationship between visitor demographics and types of criminal offenses in Miami-Dade County, Florida, demonstrated that hotel visitors' demographic characteristics like gender and residency/country of origin are correlated with crimes of robbery and burglary. Ho et al. (2009) analyzed the effects of hotel guests' characteristics on criminal victimizations, addressing that most hotel crimes were property-related, burglary and theft were two major crimes committed against hotel guests. The studies above, from the angle of demographic and hotel location, gave well implications for the stakeholders to prevent personal and property damage from crime. However, there is still a lack of literature consider in the spatial factors of hotel and crimes. Also, sparse studies had investigated into the internal structure of homestaying lodging properties and their possibilities to attract the interest of criminals.

In crime prevention, the Routine Activity Theory (Cohen and Felson, 1979; Felson, 1986, 1994)5 and Crime Pattern Theory (Brantingham and Brantingham, 1993) believed that crime happens when the activity space of a victim or target intersects with the activity space of an offender, while the target and the offender must be at the same place at the same time. Additionally, three other types of controllers—intimate handlers, guardians and place managers—must be absent or ineffective. Based on the theory, several interrelated research topics on crime prevention had emerged in tourism and hospitality research. Tourism has been proved of having boost crimes, (Brunt, 2000; Altindag, 2014; Adam, 2015; Mehmood, 2016; Montolio, 2016) this was largely due to the special signals tourists carries (Ryan, 1993) and their lifestyle that are particularly pertinent (Gottfredson, 1984; Maxfield, 1987) to criminal victimization. Some case studies also provide evidence to support the aforementioned causes of crimes (Dimanche.1999). In areas of criminology, spatial factors are more considered into analysis. Harper (2013) tested the spatial patterns of robbery at New Orleans and found that simple tourist's robbery concentrates within tourist attraction areas while aggravated tourist robbery concentrates in primarily residential places without attractions and police presence. Maltz (1990) used mapping technology to explain the patterns crimes appears in communities. Some studies focused on relationships between crime and special places. Mauby (2014) created a model to explain where and why offenses are committed in rural areas, fear of crime, and what crime reduction measures might be most effective. As for the factors alter the crime activeness, early studies show that crimes are more concentrated in high-density housing, or vertical communities (Healy & Birrell 2006; Newman & Kenworthy 1989). Recent studies revealed that crimes often concentrated on particular surrounding facilities John (2015). Yet there are rare detailed discussions based on the type of crime and facilities.

1.2 Crime Pattern Theory

The questions and assumption of this study is based on crime prevention theory. For a crime to occur in a lodging site, people who take care of the site such as janitors, apartment managers, lifeguards must be absent, ineffective or negligent (Eck, 1994). In this regard, Airbnb lodging type with less supervision are more likely to attract offenders. Moreover, criminal opportunities found at sites that come to the attention of offenders have an increased risk of becoming targets (Brantingham and Brantingham. 1993). While a few criminals may seek out uncharted areas, most will conduct their searches within the areas they become familiar with through noncriminal activities. In this regard, the Airbnb lodging sites are grouped by the level of accessibility to crime target, which was operationalized into different room type (shared room, private room and entire home). This grouping also matches the degree of absence of third-party supervisions. According to the definition of crime law, the criminal activities this study are going to discuss are divided into two types: (1) Violent crime, including murder, rape, robbery, aggravated assault. These offenses involve force or threat of force. (2) Property crime, including the offenses of burglary, larceny-theft, motor vehicle theft. The object of the theft-type offenses is the taking of money or property, but there is no force or threat of force against the victims.

1.3 Spatial Heterogeneity

Spatial dependence come from Tobler's (1970) First Law of Geography, and is determined by similarities in position and attributes" (Longley et al., 2005, p. 517). It shows the extent of the similarity between variables that are spatially nearby, closer the distance is, higher dependency they might got (Mennis & Jordan, 2005). When using non-spatial andstatistical methods to analysis spatial data, Anselin (1988) found if variables are autocorrelated, large residuals are likely to occur. Spatial heterogeneity refers to the variations of the relationships between predicted and explanatory variables over space (Mennis & Jordan, 2005). It occurs under the effect of spatial dependency. Regression models lacking spatial heterogeneity would result biased parameter estimates and false significance tests (Anselin, 1988). Spatial regression explores the non-stationary spatial patterns between variables. Geographically weighten regression has become a popular method in modeling spatial heterogeneity data. By adding geographic coordinate into the regression model, it give rise to the model performance and explanatory power (Kim, 2016).

There are previous researches explore the stationary relationships between lodging sites and crime data, yet seldom has taken the spatial factors in. Given that both lodging sites clusters and criminal activities carry strong spatial features, and their relationships could vary on destinations, there comes a great necessisty to discover the spatial pattern inside.

Based on the discussions above, three interrelated questions frame this study:

Question 1: Is there a spatial relationship between the geographical locations of Airbnb rental sites and incidents of criminal activities?

Question 2: Is there a spatial relationship between the geographical locations of Airbnb rental types (shared home, entire property, room in home) and incidents of criminal activities?

Question 3: Is there a spatial relationship between geographical location of Airbnb rental sites and types of criminal activities (property, violent crime and different criminal categories)?

Question 4: Is there any patterns of spatial heterogeneity regard to the relationships between Airbnb and crimes?

2 Methods

In this study, county was used as unit of analysis due to data availability. The state of Florida includes 67 counties. Figure illustrates the distribution of Airbnb (n=63,446) and the county boundaries in the state of Florida.

