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The Red-Light Network: Exploring the Locational Strategies of Illicit Massage Businesses in Houston, Texas

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ABSTRACT

Illicit massage businesses (IMBs) play a considerable role in sex trafficking in the United States. Sometimes referred to as erotic massage parlors or Asian massage parlors, IMBs act as nodes within human and sex trafficking networks across the United States, where exploitation, involuntary servitude, and contemporary slavery are common occurrences. IMBs represent the largest component of the sex industry trend toward “indoor” sex work, in which meeting locations for sex workers and customers are prearranged, so there is no requirement that sex workers be publicly visible for customers to identify them. The lower visibility of contemporary sex work makes it difficult to identify locations where such activity occurs. As a result, research examining spatial, temporal, and economic prevalence of IMBs draws almost entirely on anecdotal evidence, and the accuracy of the analyses is somewhat questionable. This study begins to address this problem in an examination of the IMB industry in Houston, Texas. The research draws on user-generated data from online IMB review sites to identify IMB locations. This research further examines the geographic distribution of IMBs in the city to understand the spatial and situational characteristics most correlated with active IMBs.

KEYWORDS

commercial sex work;
informal economy; location
intelligence

The commercial sex trade is thriving in contemporary U.S. cities. Illicit massage businesses (IMBs) are found in most metropolitan areas across the United States, and constitute one of the largest sectors of the “indoor” sex trade. During the same time period, antitrafficking organizations, such as Polaris Project, have become increasingly vocal about the intersection of massage parlors and sex trafficking, with that organization dedicating a page on its Web site to explaining the ways in which these “fake massage businesses” are engaging in sex trafficking. Nevertheless, massage parlors are an understudied niche of the broader sex trafficking discussion (Weitzer 2009). IMBs are retail storefronts that advertise some type of personal care services. Most typically the service advertised is a massage (full body, foot massage, or Asian/Chinese/Thai massage) but illicit services have also been documented in hair and nail salons, health spas, and more. IMBs are differentiated from legal retailers of the advertised services because once a client enters the IMB, additional, illegal sexual services are available for purchase as well. The services provided vary to some extent from location to location, but as businesses that generate revenue by providing sexual services, IMBs are the contemporary manifestation of the historic brothel. From a geographic standpoint, IMBs are unique because they hide in plain sight. They are part of the commercial landscape, no longer concentrated by policing or social pressures into a red-light district.

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There is a moral and ethical imperative to understand the scope of IMBs for a variety of reasons. First, they are hubs within human and sex trafficking networks (Bales and Lize 2005; Levar, Kanouse, and Berry 2005; Weitzer 2009; Dank *et al.* 2014). Many of the sex workers are not voluntary participants, but rather are human and sex trafficking victims. Workers are often moved from one IMB to another by their traffickers both within a particular metro area and along established intercity and interstate trafficking networks. Each IMB is a node within the network where interventions are possible, where victims can be pulled out of modern sex slavery. Understanding the spatial distribution of IMBs, as well as their locational and operational strategies, from a business geography perspective is critical because these are not just nodes where interventions could take place, but each IMB is a location where revenue is generated within the human trafficking network. Better understanding of IMBs from a business-geography perspective should generate more effective policy and policing that reduce human trafficking networks' ability to profit from the illicit sex trade.

IMBs operate as traditional brick-and-mortar retail establishments. The only distinction between an IMB and a legal personal health services retailer like Massage Envy is that the services available include sex acts¹ rather than therapeutic or medical rehabilitation massage. Because IMBs work from fixed retail locations, if you can identify the IMB sites, it is possible to analyze this black-market activity in the same way that geographers have studied formal and legal sector business and retail activities. Indeed, site-based analysis is one of the foundational elements of applied economic geography, but to date, very little research focused on illicit or black-market activity has incorporated these approaches. The analysis presented here represents a fundamental step forward in the study of illegal or black-market economic activity from a geographic standpoint. Almost all previous research examining illicit economic activity lacks specific data for sales locations and consumer locations. The lack of data is due to the illegality of the trade, so that records of activity could be used as evidence by prosecutors if the participants were arrested. Indeed, locational data included in arrest records are often used in analyses of crime patterns in cities. This is an improvement over aspatial analyses of crime, but arrest data are insufficient for business analysis because arrest records are incomplete at best. Not all retailers of a particular illicit good or service get arrested. As such, the locations of arrests reflect police enforcement priorities rather than the supply- and demand-based spatial constraints of each illicit business. Within human trafficking research there are also challenges in obtaining reliable locational data, as most of the data are drawn from qualitative research, interviews with rescued human and sex trafficking victims. This research provides considerable depth and detail regarding the experience of victims and, to a lesser extent, the day-to-day operations of the sex trafficking industry. The qualitative research lacks the comprehensive spatial data needed to map and better understand the locational strategies employed in the human and sex trafficking industry.

This article is the first to study the locational strategies of IMBs from a traditional retail geography perspective. Drawing on user-generated data from online IMB review sites, we mapped 292 active and 144 recently closed IMBs in the Houston metropolitan area. These locational data are then used to answer four related research questions:

1. What is the spatial distribution of IMBs in the Houston metro area?
2. Do we see evidence of business clustering or agglomeration of IMBs within the region?
3. What are the characteristics of IMB neighborhoods compared with the rest of the metro area?
4. Are there particular spatial, demographic, or locational characteristics that are associated with IMB clustering at the neighborhood scale?

Literature review

Geographers have studied prostitution and the sex trade for some time. Within the discipline, Hubbard is perhaps the most prolific expert on prostitution and red-light districts. His work examines red-light districts and the policing of sex work in cities within two related frameworks. Hubbard (2008) argued that the geography of sex work in Western Europe and the United States can only be understood as the result of heteronormative morality imposed on sex workers and their clientele. The normative definition of sex work as immoral or unethical has historically forced the activities into marginal urban

spaces (Hubbard 1997, 1998). Hubbard later observed that targeted policing of street prostitution also served neoliberal economic interests by first pushing deviant activities like street prostitution into particular areas thereby, devaluing property and making those spaces candidates for urban redevelopment and gentrification. During the redevelopment process, policing would be enforced, thereby “cleansing” the space of deviant activities (Hubbard 2004). This compelling body of work demonstrates the social production of urban space quite clearly. It does not, however, engage in much detail with the spatial and economic strategies employed by sex workers and their clientele.

The general model of illicit retail marketplaces suggests that there are two key risks inherent to illicit markets that make them distinct from legal markets. First, buyers and sellers risk arrest if police enforce laws related to their transaction. Second, they cannot rely on state or legal institutions to enforce market rules. This second risk is exacerbated by the challenges buyers and sellers face obtaining accurate information on which they can evaluate the other’s trustworthiness. As a result, this model suggests that buyers and sellers will use one of two approaches to manage these risks. They might only do business through social networks, which would limit total sales but ensure a higher degree of safety from arrest or robbery. More ambitious buyers and sellers might use the rhythms of everyday life to identify locations where risks can be minimized. In the case of the illicit sex trade, this led to the establishment of red-light districts where police enforcement would be minimal and norms of market rules are established informally in place in ways that both buyers and sellers can easily learn and follow (Eck 1995).

Throughout much of the work on geographic analysis of red-light districts there is an implicit assumption that the locations are the direct result of policing and the establishment of “tolerance zones” where legal enforcement is minimal (Herbert 1997; Hubbard 1997). This was likely accurate even until the mid-1990s. Today, however, this is simply not the case. The contemporary sex work economy has undergone several changes that have fundamentally altered the geographic imprint of the industry. One overarching pattern is a large-scale shift toward “indoor” sex work, in which meeting locations for sex workers and customers are prearranged, so there is no requirement that sex workers be publicly visible for customers to identify them (Weitzer 2009). IMBs represent the largest component of the indoor sex trade in U.S. cities (e.g., Sivasankaran 2014; White 2014; Rood 2016; Birr 2017). The industry is further subdivided as a result of technological advances and the limits of police authority in private spaces. The contemporary sex trade has four generalized sectors that are differentiated by the method of establishing a meeting place for the customer and sex workers; whether the meeting place is a fixed location; whether the meeting place is in a public space like the street or a private space like an IMB or hotel room; the transaction cost; and the race, ethnicity, or nationality of the customer base. The four generalized sectors are as follows.

1. *Private escorts.* Escorts coordinate meeting places with customers either through direct contact via phone, text message, e-mail, or other digital communication methods, or have meeting places set by their managers or pimps, who contact clients directly. Escorts’ meeting places are not spatially fixed, so they can arrange meetings at locations that are agreeable to the seller and buyer. There is no explicitly racial component to the locations where escorts provide illicit services. Private escorts are considered part of the indoor sex trade. Escorts also typically draw the highest cost per transaction.
2. *Cantina-model brothels.* Cantina-model brothels are another component of the indoor sex trade. Cantina-model brothels are bars or restaurants located in majority Latino neighborhoods where services beyond food and drink provision are available to customers. The per-transaction cost tends to be low compared to other sectors of the commercial sex industry. As brick-and-mortar establishments, cantina-model brothels have fixed locations. The availability of illicit services at each cantina is advertised through social networks based on race, ethnicity, or nationality. They engage in no digital advertising, but in some cases advertise services on business cards that include the address, phone number, or both of the establishment. These cards are then delivered directly to target customers (often majority male migrant communities). Research published by the Polaris Project suggests that proprietors of cantina-model brothels can be very cautious in their evaluation of potential clients (Couture and Kimball 2016). For example, proprietors of Mexican nationality might deny entry to men with accents that suggest they are from other

Spanish-speaking countries. As a result, accurate locational data regarding cantina-model brothels is very difficult to access.

3. *Illicit massage businesses.* IMBs make up the largest component of the indoor sex trade in the United States. These shops operate from fixed locations. The meeting place for buyers and sellers is advertised online through Web sites like backpage.com and the online review sites like www.rubmaps.com. The transaction cost varies between locations and depends on services provided. Online advertisements only include the “door price,” which is the cost to enter a private room with a masseuse, at which point the final services and cost negotiations take place. To date there is no quantifiable evidence that race affects locational decisions for IMBs, but colloquial references to “Asian massage parlors” suggest there might be. We examine this in detail later in the study.
4. *Street prostitution.* Street prostitution is the lone remaining outdoor component of the commercial sex trade. The areas where sellers congregate develop a reputation for that activity and buyers looking for commercial sex can access these public and quasi-public spaces to negotiate services, cost, and so on. The locations of street prostitution are fixed in the short term, but policing efforts can relocate activity in the long term. This is the only sector in which policing can immediately change meeting location as the sex workers move through public and quasi-public spaces such as sidewalks, parking lots, private alleys, and so on. Street prostitution tends to be concentrated in low-income or marginal urban spaces. The actual sex services are delivered in more private locations such as hotel rooms or private residences near the public market. The geographic distribution of red-light districts is tied to marginal urban spaces more than spaces where particular racial groups or nationalities reside.

