Dismantling the Psychiatric Ghetto: Evaluating a Blended-Clinic Approach to Supportive Housing in Houston, Texas

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Locational decisions based on stigma and low funding have handicapped the efficiency of community based mental healthcare in the United States since 1963. However, the pattern of services in the 21st century American South remains largely unknown. This thesis addresses this gap in knowledge by using a mixed methodology including location allocation, descriptive statistics, and qualitative site visits to explore the geography of community clinics offering both physical and mental health services. The City of Houston has proposed using these facilities to anchor new supportive housing, but introducing more fixed costs to a mismatched system could create more problems than solutions.

The findings of this study suggest the presence of an unnecessary concentration of services in the central city and a spatial mismatch between accessible clinics and the poor, sick people in need. Furthermore, this research reveals a new suburban pattern of vulnerability, calling into question long-held assumptions about the vulnerability of the inner city. Building supportive housing around existing community clinics, especially in the central city, may further concentrate vulnerable people thereby contributing to intensifying patterns of service-seeking drift and the continued traumatization of mentally ill homeless persons in Houston.
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1. INTRODUCTION

Americans who have experienced homelessness die, on average, 25 years earlier than those who have not (Hwang 2001). This longevity gap is not due to any condition specific to homelessness; rather, it is the result of a complex of poor physical, mental, and behavioral health, of which homelessness is a common symptom. During most of the nineteenth and twentieth centuries the poor, sick, and insane were confined to asylums and other institutions (Foucault 1988). This practice eventually came to be regarded as cruel, and community-based care programs promised to reintegrate this vulnerable population back into society. However, the implementation of these programs was geographically flawed, resulting in the concentration of homeless and mentally ill people into service-dependent ghettoes. The 25-year longevity gap demonstrates how the current social service system is failing this population.

Unfortunately, little is known about the current spatial distribution of services for the mentally ill and homeless. Furthermore, most of the research in this area was conducted during the 1970s and 80s in California and a handful of northern states. The culture and politics of the American South are quite different, and funding priorities have shifted over the past four decades. This thesis seeks to bridge these gaps by examining the spatial distribution of community clinics offering both mental and physical health services in Houston, Texas.
2. BACKGROUND

In 1963 the Community Mental Health Centers Act radically changed how mental health care is delivered to low-income, mentally ill Americans. Community-based clinics and public housing replaced asylums, ostensibly so patients could remain in their home neighborhoods. The term deinstitutionalization refers to the movement of people from these mid-century asylums to community care (Wolch, Dear, and Akita 1988). Unfortunately, flawed implementation handicapped the effort and inadvertently created what Michael Dear termed “psychiatric ghettos” in inner-city areas (Dear 1977a).

Aftercare facilities and community clinics located in the areas where public monies were available, rents low, and political opposition negligible (Dear 1977a). Social stigma and political opposition limited the available funds. Funding is rare in unincorporated towns or places with homogenous rich or poor populations. Therefore, these facilities located only within economically heterogeneous municipalities, most commonly large cities (Joassart-Marcelli and Wolch 2003). Low funding forced these services to areas with cheap rent, usually in blighted, inner-city neighborhoods or industrial landscapes. The discharged mental patients had little money, few job prospects, and limited transportation so they followed the services and settled in the same areas (Dear 1977a).

Research shows recovery outcomes are best when people are allowed to stay in their own neighborhoods close to familiar schools, jobs, and social networks (Wolch, Dear, and Akita 1988). Any kind of relocation is anxiety provoking, and the additional stress of poverty and shame associated with homelessness adds to psychological distress (Knoop 2008). The implementation of community-based care may have created a system that does exactly the
opposite of its stated goal by forcing the relocation of mentally ill and homeless persons, to the detriment of their health. This process is called service-seeking drift, and it continues to this day in large cities such as Miami (Rukmana 2011).

Following this line of research, Michael Dear and his colleagues in urban geography laid the groundwork for mental health geography in North America. Dear believed that using location-allocation models to find sites for mental health facilities could repair the issues created by deinstitutionalization (Dear 1978). He distills his most significant findings into four principles we must keep in mind when planning where to place services for the mentally ill (ibid.). First, patients must accept the sick role in order to pursue services. In other words, patients must recognize first that they are sick and second they must accept the legitimacy of mental health care. This is often quite culturally patterned due to the near universal stigma of mental illness and the lack of definitive biomedical testing. Second, consumers cannot rationally evaluate the services offered. Clinics offer different providers, treatments, and therapeutic approaches; most consumers have no idea what will be most effective. Third, mental healthcare has a wide range of positive societal externalities, including reductions in homelessness and crime. Finally, we must remember that distance decay may work differently for mental healthcare. People may forego a nearby clinic to attend one in the next town if the risk of being caught is high.

Tools of the Medical Geographer

Medical geography’s command of location-allocation modeling may be why Michael Dear’s attitude toward the field changed from highly critical in 1996 to collaborative in 2000.
Medical geographers possess both the quantitative skill and the theoretical frameworks necessary to reinvigorate the field of mental health geography.

Medical geographers often use the disease ecology model to explain variations in health across space (Bennett 2004). This model attributes disease to biological, behavioral, and environmental factors. To take an example from mental health, we can examine schizophrenia in this manner. Schizophrenia has been linked to genetics and prenatal conditions. However, not everyone with the predisposition develops the disease. People are more likely to develop symptoms if they have symptomatic family members or abuse drugs or alcohol. Schizophrenia is also more common among urban dwellers and migrants. In fact, the likelihood of new immigrants developing schizophrenia increases if the receiving community is very small (Dealberto, Middlebro, and Farrell 2011; Kelly 2005). For example, Houston is home to a large group of Vietnamese immigrants but few people from Bhutan; we can expect that new Bhutanese immigrants will experience schizophrenia more often than the Vietnamese, all other factors being equal. Clearly, social and environmental factors contribute to who gets schizophrenia and where.

Most quantitative methods in medical geography use the disease ecology framework. Demand estimation and location-allocation models often incorporate indicators such as poverty, gender, and race. By spatially relating disease rates to race, gender, and income, medical geographers are able to detect new patterns of disease spread and neighborhood factors influencing health. Social critique is implicit in these results. However, political, historical, and structural processes are difficult to explain using such methods. Thus, political ecology offers a different theoretical framework more suited for this task.
Usually political ecology focuses on how interlocking processes at multiple scales combine to distribute various phenomena across space (Peet, Robins, and Watts 2011; Biersack and Greenberg 2009; Zimmerer and Bassett 2003). One advocate of this approach to health geography is Geoffrey DeVerteuil who called for incorporating a structural violence framework at the 2013 International Medical Geography Symposium (DeVerteuil 2013). Structural violence, a term coined by medical anthropologist Paul Farmer, refers to mental or physical injury that comes to individuals as a result of human created systems, not physical interpersonal violence (Farmer 2005). DeVerteuil also studies mental illness and homelessness in North America, and his work highlights how the homeless are victimized by what he terms “post-justice” cities in the 21st century (DeVerteuil et al. 2009).

A structural perspective is also necessary to explain who is homeless and why. For example, Johnson (2010) uses the political ecology approach to explain why the black population has historically been overrepresented among the homeless. In antebellum America free blacks that escaped to the North were considered homeless, filling the shelters. After emancipation millions were suddenly homeless, and the share cropping system did little to improve their economic standing. Black migration out of the south compounded the issue in northern cities; redlining limited housing options, and landlords artificially inflated prices in the few places where black tenants could rent property. New Deal programs removed land rights from black tenure farmers and gave them to white landowners. Home loans were not extended to non-whites in the post-World War II housing boom. The deindustrialization of the economy cost more black jobs than white jobs, and the homeless population today continues to reflect these historical inequalities.
The Changing Geography of Mental Health Services

As DeVerteuil’s work highlights, structural violence against the mentally ill and homeless continued well past the 1960s and 70s. Social stigma continues to drive siting decisions for mental health services (DeVerteuil 2000). Zoning and political opposition trap facilities serving this population in resource poor neighborhoods. Moreover, the rise of non-profits makes the system even more complicated. Do non-profits consider spatial issues when planning? Do government agencies consider such concerns when allocating grants? Answers are unclear.