Geographic data such as county boundaries were acquired from the Florida GIS data library (http://www.fgdl.org/metadataexplorer/explorer.jsp). Airbnb types and locations were collected from the AIRDNA (https://www.airdna.co/). Data of the criminal activity counts of 2015 in state of Florida were collected from Florida Department of Law Enforcement (FDLE) and the Simply Map (http://geographicresearch.com/simplymap/). The criminal activity counts were standardized into crime index, where 100 point stands for average crime level, points above 100 stand for above average and vice versa. Two data sheet were splited and organized at the county level, serving the purpose for zonal-based spatial analysis. Control variables were obtained from North American Industry Classification System (NAICS)[6]. In total 19 variables were used for the study as Table 1.

Table 1 Dependent Independent and Control Variables

Variable	**Operational definition**	**Abbreviation**
Total Crime Index (IV, DV)	Total Crime Index	TCI
Crime Type: Property Crime Index(IV)	Property Crime Index	PROPTY
Crime Type: Violent Crime Index(IV)	Violent Crime Index	VIOLENT
Crime Type: Murder/Rape Crime Index(IV)	Murder and Rape Crime Index	MR
Crime Type: Robbery Crime Index(IV)	Robbery Crime Index	ROBBERY
Crime Type: Assault Crime Index(IV)	Assault Crime Index	ASSAULT
Crime Type: Burglary Crime Index(IV)	Burglary Crime Index	BURGLARY
Crime Type: Larceny Crime Index(IV)	Larceny Crime Index	LARCENY
Crime Type: Motor Vehicle Theft Crime Index(IV)	Motor Vehicle Theft Crime Index	MVT
Spatial location of all Airbnb sites(DV)	KDE of all Airbnb sites	ALL
Room Type: Spatial location of shared rooms(IV)	KDE of shared rooms	SHARE
Room Type: Spatial location of private rooms(IV)	KDE of private rooms	PRIVATE
Room Type: Spatial location of entire	KDE of entire homes	ENTIRE

[6] https://www.census.gov/eos/www/naics/

homes(IV)		
Population Density(CV)	KDE of population by county	POPD

The study applies geographically weighted regression (GWR) to explore the spatial relationships between the location of Airbnb facility and the criminal activities. It is assumed that (1) Violent crimes are less likely to occur in high Airbnb density area, where property crime has more chance to occur. (2) The leasing type that provides with more public space will attract more property crime, for there are more shared activity space between victims and offenders. Thus, prepositions were put forward in accordance with the research questions:

1) Positive relationships exist between densities of Airbnb and crimes.
2) Positive relationship exists between Airbnb density and density of property crime, negative relationship exists between densities of Airbnb and violent crime.
3) The relationships between Airbnb and crimes are altered by crime categories (MR, MVT, ROBBERY, ASSAULT, BURGLARY and LARCENY).
4) Airbnb listing type alters the relationship with crimes: shared room has higher correlations with crimes than private room than entire home.
5) Spatially varying relationships exist between densities of Airbnb and crimes.

For question 1, spatial autocorrelation was employed, a positive, significant was identified between Total Crime Index and ALL Airbnb sites.

For question 2, Model 1 (Dependent Variable: ALL; Independent Variable: PROPTY, VIOLENT) and Model 2 (Dependent Variable: ALL; Independent Variable: MR, ROBBERY, ASSAULT, BURGLARY, LARCENY, MVT; Control Variable: POPD) was built based on geographic weighted regression (see Table 2 and Table 3).

For question 3, Model 4 (Dependent Variable: TCI; Independent Variable: SHARE, PRIVATE, ENTIRE; Dependent Variable: TCI) was built.

For question 4, mappings were conducted to visualize the levels of spatial relationships, based on which regional comparisons were made. Every local coefficient was calculated and grouped at county level.

Table 2 Model Building

	Dependent Variable	**Independent Variable**
Model 1	KDE of all Airbnb sites	PROPTY, VIOLENT
Model 2	KDE of all Airbnb sites	MR,ROBBERY,ASSAULT, BURGLARY,LARCENY,MVT
Model 3	Total Crime Index	SHARE, PRIVATE, ENTIRE

3 Results

3.1 General relationships

For question 1, significant correlations were found between the density of Airbnb and crimes.

For question 2, the relationship is confirmed as varying by crime types, positive correlations were found in property crime, while negative correlations exist in violent crime. All variables

(PROPTY, VIOLENT, and TCI) showed evidence of significant spatial variation in parameter estimate values based on the rho value. The mean of the local coefficients for these variables were 1,366.82, PROPTY, -1,078.68, VIOLENT (see Table 3). For the model fit, the range of local adjusted R2 was from a minimum of 0.05 (Baker, Nassau, and Pinellas Counties) to a maximum of 0.45 (Osceola) and with a mean of 0.24 (Figure 1). The model had the best explanatory power (> 0.34 [1 standard deviation above the mean]) in the Counties of Brevard, Indian River, Okeechobee, Orange, Osceola, Seminole, St. Lucie, and Volusia. However, the model had very low explanatory power (< 0.14 [1 standard deviation below the mean]) in the Counties of Alachua, Baker, Bradford, Columbia, Hamilton, Jefferson, Madison, Lafayette, Leon, Suwannee, Union, and St. Johns.