Each of these four sectors operates with different locational strategies to overcome the two main inherent risks in illicit markets. Of all the sectors, IMBs operate most similarly to legal brick-and-mortar businesses. Moreover, thanks to legal protection from warrantless searches of private property it is very difficult for police agencies to build cases against IMBs for operating as brothels. This is a challenge for municipal policing, but allows IMBs to be studied much like legal retailers.

Locational analysis of gray- and black-market economic activity

To date, there are no empirically derived estimates of IMB locational strategies. The lack of empirical rigor in analysis of economic activity is a common shortcoming in research on informal (gray-market) and illicit (black-market) economies (Portes, Castells, and Benton 1989; Venkatesh 2006). IMBs are at their essence retail establishments providing a service to area clientele. Economic geographers have studied the relationship between retail location and economic performance for more than forty years (Epstein 1971; Wrigley and Lowe 1996). In the formal, or licit, economy, analysis is rather straightforward. For example, Wal-Mart stores in the United States have “consistently demonstrated a high degree of location intelligence,” first by identifying underserved rural areas and locating their stores to meet demand, and later urban areas with robust retail options by offering lower prices than competitors thanks to spatial innovations in supply chain and distribution networks (Rice, Ostrander, and Tiwari 2016, 641). Fast-food franchises use entirely different spatial strategies, targeting areas around middle and high schools. By locating near schools, fast-food franchises place themselves in the everyday paths of travel of likely customers (Austin *et al.* 2005; Thomadsen 2007).

The challenge of identifying locational factors that produce better or worse outcomes is considerably more difficult when examining gray- or black-market economies. That does not mean it is impossible, however; it typically just takes much more time collecting data in the field. For example, a recent analysis of informal day-labor hiring site locations in the San Diego metro area found that the sites, where mostly men wait to be hired for short-term construction and agricultural work, were located in neighborhoods with significantly higher levels of employment in those industries. Despite being informally established, the locations of day labor hiring sites are remarkably static, similar to brick-and-mortar retail establishments like Wal-Mart and McDonalds. This is not the case for informal street vendors, who make use of their own mobility to improve economic outcomes. Hays-Mitchell’s (1994) research in Peru found that vendors relocated several times during the day to place themselves in the paths of

travel of potential customers, targeting central business districts at certain hours, and specific high-traffic side streets during times of day that customers were moving between home and work. Whether the good being sold is legal or illegal, the basic spatial strategy is the same: “When businesses chose locations for their stores they should know where their potential customers are located and how far those customers are willing to travel to purchase the goods that the business provides” (Crotty 2015, 6). Retail outcomes are further influenced by consumers’ perceptions of brand, shopping experience, or other nonspatial factors. Increasingly, each consumer’s perception is shaped by online interactions, including review sites like Yelp.com (Racherla and Friske 2012; Zhu and Zhang 2010; Cummins *et al.* 2014). The analysis presented in this article follows the preceding examples of quality informal-sector analysis by drawing on user-generated data from online review sites to create an original, empirical data set from which the locational strategies of IMBs can be analyzed.

Study area and research methods

The Houston metro area is home to roughly 6.5 million people, making it the fifth largest metropolitan statistical area (MSA) in the United States. It is also one of the most ethnically diverse (Mejia 2017). The City of Houston is also noteworthy for its commitment to fighting human trafficking. The city reached a settlement in 2014 (Fernandez 2014) with the owners of several exotic and nude dance clubs that established a fund to support an antitrafficking task force within the Houston Police Department (HPD). Despite these efforts, human and sex trafficking remain a problem, as cantina-style brothels are common enough that the Polaris Project refers to this sector of the commercial sex industry as the “Houston model” (Couture and Kimball 2016). IMBs also operate openly and in such numbers that the vice squad “cannot keep up with them all” (Wang 2010). The large scope of the industry makes Houston an excellent case study site for analyzing the geography of IMBs.

To examine the geography of IMBs in Houston we first needed to identify IMB locations. As discussed previously, IMBs advertise their services in online review sites such as ICCE.com and Rubmaps.com. Drawing from user-generated data on Rubmaps.com on December 1, 2015, we identified 292 IMBs listed as “open” and an additional 144 listed as “closed.” These locations were geocoded and a number of attributes were recorded for each IMB: address, number of reviews for the IMB, average cost per service,² the types of payment accepted (cash only, credit accepted), and the ethnicities of sex workers at the IMB (white, Latina, ebony, Asian, Chinese, Korean, Thai, Japanese).

Rubmaps.com makes no effort to verify the validity of the data on the site; in fact, the legal disclaimer users must agree to before entering the site makes this point explicitly (see Figure 1). Despite this disclaimer, Rubmaps.com is a Web site specifically dedicated to facilitating the commercial sex trade. Previous research examining illicit massage parlors has documented their use by pimps and

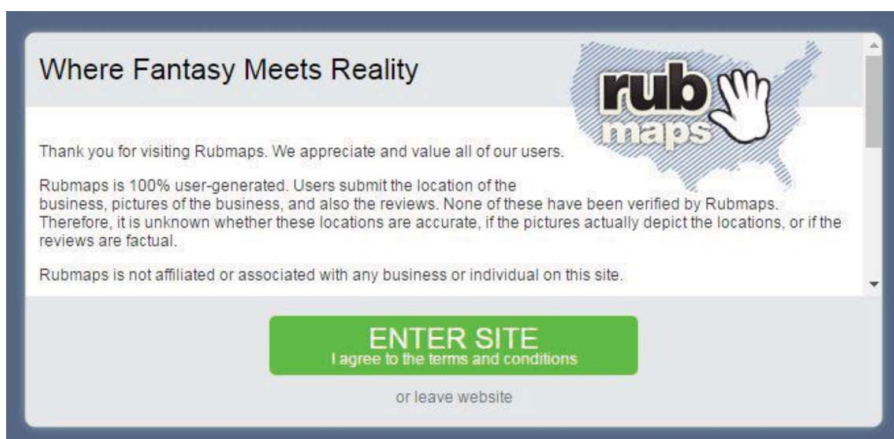


Figure 1. Rubmaps.com legal disclaimer.

massage parlor owners and managers as an important method of advertising illicit services available to potential customers (Janson 2013). As such it is reasonable to expect that many of these unverified sites are indeed offering commercial sex services. The challenge of verifying user-supplied geospatial data is not limited to the illicit sphere (Goodchild 2007; Flanagan and Metzger 2008; Haklay 2010), but is an important question facing researchers drawing on user-generated data examining a wide range of issues, from land use patterns (Wang, Ye, and Tsou 2016) to public health crises (Kim *et al.* 2017) to natural hazard response (Wang, Ye, and Tsou 2016; Burns 2018). In an effort to validate the locational data, and to produce estimates of consumer traffic at the IMBs,³ we selected forty-five IMBs for video surveillance. The sample sites were selected to be geographically representative: more survey sites in areas of apparent clustering than areas with few sites, but at least one site in each identified cluster area. The sample sites were also selected to include locations across the range of total reviews posted to Rubmaps.com. The sample included the site with the highest number of reviews (102), as well as six locations with zero reviews posted. The average number of reviews across the sampled sites was 18.91.

Video surveillance of customers is a common research methodology within the retail sciences and our surveillance was designed to ensure that no identifiable information about customers was recorded (Whyte 1988; Underhill 1999).⁴ Cameras were placed in public spaces and oriented to record the front entrance of each target IMB for twenty-four to forty-eight hours. The video was then analyzed to count the number of patrons, their gender, and mode of transport (personal vehicle, bus, bicycle, pedestrian). Sites were only considered valid if more than 90 percent of customers were male and the visit time was over thirty minutes. Through the validation process four massage businesses were removed from the database because the majority of their customers were female. Two IMBs were located such that they were not visible from the street and therefore could not be verified.⁵ Another seven establishments appeared to be closed indefinitely. In all we were able to verify thirty-two of the forty-five sites. Extrapolated to the entire “open” IMB data set, this suggests that at least 70 percent of the IMB locations are correctly identified as illicit businesses. We believe the number is likely closer to 90 percent as only four of the forty-five sample sites were empirically determined to be legitimate massage businesses. IMBs open and close with great frequency, so the locations that closed between our data collection and verification likely reopened in other nearby spaces. There is also little reason to believe the sites in unobservable locations were not IMBs. Finally, there is no clear spatial pattern for the sites that were closed or proved to be legitimate (see Figure 2). As such, we removed the four sites with primarily female clientele and used the remaining 288 sites identified as open without adjustment in each stage of quantitative analysis. The following sections use these locational data in combination with census-tract-level data from the 2010 to 2014 American Community Survey (ACS) and 2016 employment site data from ESRI’s Business Analyst database to answer the following research questions.

1. What is the spatial distribution of IMBs in the Houston metro area?
2. Do we see evidence of business clustering or agglomeration of IMBs within the region?
3. What are the characteristics of IMB neighborhoods compared with the rest of the metro area?
4. Are there particular spatial, demographic, or locational characteristics that are associated with IMB clustering at the neighborhood scale?

Findings

A cursory examination of the 288 open and 136 closed IMBs in our data set reveals some interesting patterns (see Figures 2 and 3). There is a clear concentration in an east–west corridor from near downtown Houston toward the southwest. There is also a corridor of IMBs in the northwest side of Houston following the Highway 6–FM 1960 major roads. Several other small clusters exist: on the east side of the city just off of Interstate 10, along Interstate 45 between the 610 Loop and Beltway 8, and on the southeast margins of the MSA near Clear Lake and League City. There does not appear to be a clear pattern for where IMBs have closed. The closed locations are found in the same generalized locations as operating establishments. This is consistent with reports about IMB operation in the city: In some cases businesses close and reopen in the same location under a different name (Wang 2010).