Another trend is the push toward privatization (DeVerteuil 2000). Hospitals and prisons now profit from the suffering of others, which was not commonly the case at the time of deinstitutionalization. This has fundamentally changed the way healthcare is provided to vulnerable populations (Andrews and Evans 2008). In general, policy has taken a decidedly punitive turn over the past decade in most American cities (DeVerteuil et al. 2009). More than ever the homeless are punished as a means to “clean up the streets”.

As the inpatient psychiatric population decreased steadily the population of America’s prisons increased exponentially. This trend has come to be known as hyperincarceration (Dumont et al. 2012). It is now estimated that half of American inmates suffer from mental illness. Many of these people are homeless, and will be released back on the streets with nothing to show but a longer criminal record that may disqualify them from welfare benefits. Recently released inmates are a particularly vulnerable group, especially those addicted to alcohol or drugs. Because they are no longer accustomed to their substance of choice, many
immediately return to the dosage they were using before withdrawal and subsequently
d overdose (ibid).

Far from an improvement since the time of Michael Dear, the current behavioral health
care system is more fractured, punitive, and stigmatized than ever. One recent study shows
that in Washington, D.C., mental health services cluster away from areas of low socio-economic
status, implying worse access for the poor (Metraux et. al. 2012). In Massachusetts
rehabilitation facilities are usually counter intuitively built in areas flagged by the police for high
drug activity (Pierce et al. 2012). In one of the few service-seeking studies conducted recently,
Rukmana (2011) found that homeless families in Miami are more likely to drift towards
services, while homeless individuals simply churn though the system. In other words, new
homeless groups are flowing into the city while the older ones remain trapped in the service-
dependent ghettos.

DeVerteuil (2009) calls for paying closer attention to hospitals, drop-in-centers,
psychiatric facilities, rehabilitation centers, jails, and prisons in addition to emergency shelters,
community clinics, and supportive housing. A dizzying web of referrals, transfers, and
discontinuous care obfuscate the movement of poor people through these institutional
channels. The structural approach rejects the idea that any shelter can be studied in a vacuum
from the larger forces determining who needs the services, who pays for it, who defines
eligibility, and why the building is located where it is.

Other trends continue to slowly emerge. In 1998 Crane and Takahashi released a study
on suburban homelessness. By exploring the needs of homeless persons in Orange County,
California, they discovered that people who remained in this area rarely suffered from mental
illness and most had lived in the county for more than 10 years. Therefore, either the nature of homelessness is different in urban and suburban regions or there is a self-sorting mechanism whereby the neediest people (especially the mentally ill and addicted) drift to central cities.

The Role of Place in Recovery

Immediate environments also profoundly affect health on an individual scale. The detrimental psychological effects of place are clear in the literature on homelessness and mental illness, though it has not yet been clearly tied to any particular conceptual framework. For more than twenty years homelessness has been known to be a risk factor for mental illness (Goodman, Saxe, and Harvey 1991). Becoming homeless is traumatic and the trauma can be cumulative if ongoing conditions of violence and hardship persist. While some people become homeless due to previous mental illness, many only develop symptoms, such as depression and anxiety, after they lose their home. Recovery outcomes in shelter environments are very poor (ibid.). It appears as though psychological distress cannot abate while external stress on the body continues; they are the same.

Neo-phenomenology, best outlined by Simonsen (2012), focuses on breaking down operationalized versions of mind-body dualism. Drawing on the works of Merleau-Ponty, Simonsen argues that the body both acts and is acted upon; it is responsive and political. She writes: “Emotions are neither ‘purely’ mental nor ‘purely’ physical, but ways of relating and interacting with the surrounding world (Simonsen 2012, p. 17).” That is, researchers working within the neo-phenomenological framework embrace the concept of embodiment. Exterior conflicts, trauma, and stress create psychological suffering that can manifest both physically
and socially. To critics, phenomenology in its original form bordered on naturalism and reintroduced mysticism into geography, but neo-phenomenology embraces quantitative research methods and rigorous experimental design. Emotions are real phenomena with tangible and testable effects that impact the human systems we create.

Implied in the discussion of neo-phenomenology is the importance of place. In his study on Apache attachment to place Keith Basso writes: “Places possess a marked capacity for triggering acts of self-reflection, inspiring thoughts about who one presently is, or memories of who one used to be, or musings on who one might become (1996 p.55).” Basso observed this in a positive context; the Apache people used the western landscape to teach each other about morals, coping skills, and history. Nonetheless, this intimate psychological connection to place can be destructive as well.

Geographers studying homelessness use the term retraumatization to refer to the specific trauma of becoming homeless and moving to a different place for services or support (Wolch, Dear, and Akita 1988). People must leave their home neighborhoods in order to venture to the areas with food, housing, or health services, leaving behind jobs, cars, schools, family, friends, and familiar landmarks. Home is replaced by industrial or commercial landscapes full of uncaring, terrified, and sick people. If place, like Basso says, can trigger thoughts of who one is and who one can become then what thoughts must such an environment engender? One story comes from a woman waiting for supportive housing:

I don’t pray! Pray for what? I been prayin’ all my life and I’m still here. When I came to this hotel I still believed in God. I said: ‘Maybe God can help us to survive’. I lost my faith. My homes. And everything. Ain’t nobody- no God, no Jesus- gonna help us in no way. God forgive me. I’m emotional...I’m scared to sleep. If I eat, I eat one meal a day. My stomach won’t allow me. I stay in this room. I hide. (Flannery 2003, p.67)
One common reaction to retraumatization is learned helplessness (Goodman, Saxe, and Harvey 1991). Suddenly, formerly competent people need much more support than ever before because they come to believe the low expectations placed upon them. Unfortunately, another common reaction to these conditions is suicide. Homeless people consider suicide ten times more often than the national average (Fitzpatrick et al. 2012).

While neo-phenomenology is relatively new, it dovetails with emerging work on vulnerable place theory. Vulnerable place theory incorporates political ecology, sense of place, and human agency to describe the dynamic process of human-environment interaction. In Oppong and Harold’s formulation place vulnerability has three basic components: vulnerable places attract vulnerable people, vulnerable people create and recreate vulnerable places, and vulnerable people attract more vulnerable people (2009). Crucially, these processes apply whether the people in motion are migrating voluntarily or due to forces outside of their control.

Vulnerable place theory is clearly demonstrated through the dynamics of the typical emergency homeless shelter. People come to the shelter at first by finding the information on their own, referrals from case managers, and orders from policemen or hospitals (DeVerteuil et al 2009). As the population grows so too do the issues: tuberculosis and influenza spread in densely populated sleeping areas, poverty leads to high rates of theft, prostitution, and drug dealing, psychological stress makes people irritable and more likely to escape into various vices (Johnson and Fendrich 2007). Services may become overwhelmed from demand, yet more people come. Some people come to join friends and family at the shelter, while others are drawn by the new black market opportunities (Pluck, Lee; and Parks 2007). Later arrivals are likely to find the shelter is dirty, dangerous, and scary, largely due to the concentration of
vulnerable people in one place. This is also an example of structural violence, since the shelter is not a prison and was not designed to punish people, but in the end the system that grows up around it creates excess harm for users.

Unsurprisingly, people recover better in neighborhoods with high levels of social capital, but few services are built in such areas. One national study shows that rehousing placements are usually in neighborhoods with the same quality of life when compared to where clients lived before they became homeless (Tsai, Mares, and Rosenheck 2011). Vulnerable people are simply being shuffled around vulnerable places. This creates ideal conditions for serial homelessness. Neighborhood factors continue to be ignored, deepening the vulnerability of people already battered by the dual burden of homelessness and mental illness.