Table 3 Results of Regression of by Crime Type (Model 1)

Variable	OLS coefficient	GWR coefficients (β)			Rho (spatial variability)	Range
	β	Minimum	Mean	Maximum		
Intercept	1,330.51	998.27	1,348.12	1,593.47	0.42	595.2
PROPTY	1,247.89	-17.95	-1,366.82	5,128.98	< 0.05	5,146.93
VIOLENT	-998.96	-4,066.51	-1,078.68	-34.62	< 0.05	4,031.89
Adjusted R^2	0.18	0.05	0.24	0.45		0.41
Condition index		20.66	27.19	29.48		8.82
n = 67; AIC_c (OLS) = 1,578.32; AIC (GWR) = 1,568.31; Neighbors = 23						

Note. Rho: Rho value by Monte Carlo analysis; β: Regression coefficient; AIC_c: Corrected Akaike's information criterion

For the individual crimes categories, three variables (MR, ROBBERY and LARCENY) showed evidence of significant spatial variation in parameter estimate values based on the rho value. The mean of the local coefficients for these variables -814.25, MR, 900.66, ROBBERY, 270.27, MVT. Positive correlations were found from ROBBERY and MVT, while negative correlations were recognized from MR (see Table 4). For the model fit, the range of local adjusted R2 was from a minimum of 0.15 (Madison County) to a maximum of 0.60 (Brevard County) and with a mean of 0.37 (

Figure 2). The model had the best explanatory power (> 0.49 [1 standard deviation above the mean]) in the Counties of Brevard, Indian River, Lake, Martin, Okeechobee, Orange, Osceola, Polk, Seminole, St. Lucie, and Volusia. However, the model had very low explanatory power (< 0.25 [1 standard deviation below the mean]) in the Counties of Bay, Calhoun, Gadsden, Hamilton, Holmes, Jackson, Jefferson, Lafayette, Leon, Liberty, Madison, Suwannee, Taylor, Wakulla, and Washington.

Table 4 Results of Regression by Individual Crime Kind (Model 2)

Variable	OLS coefficient	GWR coefficients (β)	Rho	Range

	β	Minimum	Mean	Maximum	(spatial variability)	
Intercept	84.13	61.92	86.36	101.12	0.56	16.99
MR	-974.33	-1,768.31	-814.25	-57.76	< 0.05	1,710.55
ROBBERY	709.50	-173.89	900.66	2,248.27	< 0.05	2,422.16
ASSAULT	-177.87	-994.03	-114.65	846.21	0.57	1,840.24
BURGLARY	65.53	-1,299.43	-120.70	1,419.12	0.89	2,718.55
LARCENY	-255.80	-861.41	126.69	1,726.65	0.25	2,588.06
MVT	865.47	-319.32	270.27	1,155.99	< 0.05	1,475.31
Adjusted R^2	0.25	0.15	0.37	0.60		0.45
Condition index		21.58	24.09	29.19		7.61
n = 67; AIC_c (OLS) = 1,577.81; AIC (GWR) = 1,552.35; Neighbors = 24						

For question 3, the regression result of Model 3 shows that SHARE is positively correlated with the crime occurrence, while the PRIVATE and ENTIRE carry negative correlations. All variables (SHARE, PRIVATE, ENTIRE) showed significant spatial variation in parameter estimate values based on the rho value. The respective means of the variables were 0.06537, SHARE, -0.0063, PRIVATE, and -0.000079, ENTIRE (see Table 5). For the model fit, the range of local adjusted R2 was from a minimum of 0.17 (Flagler, Volusia, and Seminole Counties) to a maximum of 0.27 (Escambia County) and with a mean of 0.19 (Figure 3). The model had the best explanatory power (> 0.21 [1 standard deviation above the mean]) in the Counties of Bay, Escambia, Homes, Jackson, Okaloosa, Santa Rosa, Walton, and Washington. However, the model had very low explanatory power (< 0.175 [1 standard deviation below the mean]) in the Counties of Flagler, Volusia, and Seminole Counties.

Table 5 Results of Spatial Regression by Room Types (Model 3)

Variable	OLS coefficient	GWR coefficients (β)			Rho (spatial variability)	Range
	β	Minimum	Mean	Maximum		
Intercept	116.9472	107.1532	116.0857	129.8248	0.28	22.6716
SHARE	0.06334	0.05216	0.06537	0.09107	< 0.05	0.03891
PRIVATE	-0.0063	-0.0108	-0.0063	-0.0039	< 0.05	0.0069
ENTIRE	-0.000093	-0.000193	-0.000079	-0.000008	< 0.05	0.00008
Adjusted R^2	0.15	0.17	0.19	0.27		0.10
Condition index		13.68	16.59	29.98		16.3
n = 67; AIC_c (OLS) = 627.77; AIC (GWR) = 641.50 ; Neighbors = 19						

3.2 Spatially varying relationships

For question 4, the relationships between Airbnb clusters and criminal activities varies across the studied area. Figure 5-Figure 12 map the spatial distribution of local coefficients and local R2 for those independent variables that had significant rho values.

Model 1 TCI (Figure 5**).** Strong positive correlations (local coefficient > 785.79 [2 standard deviations above the mean]) were observed in the Counties of Brevard, Orange, Indian River, and Seminole. Strong negative correlation (local coefficient < -883.33 [2 standard deviations below the mean]) were observed in the Counties of Citrus, Hernando, Pasco, and Polk.

Model 1 PROPTY (Figure 5**).** Strong positive correlations (local coefficient > 4,204.74 [2 standard deviations above the mean]) were observed in east side counties like Brevard and Osceola. Negative correlations (local coefficient < 0.00) were observed in the middle north counties as Columbia, Hamilton, Lafayette, and Suwannee.

Model 1 VIOLENT (Figure 6**).** Strong negative correlations (local coefficient < -3,077.56 [2 standard deviations below the mean]) were observed in east side counties like Brevard and Osceola. Relatively less negative correlations (local coefficient > -144.9 [1 standard deviation above the mean]) were observed in the northern counties like Bay, Gulf and Columbia.