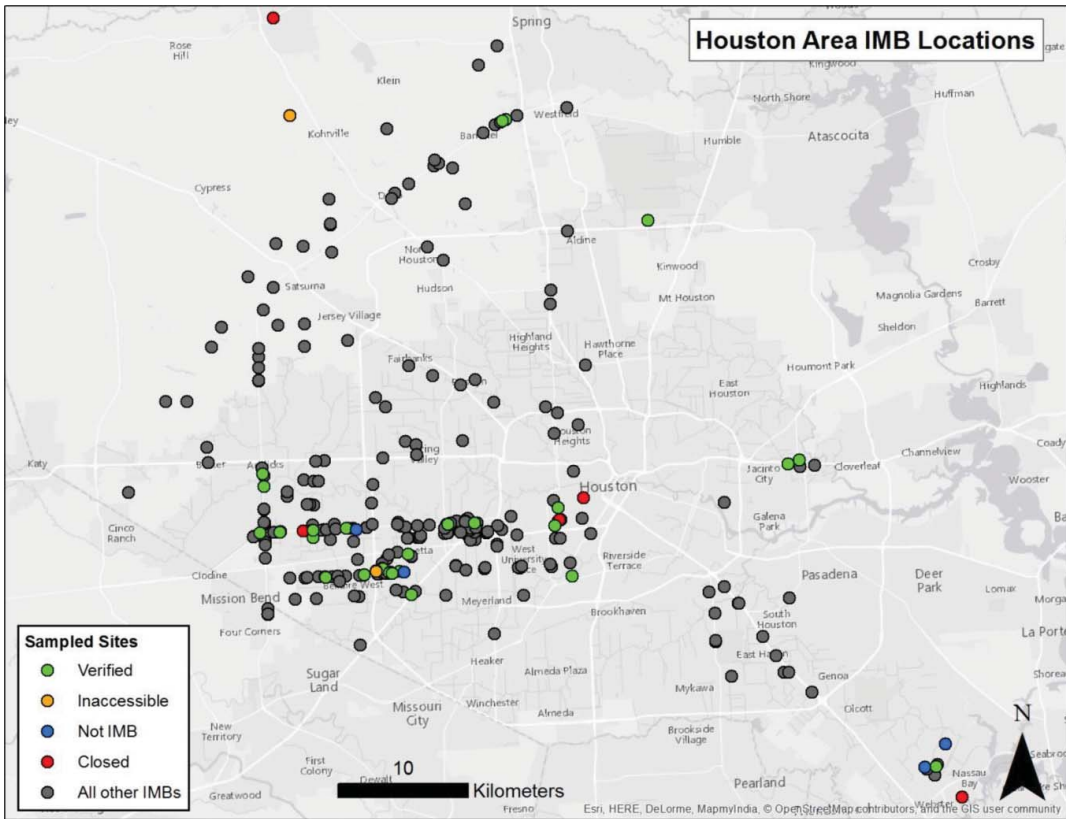


Figure 2. Field verification status for illegal massage business (IMB) sites in the study.

IMB neighborhood analysis

Improved policy regarding IMBs requires a thorough understanding of the locational decision-making process for IMB proprietors at multiple scales. For example, at the regional scale, why are IMBs located in particular neighborhoods and not others? The near complete overlap of open and closed IMBs in Houston suggests that IMB proprietors target specific areas, regardless of police enforcement strategies. Continued success for any business requires consistent ability to generate revenue. In this regard, IMBs are no different than legal businesses. If revenue generation is low an IMB proprietor will be forced to relocate or close operations. Therefore, one would expect IMBs to be located in areas where they are accessible to the greatest number of potential customers. Previous research on the commercial sex trade has argued that proprietors target areas with high levels of male employment, as men are the primary customers (Monto and McRee 2005; Brewer *et al.* 2007; Duschslag and Goswami 2008; Farley, Bindel, and Golding 2009). Qualitative findings from the Polaris Project showed that cantina-model brothels target areas based on ethnicity or nationality (Couture and Kimball 2016). IMBs might also target neighborhoods with residents of a particular race, ethnicity, or nationality. If IMBs are concerned about negative attention from community members or the police, they might opt for different locational strategies. Families with children might be more likely to view IMBs as a neighborhood threat and work to shut them down. If this is the case, IMBs might target areas where nonfamily households are dominant. Similarly, if IMB proprietors are concerned about police enforcement, they might target lower income areas or neighborhoods with socially marginalized residents. It is also possible that the locations of IMBs are driven more by proximity to areas where their customers work, rather than where their customers live. If this is the case, IMBs should be located

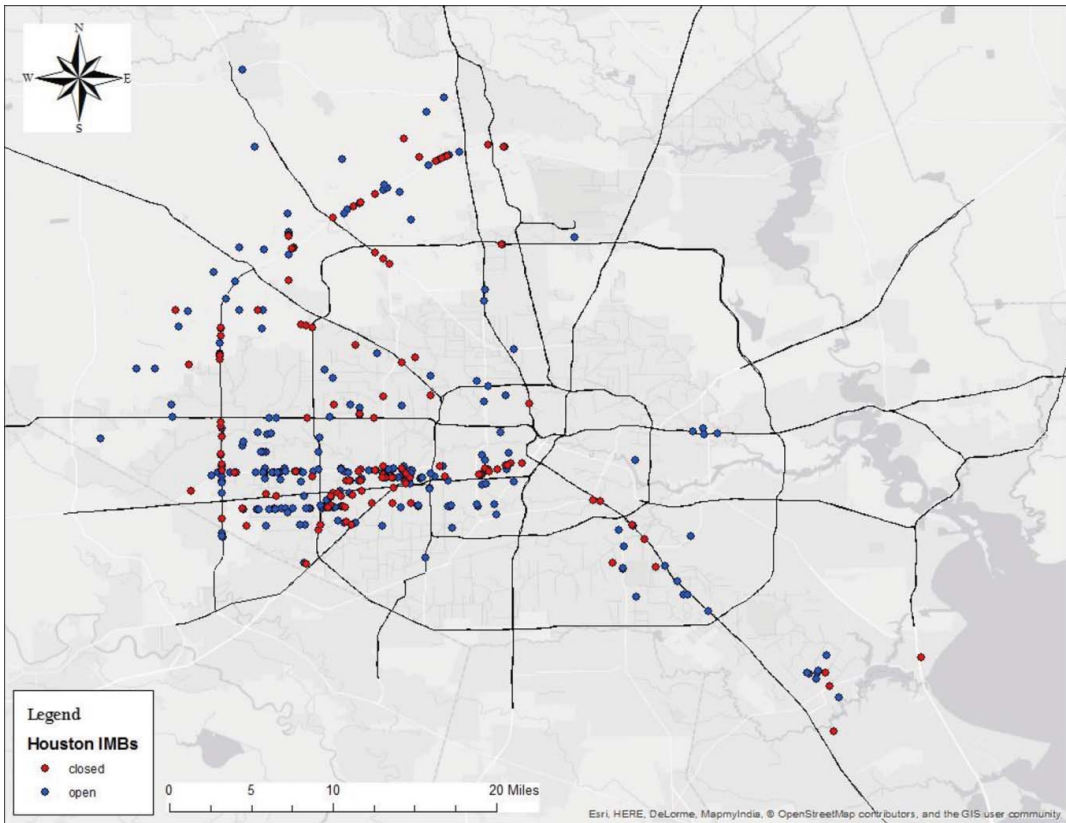


Figure 3. Illicit massage businesses (IMBs) in the Houston Metropolitan Statistical Area by operating status.

in areas where employment density is high. Because most IMB customers are male, IMBs might be found in areas where industries that primarily employ men (e.g., construction, mining and extractive industries) are concentrated.

To better understand the locational strategies of IMBs we conducted an analysis at the regional scale. A two-sample *t* test was used to compare the demographic characteristics of IMB neighborhoods with the rest of the Houston MSA. For this study, IMB neighborhoods are defined as the census tracts with any portion falling within one kilometer of any of the 288 open IMBs across the region. IMB neighborhoods are defined this way for two reasons. First, the census tracts are small enough to provide geographic specificity but large enough to incorporate residents and activity occurring around, but not directly adjacent to, IMBs in the analysis. For example, the definition includes potential customers who do not live directly adjacent to an IMB. This definition also includes the populations with the most exposure to IMBs and the greatest likelihood of alerting police to illicit activity. Second, using census tract-level data allows for easy replication of this approach to study other MSAs across the United States. [Figure 4](#) shows the IMB neighborhoods included in this analysis.

This regional analysis is based on data profiles that include eighty-four total variables, eighty-two of which were drawn from the 2014 ACS (DP02, DP03, DP04, and DP05) and 2016 employment-site data from ESRI's Business Analyst database (see [Table 1](#)). Two additional variables, population density and employment density, were calculated in ArcGIS 10.3 (ESRI 2014). Sociodemographic data such as population density, percent white, percent black, percent Asian, percent Chinese, and so on, are used to test whether IMBs target neighborhoods based on race, ethnicity, or nationality. Data on households were used to determine if neighborhood household characteristics influence IMB locations. Employment, educational attainment, and income data were similarly used to determine if IMBs target

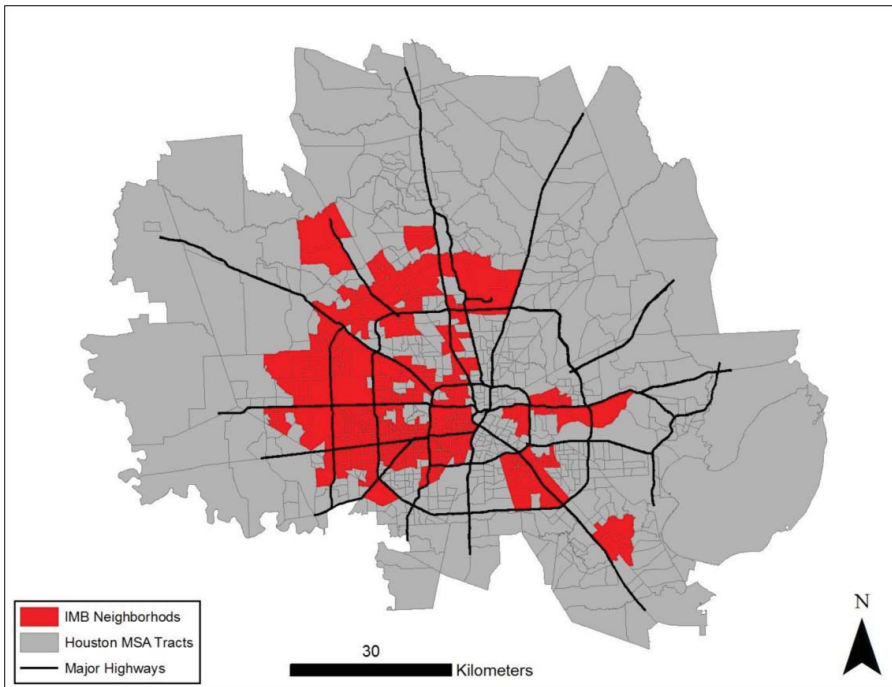


Figure 4. Illegal massage business (IMB) neighborhoods in the Houston Metropolitan Statistical Area (MSA).

neighborhoods where potential customers are located. We included a great many variables because so little is known about the locational strategies of IMBs. This analysis provides insight regarding attributes that potentially attract IMBs to an area, attributes that IMBs avoid in their site selection, and attributes that do not figure into the locational strategy.