Another example of vulnerable places comes from a study of the follow-up appointment retention rates of patients discharged from psychiatric hospitals. If the assigned clinic was more than ten minutes away from their home people were exponentially less likely to attend sessions, demonstrating simple distance decay. The more significant finding was that people were unwilling to go to neighborhoods with higher rates of crime than the place they lived for services (Mennis, Stahler, and Baron 2012). Beyond the basic self-preservation instinct, mentally ill people react to dangerous environments by avoiding them, for their own health (Whitley 2011). Even if patients are not physically assaulted, being in a higher stress environment is not conducive to productive therapy sessions, so they will not go. The clinic was built in a place that was too vulnerable, so people with a choice avoided it.

In the worst case scenario clinics are located in neighborhoods where they cannot be effective because of the environment. Rachlis et al. (2010) visited the poorest zip code in
Toronto and interviewed intravenous drug users. Eight years later they returned for follow-up interviews. The people who stayed in the zip code showed no significant progress toward recovery, despite a high concentration of mental health clinics and rehabilitation facilities. However, a sizable proportion of the population moved out of the zip code to rural areas around Canada with little to no access to recovery services. This group showed remarkable improvement; the majority no longer used drugs. It appears that neighborhood quality can completely subvert the intended purpose of community-based care.

Houston as a Case Study

For this study I will focus on Houston, Texas. No studies on the spatial distribution of mental health facilities have been done in the American South where city structures are more dispersed and sprawling with poorer access to public transportation and social services (Chircop 2011). Houston is the fourth largest city in the US, and a national leader in neoliberal policy. Houston is the largest city in the country without zoning and infrastructural development requires heavy lobbying on the part of citizens. (City of Houston 2014; Fisher 1990). Houston also sits right in the middle of the Sun Belt, the southern tier of states where immigration rates are high. As one of the fastest growing cities in the country with one of the thinnest social safety nets Houston is an ideal place to study the current patterns of services for the homeless and mentally ill.

Within the US, Texas budgets the least for mental health per capita, spending only $38.99 per Texan in 2010 (The Henry J. Kaiser Family Foundation 2013). See Table 2.1 for a comparison between Texas and a few other selected states. Texas is home to the fourth and
fifth largest cities in the country, Dallas-Fort Worth and Houston. The National Coalition for the Homeless ranks these cities as the 6th and 7th meanest American cities for homeless persons (National Coalition for the Homeless 2005). Historically, Houston favors punitive laws against loitering, littering, and assembly rather than implementing recovery and rehabilitation programs. On any given night there are about 5,300 homeless persons in Harris County, the county containing the vast majority of the City of Houston. (Houston Coalition for the Homeless 2014). Texas is also contributing to the exponentially rising incarceration rate; as a result, the Texas Department of Correctional Justice is the largest mental health provider in the state (Dumont et al 2012). While the Texas legislature recognizes the expense associated with housing non-violent, mentally ill inmates, its response is to simply freeze funding for services at current low levels instead of making even deeper cuts (Texas Tribune 2011).

Table 2.1. Mental health spending, 2010 (The Henry J Kaiser Foundation 2013)

<table>
<thead>
<tr>
<th>State</th>
<th>Per Capita Annual Spending on Mental Health ($)</th>
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<tr>
<td>Texas</td>
<td>38.99</td>
</tr>
<tr>
<td>Louisiana</td>
<td>62.37</td>
</tr>
<tr>
<td>Colorado</td>
<td>88.41</td>
</tr>
<tr>
<td>Mississippi</td>
<td>114.95</td>
</tr>
<tr>
<td>California</td>
<td>152.60</td>
</tr>
<tr>
<td>Arizona</td>
<td>221.27</td>
</tr>
<tr>
<td>New York</td>
<td>256.31</td>
</tr>
<tr>
<td>Alaska</td>
<td>310.01</td>
</tr>
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</table>

Nevertheless, the winds may be shifting in Houston. In early 2013 Mayor Annise Parker announced an ambitious plan to house 2,000 chronically homeless street people within five years, and 1,000 within the next two (Mitchell 2013). The target population for the proposed housing initiative comprises the most difficult cases within the homeless system. Most people experience homelessness as a traumatic but brief interruption to their lives, but some sink into chronic homelessness. Chronically homeless people have either been homeless for more than
12 months or have experienced at least 4 instances of homelessness within the past 3 years (Metro Dallas Homeless Alliance 2012). The target population in Houston sleeps primarily on the streets. About half have serious mental illness and half suffer from a chronic health condition. A third have been the victim of violent crime, and a third are employed (Mitchell 2013). One characteristic that cannot be attributed to this group is the desire to remain homeless. In a 2007 census of the homeless in Fort Worth interviewers asked, “Do you want end your homelessness?” and 96.9 percent responded with a yes (Tarrant County Homeless Coalition 2007). These are also the most costly homeless people for taxpayers. They tend to use the emergency room for primary and mental health care, running up thousands of dollars in medical bills. This population is also more likely to be incarcerated for brief periods, costing the state to keep them housed as well as footing the bill for legal services of both prosecution and defense.

Houston’s approach relies on building enough supportive housing to accommodate these 2,000 people. In Texas, a government body rarely administers emergency shelters. For example, in 2008 Dallas opened The Bridge, a state of the art homeless shelter and service hub, but shortly after contracted it out to non-profit organizations (Merten 2009). Most emergency services are administered by non-profit and faith-based organizations. The city government has little to no power over their services, referrals, and policies (Interview with Mandy Chapman Semple 2013). Furthermore, the transitional housing model works primarily for families in need of a very short-term place to stay. People with chronic homeless issues may never “get better” and may never be able to live on their own. Therefore, the supportive housing model of
guaranteed housing and services works best for the target population (United States department of Housing and Urban Development 2013; Levitt et al. 2012).

The efficacy of supportive housing can vary widely. When placed in vulnerable areas with high rates of crime, poverty, and weak social coherence these programs are less effective than when people are placed in an area with job opportunities, affordable housing, and higher levels of education (Rachlis et al. 2010; Pierce et al. 2012). Therefore, the City of Houston now demands that scattered supportive housing have easy access to a federally qualified community clinic offering both primary and behavioral health services. The blended approach is a way of working around the overloaded Mental Health and Mental Retardation Authority and provider shortages. Planners hope primary care providers will be able to open up mental health conversations among people who may be ignorant of or stigmatized by mental illness (Interview with Mandy Chapman Semple 2013).
3. RESEARCH QUESTIONS

If the existing blended-service clinics in Houston are concentrated in blighted, dangerous areas like homeless services in other cities then building housing around them will only compound the concentration of vulnerable people in vulnerable places. On the other hand, if clinics are already equitably and efficiently distributed across the landscape then more clinics may not be needed. Therefore, this paper seeks to answer the following research questions:

• What is the geography of blended-service community clinics in Houston? Which areas are served, unserved or underserved? What are the distinguishing characteristics of the un(der)served areas?

• Given the stated goal of the City of Houston to provide all chronically homeless persons with medical care and supportive housing, where should new blended-service clinics be located?

• How do you define demand for this type of facility?
4. METHODS

I first found the nearest neighbor index of the existing blended-service community clinics in Houston to determine the degree spatial clustering. Then I ran a Ripley’s K function on the data to further explore the distribution of clinics in the city. Ripley’s K shows the degree of clustering at various distances (Dixon 2002). Using these processes I assessed first and second order effects prior to building a demand surface.