Model 2 MR (Figure 7). Strong negative correlations (local coefficient < -1,314.63 [2 standard deviations below the mean]) were observed in the middle north-east counties like Orange, Lake and Volusia. Relatively less negative correlations (local coefficient > -313.87 [1 standard deviation above the mean]) were observed in the north-west counties like Santa Rosa, Walton, Madison.

Model 2 ROBBERY (Figure 8**).** Strong positive correlations (local coefficient > 1,716.24 [2 standard deviations above the mean]) were observed in the middle south-east counties like Palm Beach, Glades, Martin. Negative correlation (local coefficient < 0.00) were observed in the middle west and south counties like Sarasota, Miami-Dade, Monroe.

Model 2 MVT (Figure 9)**.** Strong positive correlations (local coefficient > 661.65 [1 standard deviation above the mean]) were observed in the middle counties like Orange, Lake, Hernando. Strong negative correlation (local coefficient < -121.11 [1 standard deviation below the mean]) were observed in the south-east counties like Broward, Palm Beach, Martin.

Model 3 SHARED (Figure 10). Positive correlations (local coefficient > 0.07413 [1 standard deviation above the mean]) were observed in the north-west counties of Escambia and Santa Rosa. Relatively less positive correlation (local coefficient < 0.05663 [1 standard deviation below the mean]) were observed in the middle-east counties like Orange, Osceola, Brevard.

Model 3 PRIVATE (Figure 11). Negative correlations ((local coefficient < -0.0086 [1 standard deviation below the mean]) were observed in the north-west counties like Gulf, Escambia and Santa Rosa. Relatively less negative correlation ((local coefficient > -0.0042 [1 standard deviation above the mean]) were observed in the south-east counties like Miami-Dade, Broward and Palm Beach.

Model 3 Entire House/APT (Figure 12)**.** Negative correlation (local coefficient < -0.000127 [1 standard deviation below the mean]) were observed in the south-east counties like Miami-Dade, Palm Beach and Monroe. Relatively Negative correlations (local coefficient > -0.000031 [1 standard deviation above the mean]) were observed in the middle-north counties like Hamilton, Columbia and Leon.

The variability in the model parameters suggests that the relationship between entire house/apartment and crime index is not stationary.

4 Conclusions

This study proved a significant, positive spatial relationship between Airbnb and crimes. Crime type(property/violent) act as a moderator which alters the direction of the relationship: Airbnb is positively related with property crime, and negatively related with violent crime. Individual crime kind also identified as a moderate factor: out of 6 selected crimes, robbery and motor vehicle theft have positive relations with Airbnb, murder and rape have negative correlation. The relationship pattern also varies by room type, shared rooms positively related with the crime, while the private rooms and entire home has negative correlations.

All the above relationships have a spatial heterogeneity across the studied area. The middle-east area of Florida, as Orange and Seminole county, has the highest crime and Airbnb correlations, property crime, robbery and motor vehicle theft in particular. Yet total violent crime, murder and rape in particular, has the strongest negative correlations in this area. Among all the coefficients distribution patterns, property crime occupies the largest area in the middle-east of Florida. When look into the spatially varying relationship of crime and Airbnb, room listing type also play an active role. Unlike private and entire home, shared rooms are higher related with crimes in north-west Florida. Meanwhile, entire homes are higher related with crimes in south Florida. Shared rooms in north-west Florida also need to take attentions on criminal activities.

5 Implications

Contrary to common theoretical assumptions, in less tourism intense areas, shared room type is the most solid crime-related listing type. Hosts and renters should take extra cautions when renting shared or share lodgings in less touristy areas. Also, pertinent crime precaution measures should be taken in different regions: In central Florida, where Disney park locates, motor vehicle theft, robbery are more likely to jeopardize the safety of Airbnb users. Even if robbery belongs violent crime, more frequently it is initiated from property looting purpose, though in a drastic manner. For other types of violent crime, less concerns need to be paid, since personal crimes are less likely to happen under massive supervisions.

From this study, the destination administration section (DMO particularly) has the opportunity to gain greater insights. It is timely to create a targeted training programs as well as policy guidelines for home-sharing renters in their destination. The information garnered from this study also provide the industry with empirical support to demonstrate the need for greater cautions in running the home-sharing business and protect the safety of their visitors.

6 Future Study

To interpret the spatially varying strength of the correlations between crime and Airbnb, additional factors need to be introduced. Inferring from previous research, tourism intensity level may have a mediation effect on crime's impact on Airbnb lodging. A linear combination of tourism tax percentage, rent rate, disparity in tourism sales, and percentage of hotel rooms to residential rooms can be introduced in future studies.

7 References

"The rise of the sharing economy", EY website, http://www.ey.com/Publication/vwLUAssets/ey-the-rise-of-the-sharing-economy/$FILE/ey-the-rise-of-the-sharing-economy.pdf, October 2017.

“10 incredible Airbnb horror stories”, Fox News websit, http://www.foxnews.com/travel/2014/05/08/10-incredible-airbnb-horror-stories.html, May 08, 2014

Mike McPadden, AIRBN-BAD BEHAVIOR: 5 SEX CRIMES COMMITTED BY AIRBNB USERS, http://crimefeed.com/2016/09/airbn-bad-behavior-5-sex-transgressions-by-users-of-the-popular-travel-service/. September 28, 2016

Kristen V. Brown, How criminals use Uber, Tinder and Airbnb, http://fusion.net/story/241225/crime-in-the-era-of-sharing/, December 7,2015

Chris Gibbs. Airbnb and the impact on the Canadian hotel industry, http://www.ryerson.ca/content/dam/tedrogersschool/htm/documents/ResearchInstitute/CDN_Airbnb_Market_Report.pdf, June 2016

Winkler, R. & MacMillan, D. 2015, The Secret Math of Airbnb's $24 Billion Valuation; Home-rental site's revenue projected to top more than $900 million, Dow Jones & Company Inc, New York, N.Y.