***T* test results**

The findings from the difference of means test highlight the importance of race and nationality, housing characteristics, and the number of family households for IMB locations. IMB neighborhoods are home to a larger percentage of Asian residents, including those of Chinese, Japanese, and Vietnamese ancestry. Measures for percent white, percent Hispanic, and percent Mexican proved to be inconclusive, but percent black proved to be negatively correlated with IMB presence, suggesting that IMBs avoid majority black neighborhoods. IMBs also avoid locating in neighborhoods with large numbers of family households and households with children. IMBs are strongly correlated with neighborhoods where the percentage of the population with a bachelor's or graduate-level degree is higher than regional averages. Interestingly, the results regarding income and wealth are somewhat inconclusive: Median household income was not statistically significant, but per-capita income is strongly positive. Despite higher levels of per-capita income, median disposable income is strongly negative. In fact, it is the strongest *t* value in the entire data set at -14.1 . Measures of net worth are also both negative. Finally, home ownership rates are lower in IMB neighborhoods compared to the region as a whole.

Taken together the *t*-test results paint a fairly clear picture: IMB neighborhoods are home to relatively well-educated populations, many of whom are renters and live in nonfamily households. These residents have higher than average incomes, but have lower net worth than the residents of non-IMB neighborhoods. The population of IMB neighborhoods includes a higher percentage of Asian residents (and several nationalities that typically fall within the Asian racial category) and a lower percentage of black residents than regional averages, but it is important not to overstate the role of race in IMB locational decisions, as there is



Table 1. *t* test results comparing illegal massage business neighborhoods with regional averages.

Variable	<i>t</i> value	<i>p</i> value	Mean X	Mean Y	Significance	Direction
Total population	-2.0639	0.03922	5588.17	3808.52	0.95	Negative
Population over 25 years	-1.6266	0.1041	3586.5	3808.52	N/A	—
Population density	0.21305	0.8313	29876	25989.7	N/A	—
Total households	-0.4847	0.6280	2029.58	2064.08	N/A	—
Family households	-2.4959	0.01269	1303.86	1449.78	0.975	Negative
Family households with children	-2.3307	0.01992	655.624	740.367	0.975	Negative
Family households married	-2.7063	0.006892	898.447	1033.68	0.99	Negative
Nonfamily households	4.1066	4.27E-05	725.721	614.295	0.999	Positive
Average household size	-4.1168	3.28E-05	2.7405	2.89344	0.999	Negative
Average family size	-3.2468	0.001197	3.36666	3.47172	0.995	Negative
Percent without high school diploma	-0.3862	0.19961	0.19961	0.20827	N/A	—
Percent high school graduates	0.9669	0.3338	0.80039	0.79065	N/A	—
Percent bachelor's degree or higher	4.1857	3.03E-05	0.35183	0.29324	0.999	Positive
Labor force	-0.8393	0.4014	3013.56	3110.81	N/A	—
Employed population	-0.6559	0.512	2815.59	2815.59	N/A	—
Unemployed population	-2.5601	0.01058	196.858	220.509	0.975	Negative
Employment density	6.7461	2.28E-11	3273.99	2327.95	0.999	Positive
Occupations: Residence aggregation						
Management, business, science, and arts	-0.3256	0.7448	1044.35	1065.37	N/A	—
Service sector employees	0.71047	0.4775	495.276	480.945	N/A	—
Sales employees	-1.2171	0.2238	643.592	643.592	N/A	—
Natural resource, construction, and maintenance	-0.6085	0.543	301.745	311.078	N/A	—
Production, transportation, and material moving	-1.3525	0.1765	330.626	352.415	N/A	—
Agriculture, forestry, fishing, hunting, and mining	-0.1146	0.9088	103.516	104.531	N/A	—
Industries: Residence aggregation						
Construction industry	-0.8627	0.3885	244.905	255.258	N/A	—
Manufacturing industry	-1.8101	0.07051	273.058	299.655	0.9	Negative
Wholesale trade industry	-0.1978	0.8432	107.795	109.222	N/A	—
Retail trade industry	-0.2256	0.8215	307.929	311.103	N/A	—
Transportation, warehousing, and utilities	-2.6468	0.008224	152.355	176.682	0.99	Negative
Information industry	0.09094	0.9276	38.8605	38.6054	N/A	—
Finance, insurance, real estate, rental, and leasing	0.43835	0.6612	174.126	170.125	N/A	—
Professional, scientific, administrative, and waste management services	2.5532	0.01079	415.268	371.959	0.975	Positive
Educational services, health care, and social assistance	-1.9796	0.04796	513.768	570.129	0.95	Negative
Arts, entertainment, recreation, accommodation, and food services	1.4131	0.1579	254.079	238.675	N/A	—
Other services, except public administration	1.0678	0.2858	169.621	161.541	N/A	—
Public administration	-3.718	0.0002093	60.3079	80.5232	0.99	Negative
Class of worker: Residence aggregation						
Private wage and salary workers	-0.1501	0.8807	2377.35	2391.07	N/A	—
Government workers	-4.0795	4.79E-05	243.4	311.427	0.99	Negative
Self-employed in own not incorporated business workers	1.1356	0.2563	190.184	181.365	N/A	—

considerable diversity in IMB neighborhoods. The percentage of Asian residents is 0 in 56 of the 380 IMB neighborhood tracts, whereas more than 50 percent of residents are Black in 13 of the tracts. Further analysis is required to better understand the locational strategies employed by Houston-area IMBs.

Measuring clustering of IMBs

The preceding regional analysis is clearly influenced by the patterns of clustering that make large swaths of west Houston part of IMB neighborhoods, whereas most of east Houston tracts are outside of IMB neighborhoods. To better understand the geography of IMBs in Houston, we used a G_i^* cluster analysis to test for statistically significant clustering based on the number of IMBs located within each census tract (see Figure 5). The G_i^* identifies spatial clusters of high or low values for a variable of interest by measuring the value of that variable for all of the features within a defined neighborhood and comparing that neighborhood-level value to the values of the entire study area (Mitchell 2005). In our analysis the distance bandwidth used to define the neighboring census tracts was set to three miles. This bandwidth was chosen as a rough measure of relative accessibility of each IMB. The majority of IMBs are located on major roads in the region, which have an average travel speed of ~ 30 mph (48.4 kmph) after accounting for traffic, stop lights, and so on. As such, three miles is the distance an average auto-based customer could travel in ten minutes.⁶ The results show statistically significant clustering extending from downtown Houston in the east to the western margins of the MSA. The clustering analysis also shows statistically significant areas of IMB absence just east of downtown Houston. Nonetheless, the G_i^* analysis shows the largest clustering pattern clearly: IMBs are found in greater numbers in west Houston, between Interstate 10 and Interstate 59. In the following section, we build on the G_i^* analysis to examine the relative importance of particular tract-level characteristics for IMB clustering across space.

Exploratory and ordinary least squares regression results

The regional analysis suggests that there are a number of variables that are correlated with IMB location in the Houston area. To better understand the correlation between neighborhood characteristics

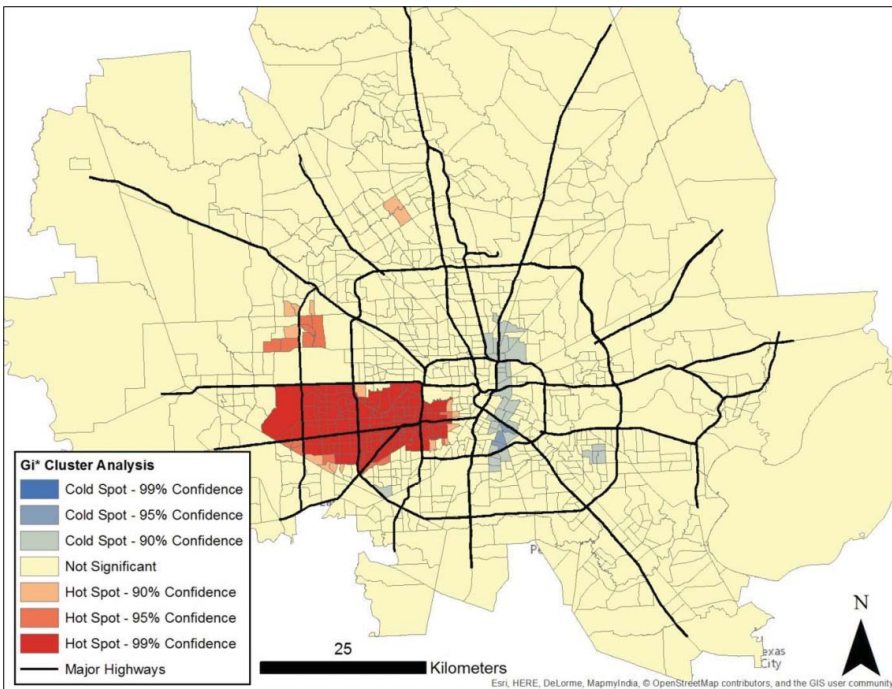


Figure 5. G_i^* cluster analysis results for Houston-area illegal massage businesses.

and IMB locational strategies we conducted exploratory and ordinary least squares (OLS) regression analysis as well as geographically weighted regression (GWR). We began our regression analysis by performing an exploratory regression analysis tool in ArcGIS 10.3 to reduce the number of potential variables to explain IMB clustering. The z scores calculated from the G_i^* analysis served as the dependent variable in our initial exploratory regression. The z score output from the G_i^* analysis is a quantitative measure of IMB clustering at the tract level. We included each of the thirty-six variables that proved to be significant in the regional t test analysis as potential explanatory variables in the initial exploratory regression. The exploratory regression results identified average household size; foreign-born population; manufacturing industry employees; employees in educational services, health care, and social service industries; percent Asian population; median disposable income; and employment density as variables with significant global relationships with IMB clustering t scores. We then ran OLS regression with tract-level clustering t scores as the dependent variable and these seven explanatory variables. The results are displayed in Table 2. All of the variables are highly significant with p values under 0.001.