In order to estimate demand for blended-service community clinics I used the Collaborative Psychiatric Epidemiology Surveys (CPES) to find the significant correlates predictive of self-rated health. The CPES was a massive survey project undertaken by the National Institute for Mental Health (NIMH) between 2001 and 2003. The complete data set consists of 20,000 cases and over 6,000 variables related to mental health. The CPES is the most comprehensive publicly available survey of American mental health. For mental health, surveys are more useful than utilization data. Utilization data is inevitably flawed because the location of mentally ill people changes with the location of services (Curtis 2010). In other words, mentally ill people are quite likely to drift toward services; once the psychiatric ghetto is established utilization data will simply reflect the concentration of vulnerable people in space.

For this analysis the CPES variable of interest is self-rated physical and mental health status in the past 30 days, on a scale of 0 to 100. This variable is ideal for two reasons. First, it incorporates both mental and physical health, useful for the blended clinic approach. Second, a client-based metric addresses a serious issue with measuring demand for mental health services. In order to seek mental health services a person must recognize and accept the sick role (Dear 1977b). However, some groups are more likely to perceive their own issues as poor
health than others. Therefore, a self-rated score should be more indicative of whether a person pursues health services or not. Indeed, preliminary exploratory research confirms this initial hypothesis. The self-rated wellness score is more highly correlated to whether a person has visited any health professional in the past 30 days than any rating calculated by the NIMH collectors. This is true for every type of provider, from psychiatrists to faith healers (Table 4.1). Self-rated wellness is also the 30-day functioning variable with the highest correlation to the question, “have you ever been homeless?”

Table 4.1. Self-Rated Wellness and the Likelihood of Visiting a Mental Health Professional

<table>
<thead>
<tr>
<th>Ever visited practitioner for mental health</th>
<th>Self-Rated Wellness, 30-day</th>
<th>Physical Health Status, 30-day</th>
<th>Mental Health Status, 30-day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Psychiatrist</td>
<td>.241**</td>
<td>.069*</td>
<td>.064*</td>
</tr>
<tr>
<td>General Practitioner</td>
<td>.238**</td>
<td>.121**</td>
<td>.058*</td>
</tr>
<tr>
<td>Other medical doctor</td>
<td>.252**</td>
<td>.085**</td>
<td>.097**</td>
</tr>
<tr>
<td>Social Worker</td>
<td>.237**</td>
<td>.098**</td>
<td>.068*</td>
</tr>
<tr>
<td>Religious or Spiritual Advisor</td>
<td>.170**</td>
<td>.092**</td>
<td>.080**</td>
</tr>
</tbody>
</table>

While the geographic information available in the CPES is limited to large national regions, this data can be related to known spatial data sets like the United States Census. Once I limited the data to cases containing the self-rated wellness variable (10,327 cases) the data set was further condensed to contain only economic and demographic variables that are also represented in the 2000 or 2010 census or the 2011 American Community Survey 5-year data. These variables include income, race/ethnicity, gender, sex, age, disability, education, marital status, and household size.

The CPES also divides the cases by four geographic regions: south, west, northeast, and mid-west. Bivariate correlation was applied to both the national and the southern data set to determine if the patterns are different. As Table 4.2 shows, the relationship between wellness
and other variables changes over space. Therefore, to get the most accurate regression equation for Houston I limited the analysis to only the 3,662 cases from the southern region.

Table 4.2. Correlations between SES variables and self-rated wellness

<table>
<thead>
<tr>
<th>Variable</th>
<th>National</th>
<th>Southern Region</th>
<th>Northeastern Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Disability</td>
<td>.365**</td>
<td>.385**</td>
<td>.342**</td>
</tr>
<tr>
<td>Mental Disability</td>
<td>.293**</td>
<td>.297**</td>
<td>.300**</td>
</tr>
<tr>
<td>Out of Work Force</td>
<td>-.235**</td>
<td>-.305**</td>
<td>-.274**</td>
</tr>
<tr>
<td>Income</td>
<td>.173**</td>
<td>.197**</td>
<td>.166**</td>
</tr>
<tr>
<td>Years of Education</td>
<td>.154**</td>
<td>.172**</td>
<td>.148**</td>
</tr>
<tr>
<td>Hispanic</td>
<td>null</td>
<td>.079**</td>
<td>-.059**</td>
</tr>
<tr>
<td>Black</td>
<td>-.087**</td>
<td>-.096**</td>
<td>null</td>
</tr>
</tbody>
</table>

Next, I created a data set containing the variables necessary for computing the regression equation for each census. Census tracts are the smallest areal unit available with comprehensive demographic and economic information. I reconciled the data from the 2000 and 2010 censuses using sidewalk files available directly from the bureau. This step is crucial since tract boundaries change each decade. Once the dataset was constructed I used the multiple regression equation derived from the CPES data to compute a wellness score for each tract. The wellness score can be treated as a percent, so an illness score is simply the wellness score subtracted from 100.

Finally, I weighted the illness score by the number of people living below poverty in each tract to create a demand surface. Even if poverty is not a significant correlate, only those living under poverty qualify for the clinics. This weight was then used as the demand input in the location-allocation models.

Next, I built a location allocation model using Esri’s ArcMap software. The p-median model has been shown to be useful in health contexts with less than ideal information.
available. For example, Oppong (1996) used the p-median to account for inaccessibility caused by the rainy season. Xi et al. (2013) more recently used neighborhood characteristics along with the p-median to improve the location of emergency services in China. This method is flexible enough to work with many restraints and variations on input data. I have chosen to use the p-median technique, which minimizes the sum of the distances from each demand point to its nearest facility. This method should create the most convenient catchment areas for the intended users, reducing overall travel distance. The Esri software solves the p-median using the Tietz and Bart heuristic. Tietz and Bart routinely creates optimal solutions and the processing time is manageable for this amount of data. Therefore, the p-median can place clinics where they are needed, so people can travel less distance and do not have to consider leaving their schools, families, and jobs.

To build the model I will use TIGER/LINE shapefiles from the US Census to build a network file for the Houston metropolitan area. I will use the centroids of all tracts within the City of Houston as both demand and candidate points. I created a list of required sites using the Texas state directory of federally qualified health care providers (FQHCPs) available through the Texas Department of State Health Services. I limited this list to clinics offering both mental and physical care through Internet searches and phone calls. I am including FQHCPs within the metropolitan area but not in the City of Houston because there is no requirement that people attend a clinic in the same city or county as their home. I first ran the model with no new clinics to determine the median distance traveled among the 21 existing clinics. Then I added one clinic at a time until I sited 5 new clinics. Between iterations I investigated the median distance traveled and how the allocation of demand changed.
Then, I created maps of Houston using the clinic catchment areas as spatial support. Using 2010 Census data I examined the race/ethnicity, poverty rate, wellness scores, age, and average household size by catchment area. I also used the census data to calculate a vulnerability index based on unemployment, rental housing availability, and crime rates by tract and by catchment area (Mennis, Stahler, and Barron 2012).

Finally, I also conducted site visits to each of the five selected sites to assess environmental characteristics. The appendix contains my assessment instrument. I am looking for sidewalks, maintenance, vacancies, services, business mix, and green space, but I have plenty of space to record other interesting or salient details of the landscape.
5. RESULTS

To determine the first and second order effects of the distribution of clinics in Houston I applied Nearest Neighbor and Ripley’s K analyses to the data. Run at the city level, the nearest neighbor ratio is 1.00 with a p-value of 0.991; the distribution is random. When the community clinics are analyzed at the metropolitan scale I do find a significant clustering effect (NNR= .61, p=.000001). However, this may simply be due to more population or more poverty in the central city. The Ripley’s K analysis showed no significant clustering or dispersion at any distance. The clinics in Houston follow a random spatial pattern based on these two metrics. However, since these procedures do not take population or need into account I still must calculate demand to determine if spatial mismatch exists.