Marshall, A. (1994). It’s time for the hotel industry to get up in arms over security. Hotel & Motel Management, 209, 13.

Ryan, C. (1993). Crime, violence, terrorism and tourism: An accidental or intrinsic relationship? Tourism Management, 14,173-183.

Wagstaff, J., Lague, D., & McBeth, J. (2003). Time to get tough. Far Eastern Economic Review, 166, 12-16.

L. Berger, "Hotel Crime: Are You Safe As You Think," Corporate Dauel 8 (November 1992): 26-29.

C JonesR I Mawby. 2005, Hotel Crime: Who Cares? Crime Prevention & Community Safety, July 2005, Volume 7, Issue 3, pp 19–35

Huang, W.S Wilson; Kwag, Michael; and Streib, Gregory (1998) "Exploring the Relationship Between Hotel Characteristics and Crime," Hospitality Review: Vol. 16: Iss. 1, Article 9.

Zhao J, Ho T, Chen C. Crimes against hotel visitors: An empirical study in Miami-Dade County, Florida[J]. Journal of Hospitality Legal, Safety and Security Research, 2004, 2: 1-12.

Ho T, Zhao J, Brown M. Examining hotel crimes from police crime reports. Crime Prevention and Community Safety: An International Journal. 2009;11(1):21-33.

Lawrence Cohen and Marcus Felson, « Social Change and Crime Rate Trends : A Routine Activity Approach », American Sociological Review, 44 (4), 1979, pp. 588–608

Brantingham, P.L. and P.J. Brantingham(1993). "Environment, Routine and Situation: Toward a Pattern Theory of Crime." Advances in Criminological Theory 5:259-294.

Altindag DT. Crime and International Tourism. Journal of Labor Research. 2014;35(1):1-14.

Adam I, Adongo CA. Do backpackers suffer crime? Empirical investigation of crime perpetrated against backpackers in Ghana. Journal of Hospitality and Tourism Management. 2016;27:60-7.

Mehmood S, Ahmad Z, Khan A. Dynamic relationships between tourist arrivals, immigrants, and crimes in the United States. TOURISM MANAGEMENT. 2016;54:383-92.

Montolio D, Planells Struse S. Does Tourism Boost Criminal Activity? Evidence From a Top Touristic Country. Crime and Delinquency. 2016;62(12):1597-623.

Brunt P, Mawby R, Hambly Z. Tourist victimisation and the fear of crime on holiday. Tourism Management. 2000;21(4):417-24

Gottfredson, M. (1984). Victims of crime: The dimensions of risk. London: HMSO (Home Office Research Study No. 81).

Fotheringham, S. A., Charlton, M., & Brunsdon, C. (1998). Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. Environment and Planning A, 30, 1905–1927.

Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region. Economic Geography, 46(2), 234–240.

Longley, P., Goodchild, M. F., Maguire, D., & Rhind, D. (2005). Geographic information systems and science. New York, NY: Wiley.

Mennis, J. L., & Jordan, L. (2005). The distribution of environmental equity: Exploring spatial nonstationarity in multivariate models of air toxic releases. Annals of the Association of American Geographers, 95(2), 249–268.

Anselin, L. (1988). Spatial econometrics: Methods and models. Boston, MA: Kluwer Academic Publishers.

Healy, E., Birrell, B. (2006) Housing and community in the compact city, AHURI Final Report No. 89, Australian Housing and Urban Research Institute Limited, Melbourne.

Maxfield MG. Household Composition, Routine Activity, and Victimization: A Comparative Analysis. Journal of Quantitative Criminology. 1987;3(4):301-20.

Dimanche, Frederic, and Alenna Lepetic. "New Orleans tourism and crime; a case study." Journal of Travel Research, Aug. 1999, p. 19+. Expanded Academic ASAP

Harper DW, Khey DN, Nolan GM. Spatial Patterns of Robbery at Tourism Sites: A Case Study of the Vieux Carré in New Orleans. American Journal of Criminal Justice. 2013;38(4):589-601.

Maltz, M. D., Gordon, A. C., & Friedman, W. (1991). Mapping crime in its community setting: Event geography analysis. New York: Springer-Verlag.

Mawby RI. Exploring the relationship between crime and place in the countryside. Journal of Rural Studies. 2015;39:262-70.

Eck J E, Weisburd D L. Crime places in crime theory[J]. Crime and place: Crime prevention studies, 2015, 4.

Eck, John E. (1994). Drug Markets and Drug Places: A Case Control Study of the Spatial Structure of Illicit Drug Dealing. Unpublished Ph.D. dissertation, University of Maryland, College Park.

Kim JW. Measuring the equity of recreation opportunity: A spatial statistical approach [dissertation]. ProQuest Dissertations Publishing; 2015.