Percent Asian has the largest coefficient value within the model at 5.21 ($p < 0.0001$). Average household size has a strong negative relationship with IMB clustering (coefficient value -1.40 , $p < 0.0001$). The remaining five variables are also statistically significant, but have substantially lower coefficients. None of the remaining five variables has a coefficient over ± 0.01 . The adjusted R^2 for the OLS model is 0.40, suggesting that these variables collectively explain about 40 percent of variation in IMB clustering. The model showed no problematic bias due to multicollinearity as variance inflation factor values for all variables were under 3.1. The corrected Akaike's information criterion (AICc) for the model was 3951.17. After running the OLS regression we tested for spatial clustering in the residual errors using the Moran's I test. These models demonstrated a high degree of spatial autocorrelation, meaning the residual errors from the global model were highly clustered (Moran's $I = 0.550311$, $Z(I) = 109.25$). As such, we employed GWR, a local regression model that is well suited for examining relationships with a high degree of spatial non-stationarity.

Geographically weighted regression results

GWR addresses issues of spatial variability by generating a separate regression equation for each observation. This allows GWR to be used to explore local variations in the relationships between variables (Chalkias *et al.* 2013; Bereitschaft and Cammack 2015).⁷ Like the G_i^* analysis, GWR results are highly dependent on the way that spatial relationships are defined in the regression equation. We set a three-mile band as the fixed distance for GWR neighborhoods so that the G_i^* and GWR analyses used consistent neighborhood definitions.

The results of our GWR analysis (see Table 3) are considerably better than was observed through the global OLS regression. The adjusted R^2 improved from .40 to .86, suggesting that allowing for local

Table 2. Results from the ordinary least squares regression model.

Variable	Coefficient	SE	T statistic	Probability	VIF
Intercept	2.157455	0.494366	4.364082	0.000018	N/A
Average household size	-1.40104	0.153533	-9.12535	0	1.531716
Foreign-born population	0.000851	0.000096	8.901575	0	3.03389
Manufacturing industry employees	-0.00175	0.00043	-4.0755	0.000057	2.585993
Educational services, health care, and social assistance	-0.00113	0.000207	-5.47832	0	2.397638
Percent Asian population	5.124194	1.094214	4.862992	0.000005	1.610406
Median disposable income	0.000021	0.000003	6.414679	0	1.481687
Employment density	0.000377	0.000037	10.32231	0	1.321127
Overall model performance					
Multiple R^2	0.411976				
Adjusted R^2	0.407463				
Corrected Akaike's information criterion	3951.169761				

Note: VIF = variance inflation factor.

variation more than doubled the explanatory power of the model. The corrected AICc fell from 3,951 to 1,051. A drop of three or more points in AICc is considered sufficient improvement to justify using the second model, so a drop of 2,900 points is certainly evidence for the value of GWR for understanding IMB spatial clustering (Fotheringham, Brunson, and Charlton 2002). The Moran's *I* test still shows statistically significant clustering of the residual errors in the GWR model. This likely means that there our model is missing one or more important variables. We return to this issue later.

A series of choropleth maps were created to examine the spatial variation in model effectiveness and residual error, as well as the variation in variable coefficients across the study area. In GWR the coefficients vary from location to location, so each is not necessarily positively or negatively associated with the clustering *z* score. Clear patterns emerge, however, that reinforce the directionality of each variable established in the OLS regression. For example, Figure 6 highlights the tract-level coefficients for the percent Asian variable, which showed a strong positive relationship with clustering *z* scores in the OLS model. In the GWR model the local coefficients for percent Asian are strongly positive in many of the areas of substantial clustering. Yet, in the strong area of clustering closest to downtown Houston, the coefficients are smaller or even negative, suggesting that other variables are responsible for clustering in those parts of the city. Figure 7 shows the coefficients for median disposable income are strongest in the part of the main IMB clustering area where percent Asian was weakest. The coefficients for employment density are the most clearly positive in areas of IMB clustering (see Figure 8). Employment density coefficients are positive throughout the entire main area of IMB clustering west of downtown Houston. The coefficients are also strongly positive along the Highway 6–FM 1960 corridor that runs from west to north Houston. There is also a zone of strong positive coefficients for employment density in the southeast part of the region, near the municipalities of Clear Lake and League City. Although it did not register as statistically significant clustering in the G_i^* analysis, there are several IMBs in that area, which local employment density might help explain. The final variable that was positively associated with IMB clustering in the OLS model was foreign-born population. In the GWR model, foreign-born population is negatively correlated with IMB clustering throughout most of the metro area (see Figure 9). The areas where it has a positive coefficient are mostly zones of IMB clustering, although there is also a small zone of negative coefficients in the main IMB clustering zone.

Average household size, education and health care service industry employees, and manufacturing industry employees were the three factors with negative relationships to IMB clustering in the OLS model. In the GWR model, they all showed strong negative coefficients in the primary area of IMB clustering. Of the three variables with a negative relationship to IMB clustering, average household size has the clearest association. The coefficient for average household size is most negative in the three areas with noticeable clusters of IMBs in the city: the northern cluster near Interstate 45 and FM 1960, the southeastern cluster near Clear Lake and League City, and the main cluster that extends west from downtown Houston.

The coefficient maps for the two industry employee residences are more complicated than is the case for average household size (Figures 10, 11, and 12). The coefficients for education and health

Table 3. Results from the geographically weighted regression model.

Variable	Minimum	25th quartile	50% quartile	75% quartile	Maximum	<i>SD</i>
Intercept	−3.476371	−1.2244272	−0.194968	2.675661	18.44492	4.334086
Average household size	−4.304556	−1.295104	−0.32566	0.005977	1.467277	1.048804
Foreign-born population	−0.000556	0.000085	0.000266	0.000774	0.002901	0.000669
Manufacturing industry employees	−0.011449	−0.001628	−0.000379	0.00018	0.004188	0.002392
Education, health services employees	−0.007771	−0.00096	−0.000239	0.000205	0.004761	0.001848
Percent Asian population	−13.72412	−0.671675	1.55676	3.5303	27.5654	3.571326
Median disposable income	−0.000081	−0.000001	0.000008	0.000022	0.00005	0.000017
Employment density	−0.00096	−0.000059	0.000056	0.000172	0.001069	0.00017
Overall model performance						
Multiple R^2	0.9002					
Adjusted R^2	0.8661					
Corrected Akaike's information criterion	1051.069					

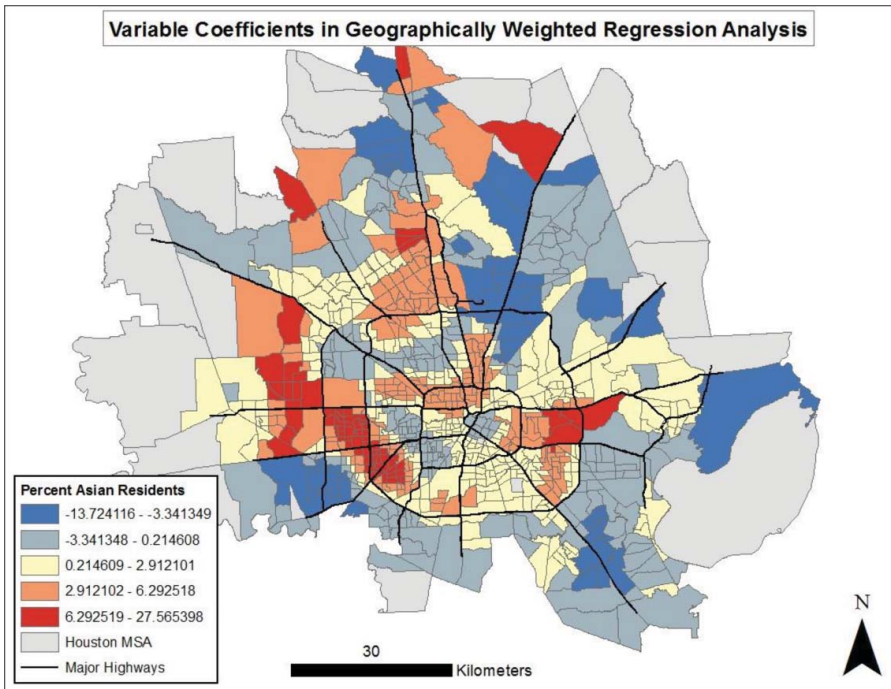


Figure 6. Geographically weighted regression tract-level coefficients for percentage Asian. Note: MSA = metropolitan statistical area.

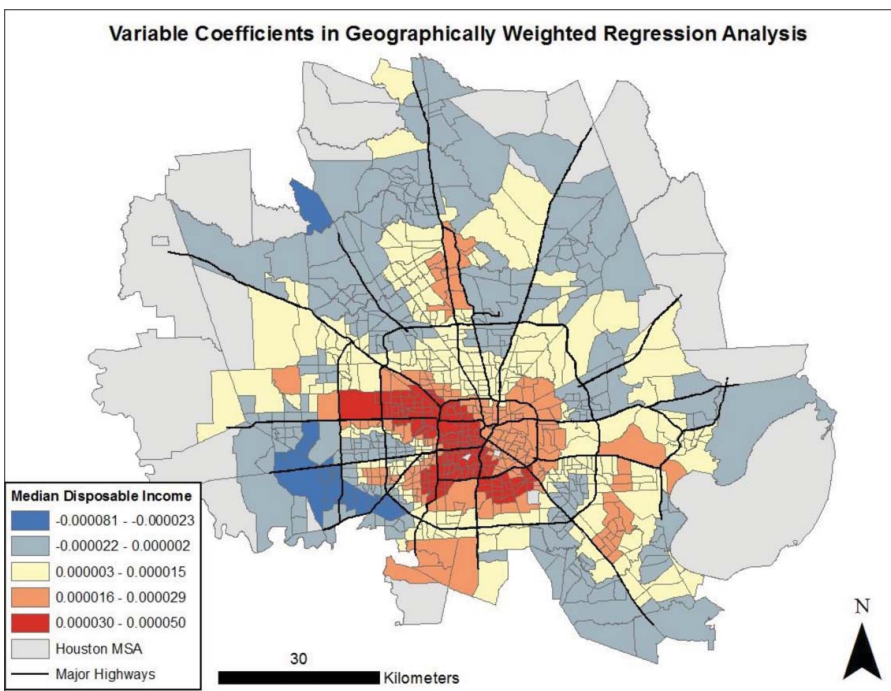


Figure 7. Geographically weighted regression tract-level coefficients for median disposable income. Note: MSA = metropolitan statistical area.