Computing Wellness Scores

Stepwise regression applied to the southern region CPES data produced a regression model based on spatially available variables that can explain 27 percent of the variation in self-rated wellness scores (R=.518, $R^2=.268$). The final equation is:

Wellness = 40.416 + (4.49 × Physical Disability) + (3.43 × Emotional or Mental Disability)
− (6.49 × Out of Work Force) + (2.88 × 10$^{-5}$ × Household Income)
− (.110 × Age) + (1.47 × Years of Education) − (2.42 × Divorced)
+ (1.09 × Learning Disability) − (4.49 × Black) + (2.76 × Hispanic)

To apply this equation to the study areas I calculated either the proportion of people in the tract with the characteristic (disabilities, out of work force, divorced, race/ethnicity) or the median tract value (income, age, education).
Figure 5.1 shows wellness scores across Houston City of Houston. The most striking pattern is the spread of very low wellness scores from the central city out to the suburbs in three spokes: south, northwest, and northeast. Low scores also appear in the northwest part of Harris County and in the east, outside of the Houston city limits. Higher wellness scores are found in more suburban areas and in an area directly west of downtown. This region contains young urban professionals and older wealthy Houston families.

Figure 5.1. Calculated wellness scores across Houston by tract

The chaotic nature of the city boundaries makes it difficult to interpret the northern part of the city, but there are two large non-contiguous regions Houston has absorbed in this area. One is the northernmost light blue area directly north of the city center. This is
Greenspoint, a notorious suburban slum near the airport where the majority of Katrina refugees were relocated. The second important area is to the northeast of Greenspoint. This area is a relatively wealthy suburban area and has mid-range to high wellness scores. The bizarre shape of Houston is due to constant expansion efforts, but this leaves small pockets in need of services and physically separated from the “mainland.”

Computing Demand for Mental Health Services

To obtain a final demand surface for location-allocation modeling I multiplied the illness score by the population under poverty. The illness score is simply one hundred minus the wellness score. I am treating this number as the ratio of people likely to report ill health within 30 days. I multiplied this ratio by the number of people under poverty because that is the population targeted by community health clinics. Therefore, my final demand weight is the population under poverty we would expect to report ill health, given the results of the CPES analysis.

In the city the demand surface is quite similar to the pattern of wellness (Figure 5.2). Low demand exists in the richer neighborhoods west of downtown while demand is high in the surrounding poor (and minority-heavy) areas. Deep reds indicate high demand in the northern part of the city, where spaghetti-like boundaries separate the City of Houston and unincorporated Harris County. The high-demand tracts within the boundaries will be used in location-allocation, but neighboring tracts that fall within the unincorporated areas will be left out.
Figure 5.2. Calculated demand for blended-service clinics in Houston by tract

Location-Allocation

The location-allocation results for the first four clinics can be found in Figure 5.3. If only one new clinic is built it should be in the far northern extent of the city in the edge city of Greenspoint. The second clinic is drawn to Southeast Houston, while the third is located in nearby Ellington. Both the second and third clinics are pulled to the southeast leg of Houston, which borders Interstate 45 and where there are currently no clinics. The fourth and fifth clinics are sited in the western portion of the city. Clinic four, in Southwest Houston, is quite close to
the city edge and the border between Harris and Fort Bend County. The fifth clinic (Figure 5.4) is located in the Westside neighborhood, just north of Interstate 10.

![Maps showing location-allocation results for the first four new clinics.](image)

**Legend**
- Orange circles: New Clinics
- Black circles: Existing Clinics
- Light grey: City Boundary
- Dark grey: Harris County

**Figure 5.3. Location-Allocation results for the first four new clinics**

Table 5.1 shows the median travel distance from the demand points to the clinic by catchment area. Some clinics have very small distances, suggesting small catchment areas and very good access for those living there. At the bottom of the list are clinics with very large distances between demand and the facility. In these large catchment areas, spatial access to services is much poorer. It is possible that there is a very high density of need in the small catchment areas and very little in the large; to compare the two I also made a table of how...
much of the demand was allocated to each clinic (Table 5). While I did not use a greedy approach to adding clinics, I still need to determine how the demand is distributed among the clinics to determine if I should expect to see overwhelmed or empty clinics.

Table 5.2 shows the percent of demand allocated to each clinic after each run of the \( p \)-median model. Running the model without adding any new clinics shows the three clinics-HOPE Clinic, Methodist Satellite Community Clinic, and the Pasadena Health Center—are responsible for more than 13 percent of the demand each. None of these clinics are in the central city; in fact, Pasadena Health Center is not even within the Houston City limits. These three clinics also have above average median distances-3.78, 6.51, and 7.25 miles respectively. On the other hand, three clinics-Montrose, Memorial Main Campus, and Riverside-draw less than one percent of demand each, and all three are located within two miles of the central business district. All three of these clinics have median distances lower than two miles.
Table 5.1. Median Travel Distance by Clinic in Miles

<table>
<thead>
<tr>
<th>Clinic</th>
<th>Existing</th>
<th>One</th>
<th>Two</th>
<th>Three</th>
<th>Four</th>
<th>Five</th>
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<tbody>
<tr>
<td>Riverside</td>
<td>1.35</td>
<td>1.35</td>
<td>1.35</td>
<td>1.35</td>
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<td>4.56</td>
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<td>3.38</td>
<td>3.15</td>
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</table>

The new clinic in Greenspoint would draw some of the demand from the Memorial Satellite Clinics and Acres Homes Health Center. The Southeast Houston and Ellington Clinics are quite close together, and pull in clients primarily from the Pasadena Health Center. The Southwest Houston and Westside clinics draw comparatively less demand, drawing clients from the Baker-Ripley clinic and HOPE Clinic, respectively. By the time we site five new clinics, the Greenspoint clinic serves the most demand, over 10 percent by itself. The five new clinics
<table>
<thead>
<tr>
<th>Clinic</th>
<th>Existing</th>
<th>One</th>
<th>Two</th>
<th>Three</th>
<th>Four</th>
<th>Five</th>
</tr>
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<td>Riverside</td>
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<td>0.80%</td>
<td>0.90%</td>
<td>0.90%</td>
<td>0.90%</td>
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<tr>
<td>Montrose</td>
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</tr>
<tr>
<td>Independence Heights</td>
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</tr>
<tr>
<td>Memorial Main Campus</td>
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<tr>
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<tr>
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<tr>
<td>West Houston Clinic</td>
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<td>1.30%</td>
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<td>1.50%</td>
<td>1.50%</td>
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</tr>
<tr>
<td>Methodist Satellite</td>
<td>13.30%</td>
<td>6.30%</td>
<td>6.60%</td>
<td>7.00%</td>
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<td>14.00%</td>
<td>7.80%</td>
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<td>1.10%</td>
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<tr>
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<td>6.20%</td>
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<td>6.80%</td>
</tr>
<tr>
<td>Ellington</td>
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<td>-</td>
<td>-</td>
<td>5.60%</td>
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<td>Southwest Houston</td>
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<td>-</td>
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<td>-</td>
<td>4.10%</td>
<td>4.20%</td>
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<tr>
<td>Westside</td>
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<tr>
<td>Total Share, New Clinics</td>
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<td>17.80%</td>
<td>21.50%</td>
<td>26.60%</td>
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</table>
together serve nearly a third of the demand, while the other 21 divide the rest. With each new clinic I add the total share of demand increases significantly, suggesting that all of these clinics are meeting unmet (or underserved) demand.

Comparing median distance and demand, we can see that the dominant pattern is the longer the distance the higher the demand. This is not true in every case. Clinics outside of the city limits, such as Sugarland, have very little demand and long distances. However, it does not appear that the present configuration of clinics was planned to maximize convenience or attendance.

Figures 5.5 and 5.6 show how the median distance changes by catchment area as we add new clinics. We can see form these maps that there are quite a few missing tracts, especially towards the center part of the city. ArcGIS will remove any demand point with close to zero demand; these tracts simply do not contain many poor people. The tracts in the city are quite small both because of the close proximity of other clinics and the dearth of demand in several tracts.