U.S. Department of Justice.(2016).Crime in the United States,2015.https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/offenses-known-to-law-enforcement/violent-crime/violentcrimemain_final.pdf

U.S. Department of Justice.(2016).Crime in the United States,2015.https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/offenses-known-to-law-enforcement/property-crime/propertycrimemain_final.pdf

Florida Department of Law Enforcement. http://www.fdle.state.fl.us/cms/Search.aspx?searchtext=crime+by+zip+code&searchmode=anyword

Appendix A: Heterogenous of local model fit

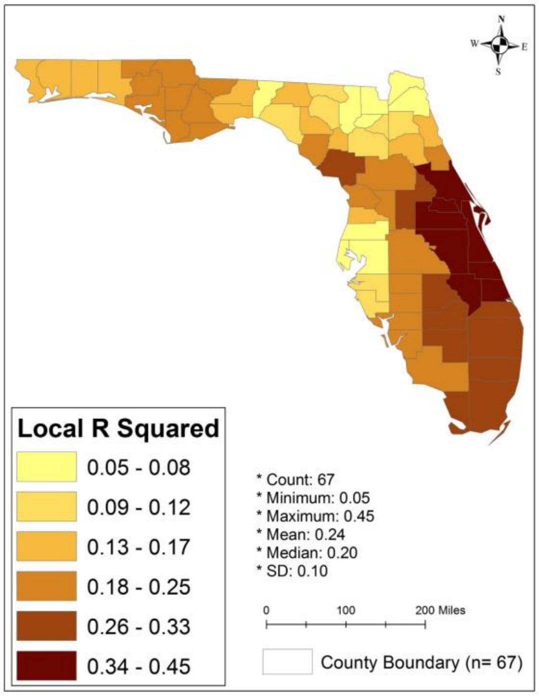

Figure 1 Spatial Distribution of R^2 for Model 1

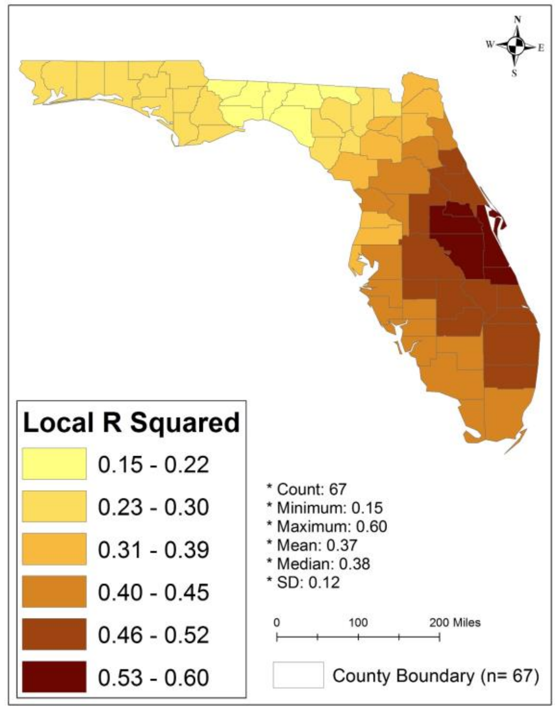

Figure 2 Spatial Distribution of R^2 for Model 2

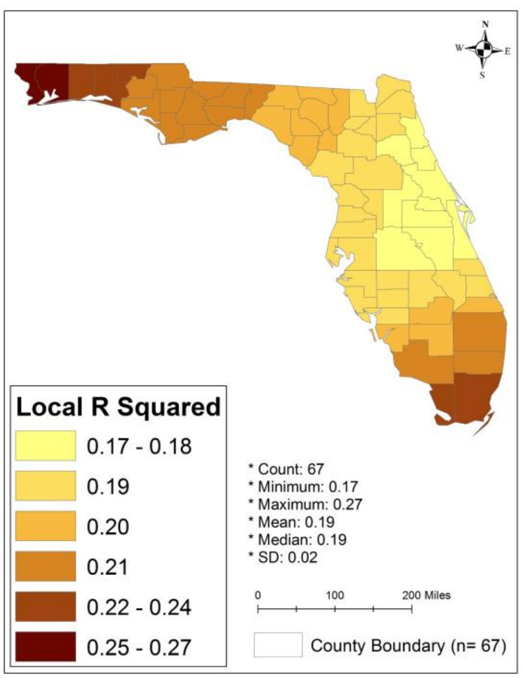

Figure 3 Spatial Distribution of R2 for Model 3

Appendix B: Heterogenous of local relationship by crime type

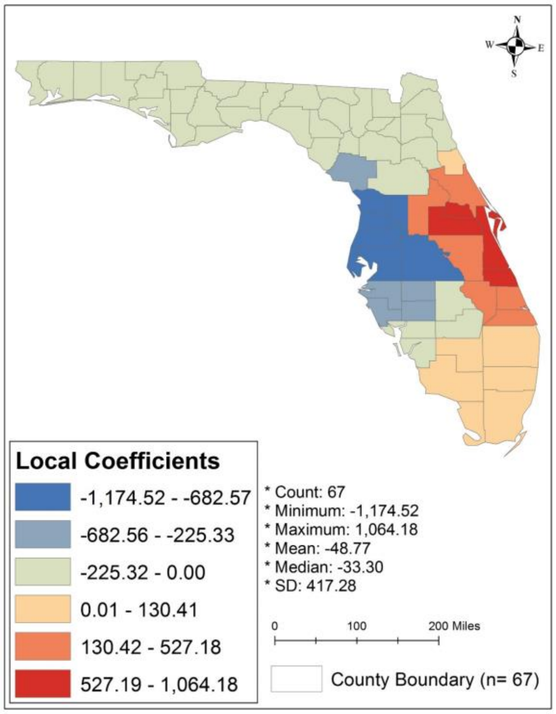

Figure 4 Local coefficients of Airbnb related with total crime

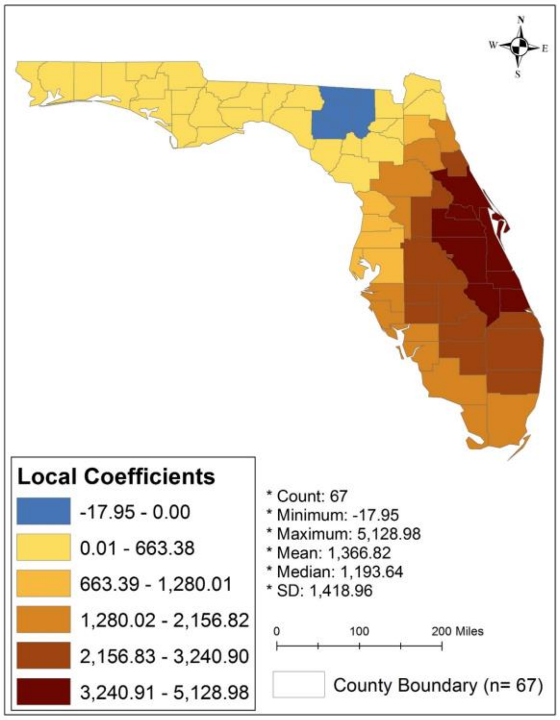

Figure 5 Local coefficients of Airbnb related with property crime

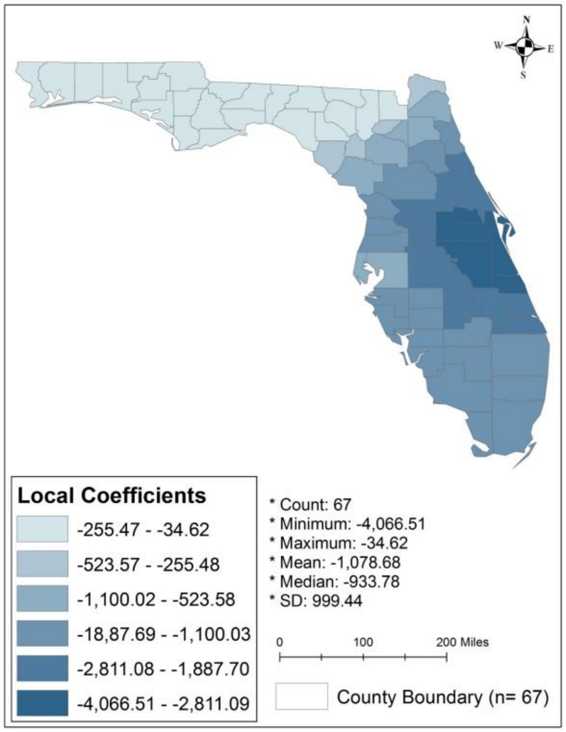

Figure 6 Local coefficients of Airbnb related with violent crime

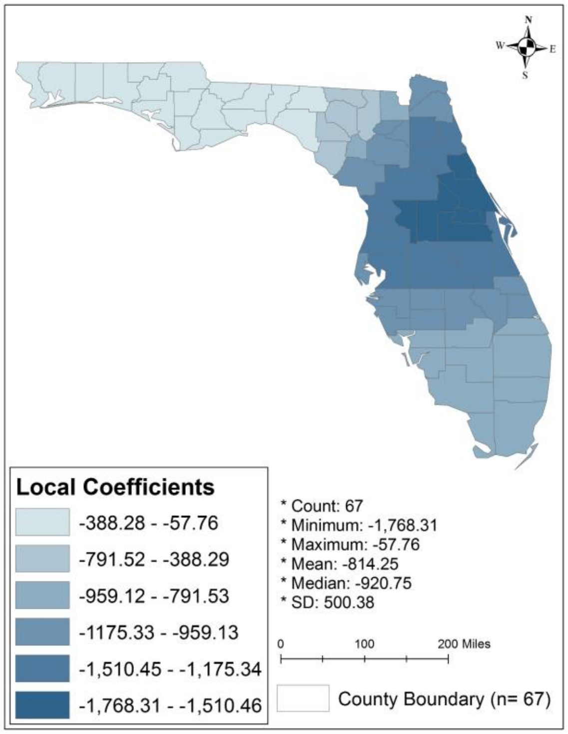

Figure 7 Local coefficients of Airbnb related with murder and rape

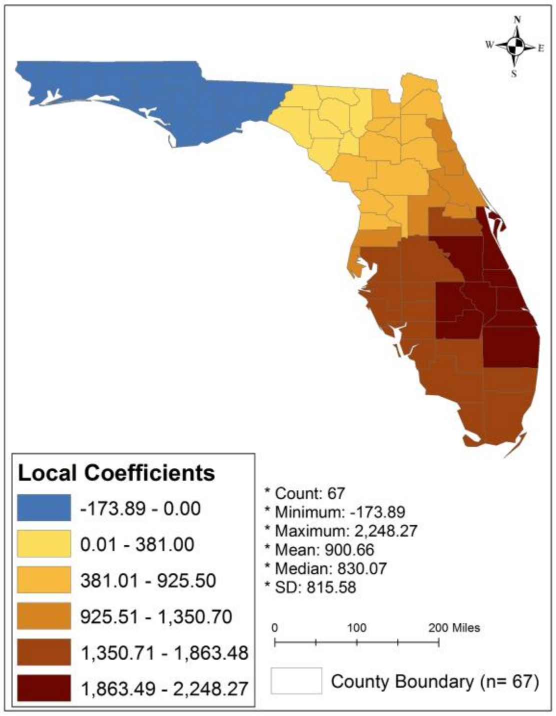

Figure 8 Local coefficients of Airbnb related with robbery

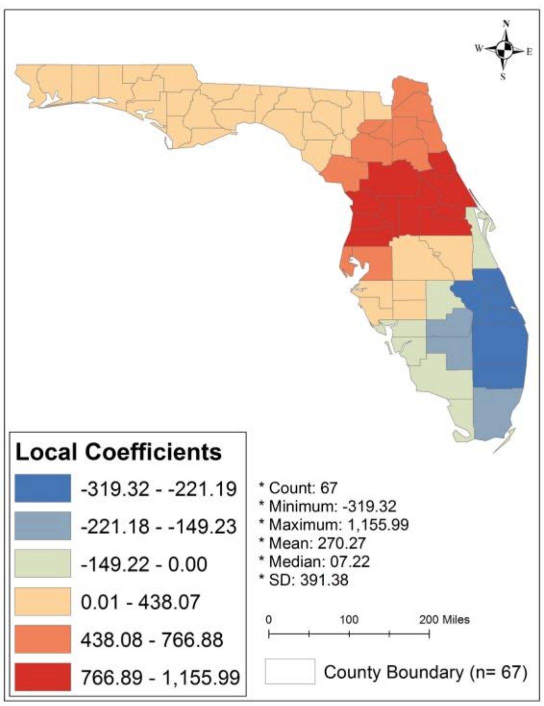

Figure 9 Local coefficients of Airbnb related with motor vehicle theft

Appendix B: Heterogenous of local relationship by listing type

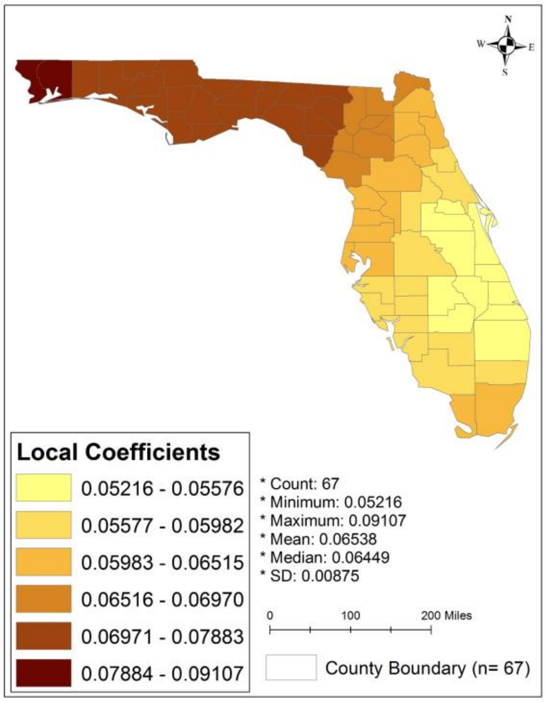

Figure 10 Local coefficients of crimes related with shared room

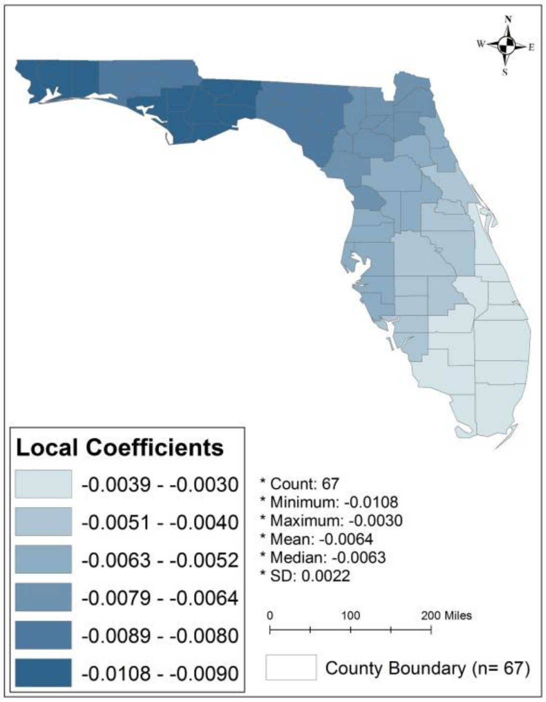

Figure 11 Local coefficients of crimes related with private room

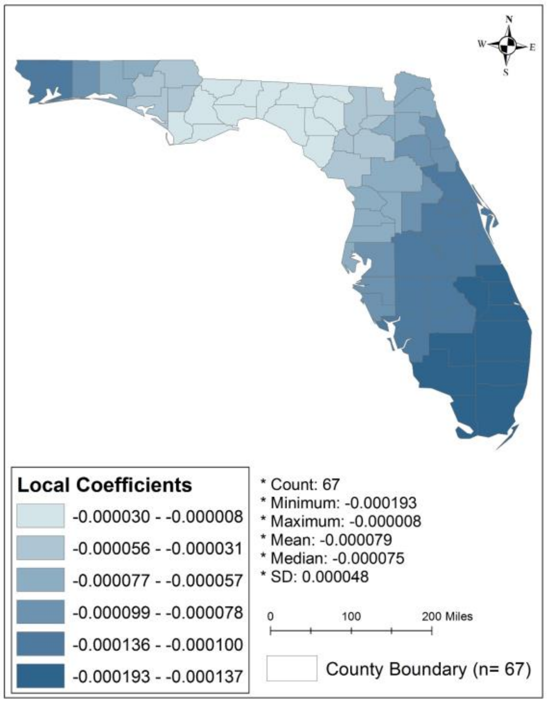

Figure 12 Local coefficients of crimes related with entire house