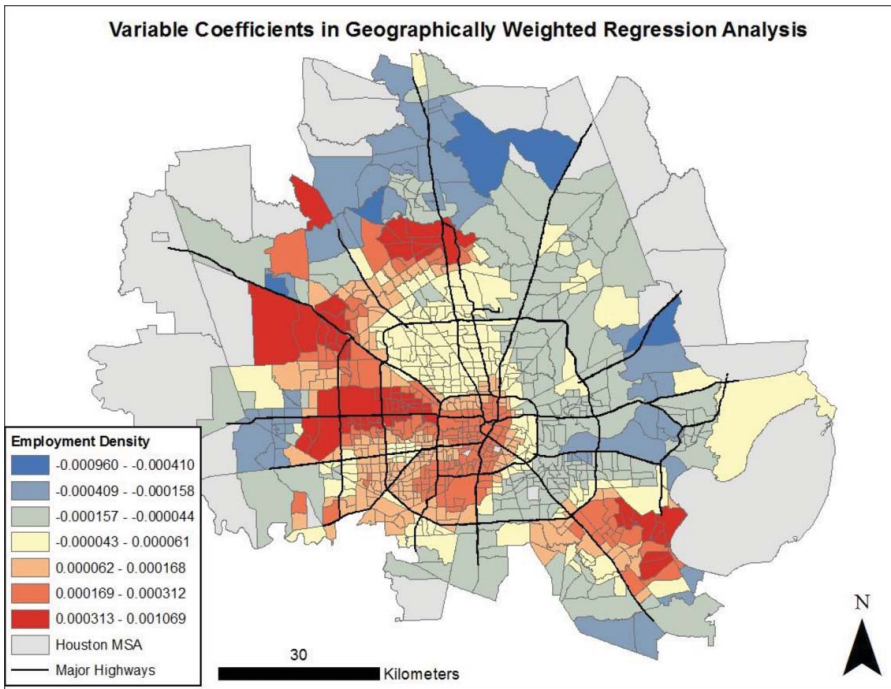


Figure 8. Geographically weighted regression tract-level coefficients for employment density. *Note:* MSA = metropolitan statistical area.

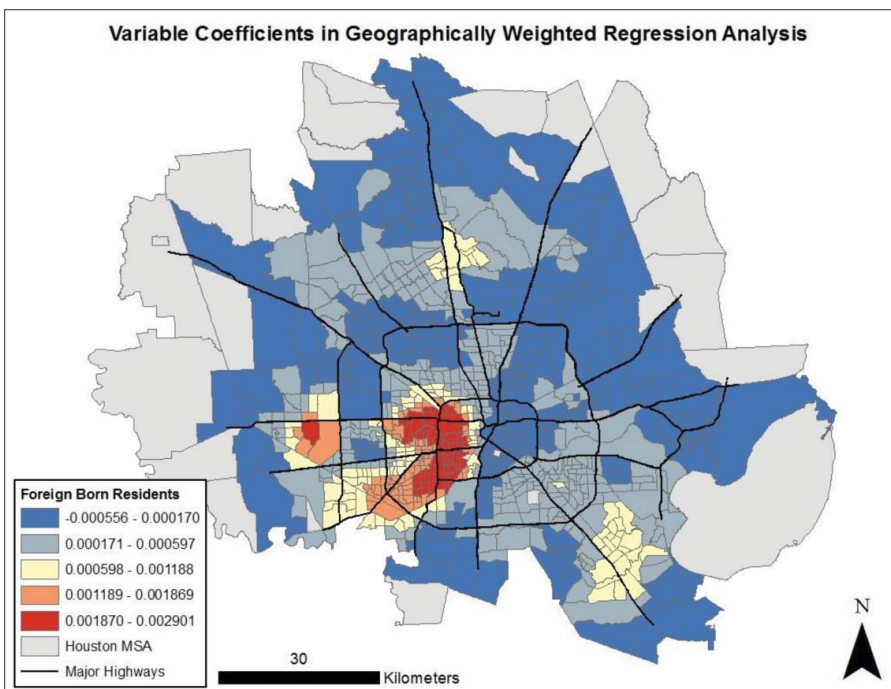


Figure 9. Geographically weighted regression tract-level coefficients for foreign-born residents. *Note:* MSA = metropolitan statistical area.

services employees are negative almost everywhere in the region, including most of the areas of IMB clustering. There is an exception, however, in the northern center of the primary IMB cluster where the education and health services employees' coefficients are positive. The coefficients for manufacturing employees are similarly variable across space and within the primary IMB cluster. The coefficients for manufacturing employee residences are negative throughout most of the city and the primary IMB cluster. The one quite noticeable exception is near the intersection of Interstate 59 and the Westpark tollway, in the center of the primary IMB cluster. The inconsistency in coefficients for both of the industry employee residence variables within the primary IMB cluster raises questions about the variables' explanatory power in the model and the general relationship between the residential patterns of people who work in these industries and the locational strategies of IMBs. These issues are expanded on in the following discussion of the GWR model's overall performance.

The local R^2 results (see Figure 13) show the variability in explanatory power of the GWR model. The model performs better in areas where there is little to no IMB clustering. The outer fringes of the metropolitan area, the north-south corridor of statistically significant IMB absence just to the east of downtown Houston, and the east-west corridor of IMB absence just north of Interstate 10 are all areas with relatively high local R^2 values. The model performance is lowest, ranging from R^2 values of 0.077 to 0.530, in the areas where IMBs are actually clustered. The GWR model, as specified, is very effective in explaining why clustering is not happening in particular areas, but is much less effective in explaining why clustering is happening. From this we must conclude that the variables that are negatively correlated with IMB clustering—average household size, manufacturing employment, median disposable income, and education and health services employment—are properly identified as deglomerative forces for IMB clustering. The variables that are positively correlated with IMB clustering—percent Asian, foreign-born population, and employment density—do not sufficiently explain IMB clustering on their own. Future analysis will need to identify additional variables to improve our collective understanding of the locational strategies of IMBs. In the following discussion we propose a number of

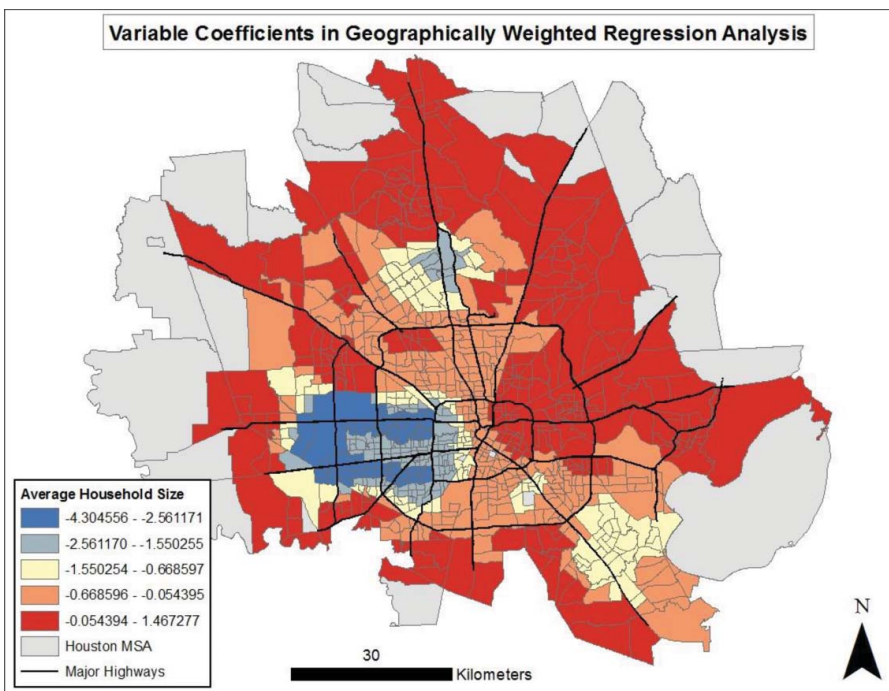


Figure 10. Geographically weighted regression tract-level coefficients for average household size. *Note:* MSA = metropolitan statistical area.

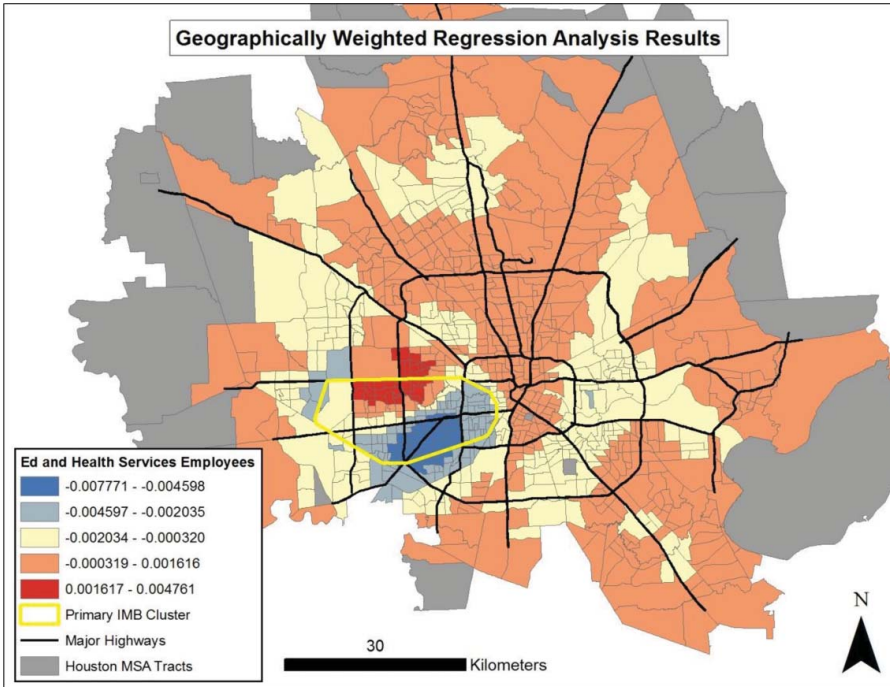


Figure 11. Geographically weighted regression tract-level coefficients for education and health services employees. *Note:* IMB = illegal massage business; MSA = metropolitan statistical area.

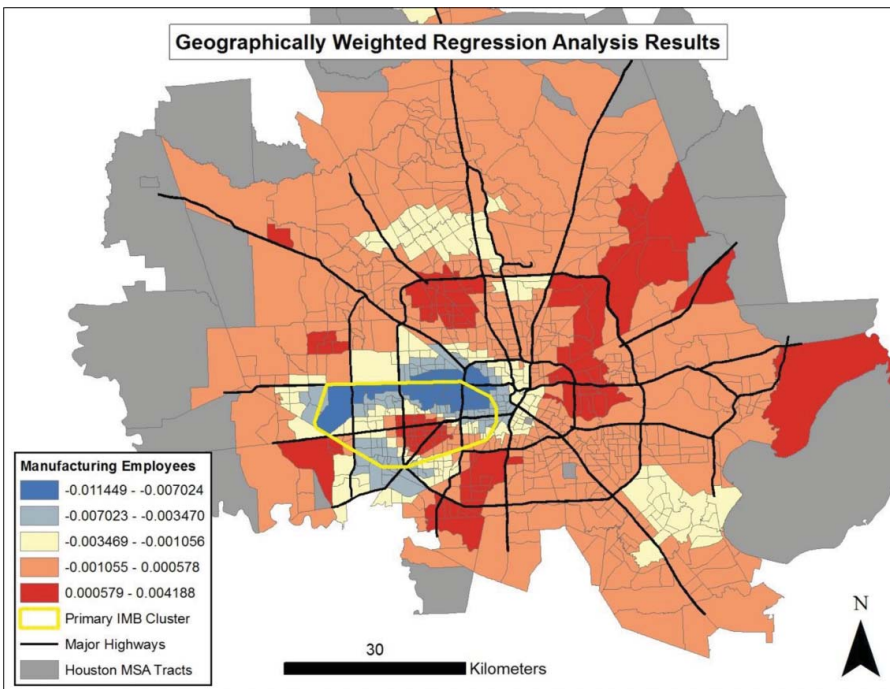


Figure 12. Geographically weighted regression tract-level coefficients for manufacturing employees. *Note:* IMB = illegal massage business; MSA = metropolitan statistical area.

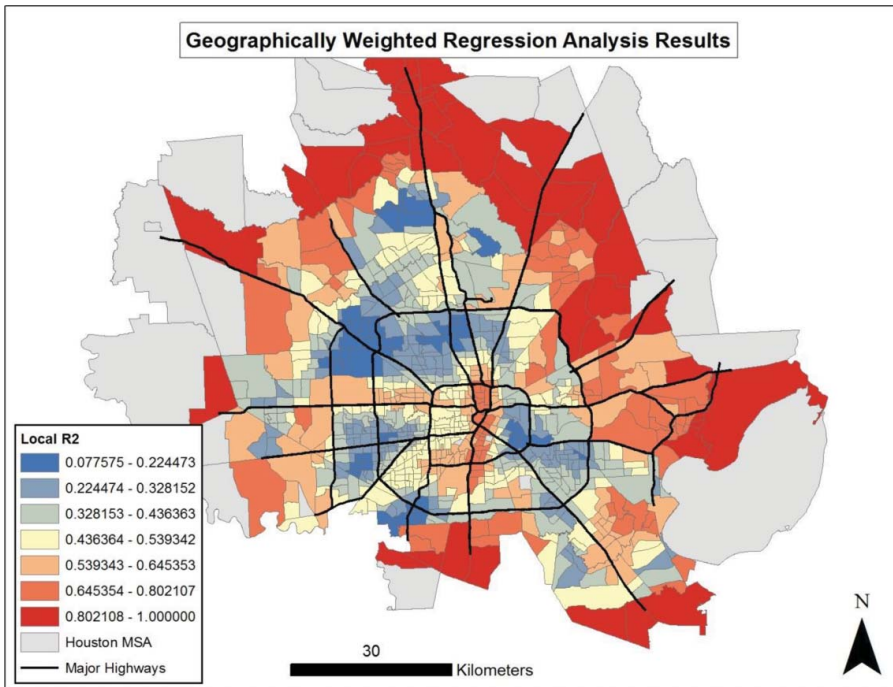


Figure 13. Tract-level R^2 results from the geographically weighted regression model. *Note:* MSA = metropolitan statistical area.



Figure 14. Examples of illegal massage businesses (IMBs) in the greater Houston area. Top left: Example of an IMB massage parlor. Opaque window covers are quite common for IMBs. Top right: Much of the retail space in the complex where the IMB shown in the top left picture is located is vacant. Bottom right: The IMB in this photo is found in a strip mall in a majority Chinese ethnoburb in west Houston. Bottom left: IMBs are hardly invisible within the Houston retail landscape, occasionally operating directly adjacent to high-traffic shops such as Starbucks.

additional variables that could be included and might improve the performance of both the OLS and GWR models in future research.

Concluding discussion and limitations

Our analysis of IMBs begins the process of analyzing black-market retail geography. The variables that were found to be significant in the neighborhood versus metro area t tests provide some insight about the particular characteristics that make IMB neighborhoods unique compared to the region as a whole. IMB neighborhoods are home to a larger percentage of Asian residents and a lower percentage of black residents than the regional averages. The residents of IMB neighborhoods are more likely to be college graduates, but less likely to work in manufacturing, education, or health services industries. IMB neighborhoods are also home to more nonfamily households than regional averages, but that result might be connected to land use more than consumer behavior.

Our largest concern regarding the findings from this case study is the validity of the variables that proved significant in the OLS and GWR analyses. We believe that several of the variables are reflections of land use rather than the specific demographic or employment characteristics they represent. As one examines the visual landscape of IMB neighborhoods in the greater Houston area, strip-mall-style commercial retail establishments appear to be the preferred location for IMBs across the metropolitan area (see [Figure 14](#)). Manufacturing firms do not tend to operate out of strip malls, so it stands to reason that there would be a negative spatial correlation with manufacturing employment. Similarly, schools and hospitals, which represent the largest employers in the education and health services fields, are not often located along commercial corridors. A negative relationship between employment in those fields and IMB clustering therefore makes sense. Law offices, however, are often located along commercial corridors, which might explain the results from the t tests that showed significantly higher employment in the legal profession in IMB neighborhoods than the region as a whole. Finally, household size is closely connected to housing type, with larger families typically living in single-family residences, rather than apartment complexes or other types of multifamily housing. Apartment complexes and multifamily housing are found closer to commercial areas in Houston than are single-family residences. As such, the correlation between household size and IMB clustering is likely the result of overlap between commercial and multifamily housing land uses.

All of this suggests that land use is an important component of IMB locational strategies, which is not in and of itself a surprising result. It is not possible to prove, however, because the city of Houston has no formal zoning laws. It is unique in this regard, as it is the largest North American city without such laws. This presents a particular set of challenges for quantitative spatial analysis in general and some specific limitations for this study. In the absence of zoning data it is not possible to calculate variables based on the total or percentage of commercial space per census tract. Beyond basic zoning data, we believe that tract-level data on the commercial real estate market would be tremendously helpful. Many of the IMBs we observed for this study are located in strip-mall commercial spaces that are at least 50 percent vacant. Data on commercial vacancy rates would also be helpful in determining the drivers of IMB location. Future comparative studies in other North American cities should incorporate these land-use and real estate variables directly, instead of the demographic proxies we identified, which we believe add variability and error to the analysis.

The challenge of identifying the locational characteristics that drive IMB clustering is not limited to Houston's *laissez faire* approach to urban planning. More traditional methodological challenges also affected the findings in this analysis. The G_i^* analysis did not identify the FM 1960 corridor in northwest Houston as an area of statistically significant clustering, despite the clear connection between IMB locations along the thoroughfare. This is likely due to the modifiable areal unit problem that can occur with polygon-based statistical analysis. Because the road acts as the boundary between census tracts along the entire corridor, the statistical measure of clustering is diminished as IMBs located on the north side of the road are grouped in one tract whereas IMBs across the street are aggregated to tracts on the south side of the corridor. Nonetheless, there is clear evidence of the importance of transportation corridors for IMB location; Bellaire Boulevard, Westheimer, Richmond, Highway 6, and FM 1960 are all key roads in the Houston IMB

landscape. Future research should incorporate accessibility measures based on traffic flows, in combination with demographic data, to perhaps explain IMB locational strategy and clustering more completely.

Finally, this analysis examines just one of the “types” of illegal sex work found in the city of Houston, and common to most major U.S. cities. As such, the spatial patterns observed should not be understood as encapsulating all of the illegal sex trade in Houston. Rather, in areas where IMBs are absent, other types of sex trade are likely to occur. The ubiquity of the commercial sex trade in Houston raises questions about the production of commercial sex spaces within North American cities. The traditional understanding of a red-light district, occupying a few blocks of an area of urban disinvestment, is insufficient for describing the primary zone of IMB concentration in Houston: a 20 mile by 5 mile zone in which commercial sex is available every few hundred yards, and brothels operate directly adjacent to Starbucks coffee shops and other icons of the commercial landscape. Indeed, it appears that the commercial sex trade is not an aberration within the retail landscape of Houston, but rather a foundational component of that landscape.

Notes

1. The federal definition of a commercial sex act is “any sex act on account of which anything of value is given to or received by any person” (18 U.S. Code § 1591). A sex act is defined in 18 U.S. Code § 2246 as follows:
 - (A) contact between the penis and the vulva or the penis and the anus, and for purposes of this subparagraph contact involving the penis occurs upon penetration, however slight;
 - (B) contact between the mouth and the penis, the mouth and the vulva, or the mouth and the anus;
 - (C) the penetration, however slight, of the anal or genital opening of another by a hand or finger or by any object, with an intent to abuse, humiliate, harass, degrade, or arouse or gratify the sexual desire of any person; or
 - (D) the intentional touching, not through the clothing, of the genitalia of another person who has not attained the age of 16 years with an intent to abuse, humiliate, harass, degrade, or arouse or gratify the sexual desire of any person.
2. The average cost per service is understood to be the “door fee,” or price to enter the establishment, plus tip.
3. For more on the consumer traffic component of this project see Bouché and Crotty (2017).
4. The research methodology for this project was reviewed and approved by an institutional review board.
5. One IMB was located in a gated apartment complex. The other was inside a purported pharmacy.
6. There is considerable variation in scholarly analyses of consumer mobility and decision making (Van Acker, Goodwin, and Witlox 2016). The speed measure used in this analysis is based on standardized 35 mph speed limits on major roads in Houston, Texas.
7. For more discussion of GWR methodology see Fotheringham, Brunson, and Charlton (2002).