Before I put in any new clinics the shortest distances can be found in the central city and the longest in the suburbs; this simply supports the findings in Table 5.1 and 5.2. However, by the time I have places five new clinics (Figure 5.6) the area of short distance (and therefore better accessibility) has increased quite a lot, spreading towards the southern suburbs especially. The Greenspoint clinic, serving the widely dispersed northeast Houston area, has very long distances, but for the most part every catchment area around the edge of the city has improved accessibility.
Figure 5.5. Median distance in miles by catchment, existing clinics and first two new clinics
Figure 5.6. Median distance in miles by catchment, third, fourth, fifth new clinics

Figure 5.7 shows the spatial distribution of the final 26 clinics, sorted by percent of demand served. I split the 21 clinics in half, based on the results of the p-median model. The clinics with the lowest demand weights fall into two categories. The first is clinics outside of the City of Houston limits. This is to be expected and can be explained by edge effects. These clinics
are built to serve primarily residents who do not live in the city. The second category comprises clinics that are nearest the central city. This pattern is clearer when we compare the results with the spatial distribution of the clinics serving the most demand. These high-demand clinics appear to circle around the central city in a fairly well dispersed ring. A quick nearest neighbor analysis confirms the pattern. The clinics in highest demand show a random distribution (NNR=1.05, p=.79), but the lowest demand clinics exhibit significant clustering (NNR=.54, p=.01). These results mirror the results of the distance analysis shown in Figure 5.5 and 5.6.

![Figure 5.7. The spatial distribution of blended-service community clinics, by demand served, including new clinics](image)
Characterizing Neighborhoods

To explain why the new clinics are where they are, as well as to characterize the areas that may be un- or underserved, I used the catchment areas created by the final iteration of the p-median model. All tracts assigned to a facility were dissolved and their census information combined. Figure 5.8 shows wellness scores in the 26 catchment areas. The five new clinics appear to be in areas with relatively high wellness scores, especially when compared to the areas directly east and south of the central city. The small catchment sin the central city exhibit the highest wellness scores on the map, suggesting that the vulnerability of the central city may be commonly over estimated.

Figure 5.8. Wellness scores for each clinic catchment
Because demand was also calculated using poverty data Figure 5.9 shows the percent of people under poverty in each clinic catchment area. Greenspoint and Southeast Houston are above the Houston average poverty rate. Surprisingly, the percent of people under poverty in Ellington, Westside, and Southwest catchment areas is below the city average of 18.6 percent. The most striking feature of this map, however, is the concentration of high poverty in the eastern part of the city, well outside of the central city and its easily accessible clinics.

Figure 5.9. Poverty by catchment area.

Another variable we can use to characterize neighborhoods is age. The nature of homelessness is changing. A few decades ago homeless families were an anomaly; today half of the homeless individuals in Houston are women and children (Houston Coalition for the Homeless 2014). Figure 8 shows the percentage of residents younger than 16. There are fewer young people in the central city than in the suburban areas to the north and southwest. The
Figure 5.10 Percent of residents under 16 years of age.

Figure 5.11 Percent of resident 65 years of age and older
clinics in Greenspoint and Southwest Houston can expect to see more children while clinics in the central city and south Houston serve a proportionally large elderly population.

I also chose to analyze household size. Household size could indicate how many large families are in the area or which areas are somewhat overcrowded. Figure 5.12 shows household sizes across Houston. Greenspoint and Southeast Houston contain very large household sizes. Since Greenspoint has a very large youth population we can assume that there are large young families in the area. Southeast Houston, however, does not have an especially high concentration of children; therefore there may be large households containing multiple adults. Household sizes are very small in the central city, increasing around the rim of the city limits.

Figure 5.12. Average household size around the clinics. The city average is 2.78
Finally, I wanted to characterize the neighborhoods by what races/ethnicities live nearby. I chose to focus on black and Hispanic groups since African-Americans have always been overrepresented among the homeless and the Hispanic population is growing quite rapidly. Figure 5.13 shows the distribution of black residents around the clinics. Greenspoint and the western clinics serve areas with a larger proportion of black residents than the city average. The results are quite different on the southeast side, where the percentage of black residents is well below average. The percent black in the small catchment areas of the central city is quite low and is much higher in the inner suburban ring.

![Percent Black Map](image)

Figure 5.13. Percent black in the areas surrounding new clinics. The city average is 23.6 percent.

Looking at the largest racial/ethnic group in Houston, Figure 5.14 shows the distribution of Hispanic residents in relation to the five new clinics. Southeast Houston stands out immediately, since over three-fourths of the population is Hispanic. Greenspoint, Ellington, and
Southwest Houston are close to the city average of 43.5 percent. The Westside catchment area contains very few Hispanic residents, comparatively. Similar to the distribution of black Houstonians, the proportion of Hispanic residents in the central city is very low.

Figure 5.14. Distribution of Hispanic Residents. The city average is 43.5 percent

Calculating Vulnerability

To further assess the quality of the tracts selected by the p-median model I created a vulnerability index incorporating unemployment, rental property availability, and the total crime index available through Esri Community Analyst. To compute the index I simply added the three z-scores together. High scores indicate high vulnerability, defined as high unemployment, few rental units, and high crime. Low scores indicate more resilient environments for homeless
persons with low unemployment, many rental properties available, and low crime (Mennis, Stahler, and Baron 2012).

The results of the analysis are shown in Figure 5.15. A quarter of the existing clinics are in tracts with vulnerability scores above 1.9, and the median value is 0.3. My new clinics, in comparison, are much less vulnerable, ranging from -3.1 to -0.1.

![Figure 5.15. The vulnerability distribution of clinics in Houston](image)

I also calculated vulnerability scores by clinic catchment area, including the five new clinics. The results are shown in Figure 5.16. Southeast Houston is by far the most vulnerable site selected by the $p$-median model, while Westside should be the most resilient. Vulnerability across Houston follows a now-familiar pattern. The most vulnerable places wrap around the east side of the city, while the central city and western catchment areas are the least vulnerable. The Greenspoint catchment area may be misleading due to its sprawling, discontinuous demand points.
Figure 5.16. Vulnerability by catchment area

Table 6 shows the vulnerability score calculation at the tract level for the new clinic sites. With the exception of Ellington, unemployment is high in each tract, while rental properties are widely available everywhere except the Southeast. Notably, crime is significantly below average in all three tracts except Ellington.

Table 5.3. Vulnerability calculations for tracts selected by the model

<table>
<thead>
<tr>
<th>Tract</th>
<th>Crime Z</th>
<th>Rental Z</th>
<th>Unemployment Z</th>
<th>Vulnerability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greenspoint</td>
<td>-1.47</td>
<td>-1.75</td>
<td>0.15</td>
<td>-3.06</td>
</tr>
<tr>
<td>Westside</td>
<td>-1.12</td>
<td>-2.23</td>
<td>0.43</td>
<td>-2.95</td>
</tr>
<tr>
<td>Southwest</td>
<td>-1.34</td>
<td>-1.93</td>
<td>1.51</td>
<td>-1.75</td>
</tr>
<tr>
<td>Ellington</td>
<td>0.35</td>
<td>-0.44</td>
<td>-0.57</td>
<td>-0.66</td>
</tr>
<tr>
<td>Southeast</td>
<td>-0.63</td>
<td>0.29</td>
<td>0.19</td>
<td>-0.14</td>
</tr>
</tbody>
</table>
Observing Neighborhoods

To further evaluate the results of my location-allocation model I made site visits to each tract selected. I paid special attention to the quality of housing, services available, transportation availability, and environmental characteristics indicative of social attitudes, political influence, and general upkeep. The quality of the neighborhood can change recovery outcomes and may influence the likelihood of recurring homelessness.

Greenspoint, the first site selected by the model, is comprised mostly of older, tightly packed apartment complexes (Figure 5.17). Many of the complexes had boarded up windows, window-unit air conditioners, and one even had police tape across the entrance.