References

- Austin, S. B., S. J. Melly, B. N. Sanchez, A. Patel, S. Buka, and S. L. Gortmaker. 2005. Clustering of fast-food restaurants around schools: A novel application of spatial statistics to the study of food environments. *American Journal of Public Health* 95:1575–81. doi:10.2105/AJPH.2004.056341.
- Bales, K., and S. Lize. 2005. *Trafficking in persons in the United States*. NCJRS No. 211980. Washington, DC: U.S. Department of Justice.
- Bereitschaft, B., and R. Cammack. 2015. Neighborhood diversity and the creative class in Chicago. *Applied Geography* 63:166–83. doi:10.1016/j.apgeog.2015.06.020.
- Birr, S. 2017. Shady massage parlors are a major source of human sex trafficking. *The Daily Caller* May 15. Accessed May 18, 2017. <http://dailycaller.com/2017/05/15/shady-massage-parlors-are-a-major-source-of-human-sex-trafficking/>.
- Bouché, V. 2017. An empirical analysis of the intersection of organized crime and human trafficking in the United States. NCJRS 250955, U.S. Department of Justice, Washington, DC.
- Bouche, V., and S. M. Crotty. 2017. Estimating demand for illicit massage businesses in Houston, Texas. *Journal of Human Trafficking* 1–19. doi:10.1080/23322705.2017.1374080.
- Brewer, D. D., J. J. Potterat, S. Q. Muth, J. M. Roberts, J. A. Dudek, and D. E. Woodhouse. 2007. *Clients of prostitute women: Deterrence, prevalence, characteristics, and violence*. NCJRS 218253. Washington, DC: U.S. Department of Justice.
- Burns, R. 2018. Datafying disaster: Institutional framings of data production following Superstorm Sandy. *Annals of the American Association of Geographers* 1–10. <https://doi.org/10.1080/24694452.2017.1402673>.

- Chalkias, C., A. G. Papadopoulos, K. Kalogeropoulos, K. Tambalis, G. Psarra, and L. Sidossis. 2013. Geographical heterogeneity of the relationship between childhood obesity and socio-environmental status: Empirical evidence from Athens, Greece. *Applied Geography* 37:34–43. doi:10.1016/j.apgeog.2012.10.007.
- Couture, T., and J. Kimball. 2016. *More than drinks for sale: Exposing sex trafficking in cantinas and bars in the U.S.* Washington, DC: Polaris Project.
- Crotty, S. M. 2015. Locating day-labor employment: Toward a geographic understanding of day-labor hiring site locations in the San Diego metropolitan area. *Urban Geography* 36 (7):993–1017.
- Cummins, S., J. W. Peltier, J. A. Schibrowsky, and A. Nill. 2014. Consumer behavior in the online context. *Journal of Research in Interactive Marketing* 8:169–202. doi:10.1108/JRIM-04-2013-0019.
- Dank, M., B. Khan, P. M. Downey, C. Kotonias, D. Mayer, C. Owens, L. Pacifici, and L. Yu. 2014. *Estimating the size and structure of the underground commercial sex economy in eight major U.S. cities.* Washington, DC: Urban Institute.
- Durchslag, R., and S. Goswami. 2008. *Deconstructing the demand for prostitution: Preliminary insights from interviews with Chicago men who purchase sex.* Chicago: Chicago Alliance Against Sexual Exploitation.
- Eck, J. E. 1995. A general model of the geography of illicit retail marketplaces. In *Crime and place*, ed. J. E. Eck and D. Weisburd, 67–93. Monsey, NY: Criminal Justice Press.
- Epstein, B. J. 1971. Geography and the business of retail site evaluation and selection. *Economic Geography* 47:192–99. doi:10.2307/143046.
- ESRI. 2014. *ArcGIS Desktop: Release 10.3.* Redlands, CA: Environmental Systems Research Institute.
- Farley, M., J. Bindel, and J. M. Golding. 2009. *Men who buy sex: Who they buy and what they know.* London: Eaves.
- Fernandez, M. 2014. Strip clubs and their city call a truce. *New York Times*, January 3.
- Flanagin, A. J., and M. J. Metzger. 2008. The credibility of volunteered geographic information. *GeoJournal* 72:137–48. doi:10.1007/s10708-008-9188-y.
- Fotheringham, A. S., C. Brunsdon, and M. Charlton. 2002. *Geographically weighted regression: The analysis of spatially varying relationships.* Chichester, UK: Wiley.
- Goodchild, M. F. 2007. Citizens as sensors: The world of volunteered geography. *GeoJournal* 69:211–21. doi:10.1007/s10708-007-9111-y.
- Haklay, M. 2010. How good is volunteered geographical information? A comparative study of OpenStreetMap and ordinance survey datasets. *Environment and Planning B: Planning and Design* 37:682–703. doi:10.1068/b35097.
- Hays-Mitchell, M. 1994. Streetvending in Peruvian cities: The spatio-temporal behavior of ambulantes. *The Professional Geographer* 46:425–38. doi:10.1111/j.0033-0124.1994.00425.x.
- Herbert, S. 1997. *Policing space: Territoriality and the Los Angeles Police Department.* Minneapolis: University of Minnesota Press.
- Hubbard, P. 1997. Red-light districts and toleration zones: Geographies of female street prostitution in England and Wales. *Area* 29:129–40. doi:10.1111/j.1475-4762.1997.tb00015.x.
- . (1998). Sexuality, Immorality and the City: Red-light districts and the marginalisation of female street prostitutes. *Gender, Place & Culture* 5:55–76.
- . 2004. Cleansing the metropolis: Sex work and the politics of zero tolerance. *Urban Studies* 41:1687–1702. doi:10.1080/0042098042000243101.
- . 2008. Here, there, everywhere: The ubiquitous geographies of heteronormativity. *Geography Compass* 2:640–58. doi:10.1111/j.1749-8198.2008.00096.x.
- Janson, L. 2013. *Our great hobby: An analysis of online networks for buyers of sex in Illinois.* Chicago: Chicago Alliance Against Sexual Exploitation.
- Kim, I.-H., C.-C. Feng, Y.-C. Wang, B. H. Spitzberg, and M.-H. Tsou. 2017. Exploratory spatiotemporal analysis in risk communication during the MERS outbreak in South Korea. *The Professional Geographer* 69:629–643.
- Levar, J., D. E. Kanouse, and S. H. Berry. 2005. Racial and ethnic segmentation of female prostitution in Los Angeles County. *Journal of Psychology and Human Sexuality* 17 (1–2):107–29. doi:10.1300/J056v17n01_07.
- Mejia, B. 2017. *How Houston has become the most diverse place in America.* Los Angeles Times, May 9.
- Mitchell, A. 2005. *The ESRI guide to GIS analysis.* 2nd ed. Redlands, CA: ESRI Press.
- Monto, M. A., and N. McRee. 2005. A comparison of the male customers of female street prostitutes with national samples of men. *International Journal of Offender Therapy & Comparative Criminology* 49:505–29. doi:10.1177/0306624X04272975.
- Portes, A., M. Castells, and L. A. Benton. 1989. *The informal economy: Studies in advanced and less developed countries.* Baltimore: Johns Hopkins University Press.
- Rachera, P., and W. Friske. 2012. Perceived “usefulness” of online consumer reviews: An exploratory investigation across three services categories. *Electronic Commerce Research and Applications* 11:548–59. doi:10.1016/j.elerap.2012.06.003.
- Rice, M. D., A. Ostrander, and C. Tiwari. 2016. Decoding the development strategy of a major retailer: Wal-Mart’s expansion in the United States. *The Professional Geographer* 68:640–49. doi:10.1080/00330124.2016.1140494.
- Rood, L. 2016. Concerns grow as massage parlors spread across Iowa. *The Des Moines Register* November 17. Accessed May 18, 2017. <http://www.desmoinesregister.com/story/news/2016/11/16/concerns-grow-massage-parlors-spread-across-iowa/93291274/>.
- Rubmaps.com. 2017. Home page. Accessed January 10, 2017. www.rubmaps.com.

- Sivasankaran, A. 2014. Daley concerned about increase in massage parlors, smoke shops. *Sun Sentinel* October 21. Accessed May 18, 2017. <http://www.sun-sentinel.com/local/broward/coral-springs/fl-cspf-smoke-1023-20141021-story.html>.
- Thomadsen, R. 2007. Product positioning and competition: The role of location in the fast food industry. *Marketing Science* 26:792–804. doi:10.1287/mksc.1070.0296.
- Underhill, P. 1999. *Why we buy: The science of shopping*. New York: Simon & Schuster.
- Van Acker, V., P. Goodwin, and F. Witlox. 2016. Key research themes on travel behavior, lifestyle, and sustainable urban mobility. *International Journal of Sustainable Transportation* 10:25–32.
- Venkatesh, S. A. 2006. *Off the books: The underground economy of the urban poor*. Cambridge, MA: Harvard University Press.
- Wang, Y. 2010. Massage parlors: A blot city can't erase. *Houston Chronicle*, October 31.
- Wang, Y., T. Wang, M.-H. Tsou, H. Li, W. Jiang, and F. Guo. 2016. Mapping dynamic urban land use patterns with crowdsourced geo-tagged social media (Sina-Weibo) and commercial points of interest collections in Beijing, China. *Sustainability* 8 (11):1202. doi:10.3390/su8111202.
- Wang, Z., X. Ye, and M.-H. Tsou. 2016. Spatial, temporal, and content analysis of Twitter for wildfire hazards. *Natural Hazards* 83 (1):523–40.
- Weitzer, R. 2009. Sociology of sex work. *Annual Review of Sociology* 35:213–34. doi:10.1146/annurev-soc-070308-120025.
- White, J. 2014. Local officials struggle with massage business boom as state regulations expire. *The Sacramento Bee* February 7. Accessed May 18, 2017. <http://www.sacbee.com/news/politics-government/article2590641.html>.
- Whyte, W. H. 1988. *City: Rediscovering the center*. Philadelphia: University of Pennsylvania Press.
- Wrigley, N., and M. Lowe. 1996. *Retailing, consumption and capital: Towards the new retail geography*. Harlow, UK: Longman.
- Zhu, F., and X. Zhang. 2010. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing* 74:133–48. doi:10.1509/jmkg.74.2.133.