![Figure 5.17. Two residents carry gas through a neighborhood in Greenspoint](image)

Services and businesses in Greenspoint are quite limited. There are medical offices in the area, but all are private. There are many vacant warehouses and buildings for lease (Figure 5.18). Liquor stores tend to dominate the retail mix. A few community-based organizations such as the Northwest Youth Community Center suggest some degree of community cohesion (Figure 5.19). Because Greenspoint was established as an energy corridor in the 1970s oil boom
it has great infrastructure: sidewalks on main roads, paved drainage ditches, streetlights, covered bus stops, and landscaped medians. In addition, there is a new housing development and skate park being built. However, large amounts of dumped trash, gang graffiti, and overgrown lawns within the subdivision suggest that the area remains depressed and subject to the typical trials of urban blight.

Figure 5.18. Empty commercial properties in Greenspoint

Figure 5.19. A community center in Greenspoint
Greenspoint is a good comparison site for the second clinic in Southeast Houston. This area has clearly never had political power. Instead of landscaped medians and covered bus stops, Southeast Houston has no sidewalks, no streetlights, and no drainage ditches. These are amenities that require the political power to lobby the city government. This neighborhood was full of illegally dumped trash and standing water (Figure 5.20). Signs and services indicate that this tract is home to a large Hispanic population (confirmed by the analysis in Figure 5.14). None of the four tracts had great, healthy food options, but Southeast Houston is the only neighborhood that could be classified as a true food desert; the only place available to buy any food is the gas station. There is not even a fast food restaurant. It is little wonder, then, that this site stood out on the vulnerability map.

Southwest Houston and Ellington are comprised primarily of single-family homes. Both areas were once the new suburbs, but the original tenants have long since left to pursue possibilities in the outer sprawl. In Ellington I saw quite a bit of infill gentrification. In Houston piecemeal gentrification is the norm, since there is very little zoning (Figure 5.21). This creates a strange situation where a large gated mansion sits in the middle of a block of small houses, some abandoned. Retail and food service are the primary businesses in the area, though much of this is vice-related: bars, liquor stores, discount tobacco, and strip clubs thrive (Figure 5.22).
Figure 5.20. Standing water and overgrown signs in Southwest Houston

Figure 5.21. Two homes, one street in Ellington
The two western tracts contain a mix of both apartments and single-family housing. In both, blighted housing occupied one portion of the tract while luxury apartments or well-maintained planned subdivisions occupied the rest. In the Westside tract luxury condos and apartments are slowly overtaking the older dilapidated (and cheap) apartments (Figure 5.23). This tract runs along Westheimer Drive, one of Houston’s main thoroughfares. Food is plentiful, but the quality of food changes noticeably between the poorer and richer areas. Near the crumbling apartment buildings we can find fried chicken and fish, hamburgers, corner stores, and doughnuts. The mix slowly changes until two miles away wealthier people dine on Café Express salads, kebabs, and organic groceries.
Finally, I visited the Southwest Houston site. This tract, like Westside and Ellington, is relatively well incorporated into the urban system and there are quite a lot of services available for medical and social service needs. Food is mostly available from either fast food restaurants or specialty ethnic markets, such as African or Hispanic grocers. Because this tract is slowly drawing in planned neighborhoods and the associated homeowners associations, most of the recreational services have been privatized (Figure 5.24). There is very little publicly usable green space in these neighborhoods. This neighborhood, like all of the tracts except Westside contains more pawn stores, check cashing, and payday loan outlets than banks or credit unions, suggesting poor integration with the formal global economy.
Figure 5.24. Where HOAs and luxury apartments have been established most services have been privatized.
6. DISCUSSION

Even though the initial nearest neighbor results determined that existing blended-service community clinics are randomly distributed, I believe the rest of the analysis provides evidence of a glut of services in the central city. Based on my demand estimation, calculated using poverty and self-rated wellness, the clinics in the central city serve very small catchment areas. While accessibility in the city is high, my analysis suggests that the people who need the access are not living here, at least not permanently. The eight low-demand clinics clustered in the central city combined were allocated only 13.2 percent of the total demand. In contrast, the nine clinics on the edges of the city serve the remaining 86.8 percent. Moreover, all five of the new clinics I located were pulled to suburban areas. This distribution matches the pattern identified in other cities (Metreaux et al 2012, Rukmana 2011, DeVerteuil et al 2007, Dear 1977a).

The centrally clustered clinics may act as a structural contributor to vulnerability. If these clinics are large, clean, or well publicized then they will attract people to them. Since the clinics are so close together these vulnerable people will become concentrated in place, especially if they permanently relocate. Building supportive housing around these clinics may only deepen this vulnerability by making the central city even more attractive to highly vulnerable populations. Of course, it is also possible the city clinics are very small and therefore do not have much gravitational pull. However, this is unlikely since most of the systems have a main campus in the city and satellite facilities farther away; the satellite facilities are routinely assigned much larger proportions of demand in large catchment areas.
The readily accessible clinics in the central city have characteristics beyond demand and distance that distinguish them from the higher-demand clinics in the periphery. Surprisingly, these central clinics are in neighborhoods with low poverty, small household sizes, and fewer black or Hispanic residents than the larger peripheral catchments. The assumption that the inner city is poor, black, and underserved may be completely out of date.

In comparison, clinics with large catchment areas and high proportions of demand tend to be outside of the inner beltway. In general, these clinics are in places with more black and Hispanic residents, higher poverty rates, larger household sizes, and more children when compared to the city. Often in medical geography we use poverty and minority status as a proxy for vulnerability; if that assumption is sound then these suburban clinics are much closer to the vulnerable populations (Shih et al 2011; Carpenter-Song et al 2010; Van Zandt and Mhatre 2009). Since the distribution of these clinics is random based on a Nearest Neighbor Analysis, attaching housing may create a more vulnerable block or street, but it should not contribute to a larger “psychiatric ghetto,” a concern in the central city. These clinics may currently be overburdened, however. Each of the five clinics I created drew demand away from these outer clinics. The catchment areas of the central clinics changed very little.

The five new clinics are sited in areas with characteristics more similar to the existing high-demand clinics. Nonetheless, Houston is a very large and diverse city, and the five sites I found are spread widely across its 650 square miles. Each site is slightly different, and each can contribute to a better understanding of vulnerability in the suburbs.

The first new clinic I sited is in Greenspoint. Greenspoint was once the energy capital of Houston; a few glass high rises and corporate offices remain in the central business district. The
area rapidly became blighted after the collapse of the 1970s oil boom, as the young professionals who rushed in to claim energy jobs left just as quickly. This is why Greenspoint is comprised primarily of old, cheaply built apartment complexes. Houston city councilman Jerry Davis described Greenspoint in 2012 as, “that concrete jungle, where you’re surrounded on all sides by apartments (Moran 2012, p. 1).” Once the oil money was gone no one wanted to live in an apartment in the far suburbs, so rental prices plummeted, drawing in the poor. In 2005, 150,000 New Orleans residents permanently relocated to Houston following Hurricane Katrina, and Greenspoint absorbed about half (Dickerson 2010). Cheap, vacant apartments seemed like a great deal to FEMA and the City of Houston. The place, already vulnerable, received thousands of new vulnerable people (Henneberger 2008). A year after relocation the unemployment rate among this group was still a staggering 25.6 percent. During this first year in Houston the percentage of evacuees earning less than $15,000 a year rose from 44 percent to 74 percent (Dickerson 2010). Today Greenspoint has a reputation among Houstonians as a suburban ghetto, nicknamed “Gunspoint.”

The characteristics of Greenspoint that I have identified through this analysis confirm this vulnerability, but also question some of the assumptions commonly made about this area. Greenspoint is overwhelmingly minority majority; half the residents are Hispanic and another third are black. This is the most youthful of the five new clinic areas and the average household size is quite large. We can infer from this that there may be a lot of young families in the area. Surprisingly I also discovered that the crime index for this area is lower than the city average, despite its reputation. Moreover, Greenspoint has the highest poverty of the five new clinics. There would be little political opposition to a new clinic here. For decades Greenspoint has
been used as a dumping ground for very vulnerable people, and the model indicates consistently high need for mental and physical health services.

Unlike Greenspoint, Southeast Houston has never attracted much investment. Sandwiched between a concrete crushing facility and a chemical plant, the tract identified by the p-median model is full of small, run-down single-family housing. There are no schools, social services, grocery stores, restaurants, streetlights, sidewalks, or drainage ditches. Poverty is high, household sizes are large. The people who first settled here were the low-class industrial workers, and they remain to this day, although the dominant language has changed from English to Spanish. It is not surprising, then, that this tract is the most vulnerable of the five. In her article “Breathless in Houston” Janice Harper (2004) describes the situation many poor residents of east Houston face; environmental contamination due to heavy industry negatively impacts the health of those living there, yet they must stay there to retain employment. This is another version of vulnerability. The place is vulnerable precisely because of the jobs that attract more vulnerable people, who do not have the political or economic power to effect change. The conditions in the neighborhood continue to deteriorate. For precisely this reason I would be uncomfortable building new supportive housing in this region. By doing so we may contribute to escalating vulnerability in the neighborhood as well as among the chronically homeless people we aim to serve. Therefore, the model I built may need to be further optimized on vulnerability to find the best locations for supportive housing, not just blended-service community clinics.

Ellington, just a few miles to the southeast may provide a better location. Compared to Southeast Houston the vulnerability of the area is much lower. This area is also largely Hispanic
and young. Ellington has a lot of services, retail, and food, but it is a prime example of a vulnerable economic mix. Liquor stores, pool halls, strip clubs, and pawnshops crowd the main thoroughfares. Despite a similar relationship with industry as Southeast Houston, Ellington has the lowest unemployment of all five tracts. People may be finding jobs within the commercial district; however, some of these establishments may be contributing to the higher than average crime rate. Pool halls, nude dancers, and other vice-related commerce may attract people to the area to engage in illicit gambling, prostitution, drug sales, or gang related activity (Furr-Holden, Milam, and Fakunle 2014; Capers 2013).

The fourth and fifth clinics are located in the western part of the city, and this area appears to have a slightly higher proportion of black residents, higher median ages, and smaller household sizes. The history of Southwest Houston is quite similar to that of Greenspoint; at one point it was home to people with oil money, but they have long since left. Poorer people now occupy the apartments built during the last frenzied oil boom. Unlike Greenspoint, however, the tract containing the selected clinic site is divided in half. In one half is Ensley populated apartments with few amenities, no green space, and limited transportation. Occupying the other half is planned suburban developments with wide lawns, pools and trees-all private of course. The construction of a new social service facility here may be more politically fraught than in in Greenspoint.

Finally, the fifth new clinic is located in the Westside neighborhood, which has low poverty, small household sizes, and low vulnerability scores. This is an area that appears to be moving out of vulnerability due to new development. Developers have been moving west along Westheimer Drive for decades, and Westside appears to be right at the frontier. Older
apartment complexes are being replaced by new luxury condos, and the retail mix should start to change quickly. My census data is primarily from 2010 and the TIGER/LINE road maps I created to conduct the site visits are from 2012. By the time I visited the site in 2014 the street plan was completely different. I suspect my model placed a clinic here to serve people who have been forced out, and no longer live here. More research would need to be done to determine where these people went. We can assume they are recreating their vulnerability in a different place, and that is where we want to intervene.

Considering un- and underserved areas in general I am most concerned about the areas outside of the city limits. For example, even with five new clinics added to the 21 existing, Greenspoint still serves 10 percent of the demand by itself. However, this clinic is built on the far northern city limits, surrounded by unincorporated Harris County. These areas are vulnerable as well and exhibit high demand for services (Figure 5.2). However, this analysis only considers tracts within the City of Houston. Since individuals can attend community clinics in any city or county, the functional region does not match the formal region of the City of Houston. A clinic built with city money in Greenspoint to accommodate 10 percent of the city demand would quickly find itself overwhelmed by the need in the surrounding county; we could see three to four times the traffic we would anticipate if we only looked at the system at the city scale. Moreover, these areas will continue to be underserved with a city-focused planning model, and we should expect to see service-seeking drift continue inwards.
7. CONCLUSION

The model I built chose five clinics on the outskirts of the city limits to accommodate suburban demand. At the moment there are many blended-service community clinics in the inner city serving small catchment areas containing very little of the calculated demand. Between the inner and outer beltways, however, the existing clinics serve large populations and are less easily accessible; the new clinics were sited to relieve this stress. Based on these results I believe Houston exhibits a spatial mismatch between where needy people live and where services are most available. Introducing more fixed costs to this system (i.e. building new supportive housing) may only serve to reinforce the vulnerability of this place. The City of Houston could accidentally contribute to the continuation of the psychiatric ghetto.

This initial study is limited in many ways. The p-median model assumes that people will use the facility closest to them; this may not be the case, especially with mental health. The demand is based on who is poor and sick, not on a history of homelessness. Homelessness that occurs due to other factors like domestic violence is not accounted for. Moreover, the model I built does not consider clinic capacity. I make the assumption that resources could be evenly distributed to all of them, which is unrealistic. Finally, the model is only as good as the data. As I saw in Westside it is possible that an area of need in 2010 has completely changed by 2014. I cannot definitely say the results would be the same if I had today’s data to run the analysis.

Despite the limitations I believe further study of the geography of mental illness and homelessness in Houston would prove fruitful. As I mentioned in the discussion, analysis needs to somehow take into account the functional region of Houston as well as the formal region of the city limits. Metropolitan Houston extends far beyond the city boundary, and these are the
people that may be driving service-seeking drift patterns. For a more realistic system based on how people behave the scale of analysis needs to change.

There are other ways to use the p-median model to find new information. The demand map can be recalculated for each census year, so it is possible to build historic models of the community clinic system. This research would be able to show the change in spatial mismatch over time. We could also introduce hierarchical modeling into the mix. Just because a clinic has mental health resources does not necessarily mean it has someone qualified to administer talk therapy or prescribe psychiatric medicine. In addition, there are other non-profit and government mental health clinics spread throughout the city. My model is also limited because it ignores the veterans’ health system. A more complex model could handle all of this information. Another option would be to collect utilization data from as many clinics as possible and create an odds ratio by dividing the observed proportion of demand by the expected proportion found in the p-median results. These results could reveal drift patterns and help refine how to calculate demand for these services.

Finally, I expect that my research will continue on service-seeking migration within the city. Only Rukmana (2011) has recently attempted to describe and classify this behavior, but his analysis is quite coarse. Surveys and interviews with homeless persons in Houston may help identify origin hotspots, indicating ideal locations for early intervention. Furthermore, this would reveal more information about the push and pull factors important to homeless and mentally ill persons. Much of our current research relies on assumptions about what this population wants and needs.
This paper contributes to the literature on the geography of homeless and mentally ill persons in the United States by examining the distribution of blended service clinics in a sprawling Sun Belt city. It appears as though the issue of centrally clustered services for the homeless will not simply sort itself out through market forces. This is why geographers must be involved with public service planning. This example of structural violence has a distinct spatial flavor and geographers may have been able to stop the psychiatric ghetto before it began. Now, 50 years later, people with spatial perspectives are needed to dismantle and reform a deeply entrenched system that often hides vulnerable people instead of helping them.
8. REFERENCES


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APPENDIX

SAMPLE QUALITATIVE ASSESSMENT TOOL FOR SITE VISITS
TRACT #1

Qualitative Assessment:

Type of Community:
Residential  Industrial  Commercial  Vacant  Other (explain)

Available Services:
Grocery Store  Bank  Government (school, lib)  Health (explain)

Sidewalks:

Bus Stops:

Green Space:

Other observed environmental characteristics: