PREDICTING TREATMENT RESPONSE AND NO-SHOW APPOINTMENTS FOR LOW-INCOME AND RURAL POPULATIONS AT A COMMUNITY MENTAL HEALTH CLINIC

A Dissertation

by

DONALD KLEINE-KRACHT

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Chair of Committee,	Daniel F. Brossart
Committee Members,	Carly E. McCord
	William Rae
	James. N. Burdine
Head of Department,	Shanna Hagan-Burke

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ABSTRACT

Mental health disparities for marginalized populations are a critical issue requiring immediate national research attention. This study, which utilized archived data from a community mental health clinic in Bryan, Texas, explored how a client's level of income and rurality predicts their treatment-related outcomes. This study utilized two adult samples: a total sample (n = 330) and an outpatient clinical subsample (n = 240). A client's level of rurality was identified by the distances they travelled to the clinic and the population density of their home address, while a client's level of income was determined through their session fee derived from their income-level on a sliding fee scale. Logistic regressions were used to predict a client's positive treatment response and negative binomial regressions were used to predict No-Show appointments. This study was not able to significantly statistically predict treatment response, but was able to predict No-Show appointments. Population Density, Distance Travelled, and Session Fee were statistically significant in predicting No-Show appointments. Marginal analyses were also used to explore differences in the levels of rurality and income in the statistically significant model. Results suggest that clients living in lower populated areas, travel shorter distances, and pay lower session fees were associated with more No-Show appointments than clients in higher populated areas, drove further distances, and paid more per session. This study further provides recommendations for future research and policy-makers who aim to alleviate treatment access barriers for low-income and rural client populations.

DEDICATION

This dissertation is dedicated to my loving and supportive partner, Nina Inez Quintana. I look forward to our years ahead when working on our dissertations is only a fond memory.

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CHAPTER I

INTRODUCTION

As the United States' general population is increasing in diversity, the 2001 Surgeon General's report emphasizes more direct and thoughtful interventions to improve and maintain the health of differing ethnocultural groups (U.S. Department of Health and Human Services, 2001). While there has been a longstanding emphasis over the past half-century to reduce health disparities for differing cultural populations, mental health care has only become a focus of national health within the past two decades. Both the Institute of Medicine and the National Institutes of Health have since called for research to address disparities in mental health care that negatively impact marginalized populations the most (U.S. Department of Health and Human Services, 2001). In further agreement, the Federal Collaboration on Health Disparities Research (FCHDR) identified mental health disparities as one of four areas, among 165 other health disparity conditions, that require "immediate national research attention" (Safran et al., 2009).

Defining Health Disparities

Health disparities have been uniquely defined by several prominent agencies. These definitions are largely dependent on the agency's aim and purpose (Braveman, 2006). The National Institute of Mental Health (NIMH), Substance Abuse and Mental Health Services Administration (SAMHSA), and The Office of Women's Health all utilize working definitions of health disparities that include a broad range of categorical variables such as prevalence, morbidity, mortality, survival rates, quality of services, and outcomes (Safran et al., 2009). These variables are considered and compared from a specific population (e.g. racial, ethnic, gender, geographic, and economic) in comparison to the outcomes of the general population (Safran et al., 2009).

Braveman (2006) critiques these broad definitions and clarifies that disparities are not encompassing of all health differences across populations. Instead, a health disparity is best expressed as a form of inequality seen in a specific type of health care, such as in mental health, cardiovascular health, obesity, diabetes, etc. Additionally, these inequalities can be shaped by public policies to amend the social discrimination against marginalized populations (Braveman, 2006). Marginalized populations are defined as populations that are limited to or excluded from social, economic, cultural, or political power due to race, religion, age, gender, sexual orientation, and/or other cultural groupings (Given, 2008). As previously referenced, marginalized populations are often compared to the general population across health outcomes to identify disparities. However, as the U.S. general population is becoming more stratified, Braveman (2006) suggests that disparities and inequalities should be reflected and measured between "advantaged" and "disadvantaged" groups. The overarching aim to provide health equity is to therefore eliminate these health disparities by implementing effective social policies.

Safran et al. (2009) suggest that the CDC's definition of mental health disparities, may be the most encompassing as it specifies mental health disparities that can be seen in three categories: (1) Disparities represented in the amount of attention given to mental health compared to other public health issues, as impacted by funding, policies, research, etc., (2) Disparities between the health of an individual with a mental illness compared to those without, and (3) Disparities found between populations who receive unequal quality, accessibility, and outcomes of mental health care. While "no one research project, approach, or paper would be sufficient to address, or even fully recognize, the vast universe of mental health disparity that exists" (Safran et al., 2009, p. 1962), researchers will need to address all three categories to better alleviate this national problem. Taking a three-prong approach to reduce mental health disparities has implications for clinicians, policy-makers, and most importantly, the individuals negatively impacted by these inequalities.

This study attempts to address all three of the CDC's criteria by: (1) Utilizing mental health clinical data to explore mental health disparities in treatment-related outcomes, (2) Exploring differing treatment responses for clinical and non-clinical levels of mental health distress among marginalized populations (i.e., Low-income and rural populations), and (3) Reflecting on ways to improve treatment-related outcomes for these marginalized populations. More specifically, this study attempts to assess how the levels of income and rurality predict No-Show appointments and treatment response.

Disparities in the Literature

The Department of Health and Human Services (DHHS, 1999) acknowledges that we know more about the disparities themselves than the reasons behind them. Researchers have not been able to offer a conclusive explanation or solution to mental health disparities aside from acknowledging an assortment of barriers (U.S. Department of Health and Human Services, 2001). Additionally, much of the existing literature focuses on mental health disparities among ethnic, racial, and gender demographics (Sorkin, Murphy, Nguyen, & Biegler, 2016), while ignoring or overgeneralizing other variables such as age, sexual orientation, locale, and religion. The CDC places great emphasis on specific "social determinants" or social barriers that contribute and exacerbate these disparities, which include factors such as employment, income, and housing. Each factor can vary considerably within and between these populations confounding our understanding of mental health barriers (Safran et al., 2009). For example, it has been identified that African-American's have a single "stigma" to treatment (Gary, 2005), while African-American's who are elderly face a "double stigma" to treatment (Sorkin, Murphy, Nguyen, & Biegler, 2016; Sorkin, Pham, & Ngo-Metzer, 2009). Not only is it important to understand how each factor or "stigma" is impacted by treatment access barriers, but researchers should investigate possible interactions, when these "stigmas" become doubled or tripled.

This study examined how the levels of income and rurality predict the probability of psychotherapy clients achieving positive treatment response and having No-Show appointments. This study also explored potential interactions between income and rurality variables to better understand a potential "double stigma" to treatment, which may occur when the access barriers hindering these populations overlap.

Population Glossing

There are considerable differences between and within cultural populations. While this is known, some of the contemporary literature on marginalized populations tends to compile, overlap, and generalize the unique issues of one population to the other (Sorkin et al., 2009). This often occurs in race or ethnicity-specific measurements such as with American Indians and Alaskan Natives whom are culturally distinct, yet lumped together (Phinney, 1996; Trimble & Dickson, 2005). Additionally, the encompassing label of Hispanic comprises of several unique cultural groups and is further problematic for providing evidenced-based treatments to these populations (Trimble & Dickson, 2005). This "ethnic glossing" can be deceptive as it relates to applying policies and interventions recommended by the existing literature, which is based on findings that may be overgeneralized.

A similar form of glossing may also occur in the literature regarding rural and low-income populations. Hartley (2004) acknowledges that there is considerable variability and complexity of rural culture due to both variations in economic and educational variables, but also variations in the physical and historical environment. Rural populations, in general, face many health disparities in comparison to urban and suburban residents, such as higher rates of smoking, obesity, less nutritional diets, and less exercise (Morgan, 2002); interpretation of these outcomes become further complicated when it is noted that they also highly correlate with low-income and less-educated populations (Hartley, 2004). Additionally, within America's rural culture there lies considerable variation in health behaviors and outcomes. These regional differences suggest that research methodology and public policies aimed to address mental health disparities need to become more nuanced and specific to the population being targeted. It is therefore important to not overgeneralize treatment access barriers from one population to the other.

A consideration as to why this "glossing" may occur is due to issues of multicollinearity between populations (Murray, Trudeau, & Schaller, 2011). Multicollinearity is a statistical limitation that occurs when one or two groups cannot be significantly distinguished from one another, as they overlap in their identifiers or responses. However, much of the conventional methodological ways to determine one's belonginess to these marginalized populations can be improved upon with recent technological measurements such as geospatial analysis, which is utilized in this study.

The Need for Cost-Effective Policy Intervention

A critical consideration for community agencies and policy-makers who are focused on reducing mental health disparities is to determine how to do so effectively. Community mental health clinics are often the primary source of mental health treatment for low-income and rural populations (Jameson, Chambless, & Blank, 2009). They are typically limited in their resources to provide treatment. This includes few available providers, inadequate clinic space, limited to no access for specialized care, long wait-lists, and so forth. Therefore, when addressing mental health disparities, it is essential to identify how to serve these populations in a way that will have positive outcomes for both the community clinic and the individual in a cost-effective manner.

Research that identifies how treatment access barriers impact the outcomes of rural and low-income populations is essential to guide the allocation of limited resources to better treat these marginalized groups. Kalpinski (2014) argues that "outcomes and treatment effectiveness are vital information for those practitioners providing brief mental healthcare to individuals living below poverty level. Data that reflects positive treatment effectiveness can help provide a rationale for federally qualified healthcare centers to maintain their funding from local, state, and federal entities" (p. 70).

Previous research has identified that low-income and rural populations have worse treatment outcomes compared to the general population (Hartley, 2004; Safran et al., 2009; U.S. Department of Health and Human Services, 2001). However, it is not clearly known how these disparities are reflected within the variation of these marginalized groups. This is especially relevant as rural health researchers conclude that effective policy interventions must be based on differences among rural regions (Hartley, 2004). Research that can answer this question will aid policy-makers on the direction of their enacted interventions to have the most impact based on limited community resources.

A New Technological Methodology

Safran et al. (2009) calls for new and increasingly innovative technology to better understand treatment access barriers and mental health disparities. Previous research has been limited in scope based on the methods required to analyze, interpret, and infer conclusions from mental health disparities. Literature regarding rural and low-income populations has tended to focus on distance to the clinic (Bell, Kidanie, Cai, & Krause, 2017), annual income (Berenson, Doty, Abrams, & Shih, 2012), and insurance coverage (McGuire & Miranda, 2008) to provide an indication of their belongingness to these marginalized groups. While these indicators can be beneficial to identify individuals, they may be too inclusive or inaccurate. Furthermore, these methods are not able to detect important nuanced factors such as access to roads, bus routes, and changing financial hardships through the course of treatment, which would provide a more detailed picture of treatment access barriers for low-income and rural populations.

Geospatial analysis has become an innovative way to gather such information, as this analysis relies on gathering and manipulating satellite images and geocodes gathered through GPS, which allows for additional factors to be considered such as street addresses, postal codes, or other geographic identifiers. Geospatial analysis is also a proven effective tool in several research domains such as public health, sociology, and epidemiology (Kumar, Liu, & Hwang, 2012). Further advancements in mapping technology and geospatial programs such as ArcGIS have made this form of analysis applicable to analyzing mental health disparities. This study utilized geospatial software to determine the belongingness of mental health clients to rural and low-income groups and further provides maps noting client's access to roads, their distance in miles to the mental health clinic, and the varying population density and median household income of the area in which these clients live. There is little to no known research using this methodology (through geocoding) to identify rural and low-income populations and how their identifiers predict treatment-related outcomes.

Aim of the Study

This study's aim was to addresses several questions and issues related to mental health disparities for rural and low-income populations in southeast Texas. First, is the way this study defines rural populations as it utilizes both a Population Density variable and a Distance Travelled to the clinic variable. This aimed to address the question: "Which rurality variable (Population Density or Distance Travelled) better predicts treatment response and No-Show appointments?" Furthermore, this study aimed to explore potential "glossing" issues within the literature by determining if low-income and rural clients could be distinguished from one another in their treatment-related outcomes. This study can also be used by policy-makers to efficiently guide clinic resources to improve the probability of positive treatment outcomes for this rural and low-income sample. This study also aimed to offer recommendations to alleviate potential treatment access barriers that may be impacting the psychotherapy clients in this study. Understanding how treatment access barriers impact these populations is essential to understanding mental health disparities from a more nuanced perspective.

Last, this study offered a more detailed picture of a rural and low-income client population through a geospatial statistical program, which has only recently been possible. While the data and outcomes are most applicable to this distinct client population in this area of Texas, this innovative methodology, used in this manner, can be used by researchers to analyze mental health disparities at a national and international level. This study aimed to contribute to the rapidly growing field of geocoding, particularly as it pertains to predicting treatment-related outcomes. In final consideration, this study offers new relevant directions pertaining to mental health disparities, treatment access barriers, and low-income and rural populations that should be addressed in future research.

Research Questions:

This study attempted to answer the following questions:

1) Which rurality variable (Population Density or Distance Travelled) is a stronger predictor of treatment outcomes (RC and CSC) and No-Show appointments?
2) Which variable (Session Fee or Population Density/Distance Travelled) is a stronger predictor of treatment outcomes (RC and CSC) and No-Show appointments?
3) Will a model with rurality and income variables (Population Density, Distance Travelled, and Session Fee) better predict treatment outcomes (RC and CSC) and No-Show appointments over models with only rurality variables?
4) How do treatment-related outcomes vary across the levels of rurality?
5) How do treatment-related outcomes vary across the levels of income?

CHAPTER II

LITERATURE REVIEW

Mental health disparities are theorized to occur and worsen as a result of treatment access barriers, which in turn, negatively impacts the treatment outcomes of individuals within marginalized populations (Penchansky & Thomas, 1981). Treatment access barriers can best be defined as factors that inhibit, discourage, or otherwise prevent an individual from seeking treatment or intervention when necessary. Mental health treatment access barriers impact all Americans across cost, availability of services, specialization of services, and stigma towards mental health (U.S. Department of Health and Human Services, 1999). However, these barriers impact disadvantaged or marginalized populations most profoundly, leading to significant disparities across a number of mental health outcome measures compared to advantaged populations (U.S. Department of Health and Human Services, 2001). Furthermore, when examining mental health treatment barriers, researchers commonly focus on how these barriers negatively impact *access* to care. Treatment access, used in this manner, is described by Saurman (2016) as "enabling a patient in need to receive the right care, from the right provider, at the right time, in the right place, dependent on context" (p. 36).

Theory of Treatment Access

Penchansky and Thomas (1981) conceptualized a theory of access that assesses barriers to treatment across four dimensions: Availability (e.g., "I couldn't set up an appointment due to limited availability"), Accessibility (e.g., "I don't have a means of transportation to attend treatment"), Affordability (e.g., "I don't have insurance", "The cost for treatment was too high"), and Acceptability (e.g., "I'm worried what other people will think"). These dimensions are referenced by researchers and policy-driven agencies to better target specific mental health disparities. Additionally, Saurman (2016) goes on to add Awareness (e.g., “I don’t think I have a problem”, “I don’t know where to go for treatment?”) as a fifth dimension. This theory of treatment access not only focuses on these separate, yet interconnected dimensions, but also emphasizes the importance of adequate service design, implementation, and evaluation (Saurman, 2016). This suggests that research and interventions designed to reduce mental health disparities should focus implementation both at the individual and systemic levels.

Researchers are becoming more aware of treatment access barriers and how to categorize them. However, a significant challenge remains in conceptualizing and understanding how these barriers vary within and across marginalized populations. Not only is the effect of these barriers expressed differently within cultural groups, but the problem becomes multifaceted as there is considerable intersectionality across ethnicity, gender, religion, geographic region, age group, sexual orientation, profession, and income that cannot be ignored. When examining disparities in treatment for psychological disorders “it is crucially important to develop greater specificity in our understanding of contextual factors;” this requires an intersectional and dimensional approach (Banks & Kohn-Wood, 2002, p. 178). These considerations make it difficult for researchers to isolate the access barriers that affect which populations the most and to what degree. Additionally, there is limited research that identifies how these barriers overlap when members belong to more than one marginalized group (Alegria, Vallas, & Pumariegra, 2010).

Identifying Income

Income can best be defined as the wages, salaries, profits, rent, or any other earnings received (Case & Fair, 2007). This economic variable has been commonly used in population-based studies, particularly in addressing health disparities and inequalities. This in large part is due to income being related to socioeconomic status (SES) and is easier for participants to report and researchers to collect. SES extends to other important variables such as education, occupation, and wealth, collecting such additional information, but can be problematic to collect as it extends to marginalized populations when information is not as accessible (Snyder, Dillow, & Hoffman, 2000). SES can be conceptualized as either relative or absolute income. Relative income is derived from a person or family's savings and their prospective consumption in comparison to others within their comparative society, while absolute income relates their savings and consumption to all societies. In wealthier, developed nations, relative income is largely used as an indicator of poverty and wealth (Yu & Chen, 2016).

Income and poverty are further related constructs. In 2015, the U.S. poverty threshold for a family of four was based on an income of $24, 257, which made up 13.5 percent or 43.1 million people in the United States (Proctor, Semega, & Kollar, 2016). At the same time, the median household income was listed as $56, 516 per year for a family of four. This median income was 1.6 percent lower in 2007 and 2.4 percent lower than the income peak in 1999 (Semega, Fontenot, & Kollar, 2017). This identifies a deteriorating middle class that has left a U.S. general population more stratified at both lower and upper ends. The Gini index (the most common measure of household income inequality) has increased 5.5 percent since 1993 (the earliest year available for comparative measures; Proctor et al., 2016). This has notably increased since 2007, which reflects the financial burdens of the most recent recession. Further examination of this income inequality reveals that African-Americans and Hispanic populations make up 22% and 19% of this group respectively, which is more than double than the Non-Hispanic White population at 8%. Additionally, single mothers (27%), adults who are unemployed (31%), the disabled (27%), and those without a high school diploma (25%) are disproportionately represented in this population (Semega et al., 2017). The poverty rate among children under 18 years old is particularly concerning with 18% of all children belonging to this disadvantaged group (Semega et al., 2017). As identified, the lower-income population is growing and largely consists of already marginalized populations.

Low-income populations experience several structural inequalities across a myriad of social dimensions in America (Chen & Escarce, 2004). When identifying how this population is impacted by access to mental health care, there is substantial literature that notes structural barriers to care, such as transportation, cost, and location (Anderson & Amstead, 1995; U.S. Department of Health and Human Services, 1999; U.S. Department of Health and Human Services, 2001). However, research has revealed significant variation of access and utilization of mental health care across race, geographic proximity to services, gender, SES, and mental illness type (Drapeau, Boyer, & Lesage, 2009; Miranda & Green, 1999; Mitura & Bollman, 2003; Padgett, Patrick, Burns, & Schlesinger, 1994; Sterk, Theall, & Elifson, 2002). Slaunwhite (2015) identified that both men and women in low-income households, were significantly likely to report all types of barriers to care (affordability, accessibility, availability, and acceptability), but there were significant differences in the likelihood of endorsing certain barrier-types, such that men were more likely to report acceptability barriers, while women reported availability and accessibility barriers.

It is further important to note how the various cultural groups within the low-income population are affected and differ in their barriers of mental health treatment access. Hispanic Americans are less likely to receive mental health care than non-Hispanic White populations and are more likely to go to primary health providers than mental health specialists (Vega et al., 1998) indicating acceptability barriers to treatment. Additionally, American Indians and Alaskan

Natives report availability and accessibility barriers in comparison to other ethnic minority groups (Sarche & Spicer, 2008), African-Americans report less access to mental health services than White populations (McGuire & Miranda, 2008), and the elderly report poor access, awareness, and affordability barriers (Jimenez, Cook, Bartels, & Alegria, 2013). A significant contributor to these disparities is related to the high percentage of those uninsured and do not qualify for public coverage through their profession (Zuvekas & Taliaferro, 2003), as affordability barriers are likely interconnected with these other dimensions. Overall, ethnic minorities report significant mental health treatment access barriers across all identified barrier-types, but there are significant differences within and between these groups in terms of how they experience these barriers (Petterson, Williams, Hauenstein, Rovnyak, & Merwin, 2009).

Rural Populations

Rurality in the United States has changed significantly over the past century, and has led to rural residents becoming a minority (U.S. Census Bureau, 2011). The U.S. census (2011) reflects a populace of 308 million and identifies that 21% of the entire general population reside in either rural or small-town America. This was once 50% of the general population in the 1920s. Today, roughly half of the U.S. general population is represented in suburban or exurban communities, while 30% live in urban zones of the nation's largest cities (U.S. Census Bureau, 2011).

Defining rurality has proven a difficult task and has traditionally taken an urban-centric perspective, as urban and metropolitan areas are designated the focal point with other areas being secondary. To illustrate this point, the U.S. Census in the 1940s began collecting and tabulating block data (the smallest geographic area defined by the census) for utilization of urban communities to better distinguish areas by streets, roads, railroads, or bodies of water. For the

1990 decennial census, block data was finally tabulated for the rest of the nation due to the import and relevance to small-area geographic studies (U.S. Department of Commerce, 1994).

Rurality is also determined from county-based identifiers such as a county's political, economic, and social standing, which can "dilute or mask a rural population given their geographic size and influence" (Housing Assistance Council, 2011, p. 2). The Housing Assistance Council (HAC; 2011) has determined perhaps a more accurate depiction of rurality, which identifies housing density and distance commuting as important aspects of this cultural group. The HAC (2011) suggests that housing density is a more precise indicator of rurality as it identifies tract level data at the rural, small-town, suburban, exurban, and urban levels and is further highly correlated to population density. Population density has been shown to be an accurate way of identifying rurality (Bako, Dewar, Hanson, & Hill, 1984). A final important consideration of rurality, is noting that this construct exists on a continuum and varies considerably based on community size, population density, total population, and various social and economic factors.

The literature reflects considerable disparities for mental health treatment based on rurality. Gamm, Hutchinson, Dabney, and Dorsey (2003) note that "among 1,253 smaller rural counties with populations of 2,500 to 20,000, nearly three-fourths of these rural counties lack a psychiatrist, and 95 percent lack a child psychiatrist" (p. 97). The National Comorbidity Survey Replication revealed that residents in small towns reported significantly less mental health treatment for their reported disorders than residents of suburban and central cities (Eberhardt et al., 2001). There are also rural disparities within this marginalized population, as there are significant differences in receiving mental health treatment between rural areas nearby metropolitan areas and rural areas that are not near a metropolitan area (Freiman & Zuvekas, 2000; Petterson, 2003). Rural health experts have further identified that these disparities are an overwhelming priority and that while this issue is traditionally viewed as an urban versus rural disparity, in many cases this disparity is largest between suburban and rural populations (Gamm et al., 2003). Hartley (2004) suggests that there is a "rural culture" which reflects a pattern of risky health behaviors, stigma, and a lack of awareness of health problems. Rural residences have been identified to "smoke more, exercise less, have less nutritional diets, and are more likely to be obese than suburban residents" (Hartley, 2004, p. 1676).

Research has found it difficult to determine the exact nature or role various rurality factors play on those seeking mental health treatment as these behavioral health disparities are highly correlated with both income and education (Hartley, 2004). Additionally, there is a gap in the research noting the distinct influence of income and rurality factors, which are not traditionally controlled for and are generally glossed together when identifying this population. In some cases, research has statistically controlled for some economic variables such as insurance coverage when exploring differences between racial disparities (Goodwin, Koenen, Hellman, Guardina, & Struening, 2002; Zito, Safer, Zuckerman, Gardner, & Soeken, 2005). This analysis revealed that urban White populations receive mental health treatment more than rural residents of any racial identity (Petterson et al., 2009). Additionally, Alegria et al. (2002) identified that urban White populations were more likely to receive specialty mental health treatment than Latinx or African-American populations regardless of socioeconomic status; however, race was not a significant factor in receiving general treatment for these groups. This study suggests that barriers to treatment access affect all rural residents regardless of ethnicity, this was further supported in a follow up study by Petterson et al. (2009). Another rationale for these findings is that ethnicity and race are merely components to a more complex construct of social position that requires further research. There currently is limited research that examines how income and rurality separately affect individual and community level mental health outcomes.

One final important consideration is the occurrence of overgeneralizing characteristics between rural populations within the United States. Rural health research has identified that effective policy interventions need to be implemented based on the variations in economic, educational, physical, and historical environments (Hartley, 2004). Differing rural characteristics and cultures contribute to different outcomes being expressed, such that the rural South had higher rates of smoking, physical inactivity, poverty, and adolescent births compared to the rural West with higher rates of alcohol abuse and suicide, and the rural Northeast with higher rates of tooth decay (Morgan, 2002). Regional differences in rurality have not been extensively explored regarding mental health access and treatment. Therefore, research that is produced with the intention of policy intervention should be reflective of the unique rural culture being studied (Hartley, 2004).

Treatment Response

There has been considerable and conclusive evidence in the literature that reveals clients "get better" after they receive a therapeutic intervention (Baldwin, Berkeljon, Atkins, Olsen, & Nielsen, 2009; Lambert & Ogles, 2004). This has been shown in several notable ways, but most commonly by providing assessments pre- and post-therapeutic treatment, which reveals a change between the two intervals. This form of treatment response can be reflected in negative or positive trends and can be further used to determine treatment response at a clinical level (Cooper, Gallop, Willetts, & Creswell, 2008). Researchers have also identified key components to mark this client improvement, such as symptomatic functioning, interpersonal problems, or social role performance (Lambert & Hill, 1994; Strupp, Horowitz, & Lambert, 1997). These key components are commonly assessed by instruments that are designed to be brief, easily interpretable, sensitive to both symptoms and diagnoses, and can identify change within a short time interval (Miller, Duncan, Brown, Sorrell, & Chalk, 2006).

The dose-effect model developed by Howard, Kopta, Krause, and Orlinsky (1986) is used to determine how a dose of therapy relates and predicts positive treatment outcomes. This model shows that clients improve as sessions continue, but the impact of these doses will go down as the amount of sessions increase. Another commonly utilized model to identify therapeutic outcomes is the Good-Enough Level model (GEL) that posits clients will have various responses to treatment and therefore will vary on necessary sessions of treatment. Here, clients who terminate after a few sessions have a high treatment response rate, while those that remain in therapy for longer intervals have a low treatment response rate (Barkham et al., 2006).

Research has also shown single sessions or doses of treatment to be particularly effective. In a three-month follow-up study, 88% of clients found single sessions helpful, 98% reported feeling understood, and 96% were satisfied with their service (Hampson et al., 1999). Furthermore, “clients show a decrease in distress, improvement in general functioning, and decreased use of health services one month and four months after the walk-in visit” (Stalker, Horton, & Cait, 2012, p. 47). This research is important when considering a client’s baseline of treatment, perceived premature termination, and treatment response.

Perhaps the most common way to determine individual treatment outcomes from therapy is that of the Reliable Change Index (RCI; Jacobson & Truax, 1991). Reliable Change occurs when the difference between two scores is equal to or greater than the determined index score, which is a statistically determined value of change that is beyond standard error of that instrument. This

RCI is unique to each instrument and can vary based on the population being studied (Jacobson & Truax, 1991). Clinically Significant Change (CSC) further utilizes the RCI to determine treatment response in a meaningful way. This measure of change occurs when individuals who are at a clinical level of distress move below this clinical cutoff, while also meeting or exceeding the RCI determined by the assessment (Jacobson, Follette, & Revenstorf, 1984; Jacobson & Truax, 1991). One of the most important applications of RCI is its ability to determine meaningful RC at both the individual and group level. This has implications for providers and practices serving both clinical and non-clinical populations to evaluate their treatment effectiveness (Hansen et al., 2002).

The most important reason to identify treatment response and outcomes is to determine if the clinic is providing effective change for their clients and to ensure that these populations are being positively impacted. This is important when considering community clinics that require limited local and federal funds. When looking at treatment response rates for both rural and low-income populations, meaningful change is still found when these populations receive a dose of treatment (Hansen, Lambert, & Forman, 2002). Kalpinski (2014), utilizing survival analysis assessing the rural populating in southeast Texas, found that both RC and CSC still occurred. RC was found on average by the seventh session and CSC was found by the thirteenth session. In comparison, other studies tended to find CSC occurring between 11 to 16 sessions (Anderson & Lambert, 2001; Kopta, Howard, Lowry, & Beutler, 1994; Wolgast et al., 2005). Despite these findings, Kalpinski (2014) notes that there is much to be understood regarding treatment response for rural and low-income populations specifically and calls for future research to better explore positive treatment response and treatment effectiveness for these populations.

One explanation for these discrepant findings is that, low-income individuals and families are less likely to maintain health insurance coverage due to factors such as low employment levels and low income. This results in low-income individuals being unable to receive access to high-quality care impacting their ability to achieve positive health and wellness outcomes (Berenson et al., 2012). The disparity in treatment becomes more complex when noting that low-income individuals are at higher risk for having "multiple chronic health problems, mental illness, substance abuse, and disability" (Berenson et al., 2012, p. 4), which further negatively affects their health than those above the poverty line. While many of these issues are found in rural populations, there are additional barriers such as the physical environment and regional cultural differences related to mental health stigma. The physical environment, such as difficult road conditions in mountainous regions can prove detrimental as it pertains to one's ability to attend a therapeutic session or to receive a dose of treatment. Hartley (2004) suggests that for rural populations to have a positive treatment response there needs to be a "population approach that is sensitive to local variations in physical and cultural realities" (Hartley, 2004, p. 1677) which is often neglected by clinicians, mental health clinics, and researchers (Mitura & Bollman, 2003).

Community Resources

While the uninsured rate for the U.S. general population has lowered over the past decade, a Gallup poll revealed that the uninsured rate has increased over the 2017 year (Auter, 2017). This creates a dilemma within the national health care system as hospitals and health care providers face increasing financial difficulties related to uncompensated care costs (Lee, Dixon, Kruszynski, & Coustasse, 2010). Uncompensated care costs can be simply defined "as health care provided in which full payment is not received" (Lee et al., 2010, p. 117) while other definitions include qualifiers such as not being compensated by third party reimbursement or government subsidies (Hadley & Holahan, 2004; Hadley, Holahan, Coughlin, & Miller, 2008). While this problem persists across the levels of rurality, rural hospitals and health care clinics experience an increased rate of uncompensated care costs compared to their suburban and urban counterparts. This largely is due to rural hospitals and clinics treating an estimated 21% of the total population, and having to provide both inpatient and outpatient care when their suburban/urban counterparts can focus on either inpatient or outpatient care and rely on other agencies for support (Levit, Stranges, Ryan, & Elixhasuer, 2006). Furthermore, these rural treatment settings are also disadvantaged due to the small and marginalized patient pool they treat.

Rural treatment facilities have difficulty retaining trained professionals, are more likely to face physician and clinician shortages (Lunn et al., 2011), and are less likely to provide necessary specialty treatment (Gresenz, Stockdale, & Wells, 2000). Additionally, rural community clinics lack the available resources to train their providers adequately compared to urban and suburban settings (Callas, Ricci, & Caputo, 2000). This is critical due to the necessary cultural competencies required to effectively treat these marginalized populations (Adler, Pritchett, & Kauth, & 2013; Safran et al., 2009).

One way to potentially alleviate these issues for rural clinics is to explore clinical dropout and No-Show appointments as these clinical outcomes exacerbate uncompensated care costs as the clinic is not taking in earnings. While clinical dropout is a frequent occurrence for all mental health settings, Garfield (1986) identified that dropout is particularly of concern for community outpatient clinics where nearly half of their clients have dropped out of treatment by their eighth session. Through meta-analysis this dropout rate was identified at public clinic settings to be the highest (50%) compared to private (44%) and university counseling settings (42%; Wierzbicki &

Pekarik, 1993). Past literature has also shown that higher symptom distress better predicts client dropout than other key treatment components, suggesting the importance of attended sessions for this population (Yu, 2011). Yu (2011) further calls for continuing research to examine disparities in client dropout and how this impacts clinic resources. For mental health service organizations and clinicians with limited financial and human resources, clinical dropout presents a "gratuitous drain" (Reis & Brown, 2006), which is represented in hampered therapeutic efforts and limited treatment gains.

Client dropout negatively impacts clinicians, particularly beginning psychotherapists. High dropout rates are commonly interpreted as rejection of the clinician, which can prove demoralizing and impair clinical confidence and effectiveness (Joyce, Piper, Ogrodniczuk, & Klien, 2007; Sledge, Moras, Hartley, & Levine, 1990). This can lead to job dissatisfaction and professional burnout (Maslach, 1978). Just as funding is imperative to the success of these rural and low-income community health clinics, it is also dependent on competent and effective providers.

While clinical dropout negatively impacts client outcomes and therapeutic effectiveness, it remains a difficult construct to measure and predict accurately. An important consideration is that not all treatment dropouts should be identified as treatment failures. Dropout can be initiated by the client who may have differing expectations of the duration of therapy than their providers (Lampropoulos, Schneider, & Spengler, 2009) and clients may interpret treatment progress differently. Additionally, some clinicians believe that a portion of clients whom terminate prematurely reach their therapeutic goals regardless (Robbins, Mullison, Boggs, Riedesel, & Jacobson, 1985). Despite this, one of the better ways to predict clinical dropout is to assess No-Show appointments, which often precede this outcome (Smith, Subich, & Kalodner, 1995).

No-Show appointments are particularly damaging to mental health clinics as it leaves a scheduled appointment unattended and unpaid for (Smith et al., 1995), which is a serious problem facing clinicians, clinics, and clients (Mohr et al., 2006). Some mental health clinics can receive as high as a 67% No-Show rate, where the clinic is losing more money than is being taken in (Hampton-Robb, Qualls, & Compton, 2010). Additionally, for community health clinics, valuable resources are lost on clients who do not attend necessary treatment, which could be used to treat clients with higher levels of motivation. This problem leads to longer waitlists, increased symptom severity for clients not in treatment, and increases the likelihood that waitlisted clients will dropout before treatment starts (Rodolfa, Rapaport, & Lee, 1983).

Treatment dropout and the preceded No-Show appointments share a negatively relationships as they impact one another. This pattern is most pervasive for marginalized populations and the clinics who serve them. Lester and Harris (2007) found that individuals who are divorced, unemployed, and have children were less likely to attend their treatment. Additionally, Mohr et al. (2010) reported that women, ethnic minorities, and those that were single had higher levels of nonattendance than their counterparts. These groups are more likely to belong to low-income populations. Financial barriers have also been seen to influence No-Show appointments, as individuals may have a lack of funds to get to a session, pay for a session, and are less likely to have health insurance coverage (Sareen et al., 2007). Client income has been seen to have a significant negative impact on client attendance as those of the largest income range (70,000+) attended 78% of the time, while those of the lowest range (11,000) attended 53% of the time (Hampton-Robb, Qualls, & Compton, 2003). Mojtabai et al. (2011) concludes that these financial barriers have been steadily worsening throughout this past decade.

Summary of the Literature

Mental health disparities have continually been referenced as a critical health area that needs to be addressed and better understood within the research (Safran et al., 2009). Treatment access barriers have been associated as underlying contributors to these disparities by how they negatively impact the health outcomes of marginalized populations the most. Penchasky's (1981) theory of access identifies four main dimensions of treatment barriers: Affordability, Accessibility, Acceptability, and Availability. A fifth dimension, Awareness, has been more recently accepted as a treatment barrier (Saurman, 2016). While all populations experience these barriers to various degrees, marginalized populations experience them more significantly and the interactions felt by these dimensions negatively compound their reduced access to mental health treatment (Safran et al., 2009).

Much of the literature examines mental health disparities from a gender and/or ethnic-focused perspective, which often considers other cultural factors such as regionality, education, age, and income as secondary. This limits our current understanding of these treatment barriers as the causes behind them are not well understood, except that they are a product of an assortment of these secondary variables. Additionally, two distinct marginalized groups (low-income and rural populations) are often generalized together due to their often-overlapping demographics. However, these populations have different cultures, histories, and likely treatment access barriers. The degree to which these two populations vary in their treatment response and No-Show appointments is unclear. This uncertainty makes it difficult for community mental health clinics to effectively implement policies that could benefit these groups in overcoming their prospective treatment access barriers.

Furthermore, research has emphasized the importance of identifying treatment response and No-Show appointments as it pertains to mental health disparities. The literature has also shown that low-income and rural populations are disproportionately affected in various treatment outcomes compared to advantaged populations in higher-income and suburban and urban zones. However, there is limited research that compares these two marginalized populations across these two specific outcomes while controlling for confounding variables. Additionally, while it is assumed that there is a compounding effect for those who fall in both marginalized populations, such that they experience more access barriers and worse outcomes than those in one marginalized group, there is no known research that identifies this interaction.

Last, research has noted that community mental health clinics are limited in their available resources (i.e., financial funds, available clinicians, and available clinic space; Lee, Dixon, Kruszynski, & Coustasse, 2010). Due to these disadvantages, research has emphasized the importance of thoughtful allocation of resources to provide mental health treatment most effectively. Additionally, a growing critique within the literature is that diminished effectiveness of mental health treatment for these marginalized populations is due to a lack of cultural sensitivity and treatment considerations by providers (Adler, Pritchett, & Kauth, & 2013; Safran et al., 2009). Therefore, policy-makers and providers need to consider their limited clinic resources, the treatment access barriers impeded their clinical population, as well as the unique cultural experiences of their clients, to effectively alleviate these mental health disparities.

CHAPTER III

METHOD

Procedures

This study reviewed archival and deidentified client data pertaining to mental health treatment at the Texas A&M Counseling and Assessment Clinic (CAC). The CAC is a training clinic associated with the Texas A&M University's counseling psychology and school psychology doctoral programs. The clinic is located in the Bryan-College Station Community Health Center, which is a federally-qualified health center that provides health services to the surrounding communities in the Brazos Valley of Texas. The CAC provides treatment to clients with various presenting mental health concerns such as depression, anxiety, marital problems, parenting concerns, grief, family-of-origin concerns, and trauma-based therapy. Additionally, this clinic serves a diverse client population, which includes children, adolescents, emerging adults, adults, and the elderly from diffing cultural backgrounds. This clinic receives payment per session based on a sliding fee scale, which is calculated according to the client's reported annual income based on their household size at the time of their initial screening. After this fee is set, it can later be adjusted dependent on the clinic director's approval to support client's facing financial hardships.

Individual's seeking treatment at the CAC are screened to determine suitability with the counselor's level of expertise. Procedures for this screening occur over the telephone by a trained CAC staff member, are roughly 15-20 minutes, and are used to assess the client for imminent risk and suitability for receiving services at the CAC. Clients exhibiting more severe psychopathology such as a severe depressive episode, manic episode, psychosis, or high suicidality are typically referred to other mental health clinics such as the Mental Health and Mental Retardation (MHMR) authority of Brazos Valley. The majority of clients receive open-ended therapy with no predetermined session limit. The CAC offers a variety of therapy options dependent on the therapist's skill-level, specialty, and their supervisors' expertise. The type of therapy provided to the client is largely dependent on the clients' needs. All CAC therapists have been approved to be clinically capable of providing supervised psychotherapy prior to the enrollment at this training site. Furthermore, these therapists are provided with weekly group and individual supervision sessions by licensed psychologists to ensure ethical and effective treatment interventions for this client population. There are a variety of theoretical orientations used at this training clinic by trainees and supervisors, such as multimodal, cognitive-behavioral, psychodynamic, humanistic, feminist, interpersonal, multicultural, and family-systems. The effectiveness of this treatment in this setting is expected to be comparable to other settings with professional staff (Callahan & Hynan, 2005; Howard, Kopta, Krause, & Orlinsky, 1986).

Following the required screening procedures, an individual must complete a required intake with their appointed therapist. This intake appointment requires the therapist to review necessary clinic policies and procedures with the prospective client. This includes reviewing necessary informed consent policies, the potential for research use regarding de-identified and archival data, and HIPAA consent forms. The CAC continually collects client data for treatment evaluation which may subsequently be used for research. Only inactive client data from May 2011 to December 2016 was used in this study. Eligibility requirements for participation in this study included 18 years-old or older, attendance of two or more sessions, a completed electronic file (e.g., listed address, input demographic variables, and attendance records), and at least two recorded OQ-45 scores to determine treatment response.

As previously stated, the CAC's initial session with the client is referred to as the intake and evaluation session, which also determines if the individual will be accepted as a client seeking mental health care treatment. Over the following three sessions, the individual is further evaluated to insure the appropriateness of meeting the client's needs in therapy at this training clinic. If they are deemed ineligible or inappropriate for services, they are provided with the necessary resources to seek mental health treatment by an appropriate provider. This study focused on the occurrence of No-Show appointments and treatment response.

Clients typically attend weekly sessions for 50 minutes. They are routinely contacted by staff and their therapists regarding appointment reminders, as well as after missed sessions to reschedule appointments. No Contact letters are sent to the client's listed address regarding two weeks of no established contact. Furthermore, if clients do not respond to the No Contact letter within two weeks, the therapist's supervisor is notified, and the client is removed from the therapist's caseload. Procedures for changing a client's status from active to inactive requires a termination report, a file check, and a chart review by clinic staff.

For clients who were eligible for participation in this study, data from their electronic file was used to code variables that were associated with their demographic data (e.g., age, gender, and ethnicity). This included identifying the client's level of rurality from their listed home address and their income-level, as determined from their payment details on the CAC's established sliding fee scale. These data were retrieved by an employee of the CAC, deidentified, and then provided to the investigator on a password encrypted electronic spreadsheet. The accuracy of data (e.g., age, gender, ethnicity, assessment scores, and address) was checked between multiple datasets stored at the CAC's physical location. Although location data was expressed in visual maps, they only identify a general area of a client's location, not their exact location to protect against the possibility of the client being identified.

Participants

Clients who attend the CAC are primarily members within the community of Bryan-College Station, which has a combined population of 190,000, and has surrounding rural communities in Brazos, Burleson, and Robertson Counties (a combined population of 229,000; U.S. Census Bureau, 2011). The CAC's policies allow for individuals of any income-level to be enrolled and eligible for services; however, many clients are identified as below or at the poverty line based on their provided income and number of members in the household. While the presenting concern of the individual seeking treatment can vary, common concerns are depression, anxiety, grief and loss, relationship difficulties, family issues, post-traumatic stress, Attention-Deficit/Hyperactivity Disorder (ADHD), and career or vocational issues.

Approximately 656 unique adult clients were seen at the CAC between September 2011 to December 2016. Over this period, client data was gathered by several CAC staff, but information was collected inconsistently. 204 of these unique clients had incomplete or partial data pertaining to their listed addresses, attendance records, and/or demographic variables, and were therefore excluded from the analyses. Additionally, 64 clients had not completed the OQ-45 to establish a baseline and another 43 clients did not return for a second session. Despite the inconsistent nature in which this data was collected, the remaining data was thoroughly checked for inconsistencies between paper and electronic client files and found to be accurate. A sample size of 345 unique adult clients were used for analyses pertaining to RC and No-Show dependents, while a sample size of 255 were used for analyses pertaining to CSC; 90 clients did not have the required clinical level of distress at intake. Furthermore, 23 clients listed a P.O. Box address, but were still considered in the dataset because it was assumed that their residence likely belonged to the area represented by that P.O. Box address.

Demographic Information

Demographic information was collected by the CAC staff over the phone during the screening process and later checked by the appointed therapist at the client's intake session. This information included client age, gender, ethnicity, sexual orientation, education level, household income-level, and profession, and was stored securely in both electronic and paper files. Upon review, client gender, ethnicity, and age were the most consistent and accurate demographic variables measured, with household income often being rounded to the nearest interval as defined by the session fee scale (see Appendix L.). For this study, gender, ethnicity, and age were statistically controlled for in the analyses.

Measures

Session Fee

Many counseling clinics, particularly community clinics, are tailored to aid the client at their individual financial level. A sliding fee scale is a common and acceptable form of fee payment as it allows the client to pay what they can afford. The most common way to identify an individual on a sliding fee scale is to identify an individual's annual income in comparison to their household size. This scale therefore becomes related to one's identified income, socioeconomic status, and poverty status.

The sliding fee scale utilized at the CAC is used when a client calls inquiring about services and is screened before their intake session. The client self-reports their family size and annual household income to a CAC staff member who then matches this information appropriately on the CAC sliding fee scale (see Appendix L). This is further rounded to the nearest dollar, which is set on an interval scale associated with the client's income-level.

After this initial phone screening, the client is informed of their session fee and that they are expected to pay this amount after their first session. For example, a client belonging to a household of four with an annual income of $24,600 would pay $6.00 per session, while an annual income of $30,750 would pay $8.00 per session. While the sliding fee scale (see Appendix L) pertains to clients with income-levels ranging from $24,000 to $220,001 for a family of four. CAC staff members approximate session fee payments for clients who were below $24,000, so that it would continue to reflect their estimated income-level (e.g., an individual reporting $20,000 with a household of four would pay $4 per session). The CAC has changed policies regarding adjusting session fees over the course of treatment through the years of collecting data for this study. However, establishing the initial session fee with this scale has remained fairly consistent. For this study, a client's session fee was not coded or transformed, but was used in the analyses as it was recorded by the CAC staff members, as this session fee payment naturally fell on an interval scale that was already associated with one's income-level.

Two potential issues exist when utilizing a session fee to determine one's income-level. First, pertains to utilizing an interval scale, which, while highly correlated with one's reported income, is more susceptible to error as it includes a range of potential income. A second limitation pertains to the accuracy of a client's self-disclosed income level. For many clients, particularly those below the poverty line, disclosing accurate information concerning one's income-level can be challenging, stigmatizing, or otherwise problematic. While this limitation exists for the session fee variable, it also exists with other conventional methods of calculating income.

Rurality

Recent advancements in geocoding offer researchers, particularly those in public health and epidemiology, a more accurate means of measuring rurality and other demographic variables than previously possible. Geocoding is commonly used in spatial epidemiology studies as it can be used to track various variables and their impacts on a spatial level (Kumar, Liu, & Hwang, 2012). ArcGIS, a geospatial program, has been identified as one of the most accurate programs in identifying population accuracy and density (Swift, Goldberg, & Wilson, 2008). This geospatial program was measured more effective across three metrics: Completeness, similarity of geocodes, and positional accuracy. Completeness is a common metric used to evaluate geospatial programs as it identifies the match rate of addresses or other geodetic locations being identified within the program (Zandbergen, 2007, 2008). Similarity of geocodes is defined as the accuracy of the distance between assigned coordinates for the locations (Lovasi et al., 2007; Roongpiboonspoit & Karimi, 2010). Last, positional accuracy evaluates the precision of geodetic locations, commonly evaluated through satellite assessments or global positioning systems (GPS).

ArcGIS 10 was utilized for this study as it was found to provide a higher match rate and better positional accuracy than other geocoding programs (i.e., MapMarker; Kumar, Liu, & Hwang, 2012). Additionally, ArcGIS 10 provided necessary geocoding tools integrated within the software, such as geocoded addresses that automatically pinpoint on a map, available reference data sets, spelling sensitivity that allowed for more accurate positional accuracy, and, most importantly, overlaid maps created by third parties.

Thematic maps that were overlaid in this study included: 2012 USA Median Household Income created in 2011 and last updated in 2017, USA Population Density created in 2015 and last updated May 2018, and World Reference Overlay created in 2009 and last updated in March 2018. The Median Household Income map and USA Population Density map were both derived from the 2011 U.S. Census. The USA Population Density map consisted of various demographic information and allowed for census data, primarily population density to be identified at block, block group, tract, county, and/or state lines. This study utilized block level data pertaining to the population density of a client's listed address, which provided a more reliable way of measuring an individual's belongingness to a rural area than block group, tract, county, or state-identifiers. Additionally, it proved effective in determining levels of rurality within an already rural population.

The World Reference Overlay map was used to map the geographic area and included streets, roads, highways, bodies of water, and terrain. Additionally, ArcGIS's integrated Point Distance tool was used to determine a second rurality variable, a client's distance to the clinic, in agreement with this overlaid map. This tool can be used to measure the distance in various metrics between two points. For this study, the community mental health clinic was plotted among the reported client addresses and a distance in miles variable was generated capturing the distance between these areas which included the estimated drivable route.

Last, the World Reference Overlay map (see Appendix B-C), which noted highways, roads, and streets (without listed street names) and the 2012 U.S. Median Household Income map, which provided the median household income per block level, were used as descriptive tools. These overlaid maps, while not utilized in the analyses of this study, were useful tools to understand the population in question and potential treatment access barriers impacting them (e.g., access to hospitals, emergency centers, and established lower and higher income areas).

Treatment Response

The CAC evaluates individual treatment response through their reported experiences on the Outcome Questionnaire-45 (OQ-45). The CAC administers this assessment electronically to every client before every session and their providers are required to review these assessment results for risk assessment and to encourage changes in treatment if needed. These results are further stored electronically through OQ Analyst software at the CAC for research purposes with appropriate HIPAA required safeguards. While some individual administrations of the OQ-45 were not completed, saved, or administered, this was infrequent and deemed insignificant in impacting the findings of this study.

This study utilized Jacobson and Truax's (1991) approach to determine CSC, which requires: (1) an individual be assessed with an instrument capable of determining change over time, (2) the individual's initial assessment is determined to be at a clinical level of distress (e.g., a level of distress consistent with a diagnosable mental health disorder), (3) the individual's change in scores is found to be statistically reliable, and (4) the individual's final score is below a cutoff point indicating a clinical level of distress. Additionally, RC was used to determine treatment response as it is a measure of change independent of one's initial level of distress. For this measure, RC is determined through: (1) an individual's initial assessment (i.e., the first OQ-45 score), (2) an individual's last assessment (i.e., the final OQ-45 score), and (3) identifying that the difference between these scores meets or exceeds the RCI for the OQ-45 (i.e., 14 points). While client deterioration is an important consideration for measuring treatment effectiveness and is found by utilizing the RCI, it was not included in the analysis of this study, which was aimed to predict positive treatment response.

The OQ-45 is a self-report instrument that is designed to track symptom severity and psychosocial functioning of outpatient clients on a weekly basis (Lambert et al., 1996). This instrument consists of 45 items that require a client to rate their experiences on a five-point scale that ranges from never to almost always (0 to 4), and is designed to take five minutes to complete. (Lambert et al., 1996). The items are used to empirically assess the overall functioning of the individual along three domains of psychological wellbeing.

The first domain is *symptom distress*. This OQ-45 subscale is used to assess a client's common and various symptoms that are typically associated with mental disorders (Lambert, 2001). The items and their content are derived from the National Institute of Mental Health (NIMH) epidemiological survey in 1988, which includes concerns of depression, anxiety, and substance abuse (Lambert, Burlingame et al., 1996). Items that are included are "I feel no interest in things"; "I tire quickly"; and "I have difficulty concentrating." There are 25 total questions on this subscale and the level of symptom distress is determined from 100 possible points.

The second domain, *interpersonal relations*, is used to determine and evaluate frequent relational concerns in psychotherapy, such as family, friendship, and marriage. These questions were derived from preexisting literature that reported relational conflict, isolation, withdrawal, and interpersonal ruptures to be detrimental to life satisfaction (Lambert, Burlingame et al., 1996). These items include questions such as: "I feel loved and wanted"; "I have trouble getting along with friends and close acquaintances"; and "I am satisfied with my relationships with others." There are 11 questions that identify this subscale and the level of interpersonal problems is determined from 44 possible points.

The final domain, *social role*, assesses an individual's quality of life as it is determined through their roles and identity as it is established in work, leisure, and family life (Lambert, 2001). This subscale is used to identify “dissatisfaction, conflict, distress, and inadequacy” in one’s social roles (Lambert, Burlingame et al., 1996). These items include questions such as “I feel that I am doing well at work/school”; “I find my work/school satisfying”; and “I enjoy my spare time” (Lambert, Burlingame et al., 1996). This subscale consists of 9 questions and the individual’s total score is determined out of 36 possible points.

A global score of a client’s level of functioning is determined by totaling the three subscale’s scores to obtain a Total OQ-45 score that is determined from 180 possible points. Lambert et al. identified that this score provides a general assessment of an individual’s quality of life (2005). Additionally, a cutoff score (64 or higher) has been determined on this instrument to identify members likely belonging to a clinical inpatient population (Jacobson & Truax, 1991; Lambert, 2010; Lambert, Hansen et al., 1996) and indicates that the individual is experiencing a clinical level of distress or dysfunction. The OQ-45 has also been considered a sufficient measure to determine treatment outcome or treatment response in a setting that requires regular testing (Lambert, 2010; Lambert, 2001).

Psychometric properties of this instrument have been determined adequate as the internal consistency of the OQ-45 has been found high ($\alpha = .93$) for the Total OQ-45 score (subscales range from .70 to .92; Lambert, Burlingame, et al. 1996). Additionally, the 21-day test-retest correlation coefficient for the Total OQ-45 and the subscale scores range from .78 to .84 ($p < .01$; Lambert, Burlingame, et al., 1996; Lambert et al., 2002). Considering the reliability of the OQ-45, a study examining session by session changes for a sample of 157 undergraduate students found strong internal consistency reliability (.73 to .93), which was comparable to another study utilizing a community sample through an Employee Assistance Program (EAP;

Lambert et al., 1996). Furthermore, the OQ-45 has been shown to be statistically sensitive to detect change in psychotherapy clients' progress, in total and subscales scores, after receiving seven sessions of treatment (Lambert, Burlingame, et al., 1996).

Concurrent validity for the OQ-45 has also been shown to be comparable to other instruments such as the Symptom Checklist-90R (SCL-90R) (.72), Beck Depression Inventory (BDI) (.62), Zung Self-Rating Depression Scale (ZSDS) (.88), Zung Self-Rating Anxiety Scale (ZSAS) (.80), State-Trait Anxiety Inventory, Form Y-1 (STAI-Y1) (.64), State-Trait Anxiety Inventory, Form Y-2 (STAI-Y2) (.80), Inventory of Interpersonal Problems (IIP) (.63), and Social Adjustment Scale (SAS) (.60) (Lambert, Burlingame, et al., 1996). The concurrent validity for the Total OQ-45 and for all subscales were found statistically significant ($p<.01$; Lambert et al., 2002). Last, there were no statistically significant differences reflected across genders or ethnicities (Lambert et al., 2002).

A preliminary confirmatory factor analysis (CFA) identified an important consideration regarding the OQ-45's subscales, that the dimensions may not be uniquely different from one another (Mueller, Lambert, & Burlingame, 1998) as the three subscales have been found to have high intercorrelation. As an identified limitation of this instrument, these researchers suggest using only the Total OQ-45 score when tracking treatment response or clinically significant change within psychotherapy clients. The subscales scores are still useful, however, in determining one's functioning in the subscales identified focus (i.e., symptom distress, interpersonal relationships, and social roles).

A final consideration regarding the use of the OQ-45 is that self-report instruments that are administered repeatedly have been found to reflect a reduced reporting of symptomology regardless of treatment (Jorm, Duncan-Jones, & Scott, 1989). While the OQ-45 scores have been shown to decrease slightly at the second administration, this decrease has not been found to continue in subsequent administrations (Durham, 1999; Vermeersch, Lambert, & Burlingame, 2000). Researchers state that any possible test-retest effects of the OQ-45 are not cumulative (Lambert, 2001).

No-Show Appointments

The CAC utilizes Titanium, a software program, that securely stores and sorts client files and data electronically. Titanium is a commonly used program for health and mental health clinics regarding scheduling, note keeping, data form storage, and demographic tracking. By analyzing an archived client's electronic chart, this study extrapolated client's attendance and No-Show records. A client's attendance is marked and coded in Titanium by the appointed therapist according to several potential options. These options include: Client Attended, Client No-Showed, Client Cancelled, and Counselor Cancelled. This study identified the number of No-Show appointments among the total number of scheduled appointments that a client made to determine the rate of No-Show appointments per client.

Since the CAC has not enacted a No-Show policy (after a certain number of No-Show appointments the client is ineligible for services), there was some differences in the No-Show rates among clients. A No-Show appointment is defined as a missed appointment, specifically when the client did not call to cancel or reschedule. This is therefore the best way to identify wasted clinic resources, as counselor time and rooms available for counseling are limited.

Analysis

The initial research questions in the study were aimed to assess how one's level of rurality and income predicts treatment outcomes at a community mental health clinic. The analyses used in this study includes the independent variables: Age, Gender, Ethnicity, Session

Fee, Population Density, and Distance Travelled, to predict the dependent variables: RC, CSC, and the number of No-Show appointments a client has in treatment.

There are three primary independent variables assessed in this study, Population Density, Distance Travelled, and Session Fee. Population Density and Distance Travelled were used to determine one's level of rurality and are continuous in nature. Distance Travelled was further rounded to the nearest tenth decimal point of a mile. The Session Fee variable was used as an estimate of one's income-level (see Appendix L). In some of the models, interaction effects were explored between the independent variables (e.g., Distance Travelled and Population Density; Population Density and Session Fee). Interaction variables were created automatically in the analyses by Stata 14.

Demographic variables were also considered in the analyses (Age, Gender, and Ethnicity). While Age was used as a continuous variable, Gender and Ethnicity were categorical. Gender was separated between Male and Female categories with no data identifying Transgender or non-binary individuals in the sample size. Ethnicity was coded as White, African-American, Hispanic, Asian, Native American, or Other groups. This Other category consisted of less frequent self-reported ethnicities (e.g., Middle Eastern, Danish, Jewish). While the analyses used in this study allowed for various forms of independent variables in the model, considerations were made regarding the small sample sizes of Asian, Native American, and Other ethnicity groups. Given the extremely small number of individuals selecting Asian, Native American, and Other ethnicity groups, they were excluded from the analyses. Table 1 summarizes the variables utilized in this study.

Table 1.
Research Variables

	Variable	Measurement
Independent	Session Fee	Recorded session fee (determined by income level, household size)
Independent	Distance Travelled	Distance travelled between the client's address to the community clinic in miles
Independent	Population Density	Population density at the block level of a client's address
Dependent	Treatment Response (Reliable Change)	Determined if a difference between a client's baseline OQ-45 Total score and their last OQ-45 Total score is greater than 13
Dependent	Treatment Response (Clinically Significant Change)	Determined if Reliable Change has occurred and the client's baseline was at a clinical level of distress and their last score at a non-clinical level
Dependent	No-Show Appointments	A client's number of No-Show appointments that were incurred in the course of their treatment
Demographic	Age	Client's age determined at the client's first session
Demographic	Gender	Client's gender determined through the CAC's screening procedures
Demographic	Ethnicity	Client's self-described ethnicity determined through the CAC's screening procedures

Logistic Regression

The two dependent variables related to a client's treatment response, RC and CSC, were both dichotomous (e.g., either positive change occurred or it did not). For these dependent variables, binary logistic regressions were used. Logistic regression is a statistical method that utilizes the natural logarithm of the odds belonging to the outcome of interest. For example, the log-odds of achieving CSC are regressed on the continuous independent variables (Population Density, Distance Travelled, and/or Session Fee). This has utility in determining how the log-odds (as well as odds ratio) change for the dependent variable as the independent variables change.

While the research has not established a minimum sample size for logistic regression, some recommendations are provided in the literature (Peng, So, Stage, & St. John, 2002). A ratio of ten subjects to each independent variable with a minimum of 50 observations is recommended (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996; Peng, Lee, et al., 2002). For this study, the most complex model consisted of six individual variables with 240 or 330 participants, which exceeded the suggested recommendations.

Negative Binomial Regression

The dependent variable, No-Show appointments, was analyzed through a negative binomial regression distributed on the Poisson distribution. This analysis considers the counts or occurrences of events over a number of trials (e.g., the number of No-Show appointments over the Total Scheduled Sessions of a client). The Poisson distribution assumes that the variance and mean of the No-Show variable are equal. When this is violated, a negative binomial regression can be used to allow for more flexibility of the Poisson distribution (Coxe, West, & Aiken, 2009). Additionally, while the Poisson distribution considers the number of trials to be equal between subjects (e.g., the same amount of sessions for each client), this can also be accounted for by adding an exposure variable to the regression (i.e., Total Scheduled Sessions).

Preliminary Analyses

Preliminary correlational analyses were conducted between independent and dependent variables to identify potential issues of multicollinearity, but no issues were found. Additionally, preliminary allsets modeling was used to guide decisions on which independent variables to include for Models 4, 5, and 6. Allsets modeling is a useful tool to determine the independent variables that are stronger predictors for the dependent variable. This type of preliminary modeling considers the form of analysis, the number of independent variables included, and potential interactions between variables. Allsets modeling provides a number of criteria to help guide decisions, but most notably the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). A lower AIC and/or BIC suggest that the variable is a better independent variable than an independent variable with a higher AIC and BIC. However, exceptions can be made when adding complexity to the model (e.g., another independent variable or adding interaction effects) as this may increase the AIC and/or BIC, but may still improve the predictive nature of the overall model.

Goodness-of-Fit Analyses

Generalized linear models (e.g., logistic regressions and negative binomial regressions) rely on maximum likelihood methods to assess the goodness-of-fit of these models. The Psuedo R^2 value for these models differs from the R^2 commonly used in OLS analyses, as the Pseudo R^2 considers the deviance value (e.g., how much worse does a model predict the outcome than a perfect model; Coxe, West, & Aiken, 2009). Due to the reliance on maximum likelihood methods, likelihood ratio chi-square tests were used to determine the significance of the overall models, while Wald chi-square tests were used to determine the significance of individual coefficients within the models. For the logistic models, the Hosmer-Lemeshow test was also used to test the goodness-of-fit, as this is used to assess if the observed data matches the expected data. If significance is found for the Hosmer-Lemeshow test, it suggests that the data may be due to chance.

Marginal Analyses

Marginal effects were assessed within significant models. Marginal effects are commonly used to determine differences between margins or levels of the dependent variables. This provides adjusted predicted probabilities for each margin or level of interest. For example, as

Session Fee changes, the probability of achieving CSC may be different in lower Session Fee margins than higher Session Fee margins. For RC and CSC, marginal effects represent the change in odds of the dependent variable occurring across the margins. Marginal effects for No-Show appointments represent the predicted number of No-Show appointments for the selected margin. These effects also assume that the other independent variables in the analysis are held constant. Marginal effects were plotted to better visualize differences between the levels of income and rurality and how they predicted treatment response and No-Show appointments.

While ArcGIS was utilized to identify and map client rurality according to the U.S. census data in 2010, all statistical analyses were performed with Stata version 14. This program provided output that was used to: evaluate the statistical strength of the models, compare the predictive nature of these models, determine the statistical effects of the independent variables on the dependent variables, and explore marginal effects within the models. Stata was also used to plot these models including marginal effects for visual interpretation. Relationships were considered statistically significant if $p < .05$, two-tailed.

Based on this study's research questions, several models were tested. The first three models were used to determine which rurality variable (Population Density or Distance Travelled) better predicted the dependent variables (RC, CSC, and No-Show appointments), while the final three models were used to determine, which independent variables (rurality or income) were better at predicting the dependent variables. Allsets modelling was used to help guide the decisions for which variables to include in these final three models. This form of modelling assesses which variables will contribute to the significance of the overall model and considers the number of independent variables and potential interaction effects included. Given these parameters, Population Density with an interaction term with Session Fee was used in

Model 4, Distance Travelled with an interaction term with Session Fee was utilized in Model 5, and all independent variables (Population Density, Distance Travelled, and Session Fee), but no interaction terms, were included in Model 6.

Statistical Models

(1) Distance Travelled + Population Density + Distance Travelled*Population Density + *Age* + *Gender* + *Ethnicity* = Reliable Change

(2) Distance Travelled + Population Density + Distance Travelled*Population Density + *Age* + *Gender* + *Ethnicity* = Clinically Significant Change

(3) Distance Travelled + Population Density + Distance Travelled*Population Density + *Age* + *Gender* + *Ethnicity* = No-Show

(4) Session Fee + Population Density* + Session Fee*Population Density* + *Age* + *Gender* + *Ethnicity* = Reliable Change

(5) Session Fee + Distance Travelled* + Session Fee*Distance Travelled* + *Age* + *Gender* + *Ethnicity* = Clinically Significant Change

(6) Session Fee + Distance Travelled + Population Density + *Age* + *Gender* + *Ethnicity* = No-Show Appointments

CHAPTER IV

RESULTS

Descriptive Statistics of the Sample

Demographic Characteristics

This study consisted of two overlapping samples of psychotherapy clients from the Texas A&M University Counseling and Assessment Clinic (CAC). The sample consisted of data from 330 clients and did not exclude subjects based on clinical-levels of distress at intake. This sample was used to assess RC. A subsample of 240 clients that had clinical levels of distress were used to assess CSC for an outpatient clinical population (i.e., clients with clinical levels of distress at intake).

For the total sample (n = 330), the average age was 34.51-years-old (SD = 12.94 yrs) and ranged from 18 to 87-years-old. There were 123 male (37.27%) and 207 (62.72%) female clients. Clients who self-identified as White made up the majority of this sample with 219 subjects (66.36%), 32 self-identified as African-American (9.70%), and 79 self-identified as Hispanic (23.94%). There were 15 clients who consisted of other marginalized ethnicities such as Asian-American (6), Native American (4), and Other (5), but due to the sizes of these groups, these participants were excluded from the sample.

For the clinical subsample (n = 240), similar demographics were found. The average age was 34.68-years-old (SD = 12.57) and also ranged from 18 to 87-years-old. There were 82 male (34.17%) and 158 (65.83%) female-identified clients. Within this sample, 160 clients self-identified as White (66.67%), 22 self-identified as African-American (9.17%), and 58 self-identified as Hispanic (24.17%).

Additionally, demographic characteristics related to a client's level of rurality and income were evaluated. From the total sample, the average distance travelled to the clinic was 7.87 miles (*SD* = 12.02 mi) with a median of 3.4 miles and a range of 0.5 miles to 86 miles. Additionally, the average population density was 4,201.90 persons per block (*SD* = 4,461.19 ppb) with a range from 9.4 to 21,587 persons per block. The average session fee per client was $6.95 (*SD* = $5.10) with the median session fee being $6.00 per session. The session fee ranged from $0.00 to $50.00. Furthermore, the $6.00 median session fee is associated with an annual income of 24,600 for a household of four and further marks the cutoff of the federal poverty line.

Regarding the clinical sample (*n* = 240), the average distance travelled to the clinic was comparable at 8.09 miles (*SD* = 12.86 mi), a median distance of 3.4 miles, and a range of 0.7 to 86 miles. The average population density of this sample was 4,326.32 persons per block (*SD* = 4,506.64 ppb) with a range from 10.9 to 21,587 persons per block. The average session fee was found to be $6.72 (*SD* = $4.95) with the median session fee also at $6.00 and a range from $0.00 to $50.00.

Education level, employment status, and marital status were not gathered as part of this study. However, Yu (2011), who conducted a study at this specific mental health clinic, identified the demographics for this same client population in southeast Texas. This study found that roughly 30% of clients' highest education level at this clinic was either: Some High School or High School Graduates, 33% had Some College, and 26% were College Graduates or higher; roughly 10% were unable to be identified. This study further found that roughly 50% of this sample at this clinic were employed, 16% listed as students, and roughly 20% listed as unemployed; 13% were also unable to be identified. Last, Yu found that 39% of clients were listed as Single, 34% Married, and 18% Separated or Divorced; roughly 9% were unidentifiable (2011).

Clinical Characteristics

Among the total sample size (*n* = 330), 5,198 sessions were attended at this community mental health clinic with a total of 5,983 sessions scheduled. The median number of sessions attended was 8, while the average number of attended sessions per client was 15.75 (*SD* = 19.30). This was influenced by twelve clients within this sample having attended over 70 sessions each, suggesting that a smaller subset consisted of a disproportionate amount of attended sessions. No-Show percentages per client ranged from 0% to 71.43% of their total scheduled sessions. This No-Show percentage does not include rescheduled or cancelled sessions. Additionally, the median No-Show percentage per client was 12.5%, while the average No-Show percentage per client was 15.79% of their scheduled sessions.

When considering the clinical sample (*n* = 240), 4,035 total sessions were attended with 4,648 sessions scheduled. The median number of sessions was 8, while the average sessions per client was 16.81 (*SD* = 20.43) and ranged from 2 to 107 sessions. No-Show percentages per client ranged from 0% to 71.43% with the median No-Show percentage at 12.5% and the average No-Show percentage at 16.21%.

When examining treatment outcomes for the total sample (*n* = 330), the average Total OQ-45 score at the start of treatment was 80.95 (*SD* = 26.21), while the average Total OQ-45 score at their last session was 68.88 (*SD* = 29.48). The clinical cutoff for the OQ-45 is 64, which indicates that on average clients entered and left services at the CAC at clinical levels of distress. However, only 134 or 40.60% of clients in this sample achieved positive RC by their last session. Last, 31 or 9.39% of clients deteriorated over the course of treatment as determined by the Reliable Change Index.

As previously stated, the clinical subsample consisted of 240 client's that had clinical levels of distress. The average Total OQ-45 at the beginning of treatment was 93.20 (*SD* = 18.18) while the average Total OQ-45 score at their last session was 78.02 (*SD* = 26.66). Similar to the total sample, this subsample entered and left treatment on average at clinical levels of distress. However, it should also be noted that the OQ-45's Reliable Change Index is a change of 14 or more points, which suggest that on average positive RC occurred for this sample. For 54 clients or 22.5% of this sample, positive CSC was achieved by their last session. Within this subsample, 17 clients or 7.08% deteriorated over the course of their mental health treatment.

Model 1—Analysis of Population Density and Distance Travelled predicting Reliable Change

Model 1 consisted of Age, Gender, Ethnicity, Population Density, and Distanced Travelled variables predicting RC. Additionally, an interaction variable was created to explore the potential impact that Population Density and Distance Travelled had together. This model used the total sample (n = 330), but was found to be statistically nonsignificant and wasn't interpreted. The results are presented in Table 2.

Table 2.
Model 1 – Logistic Regression Analysis of Reliable Change Predicted with Population Density and Distance Travelled

Predictor		*B*	*SE* β	z-score	*Wald (p)*	Odds Ratio
Intercept		.17	.42	.41	.68	1.19
Population Density		<.00	<.00	.63	.53	0.99
Distance Travelled		<.00	.01	.19	.85	0.99
Population Density X Distance Travelled		<.00	<.00	<.00	1.00	0.99
Age		.01	.01	-1.37	.17	0.99
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	<.00	.24	-.01	.99	.99
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	.16	.46	.41	.68	1.17
	Hispanic	-.15	.50	-.54	.59	.86

Model χ^2 = 2.50, $p = .93$
Pseudo R^2 = 0.01
Hosmer-Lemeshow test = 3.26, $p = .92$
n = 330

Note: $*p < .05$. $**p < .01$

Model 2—Analysis of Population Density and Distance Travelled predicting Clinically Significant Change

Model 2 consisted of the same independent variables as Model 1, but with a different dependent variable, CSC. An interaction variable was created to explore the potential impact of Population Density and Distanced Travelled had together. This model used the clinical subsample ($n = 240$) for the analysis. Similar to Model 1, Model 2 was not found to be statistically significant and therefore wasn't interpreted. The results of this model are presented in Table 3.

Table 3.
Model 2 – Logistic Regression Analysis of Clinically Significant Change Predicted with Population Density and Distance Travelled

Predictor		*B*	*SE* β	z-score	*Wald (p)*	Odds Ratio
Intercept		-.99	.61	-1.62	.11	.37
Population Density		<.00	<.00	.54	.59	1.00
Distance Travelled		-.01	.02	-.38	.71	.99
Population Density X Distance Travelled		<.00	<.00	.64	.52	1.00
Age		<.00	.01	-.16	.87	.99
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	-.44	.32	-1.35	.18	.65
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	-.30	.62	-.48	.63	.74
	Hispanic	.18	.36	.49	.62	1.19
Model χ^2	= 4.15, *p* = .76					
Pseudo R^2	= 0.02					
Hosmer-Lemeshow test	= 7.06, *p* = .53					
n	= 240					

*Note: *p < .05. **p < .01*

Model 3—Analysis of Population Density and Distance Travelled predicting No-Show Appointments

Model 3 consisted of the same independent variables found in Model 1 and 2, but used these variables to predict the number of No-Show appointments a client would incur over the course of their treatment. The overall model was found to be significant given the Likelihood Ratio test ($\chi^2 = 23.30$, df = 8, p = 0.00), but Age, Gender, Population Density, Distance Travelled, or the interaction between the Population Density and Distance Travelled variables, were non-significant predictors as determined by the Wald chi-square tests. Therefore, these predictors were not interpreted. The results of this model are represented in Table 4.

Table 4.
Model 3 – Negative Binomial Regression of No-Show Appointments Predicted with Population Density and Distance Travelled

Predictor		B	$SE\ \beta$	z-score	*Wald (p)*	IRR
Intercept		-1.53	.05	-6.88	<.00**	0.22
Population Density		<.00	<.00	-1.59	.11	1.00
Distance Travelled		-.01	.01	-.83	.41	0.99
Population Density X Distance Travelled		<.00	<.00	-1.41	.16	1.00
Age		-.01	<.00	-1.21	.23	0.99
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	-.23	.09	-1.89	.06	.79
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	.49	.33	2.36	.02*	1.63
	Hispanic	.39	.20	2.94	<.00**	1.48
Model χ^2	= 66.92, $p < .00$**					
Pseudo R^2	= .02					
alpha	= .49, $\chi^2 = 120.79$, $p = <.00$					
n	= 330					

Note: *$p < .05$. **$p < .01$

The results in this model found that Ethnicity is a statistically significant predictor of No-Show appointments. Additionally, there were statistically significant differences between Ethnicity categories. Both African-American and Hispanic samples had higher Incident Rate Ratios (IRR; i.e., counts of No-Show appointments) than the White sample, while the African-American sample had a higher IRR than the Hispanic sample.

When considering the goodness-of-fit of the model, the Pseudo R^2 was found to be .02, suggesting that 2% of the occurrence of No-Show appointments could be accounted for by the independent variables included in this model. Additionally, the alpha found for this model, which determines how this model fits a Poisson distribution was found adequate ($\alpha = .49$, $\chi^2 = 120.79$, $p = .00$).

Model 4—Analysis of Population Density and Session Fee predicting Reliable Change

Model 4 consisted of: Age, Gender, Ethnicity, Population Density, Session Fee, and the interaction between Session Fee and Population Density to predict RC. This model expanded upon Model 1, which used the total sample (n = 330), by adding an income-related variable (Session Fee). While Population Density was not statistically significant in Model 1, it was found to be a stronger predictor for this model than the Distance Travelled variable as determined through the allsets modeling and a lower AIC and BIC than the Distance Travelled variable. The results of this model are presented in Table 5.

Table 5.
Model 4 – Logistic Regression Analysis of Reliable Change Predicted with Population Density and Session Fee

Predictor		*B*	*SE* β	z-score	*Wald (p)*	Odds-Ratio
Intercept		.03	.46	.07	.94	1.03
Population Density		.00	.00	.25	.80	1.00
Session Fee		.02	.03	.52	.60	1.02
Population Density X Session Fee		.00	.00	-.60	.55	1.00
Age		-.01	.01	-1.41	.16	.99
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	.01	.24	.06	.95	1.01
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	.17	.39	.43	.67	1.18
	Hispanic	-.13	.28	-.46	.65	.88
Model χ^2	=	2.83, $p < .90$				
Pseudo R^2	=	.01				
Hosmer-Lemeshow test	=	7.95, $p = .44$				
n	=	330				

*Note: *p < .05. **p < .01*

Similar to Model 1, which was used to predict RC from two rurality variables, Model 4 was found to be nonsignificant when adding an income-related variable. The independent variables, Population Density, Session Fee, the interaction between Population Density and

Session Fee, and Age were also not statistically significant. Although the Hosmer-Lemeshow test was in acceptable ranges ($\chi^2 = 7.95$, df = 8, p = .43), the Likelihood Ratio test was nonsignificant ($\chi^2 = 2.82$, df = 8, p = .90). Due to these findings, Model 4 was not interpreted.

Model 5—Analysis of Distance Travelled and Session Fee predicting Clinically Significant Change

Model 5 consisted of: Age, Gender, Ethnicity, Distance Travelled, Session Fee, and the interaction between Distance Travelled and Session Fee to predict CSC. This analysis used the outpatient clinical subsample ($n = 240$). Allsets modeling revealed that the Distance Travelled variable, while nonsignificant in Model 2, was better at predicting CSC than Population Density as it had a lower AIC and BIC. Table 6 presents the results of this model.

Table 6.
Model 5 – Logistic Regression Analysis of Clinically Significant Change Predicted with Distance Travelled and Session Fee

Predictor		*B*	*SE* β	z-score	*Wald (p)*	Odds-Ratio
Intercept		-1.23	.59	-2.08	.04*	.29
Distance Travelled		.06	.03	2.03	.04*	1.07
Session Fee		.09	.04	2.15	.03*	1.10
Distance Travelled X Session Fee		-.01	.01	-2.06	.04*	.99
Age		-.01	.01	-.76	.49	.99
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	-.45	.33	.17	.17	.64
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	-.71	.61	.91	.91	.93
	Hispanic	.21	.36	.57	.57	1.23

Model χ^2	=	9.52, $p = .22$
Pseudo R^2	=	.04
Hosmer-Lemeshow test	=	13.43, $p = .10$
n	=	240

Note: $*p < .05$. $**p < .01$

Model 5 was not statistically significant when it was evaluated overall with the Likelihood Ratio Test ($\chi^2 = 9.52$, df = 8, $p = 0.22$). However, statistically significant results were found for Distance Travelled, Session Fee, and the interaction between Distance Travelled and Session Fee in predicting the likelihood of achieving CSC when evaluated by the Wald chi-square tests. While these significant individual regressions are notable, they were not interpreted due to the non-significance of the overall model. Marginal effects were graphed to explore the significant individual coefficients to illustrate the change in odds of predicting CSC across the levels of rurality and income. These effects are presented in Appendix O, P, and Q for consideration.

Model 6—Analysis of Distance Travelled, Population Density, and Session Fee predicting No-Show Appointments

Model 6 consisted of the independent variables: Age, Gender, Ethnicity, Distance Travelled, Population Density, and Session Fee to predict No-Show Appointments. This model expanded upon Model 3 with the addition of an income-related variable. However, no interaction terms were included between Session Fee and the rurality variables due to elevations in the AIC and BIC found through the allsets modeling. Table 9 presents the results for Model 7.

The overall model for Model 6 was found to be significant through the Likelihood Ratio test ($\chi^2 = 26.90$, $df = 8$, p = .00). The alpha for this model was also adequate ($\alpha = .48$, $\chi^2 = 119.57$, $p = .00$). Of further note, the Pseudo R^2 (.02) suggested that 2% of the occurrence of No-Show appointments was predicted by the independent variables in this model. This suggests that there may be other variables that are more predictive of No-Show appointments that are not included for in the model.

Table 7.
Model 6 – Negative Binomial Regression of No-Show Appointments predicted with Population Density, Distance Travelled, and Session Fee

Predictor		*B*	*SE* β	z-score	*Wald (p)*	IRR
Intercept		-1.24	.07	-5.06	<.00**	.29
Population Density		<.00	<.00	-2.64	.01**	.99
Distance Travelled		-.01	<.00	-2.21	.03*	.99
Session Fee		-.03	.01	-2.29	.02*	.97
Age		<.00	<.00	-.92	.36	1.00
Gender						
	Male	(base)	(base)	(base)	(base)	(base)
	Female	-.29	.09	-2.31	.02*	.75
Ethnicity						
	White	(base)	(base)	(base)	(base)	(base)
	African-American	.39	.31	1.87	.06	1.48
	Hispanic	.36	.19	2.64	.01*	1.43
Model χ^2	= 26.90, p = <.00**					
Pseudo R^2	= .02					
alpha	= .48, χ^2 = 119.57, p = <.00					
n	= 330					

*Note: *p < .05. **p < .01*

In this model, Population Density, Distance Travelled, and Session Fee were found to be statistically significant in predicting No-Show appointments. The Incident Rate Ratio (IRR) suggests that with every point increase in the Population Density variable (i.e., 1 person per block) the likelihood of having a No-Show appointment decreases by a multiple of .99. This suggests that as Population Density increases, the likelihood of having a No-Show appointment decreases. With every point increase for the Distance Travelled variable (i.e., 1 mile), the likelihood of having a No-Show appointment also decreased by a multiple of .99. This suggests that as distance travelled increases, the likelihood of having a No-Show appointment decreases. Last, with every point increase for the Session Fee variable (i.e., 1 US dollar) there is a decrease in the likelihood of having a No-Show appointment by a multiple of .97. This suggests that as Session Fees increases, the likelihood of having No-Show appointments decreases.

Gender and Ethnicity variables were also found to be statistically significant as they predicted No-Show appointments. Additionally, there were statistically significant differences between Gender and Ethnicity groups, except for the African-American sample compared to the White sample. For gender, men had a statistically significant higher IRR than women (i.e., higher likelihood of having a No-Show appointment), while the Hispanic sample had the highest IRR over the other ethnicity categories.

Marginal effects were explored for this model to identify the change in No-Show appointments across the levels of rurality and income. These effects are illustrated in Figure 1, 2, 3, 4, 5, and 6 and presented in Tables 8, 9, and 10.

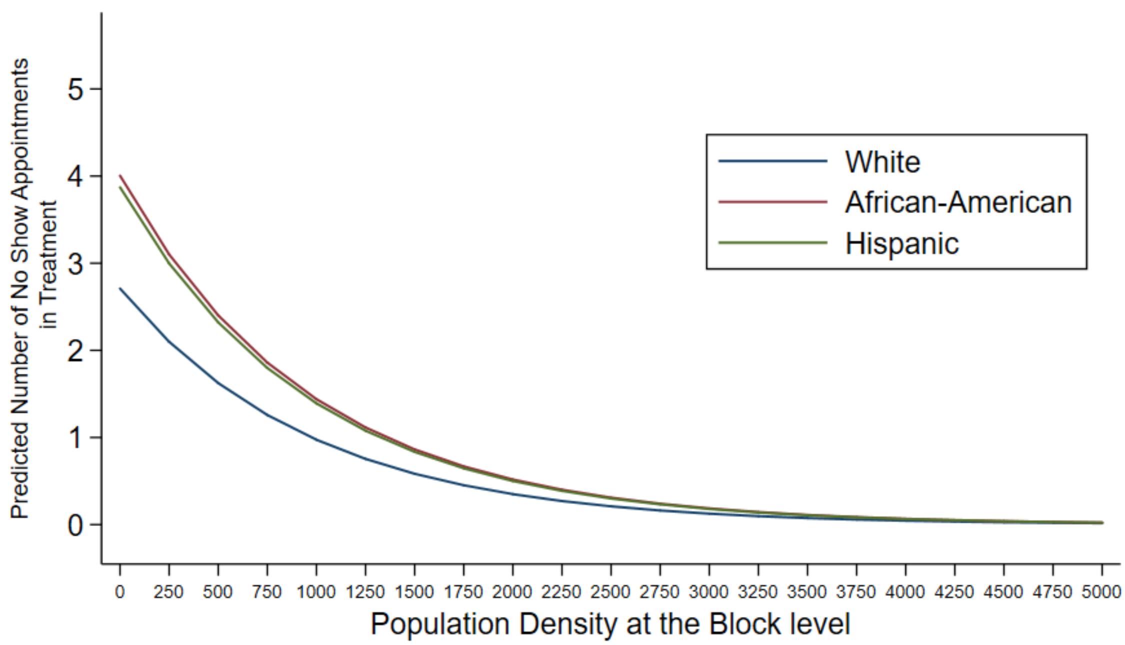


Figure 1. *Predicted No-Show Appointments separated by Ethnicity expressed over Population Density, n=330*

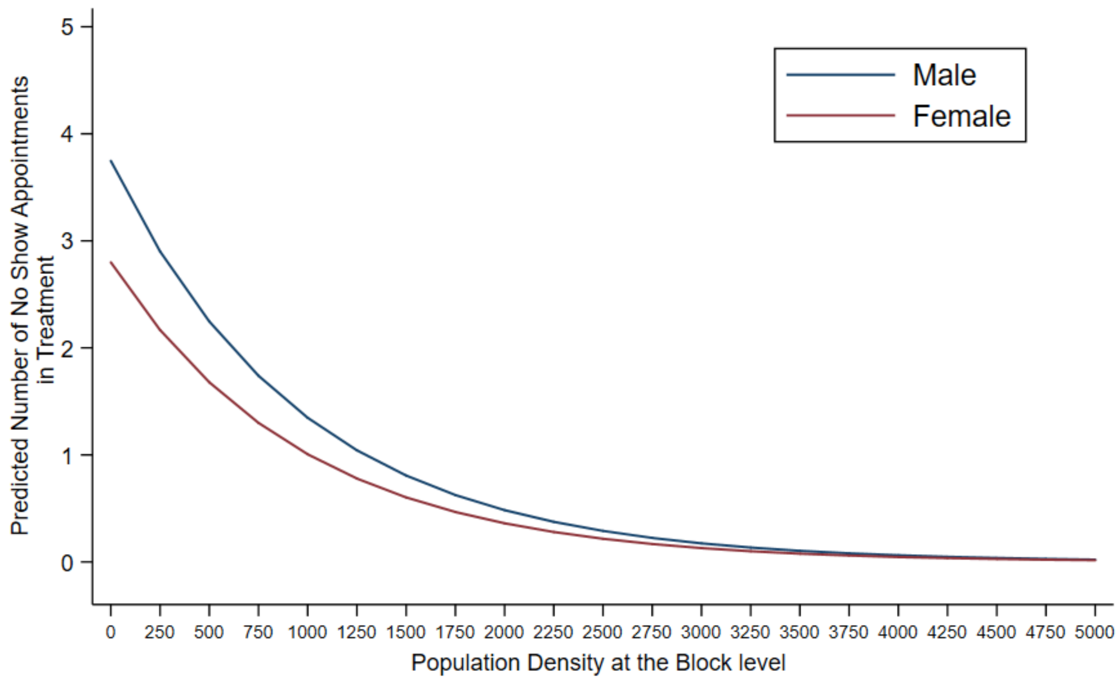


Figure 2. *Predicted No-Show Appointments separated by Gender expressed over Population Density, n=330*

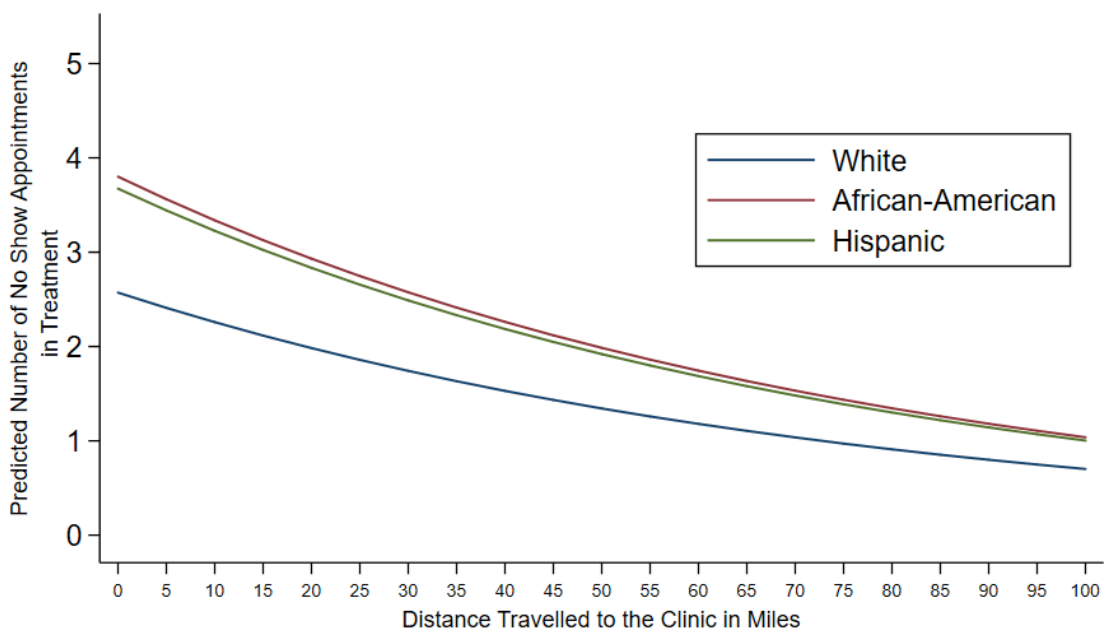


Figure 3. *Predicted No-Show Appointments separated by Ethnicity expressed over Distance Travelled, n=330*

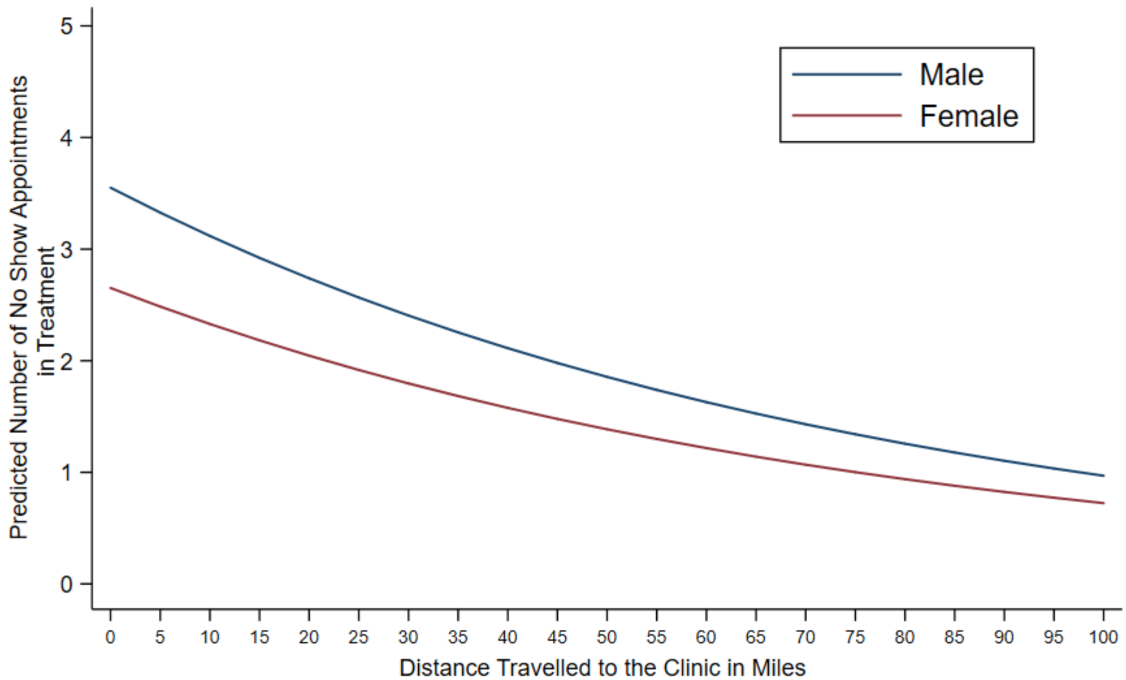


Figure 4. *Predicted No-Show Appointments separated by Gender expressed over Distance Travelled to the Clinic in Miles, n=330*

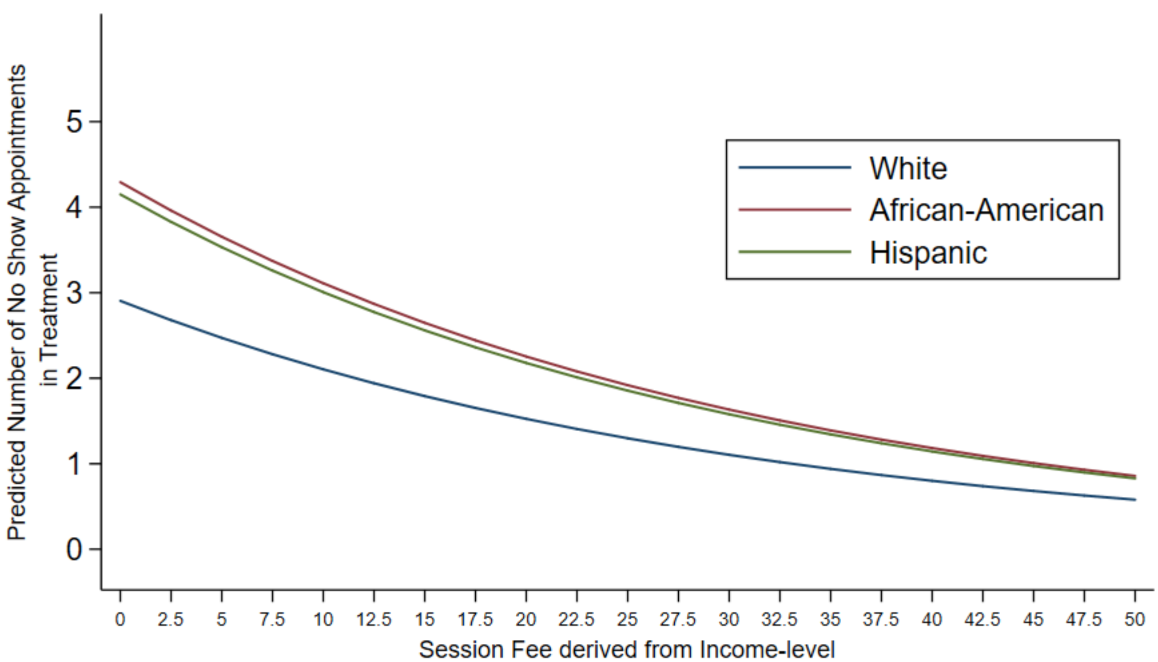


Figure 5. *Predicted No-Show Appointments separated by Ethnicity expressed over Session Fee derived from Income-level, n=330*

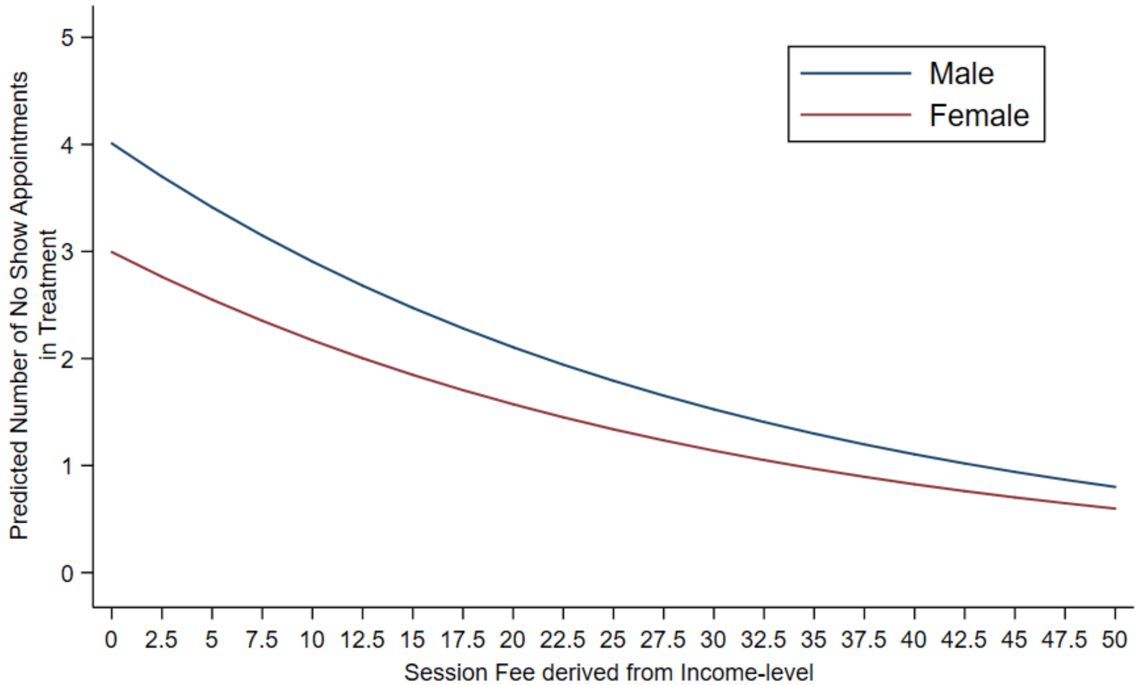


Figure 6. *Predicted No-Show Appointments separated by Gender expressed over Session Fee derived from Income-level, n=330*

Three separate marginal analyses were conducted, the first examined how Population Density predicted the number of No-Show appointments through margins of 250 persons per block (ranging from 0 persons per block to 5,000 persons per block), while holding other variables constant. The second examined how Distance Travelled to the clinic predicted the number of No-Show appointments through margins of 5 miles (ranging from 0 to 100 miles), while holding the other variables constant. Last, a marginal analysis was conducted examining how Session Fee predicted the number of No-Show appointments a client would have through margins of $2.50 (ranging from $0 to $50), while holding other variables constant.

Table 8.

Marginal Effects for Population Density at the block level

Population Density	Predicted Number of No-Show appointments				
	Male	*Female*	*White*	*Hispanic*	*African-American*
0 to 250 ppb	*3.7*	*2.8*	*2.7*	*3.9*	*4.0*
250 to 500 ppb	*2.9*	*2.2*	*2.1*	*3.0*	*3.1*
500 to 750 ppb	*2.2*	*1.7*	*1.6*	*2.3*	*2.4*
750 to 1,000 ppb	*1.7*	*1.3*	*1.3*	*1.8*	*1.9*
1,000 to 1,250 ppb	*1.3*	*1.0*	*1.0*	*1.4*	*1.4*
1,250 to 1,500 ppb	*1.0*	*.78*	*.75*	*1.1*	*1.1*
1,500 to 1,750 ppb	*.81*	*.60*	*.58*	*.84*	*.86*
1,750 to 2,000 ppb	*.62*	*.47*	*.45*	*.65*	*.67*
2,000 to 2,250 ppb	*.48*	*.36*	*.35*	*.50*	*.52*
2,250 to 2,500 ppb	*.37*	*.28*	*.27*	*.39*	*.40*
2,500 to 2,750 ppb	*.29*	*.22*	*.21*	*.30*	*.31*
2,750 to 3,000 ppb	*.22*	*.17*	*.16*	*.23*	*.24*
3,000 to 3,250 ppb	*.17*	*.13*	*.13*	*.18*	*.19*
3,250 to 3,500 ppb	*.13*	*.10*	*.10*	*.14*	*.14*
3,500 to 3,750 ppb	*.10*	*.78*	*.08*	*.11*	*.11*
3,750 to 4,000 ppb	*.08*	*.06*	*.06*	*.09*	*.09*
4,000 to 4,250 ppb	*.06*	*.05*	*.05*	*.06*	*.07*
4,250 to 4,500 ppb	*.05*	*.04*	*.04*	*.05*	*.05*
4,500 to 4,750 ppb	*.04*	*.03*	*.03*	*.04*	*.04*
4,750 to 5,000 ppb	*.03*	*.02*	*.02*	*.03*	*.02*

Note: Margins are in units of persons per block (ppb).

Table 9.

Marginal Effects for Distance Travelled in miles

Distance Travelled	Predicted Number of No-Show appointments				
	Male	*Female*	*White*	*Hispanic*	*African-American*
0 to 5 miles	*3.6*	*2.7*	*2.6*	*3.7*	*3.8*
5 to 10 miles	*3.3*	*2.5*	*2.4*	*3.4*	*3.6*
10 to 15 miles	*3.1*	*2.3*	*2.3*	*3.2*	*3.3*
15 to 20 miles	*2.9*	*2.2*	*2.1*	*3.0*	*3.1*
20 to 25 miles	*2.7*	*2.0*	*2.0*	*2.8*	*2.9*
25 to 30 miles	*2.6*	*1.9*	*1.9*	*2.7*	*2.7*
30 to 35 miles	*2.4*	*1.8*	*1.7*	*2.5*	*2.6*
35 to 40 miles	*2.3*	*1.7*	*1.6*	*2.3*	*2.4*
40 to 45 miles	*2.1*	*1.6*	*1.5*	*2.2*	*2.3*
45 to 50 miles	*2.0*	*1.4*	*1.4*	*2.0*	*2.1*
50 to 55 miles	*1.9*	*1.4*	*1.3*	*1.9*	*2.0*
55 to 60 miles	*1.7*	*1.3*	*1.3*	*1.8*	*1.9*
60 to 65 miles	*1.6*	*1.2*	*1.2*	*1.7*	*1.7*
65 to 70 miles	*1.5*	*1.1*	*1.1*	*1.6*	*1.6*
70 to 75 miles	*1.4*	*1.1*	*1.0*	*1.5*	*1.5*
75 to 80 miles	*1.3*	*1.0*	*.97*	*1.4*	*1.4*
80 to 85 miles	*1.3*	*.94*	*.91*	*1.3*	*1.3*
85 to 90 miles	*1.2*	*.88*	*.85*	*1.2*	*1.3*
90 to 95 miles	*1.1*	*.82*	*.80*	*1.1*	*1.2*
95 to 100 miles	*1.0*	*.77*	*.75*	*1.1*	*1.1*

Note: Margins are in the miles travelled from the client address to the clinic.

Table 10.
Marginal Effects for Session Fee derived from income-level

Session Fee	Predicted Number of No-Show appointments				
	Male	*Female*	*White*	*Hispanic*	*African-American*
$0 to $2.50	*4.0*	*3.0*	*2.9*	*4.2*	*4.3*
$2.50 to $5.00	*3.7*	*2.7*	*2.7*	*3.8*	*4.0*
$5.00 to $7.50	*3.4*	*2.6*	*2.5*	*3.5*	*3.7*
$7.50 to $10.00	*3.1*	*2.4*	*2.3*	*3.3*	*3.4*
$10.00 to $12.50	*2.9*	*2.2*	*2.1*	*3.0*	*3.1*
$12.50 to $15.00	*2.7*	*2.0*	*1.9*	*2.8*	*2.9*
$15.00 to $17.50	*2.5*	*1.8*	*1.8*	*2.6*	*2.6*
$17.50 to $20.00	*2.3*	*1.7*	*1.7*	*2.4*	*2.4*
$20.00 to $22.50	*2.1*	*1.6*	*1.5*	*2.2*	*2.3*
$22.50 to $25.00	*1.9*	*1.5*	*1.4*	*2.0*	*2.1*
$25.00 to $27.50	*1.8*	*1.3*	*1.3*	*1.9*	*1.9*
$27.50 to $30.00	*1.7*	*1.2*	*1.2*	*1.7*	*1.8*
$30.00 to $32.50	*1.5*	*1.1*	*1.1*	*1.6*	*1.6*
$32.50 to $35.00	*1.4*	*1.0*	*1.0*	*1.5*	*1.5*
$35.00 to $37.50	*1.3*	*1.0*	*.94*	*1.3*	*1.4*
$37.50 to $40.00	*1.2*	*.90*	*.87*	*1.2*	*1.3*
$40.00 to $42.50	*1.1*	*.83*	*.80*	*1.1*	*1.2*
$42.50 to $45.00	*1.0*	*.76*	*.74*	*1.1*	*1.1*
$45.00 to $47.50	*.94*	*.70*	*.68*	*1.0*	*1.0*
$47.50 to $50.00	*.87*	*.65*	*.63*	*.90*	*.93*

Note: Margins are in U.S. dollars.

Marginal analyses for Population Density revealed marginal effects, such that those who lived in less populated areas, particularly those below 500 persons per block, were more susceptible to have No-Show appointments (approx. 3 No-Show appointments) whereas those in margins from 3,000 persons per block and on were associated with approximately 0 No-Show appointments. Considering the marginal analyses for Distance Travelled, fewer miles travelled (e.g., margins of 0 to 5 miles from the clinic) were associated with more No-Show appointments (approx. 3 No-Show appointments) than margins that were further away from the clinic (e.g., 95 to 100 miles) which was associated with approximately 1 No-Show appointment. Last, the marginal analysis for Session Fee found that those who paid less per session (e.g., \$0 to \$2.5 per session) were associated with more No-Show appointments (approx. 3.5 No-Show appointments) than margins of higher Session Fees (e.g., \$47.5 to \$50 per session) with approximately 1 No-Show appointment.

For each of the marginal analyses statistically significant differences were found between ethnicity and gender, except for the African-American sample. This study did not examine intersectionality between these demographic variables, so interpretation and generalization of these results is cautioned. Additionally, while statistical significance was found for the marginal analyses, margin sample sizes were not equal and smaller samples were found for margins that represented further distances travelled (e.g., 95 to 100 miles), higher session fees (e.g., \$47.50 to \$50.00), and lower populated areas (0 to 250 ppb).

Summary of Analysis Results

This study utilized logistic regression to predict treatment outcomes (RC and CSC) and a negative binomial regression based on the Poisson distribution to predict No-Show appointments. The models contained two rurality variables (Population Density and Distance Travelled) and an income-related variable (Session Fee) serving as independent variables. Demographic variables (Age, Gender, and Ethnicity) were also included in the models. Six models were tested. Table 11 includes the model fit for each of the six models tested.

Table 11.
Comparison of Overall Models

	Model Fit			Hosmer-L.				
	χ^2	*df*	*p*	χ^2	*p*	Pseudo R^2	AIC	BIC
Model 1 Population Density and Distance Travelled on RC, *n*=330	2.50	8	.92	3.26	.91	.01	459.25	489.65
Model 2 Population Density and Distance Travelled on CSC, *n*=240	4.15	8	.76	7.06	.53	.02	267.77	295.62
Model 3 Population Density and Distance Travelled on No-Show Appointments, *n*=330	23.30	8	<.00**	---	---	.02	1215.34	1249.53
Model 4 Population Density and Session Fee on RC, *n*=330	2.82	8	.90	7.95	.44	.01	458.94	489.33
Model 5 Distance Travelled and Session Fee on CSC, *n*=240	9.52	8	.22	13.43	.10	.04	262.40	290.25
Model 6 Population Density, Distance Travelled, and Session Fee on No-Show Appointments, *n*=330	26.90	8	<.00**	---	---	.02	1211.74	1245.93

Note: **p* < .05. ***p* < .01

The independent variables in Model 1, 2, and 3 consisted of Age, Gender, Ethnicity, Population Density, Distance Travelled, and an interaction between them. Model 1, which evaluated how these variables predicted RC, was found statistically nonsignificant. Model 2 was also found to be statistically nonsignificant, as it explored how these variables predicted CSC.

Last, Model 3 was statistically significant and predicted No-Show appointments. Although the only statistically significant independent variable in this model was Ethnicity.

Models 4, 5, and 6 expanded upon the previous set of models by adding an income-related variable (Session Fee). Decisions on which independent variables to use for these models was determined after examining how each independent variable influenced the AIC and BIC found through allsets modeling. Model 4 consisted of Population Density, Session Fee, and their interaction, predicting RC. This model, similar to Model 1, was nonsignificant and was not interpreted.

Model 5 utilized Distance Travelled, Session Fee, and their interaction, as it predicted CSC. While some independent variables were statistically significant according to the Wald chi-square test, the overall model was statistically nonsignificant and was not interpreted.

Last, Model 6 considered both rurality variables (Population Density and Distance Travelled) and Session Fee to predict No-Show appointments over the course of treatment. No interaction terms were added to this model due to the subsequent elevations of the AIC and BIC. This model found Ethnicity, Gender, Population Density, Distance Travelled, and Session Fee all statistically significant in predicting No-Show appointments. Marginal effects were explored with this model to illustrate how the levels of rurality and income change the number of predicted No-Show appointments. These effects suggested that less populated areas, shorter distances travelled to the clinic, and lower session fees, were associated with more No-Show appointments than those residing in higher populated areas, travelling further distances, and paying higher session fees.

CHAPTER V

DISCUSSION

The initial research questions this study aimed to answer were related to how the rurality and income of psychotherapy clients predict treatment-related outcomes. Past research has found that one's income and rurality status are related to treatment access barriers, which contribute to the formation of mental health disparities. These treatment access barriers fall in Affordability, Acceptability, Accessibility, Availability, and Awareness domains and negatively impact marginalized populations the most (Penchansky & Thomas, 1981). This is noted as a critical issue requiring immediate national attention and research (Safran et al., 2009).

An additional question was aimed to determine which rurality variable (Population Density or Distance Travelled) was the stronger predictor of treatment-related outcomes. Past literature has used state, county, or city identifiers (HAC, 2011), zip code analyses (Carvalho, 2016), or an integration of income-related variables (Goodwin 2002; Zito et al., 2005) to identify rural populations. Most prominently, the research has focused on distance variables from an urban-centric point to identify rural populations (Carvalho, 2016). This study used two variables a Population Density variable and a Distance Travelled variable for predictive comparison as it pertains to establishing one's level of rurality. Population density has been recommended in the literature to identify rural status (Bako, Dewar, Hanson, & Hill, 1984), but has proven difficult to reliably measure due to limitations in the methodology. Therefore, this study used new and innovative geospatial software, ArcGIS, to identify the population density of a client's home address to the block-level as recorded in the 2010 US Census.

The final research questions, aimed to identify the best fitting model and explore how treatment-related outcomes vary across the levels of income and rurality, were to provide insight to researchers and policy-makers. These insights were hoped to lead to future research and/or guide potential clinic policies that are specifically aimed to improve treatment response and reduce No-Show appointments. While recommendations for future research and policies are provided in this chapter and drawn from these insights, these recommendations were not tested or examined and should be considered as conjecture.

The present study analyzed data from a sample of 330 psychotherapy clients and a subsample of 240 psychotherapy clients that started with clinically significant levels of distress. Data was gathered at the Texas A&M University Counseling and Assessment Clinic in Bryan, Texas. While this community mental health clinic is a training clinic for doctoral psychology students, it provides treatment as usual with outcomes assumed to be comparable to other clinics (Callahan & Hynan, 2005; Howard, Kopta, Krause, & Orlinsky, 1986). This study used logistic regressions to predict dichotomous treatment response variables (RC and CSC) and negative binomial regressions to predict No-Show appointments. Marginal effects were also produced to examine how the levels of the independent variables (Population Density, Distance Travelled, and Session Fee) changed the predicted outcome of the dependent variables (RC, CSC, and No-Show appointments).

1) **<u>Research Question One: Which rurality variable (Population Density or Distance Travelled) is a stronger predictor of treatment outcomes (RC and CSC) and No-Show appointments?</u>**

Reliable Change

Model 1 included both rurality variables (Population Density and Distance Travelled) to determine which variable best predicted RC. This model included demographic variables (i.e., Age, Gender, and Ethnicity), and the interaction between the Population Density and Distance Travelled. Model 1 was not statistically significant, as well as was Model 4, which expanded upon Model 1 with the addition of an income-related variable. However, Population Density was used in Model 4 over Distance Travelled, as this independent variable had a lower AIC and BIC found through allsets modelling. While this suggests that Population Density is likely a stronger predictor of RC than Distance Travelled, no conclusions could be made due to the overall model being statistically nonsignificant.

Clinically Significant Change

Model 2 consisted of the same variables in Model 1, but examined how Population Density and Distance Travelled variables predicted CSC in an outpatient clinical subsample. In a similar way, Model 2 was not statistically significant. Therefore, no conclusions could be made regarding which rurality variable was a stronger predictor of CSC from this model. However, in Model 5, a lower AIC and BIC was found when including Distance Travelled through allsets modelling, but this only occurred when adding an interaction effect with the Session Fee variable. Model 5 found that Distance Travelled and its interaction with Session Fee were statistically significant predictors of CSC, but in an overall statistically nonsignificant model. This suggests that Distance Travelled is likely a stronger predictor of CSC than the Population Density variable, but no conclusions could be made due to the overall model being statistically nonsignificant.

No-Show appointments

Model 3 consisted of the same independent variables as Model 1 and 2, but the dependent variable was No-Show appointments. While the overall model was found to be statistically significant, the rurality variables (Population Density and Distance Travelled) were not. For Model 6, which expanded upon Model 3, both Population Density and Distance Travelled were statistically significant, but only when including Session Fee. This model found that while both of these variables have utility in predicting No-Show appointments, Population Density has the highest significance value ($p = .01$) compared to Distance Travelled ($p = .03$). This suggests that Population Density is a stronger predictor of No-Show appointments, but only when adding Session Fee to the model.

Summary of Research Question One

Research Question One was aimed to identify which rurality variable (Population Density or Distance Travelled) was the stronger predictor of RC, CSC, and No-Show appointments. No conclusions could be made regarding which variable was a stronger predictor for RC and CSC. However, a lower AIC and BIC were found for Population Density over Distance Travelled when predicting RC, which suggests that Population Density is likely a stronger predictor for RC. In a similar way, a lower AIC and BIC were found for Distance Travelled over Population Density when predicting CSC, which suggests that Distance Travelled is likely a stronger predictor for CSC. For the No-Show appointment, Model 6 found that Population Density was the stronger predictor for No-Show appointments than Distance Travelled, but only when adding Session Fee to the model.

2) **Research Question Two: Which variable (Session Fee or Population Density/Distance Travelled) is a stronger predictor of treatment outcomes (RC and CSC) and No-Show appointments?**

Reliable Change

Model 4 expanded upon Model 1 by replacing an income-level variable (Session Fee) for the what was assumed to be the less predictive rurality variable (Distance Travelled) to predict RC. Unfortunately, Model 4 was not statistically significant, and conclusions could not be drawn as to which variable (Session Fee or Population Density) was a stronger predictor of RC. However, there was an overall improvement in the AIC and BIC in Model 4 compared to Model 1. This suggests that Session Fee is likely a stronger predictor of RC than both of the rurality variables.

Clinically Significant Change

Model 5 expanded upon Model 2 by replacing Session Fee with what was assumed to be the less predictive rurality variable (Population Density) to predict CSC. Similar to predicting RC, allsets modeling found that Session Fee was associated with a lower AIC and BIC than the Population Density and Distance Travelled variables. This suggests that Session Fee is likely a stronger predictor of CSC than the other variables.

No-Show Appointments

Model 6 expanded upon Model 3, by adding Session Fee as an independent variable. Based on the allsets modeling, no rurality variables were replaced and no interaction terms were added to this model. Model 6 was statistically significant overall and found statistically significant effects for Population Density, Distance Travelled, and Session Fee. All of the independent variables became significant when Session Fee was added, which suggests that Session Fee represents a confounding factor preventing Population Density and Distance Travelled from being statistically significant in Model 3. However, in Model 6, Population Density was associated with the highest significance value ($p = .01$) over Distance Travelled ($p =$

.03) and Session Fee (p = .02), suggesting that Population Density is a stronger predictor of No-Show appointments over the other variables.

Summary of Research Question Two

Research Question Two was aimed to identify which variable (Session Fee or Population Density/Distance Travelled) was a stronger predictor of RC, CSC, and No-Show appointments. No conclusions could be made regarding which variable was a stronger predictor for RC or CSC. However, a lower AIC and BIC were found through allsets modeling for Session Fee over Population Density and Distance Travelled for RC and CSC, which suggests that Session Fee is likely a stronger predictor for RC and CSC than the rurality variables. When predicting No-Show appointments, Session Fee improved the significance of the other rurality variables, suggesting it has utility in controlling for a confounding effect. However, Population Density was found to be a stronger predictor of No-Show appointments over Session Fee in this model.

3) **Research Question Three: Will a model with rurality and income variables (Population Density, Distance Travelled, and Session Fee) better predict treatment outcomes (RC and CSC) and No-Show appointments over models with only rurality variables?**

Goodness-of-fit tests were presented in Table 11 to compare the results of all the models tested. No model was able to predict in a statistically significant fashion RC or CSC, so no conclusions could be made regarding which variables contributed to the *best* model for RC and CSC. However, Model 6 was better at predicting No-Show appointments over Model 3 as seen through a reduction in the AIC and BIC. This model included Age, Gender, Ethnicity, Distance Travelled, Population Density, and Session Fee variables. This suggests that both rurality variables and an income-related variable are useful when attempting to predict No-Show appointments.

4) **<u>Research Question Four: How do treatment-related outcomes vary across the levels of rurality?</u>**

Separate marginal analyses were conducted for Population Density and Distance Travelled as both of these rurality variables were statistically significant in Model 6 as they predicted No-Show appointments. For Population Density, margins consisted of 250 persons per block (ranging from 0 to 5,000 ppb) and presented in Table 8. The effects found between these margins suggest that Population Density has a nonlinear negative association when predicting No-Show appointments. For example, as the levels of rurality decreased, from less populated areas to higher populated areas, the number of No-Show appointments decreased. Furthermore, the effect of rurality was greatest in margins representing lower populated areas, particularly those from 0 to 500 ppb. These margins were associated with roughly 3 No-Show appointments. This effect decreased and became negligible after margins representing 3,000 ppb and above, which was associated with roughly 0 No-Show appointments. Significant marginal differences were also found between Gender and Ethnicity variables and illustrated in Figures 1 and 2.

For the Distance Travelled variable, margins consisted of 5 miles (ranging from 0 to 100 miles travelled) and are presented in Table 9. The effects found between these margins suggest that Distance Travelled had a slight nonlinear negative association on predicting No-Show appointments. Such that, as the distance one travels to the clinic increases, the number of No-Show appointments decrease. The effect of the Distance Travelled variable was greatest in closer proximity margins (e.g., 0 to 5 miles) with approximately 4 No-Show appointments than margins representing further distances (e.g., 95 to 100 miles) which had approximately 1 No-Show appointment. Significant marginal differences were also found between Gender and Ethnicity variables and illustrated in Figures 3 and 4.

5) **<u>Research Question Five: How do treatment-related outcomes vary across the levels of income?</u>**

Similar to Population Density and Distance Travelled, Session Fee was included in a marginal analysis from Model 6. Margins consisted of $2.50 per session (ranging from $0 to $50 per session) and are presented in Table 10. Session Fee was also found to have a negative nonlinear association with No-Show appointments, such that as Session Fee increased, the number of No-Show appointments decreased. The effect of Session Fee was greatest in margins of lower session fees (i.e., $0 to $2.50) with approximately 3.5 No-Show appointments compared to margins of higher session fees (i.e., $47.50 to $50) with approximately 1 No-Show appointment. Significant marginal differences were also found between Gender and Ethnicity variables and illustrated in Figures 5 and 6.

Explanation of Findings

The research questions in this study were aimed to assess how rurality and income predict treatment-related outcomes, to explore which variables (Population Density, Distance Travelled, and/or Session Fee) were stronger in predicting these outcomes, and to examine how predicting these outcomes vary across the levels of income and rurality.

Treatment Response (RC and CSC)

This study did not find any statistically significant models pertaining to the treatment response variables (RC and CSC) and therefore no conclusions could be drawn. However, the lack of statistical findings for treatment response is notable. One possibility as to why statistical significance was not found pertains to the OQ-45 measure, as this measure does not capture all the types of treatment response. While the OQ-45 includes questions pertaining to social role and interpersonal relationships, most of the questions are focused on symptom distress, which may underestimate treatment response in other ways. More specific measures such as the Outcome Rating Scale (ORS), Wellness Assessment, and the Daily Living Activities could be used to assess different types of therapeutic change such as in daily functioning, improvements in relationships, and/or shifting interpersonal patterns.

Another possibility is that the rurality variables (Population Density and Distance Travelled) were not accurate enough, which could prevent these variables from predicting treatment response. For example, Population Density and Distance Travelled variables were coded based on the 2010 US census data, which occurred one to six years prior to data collection. Research that improves the validity of these variables, such as by using more appropriate data to code these variables, may find that rurality does predict RC and CSC. In a similar way, limitations exist in how Session Fee was used, such that it considers family size, is rounded to the nearest dollar, and is based on self-report, which may hinder the validity of this variable representing a client's income-level, and therefore preventing statistical significance from being found for RC and CSC.

It is also possible that rurality and income simply do not predict treatment response for this sample. While past research has found poorer treatment-related outcomes for rural and low-income groups (Berenson et al., 2012), this was not supported in this study as it pertains to treatment response. Two new possibilities arise: 1) living in a more rural area and being low-income does not negatively impact treatment response for this sample, or 2) this community mental health clinic successfully alleviates barriers impacting rural and low-income groups, so that it does not negatively impact their treatment response compared to clients who are more urban and higher-income. These rationales, however, are dependent on the OQ-45 being successful in capturing treatment response as well as the independent variables accurately measuring rurality and income.

No-Show Appointments

When examining how rurality predicts No-Show appointments, the independent variables (Population Density and Distance Travelled) were both statistically significant in Model 6. These findings suggest that: 1) less populated areas are associated with more No-Show appointments than higher populated areas, and 2) shorter distances travelled to the clinic are associated with more No-Show appointments than further distances travelled. At face value this finding seems contradictory in nature, as one may assume that the further a client travels to the clinic, the more *rural* they are. However, this may not be the case for this sample. A plausible explanation to this finding is that the Population Density and Distance Travelled variables represent different constructs and may not equally *capture* rural culture for this sample. This is supported by noting that the Population Density and Distance Travelled variables were not strongly correlated to one another ($r = -.28$).

Distance Travelled

Past research has considered the distance a client travels to treatment as a treatment access barrier (Desrosiers, Ibrahim, & Jacks, 2019), and has used this variable to assume a client's rural status. However, this assumption was not supported by this study, as the further one travelled for treatment was associated with a decrease in No-Show appointments. A possible explanation for this finding is that a client who travels further to the clinic may be more motivated to attend treatment than those who live in closer proximity, as further distances may create a potential buy-in effect for treatment.

Another plausible possibility for this finding, is that clients who live further away may be more aware that they are unable to attend an upcoming session, thus more likely to cancel or reschedule before their appointment time. An analysis of the reasons behind these No-Show appointments, such as through direct follow-ups with the client, could be beneficial in supporting this explanation. A final possibility, is that this finding is due to error or chance. An important note is that the sample distribution was skewed towards those living in closer proximity compared to those living further away, which may have increased the likelihood of statistical error. This distribution of clients' addresses is illustrated in geospatial maps presented in Appendix A – K. Future research could consider a more equal distribution of distances travelled for clients in their analyses to limit this possibility.

Population Density

The finding that Population Density predicted No-Show appointments, such that lower populated areas were associated with more No-Show appointments than higher populated areas is also notable. It is important to consider that the results in this study do not state that Population Density causes No-Show appointments, but rather suggest that there may be rurality factors that are captured by the Population Density variable. These rurality factors may also be associated with treatment access barriers that negatively impact No-Show appointments. If true, this study suggests that Population Density was better at capturing a more traditional definition of rural status than the Distance Travelled variable. These results further support a No-Show appointment difference between those in low populated areas compared to those living in higher populated areas.

More research should explore the *why* behind this finding. For example, it is possible that lower populated areas may lack access to cellular coverage and/or internet access, which may prevent these clients from contacting the clinic to cancel or reschedule appointments. Perhaps, lower populated areas lack access to public transportation that could be used to attend treatment. Another possibility, is that there may be more mental health stigma in lower populated areas than in higher populated areas, which contribute to higher No-Show appointments. Research should aim to answer these questions, so that rural mental health clinics can implement effective policies aimed to reduce No-Show appointments.

Session Fee

Session Fee was also found to significantly predict No-Show appointments, such that higher session fees were associated with lower No-Show appointments. While this may seem contradictory, as one may assume that lower treatment costs would be associated with less No-Show appointments, this was not supported in this study. There are several possibilities for this finding. A very likely possibility, is that Session Fee, which is derived from one's annual household income-level on a sliding scale fee, was able to capture factors associated with low-income populations. If true, Session Fee may also be associated with treatment access barriers that more heavily impact low-income individuals compared to high-income individuals.

Future research should explore the *why* behind this finding as well. It is likely that high-income clients have more availability to attend appointments than low-income clients, can more easily pay the higher session fee than low-income clients can pay the lower session fee, and higher-income clients are more easily able to cancel/reschedule sessions as they are more likely to afford cell phones or unlimited cellular plans than low-income clients who have to use their resources sparingly. In further consideration, low-income clients may also rely on more than one job for income, may not be able to afford caretakers or babysitters, and may have to rely on public transportation rather than their personal vehicles, all of which likely increase No-Show appointments. While this is theorized, research should explore ways to examine these possibilities.

Of course, it is possible that Session Fee may not be associated with treatment access barriers for low-income clients, but may capture some other construct. For example, the more a client pays for a session the more motivated they may become for treatment. This may create a buy-in effect, where clients who pay more per session may value treatment more and perceive it to be of higher quality than clients who pay less per session. Research could explore this possibility by examining differences between session fee payment when it is not associated to one's annual income or by considering the impact of adjusting a client's session fee mid-treatment on No-Show appointments.

A final consideration, is that low-income clients may enter into treatment at higher levels of distress than high-income clients. While this was not found to be the case for this sample, as low-income and high-income groups had comparable OQ-45 scores entering into treatment, this should be considered in future research.

Comparing Rurality

A secondary aim of this study was to assess which rurality variable (Population Density or Distance Travelled) better predicted treatment-related outcomes. The results in this study suggest that Distance Travelled and Population Density play a role in predicting No-Show appointments. However, Population Density better predicted No-Show appointments than Distance Travelled and was generally associated with lower AICs and BICs in the other models, albeit those models were nonsignificant.

Due to the majority of the models in this study being nonsignificant, Population Density and Distance Travelled are likely not sufficient by themselves to reliably predict the treatment-related outcomes used in this study. It is likely that there are other factors that are stronger predictors of treatment response and No-Show Appointments than the level of rurality and/or level of income of the client. For example, other variables worthy of consideration include the quality of the therapist-client relationship, clinical diagnoses, and counselor-related factors (e.g., age, gender, culture, and/or expertise of the counselor). Research should consider these factors and find ways to integrate them in predictive models when exploring clients' treatment response and No-Show appointments.

Implication of Findings

Implications from this study should be considered judiciously with awareness of this study's limitations. Overgeneralization is further cautioned when applying these findings to another client population based on region or other cultural characteristics. Despite these considerations, the findings found in this study may have implications for rural mental health researchers, particularly those aiming to predict positive treatment response and reduce No-Show appointments. Additional recommendations to the community mental health clinic this study was conducted at are provided, but these are drawn from the findings of the study as a point of conjecture.

Rural Health Research

One implication of this study is that Population Density tended to be a stronger predictor of RC, CSC, and No-Show appointments than Distance Travelled. This finding lends support to researchers considering Population Density as a potential option to identify one's rural status when exploring mental health disparities and treatment access barriers. This assumes that future research can repeat, generalize, expand upon, and eliminate the limitations found in this study to better support this conclusion that Population Density is associated with rural status. While population density has already been identified as an important construct in rural research (Bako, Dewar, Hanson, & Hill, 1984), it has been difficult to measure this based on the methodology. Therefore, this study supports the usage of geospatial analyses as a way to measure population density.

Additionally, while there is no known research that used distance travelled to predict No-Show appointments specifically, distance-related variables have often been used to identify rural status and posited as a treatment access barrier impeding treatment-related outcomes (Desrosiers, Ibrahim, & Jacks, 2019). However, this conclusion was not supported in this study, as the further distance one travelled was associated with a decrease in No-Show appointments instead of an increase in No-Show appointments. If this finding can be repeated, generalized, and further elaborated on in future research studies, it could change how research has traditionally perceived distance-related variables as negatively impacting treatment-related outcomes.

Another important consideration pertains to the finding that Session Fee, when added to the statistical models, improved the significance of the rurality variables (Population Density and Distance Travelled). One likely explanation is that Session Fee was a confounding variable preventing significance from being found when it was not controlled for. This gives merit to rural health researchers including income-related variables into their analyses. Additionally, this study recommends, as a point of conjecture, that future research explore other variables (e.g., therapeutic alliance, counselor-related factors, and clinical diagnoses), which may add to the predictive strength of models aiming to predict treatment response and No-Show appointments.

Clinical Recommendations

This study aimed to provide potential recommendations to the community mental health clinic this study was conducted at. While the provided recommendations are drawn from the findings in this study, they are pure conjecture, as the effectiveness of these recommendations were not studied or evaluated specifically. One recommendation is to lower the session fee for clients who are disadvantaged or are of low-income status. It is possible that the burden of paying low session fees may be more difficult for low-income clients than paying high session fees is for high-income clients. While not examined, alleviating or eliminating this potential financial barrier could decrease No-Show appointments for low-income clients. However, there are several other possible explanations for this finding, which need to be considered and explored (e.g., buy-in effect).

A second recommendation, given the finding that Population Density predicts No-Show appointments, pertains to better supporting clients in lower populated areas, particularly those living in areas of 0 to 500 persons per block. For example, offering and encouraging other treatment modalities for these clients may reduce No-Show appointments. Telecounseling is a unique, cost-effective treatment modality with proven effectiveness (McCord et al., 2011) and can be provided to a client from their home residence. This modality could potentially eliminate some of the barriers to treatment (e.g., negative mental health stigma, access to roads, or access to transportation) that are believed to be occurring for clients living in low populated areas.

A final recommendation is the addition of No-Show policies aimed to incentivize clients living in low populated areas and clients who pay lower session fees. It is likely that clinic policies aimed to discourage No-Show appointments for these clients would have the most effect on reducing the gratuitous drain of limited clinic resources (e.g., counselor time, available rooms, and financial costs). For example, a solution could include offering a percentage of the client's session fee payments back to the client if treatment is adhered to. However, research should support the effectiveness of these policies as they are implemented, as these policies should encourage and reduce No-Show appointments rather than serve as an additional barrier to treatment (e.g., increasing the cost of treatment).

Limitations

There were several potential limitations within this current study. First pertains to data integrity. An estimated 204 clients had incomplete or inaccurate data and could not be matched accurately to levels of income and/or levels of rurality. These clients had to be excluded from the sample. Additionally, the Distance Travelled variable, gathered through ArcGIS, assumed the best route a client would drive from their home address to the clinic address. While this is assumed through the geospatial software, it is not known if this was the actual driven route by the client. Additionally, the Population Density variable relied heavily on the decennial census data collected in April 2010, which occurred one to six years before the data was collected for this study. This suggests that the Population Density variable may be based on outdated data, but other means of gathering this information are not known. Last, 23 addresses were listed as P.O. Boxes and were included in this study, which made up roughly 7% of the total sample. While it is believed that the client's actual residence resides within the block of this P.O. Box, it is impossible to be certain. These limitations may have impacted the findings in this study. However, these issues are believed to be minimal in nature given the total sample size.

Another limitation may exist in the RC and CSC treatment response variables. These variables considered the difference between two assessments (the client's first session and their last session). Other studies have measured RC and CSC occurring between these two treatment intervals by averaging the first three sessions scores and contrasting that to the last session score. However, capturing treatment response in this way was also identified as a limitation (Kalpinski,

2014) and may further minimize potential treatment effects that can occur in one session (Stalker, Horton, & Cait, 2012).

Another limitation exists in the usage of Session Fee as an income-related variable. A client's session fee is dependent on the client's self-reported annual income and household size. Self-reported income-levels may not be entirely accurate, as it may be stigmatizing to report, inaccurate due to the client's uncertainty of their household earnings, or underreported by the client in attempts to lower the estimated session fee. Furthermore, a client's income-level is rounded to the nearest dollar on the sliding fee scale, which captures a large range of potential income-levels within each dollar interval. This suggests that there is more error in the reporting of income using these categories versus just reporting one's actual yearly income.

Another consideration should be made for the number of participants in the various ethnicities and gender subgroups. The models in this study included these demographic variables to further control potential underlying effects. However, the African-American sample (n = 32) and Hispanic sample (n = 79) were considerably smaller than the White sample (n = 219), which limited the statistical power of these regressions. This study did not look at interactions between gender and ethnicity due to the small number of participants in these groups. Generalization of the findings in this study regarding differences in ethnicity and gender should therefore be cautioned.

Future Directions

Future research can expand upon the findings in this study by exploring ways to better predict treatment response, particularly for low-income and rural psychotherapy clients. Research that uses other or multiple measures to determine treatment response may challenge the finding in this study that rurality and income did not predict treatment response. For example, the

Patient Health Questionnaire (PHQ) may be a better measure of determining change in symptom reduction than the OQ-45, while the Outcome Rating Scale (ORS), Wellness Assessment, and the Daily Living Activities may be more helpful in determining specific types of therapeutic change (Wrenn & Fortney, 2015).

Additional research considering other independent variables are worthy of inquiry such as employment status, marital status, and sexual orientation, which has not been traditionally included in disparity research with rural populations. Other mental health outcomes such as clinical dropout and attendance rates that consider rescheduled and cancelled appointments could lead to clinic policies aimed to alleviate the gratuitous drain of uncompensated care costs caused by client nonattendance. Most importantly, research that explores the stigma around mental health treatment for rural and low-income populations would be of utmost value and may increase our understanding of other access barriers that impact these psychotherapy clients apart from access and affordability barriers.

Research should also aim to explore viable solutions to the mental health disparities for rural and low-income populations. This includes exploring the effectiveness and utility of telecounseling in comparison to in-person treatment. Research may consider evaluating solutions to address affordability barriers, such as the impact of adjusting session fees mid-treatment. Similarly, research that supports potential treatment buy-in effects caused by session fees and/or the effectiveness of No-Show policies may lead to possible solutions that could improve attendance rates for community clinics.

This study is one example that shows the utility of new technological methods to explore mental health disparities. ArcGIS is one of several geospatial programs that offer a unique perspective into these rural and low-income groups and can be used to answer research questions that previously could not be answered accurately. Future research can expand upon the methods in this study by considering the impact of other transportation options such as public transportation and/or examining population density at county, tract, and/or state levels.

Given the findings of this study, it is clear that more research is needed to address mental health disparities for rural and low-income populations. Mental health disparity research has posited that the treatment barriers likely impacting these populations are complex and interconnected (Safran et al., 2009), it is therefore essential that future research aim to explore the *how* and *why* behind these potential barriers. It is hoped that if we better understand these barriers we can implement effective strategies to alleviate them and their pervasive effect.

REFERENCES

Adler, G., Pritchett, L. R., & Kauth, M. R. (2013). Meeting the continuing education needs of rural mental health providers. *Telemedicine Journal And E-Health: The Official Journal of The American Telemedicine Association, 19*, 852-856. doi:10.1089/tmj.2013.0010

Alegria, M., Canino, G., Rios, R., Vera, M., Calderon, J. Rusch, D., & Ortega, A. N. (2002). Mental health care for Latinos Inequalities in use of specialty mental health services among Latinos, African Americans, and non-Latino Whites. *American Psychiatric Publishing, 53*, 1547–1555. Retrieved from http://www.psychiatryonline.org.srv-proxy1.library.tamu.edu/doi/full/10.1176/appi.ps.53.12.1547

Alegria, M., Vallas, M., & Pumariega, A. (2010). Racial and Ethnic Disparities in Pediatric Mental Health. *Child and Adolescent Psychiatric Clinics of North America*, *19*, 759–774. http://doi.org/10.1016/j.chc.2010.07.001

Anderson, N. B., & Amstead, C. A. (1995). Toward understanding the association of socioeconomic status and health: A new challenge for the biopsychosocial approach. *Psychosomatic Medicine, 57*, 213-225. doi:10.1097/00006842-199505000-00003

Anderson, E., & Lambert, M. J. (2001). A survival analysis of clinically significant change in outpatient psychotherapy. *Journal of Clinical Psychology, 57*, 875-888. Retrieved from http://proxy.library.tamu.edu.srv-proxy1.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=mdc&AN=11406801&site=eds-live

Armstrong, T. W., Williamson, M. L. C., Elliott, T. R., Jackson, W. T., Kearns, N. T., & Ryan, T. (2019). Psychological distress among persons with upper extremity limb loss. *British Journal of Health Psychology.* https://doi.org/10.1111/bjhp.12360

Auter, Z. (2017). U.S. Uninsured Rate Rises to 11.7%. *Gallup News*. Retrieved from http://news.gallup.com/poll/213665/uninsured-rate-rises.aspx.

Bako, G., Dewar, R., Hanson, J., & Hill, G. (1984). Population density as an indicator of urban-rural differences in cancer incidence, Alberta, Canada, 1969-73. *Canadian Journal of Public Health, 75,* 152-156. Retrieved from http://www.jstor.org.srv-proxy1.library.tamu.edu/stable/41990262

Baldwin, S. A., Berkeljon, A., Atkins, D. C., Olsen, J. A., & Nielsen, S. L. (2009). Rates of change in naturalistic psychotherapy: Contrasting dose-effect and good-enough level models of change. *Journal of Consulting and Clinical Psychology, 77,* 203–211. doi:10.1037/a0015235

Banks, K. H. & Kohn-Wood, L. P. (2002). Gender, Ethnicity and Depression: Intersectionality in Mental Health Research with African American Women. *Scholarship*, 6. Retrieved from http://digitalcommons.iwu.edu/cgi/viewcontent.cgi?article=1005&context=psych_scholarship.

Barkham, M., Connell, J., Stiles, W. B., Miles, J. N., Margison, F., Evans, C., & Mellor-Clark, J. (2006). Dose-effect relations and responsive regulation of treatment duration: The good enough level. *Journal of Consulting and Clinical Psychology, 74,* 160–167. doi:10.1037/0022-006X.74.1.160

Bell, N., Kidanie, T., Cai, B., & Krause, J. S. (2017) Geographic Variation in Outpatient Health Care Service utilization After Spinal Cord Injury. *Archives of Physical Medical Rehabilitation, 98,* 341-346. doi:10.1016/j.apmr.2016.09.130

Berenson, J., Doty, M. M., Abrams, M. K., & Shih, A. (2012). Achieving better quality of care for low-income populations: The roles of health insurance and the medical home in reducing health inequalities. *The Commonwealth Fund: Issue Brief, 11*, 1-18. Retrieved from https://pdfs.semanticscholar.org/1889/d34df1a0d9043890c479f0eae8a1b7503892.pdf

Braveman, P. (2006). Health Disparities and Health Equity: Concepts and Measurement. *Annual Review of Public Health, 27*, 167-194. https://doi.org/10.1146/annurev.publhealth.27.021405.102103

Callahan, J. L., & Hynan, M. T. (2005). Models of psychotherapy outcome: Are they applicable in training clinics? *Psychological Services, 2*, 65-69. http://dx.doi.org.srv-proxy1.library.tamu.edu/10.1037/1541-1559.2.1.65

Callas, P. W., Ricci, M. A., Caputo, M. P. (2000) Improved rural provider access to continuing medical education through interactive videoconferencing. *Telemedicine journal and e-health: the official journal of the American Telemedicine Association, 6*, 393–399. doi:10.1089/15305620050503861

Carvalho, C. F. (2016). *Parent-reported treatment outcomes versus clinician judgment: Correlates of psychotherapy improvement with children* (Unpublished doctoral dissertation). Texas A&M University, College Station.

Case, K. & Fair, R. (2007). *Principles of Economics* (8th ed.). Upper Saddle River, NJ: Pearson Education.

Chen, A. Y., & Escarce, J. J. (2004). Quantifying income-related inequality in healthcare delivery in the United States. *Medical Care, 42*, 38-47. doi:10.1097/01.mlr.0000103526.13935.b5

Cooper, P. J., Gallop, C., Willetts, L., & Creswell, C. (2008). Treatment response in child anxiety is differentially related to the form of maternal anxiety disorder. *Behavioural and Cognitive Psychotherapy*, *36*, 41-48. https://doi-org.srv-proxy1.library.tamu.edu/10.1017/S1352465807003943

Desrosiers, A. S., Ibrahim, J. M., & Jacks, S. K. (2019). A barrier to care: Distance traveled affects adherence to treatment and follow-up plans for patients with infantile hemangioma. *Pediatric Dermatology, 36*, 402-403. doi:10.1111/pde.13788

Drapeau, A., Boyer, R., & Lesage, A. (2009). The influence of social anchorage on the gender difference in the use of mental health services. *The Journal of Behavioral Health Services & Research, 36*(3), 372–384. http://dx.doi.org.srv-proxy1.library.tamu.edu/10.1007/s11414-009-9168-0

Durham, C. J. (1999). Outcome Questionnaire: Repeated administrations, mechanical responding, and social desirability. (retest). *Dissertation Abstracts International: Section B: The Sciences and Engineering, 59*, 6112.

Eberhardt, M. S., Ingram, D. D., Makuc, D. M., Pamuk, E. R., Freid, V. M., Harper, S. B.,… Xia, H. (2001). *Health United States 2001. Urban and Rural Health Chartbook*. Hyattsville, MD: National Center for Health Statistics. Retrieved from https://www.cdc.gov/nchs/data/hus/hus01cht.pdf

Freiman, M. P., & Zuvekas, S. H. (2000). Determinants of ambulatory treatment mode for mental illness. *Health Economics, 9*, 423-434. Retrieved from http://proxy.library.tamu.edu.srv-proxy1.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsbl&AN=RN081819841&site=eds-live

Gamm, L. D., Hutchinson L. L., Dabney, B. J., & Dorsey, A. M., eds. (2003). *Rural Healthy People 2010: A Companion Document to Healthy People 2010. Volume 1*. College Station, Tex: Texas A & M University Health System Health Science Center, School of Rural Public Health, Southwest Rural Health Research Center. Retrieved from https://srhrc.tamhsc.edu/docs/rhp-2010-volume1.pdf

Garfield, S. L. (1986). Research on client variables in psychotherapy. In S. L. Garfield & A. E. Bergin (Eds.), *Handbook of psychotherapy and behavior change* (3rd ed., pp. 213 - 256). New York: Wiley.

Gary, F. A. (2005). Stigma: Barrier to mental health care among ethnic minorities. *Issues in Mental Health Nursing, 26*, 979–999. http://dx.doi.org.srv-proxy1.library.tamu.edu/10.1080/01612840500280638

Given, L. M. (2008). *The SAGE encyclopedia of qualitative research methods* (Vols. 1-0). Thousand Oaks, CA: SAGE Publications, Inc. doi:10.4135/9781412963909

Goodwin, R., Koenen, K. C., Hellman, F., Guardina, M., & Struening, E. (2002). Helpseeking and access to mental health treatment for obsessive-compulsive disorder. *Acta Psychiatrica Scandinavica, 106*, 143–149. doi:10.1034/j.1600-0447.2002.01221.x

Gresenz, C. R., Stockdale, S. E., & Wells, K. B. (2000). Community effects on access to behavioral health care. *Health Services Research*, *35*, 293-306. Retrieved from http://proxy.library.tamu.edu.srv-proxy1.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsbig&AN=edsbig.A62162641&site=eds-live

Hadley, J., & Holahan, J. (2003). How much medical care do the uninsured use, and who pays for it? *Health Affairs, 22*, 66-81. doi:10.1377/hlthaff.W3.66

Hadley, J., Holahan, J., Coughlin, T., & Miller, D. (2008). Covering the uninsured in 2008: Current costs, sources of payment, and incremental costs. *Health Affairs, 27*, 399–415. https://doi.org/10.1377/hlthaff.27.5.w399

Hampson, R., O'Hanlon, J., Franklin, A., Pentony, M., Fridgant, L., & Heins, T. (1999). The place of single session family consultations: Five years' experience in Canberra. *Australian and New Zealand Journal of Family Therapy, 20*, 195–200. Retrieved from https://doi-org.srv-proxy1.library.tamu.edu/10.1111/j.0814-723X.1999.00129.x

Hampton-Robb, S., Qualls, R.C., & Compton, W.C. (2010). Predicting first-session attendance: The influence of referral source and client income. *Journal of Psychotherapy Research, 13*, 223-233. https://doi.org/10.1080/713869641

Hansen, N. B., Lambert, M. J., & Forman, E. M. (2002). The psychotherapy dose response effect and its implications for treatment delivery services. *Clinical Psychology: Science and Practice, 9*, 329-343. doi:10.1093/clipsy.9.3.329

Hartley, D. (2004). Rural health disparities, population health, and rural culture. *American Journal of Public Health*, *94*, 1675–1678. doi:10.2105/ajph.94.10.1675

Housing and Assistance Council (HAC). (2011). *Rurality in the United States*. Washington, DC. Retrieved from http://www.ruralhome.org/storage/research_notes/Rural_Research_Note_Rurality_web.pdf

Howard, K. I., Kopta, S. M., Krause, M. S., & Orlinsky, D. E. (1986). The dose-effect relationship in psychotherapy. *American Psychologist, 41*, 159-164. doi: 10.1037/0003-066X.41.2.159

Jacobson, N. S., Follette, W. C., & Revenstorf, D. (1984). Psychotherapy outcome research: Methods for reporting variability and evaluating clinical significance. *Behavior Therapy, 15*, 336–352. https://doi.org/10.1016/S0005-7894(84)80002-7

Jacobson, N. S., & Truax, P. (1991). Clinical significance: A statistical approach to defining meaningful change in psychotherapy research. *Journal of Consulting and Clinical Psychology, 59*, 12-19. doi:10.1037/0022-006X.59.1.12

Jameson, J. P., Chambless, D. L., & Blank, M. B. (2009). Empirically supported treatments in rural community mental health centers: A preliminary report on current utilization and attitudes toward adoption. *Community Mental Health Journal, 45*, 463-467. doi:10.1007/s10597-009-9230-7

Jimenez, D. E., Cook, B., Bartels, S. J., & Alegría, M. (2013). Disparities in mental health service use of racial and ethnic minority elderly adults. *Journal of the American Geriatrics Society*, *61*, 18-25. doi:10.1111/jgs.12063

Jorm, A. F., Duncan-Jones, P., & Scott, R. (1989). An analysis of the re-test artefact in longitudinal studies of psychiatric symptoms and personality. *Psychological Medicine, 19*, 487-493. http://dx.doi.org/10.1017/S0033291700012514

Joyce, A. S., Piper, W. E., Ogrodniczuk, J. S., & Klien, R. H. (2007). *Termination in psychotherapy: A psychodynamic model of processes and outcomes*. Washington, DC: American Psychological Association. Retrieved from http://proxy.library.tamu.edu.srv-proxy2.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=pzh&jid=200621531&site=ehost-live

Kalpinski, R. J. (2014). *Client improvement in a community-based training clinic: As* *indicated by the OQ-45* (Doctoral dissertation). Retrieved from http://hdl.handle.net/1969.1/153497

Kindig, D., & Stoddart, G. (2003). What is population health?. *American Journal of Public Health, 93*, 380–383. doi:10.2105/ajph.93.3.380

Kopta, S. M., Howard, K. I., Lowry, J. L., & Beutler, L. E. (1994). Patterns of symptomatic recovery in psychotherapy. *Journal of Consulting and Clinical Psychology, 62*, 1009-1016. doi:10.1037//0022-006x.62.5.1009

Kuha, J. (2004). AIC and BIC: Comparisons of assumptions and performance. *Sociological Methods & Research, 33*, 188–229. https://doi.org/10.1177/0049124103262065

Kumar, S., Liu, M., & Hwang, S. A. (2012). A multifaceted comparison of ArcGIS and MapMarker for automated geocoding. *Geospatial Health, 7*, 145-151. https://doi.org/10.4081/gh.2012.113

Lambert, M. J. (2001). Psychotherapy outcome and quality improvement: Introduction to the special section on patient-focused research. *Journal of Consulting and Clinical Psychology, 69*, 147-149. http://dx.doi.org/10.1037/0022-006X.69.2.147

Lambert, M. J. (2010). *Prevention of treatment failure: The use of measuring, monitoring, and feedback in clinical practice* (1st ed.). Washington, DC: American Psychological Association.

Lambert, M. J., Burlingame, G. M., Umphress, V., Hansen, N. B., Vermeersch, D. A., Clouse, G. C., & Yanchar, S. C. (1996). The reliability and validity of the Outcome Questionnaire. *Clinical Psychology and Psychotherapy, 3*, 249-258. https://doi.org/10.1002/(SICI)1099-0879(199612)3:4<249::AID-CPP106>3.0.CO;2-S

Lambert, M. J., Hansen, N. B., Umphress, V., Lunnen, K., Okiishi, J. C., Burlingame, G. M., & Reisinger, C. W. (1996). *Administration and scoring manual for the OQ-45.2 (Outcome Questionnaire)*. Wilmington, DE: American Professional Credentialing Services.

Lambert, M. J., Harmon, C., Slade, K., Whipple, J. L., & Hawkins, E. J. (2005). Providing feedback to psychotherapists on their patients' progress: Clinical results and practice suggestions. *Journal of Clinical Psychology, 61*, 165-174. https://doi-org.srv-proxy2.library.tamu.edu/10.1002/jclp.20113

Lambert, M. J., & Hill, C. E. (1994). Assessing psychotherapy outcomes and processes. In A. E. Bergin & S. L. Garfield (Eds.), *Handbook of psychotherapy and behavior change* (pp. 72-113). Oxford, England: John Wiley.

Lambert, M. J., & Ogles, B. M. (2004). The efficacy and effectiveness of psychotherapy. In M. J. Lambert (Ed.), *Bergin and Garfield's handbook of psychotherapy and behavior change* (5th ed., pp. 139–193). New York, NY: Wiley.

Lambert, M. J., Whipple, J. L., Vermeersch, D. A., Smart, D. W., Hawkins, E. J., Nielsen, S. L., & Goates, M. (2002). Enhancing psychotherapy outcomes via providing feedback on client progress: A replication. *Clinical Psychology and Psychotherapy, 9*, 91-103. https://doi.org/10.1002/cpp.324

Lampropoulos, G. K., Schneider, M. K., & Spengler, P. M. (2009). Predictors of early termination in a university counseling training clinic. *Journal of Counseling and Development, 87*, 36-46. Retrieved from http://proxy.library.tamu.edu.srv-proxy2.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ826754&site=eds-live

Lee, D., Dixon, C., Kruszynski, P., & Coustasse, A. (2010). Uncompensated Care and Quality

Assurance Among Rural Hospitals. *Journal of Hospital Marketing & Public Relations, 20*,116-130. doi:10.1080/15390942.2010.493374

Lester, S., & Harris, S. M. (2007). Factors associated with first session nonattendance at a university-based family therapy clinic. *The American Journal of Family Therapy, 35*, 363–376. http://dx.doi.org/10.1080/01926180600814718

Levit, K., Wier, L., Stranges, E., Ryan, K., & Elixhasuer, A. (2006). *HCUP Facts and Figures: Statistics on Hospital-based Care in the United States, 2007*. Rockville, MD: Agency for Healthcare Research and Quality (US). Retrieved from https://www.hcup-us.ahrq.gov/reports/factsandfigures/2007/pdfs/FF_report_2007.pdf

Lovasi, G. S., Weiss, J. C., Hoskins, R., Whitsel, E. A., Rice, K., Erickson, C. F., & Psaty, B. M. (2007). Comparing a single-stage geocoding method to a multi-stage geocoding method: how much and where do they disagree? *International Journal of Health Geographics, 6*, 1-12. doi:10.1186/1476-072X-6-12

Lunn, L. M., Heflinger, C. A., Wang, W., Greenbaum, P. E., Kutash, K., Boothroyd, R. A., & Friedman, R. M. (2011). Community characteristics and implementation factors associated with effective systems of care. *Journal of Behavioral Health Services & Research, 38*, 327-341. doi:10.1007/s11414-011-9244-0.

Maslach, C. (1978). The client role in staff burn-out. *Journal of Social Issues, 34*(4), 111-124. https://doi-org.srv-proxy2.library.tamu.edu/10.1111/j.1540-4560.1978.tb00778.x

McCord, C. E., Elliott, T. R., Wendel, M. L., Brossart, D. F., Cano, M. A., Gonzalez, G. E., & Burdine, J. N. (2011). Community capacity and teleconference counseling in rural Texas. *Professional Psychology: Research and Practice, 42*, 521-527. http://dx.doi.org/10.1037/a0025296

McGuire, T. G., & Miranda, J. (2008). Racial and ethnic disparities in mental health care: Evidence and policy implications. *Health Affairs (Project Hope)*, *27*, 393–403. http://doi.org/10.1377/hlthaff.27.2.393

Miller, S. D., Duncan, B. L., Brown, J., Sorrell, R., & Chalk, M. (2006). Using formal client feedback to improve outcome and retention: Making ongoing, real-time assessment feasible. *Journal of Brief Therapy, 5,* 5–22. Retrieved from https://www.scottdmiller.com/wp-content/uploads/1%20Using%20Formal%20Client%20Feedback.pdf

Miranda, J., & Green, B. L. (1999). The need for mental health services research focusing on poor young women. *The Journal of Mental Health Policy and Economics, 2*, 73–80. http://dx.doi.org/10.1002/(SICI)1099-176X(199906)2:2<73::AID-MHP40>3.0.CO;2-3

Mitura, V., & Bollman, R. D. (2003). The health of rural Canadians: A rural-urban comparison of health indicators. *Rural and Small Town Canada Analysis Bulletin, 4*, 1–21. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.627.4498&rep=rep1&type=pdf

Mohl, P. C., Martinez, D., Ticknor, C., Huang, M., & Cordell, L. (1991). Early dropouts from psychotherapy. *The Journal of Nervous and Mental Disease, 179*, 478-481. http://dx.doi.org/10.1097/00005053-199108000-00005

Mohr, D. C., Hart, S. L., Howard, I., Julian, L., Vella, L., Catledge, C., & Feldman, M. D. (2006). Barriers to psychotherapy among depressed and nondepressed primary care patients. *Annals of Behavioral Medicine, 32*, 254–258. doi:10.1207/s15324796abm3203_12

Mojtabai, R., Olfson, M., Sampson, N. A., Jin, R., Druss, B., Wang, P. S., Wells, K. B., Pincus, H. A., & Kessler, R. C. (2011). Barriers to mental health treatment: Results from the National Comorbidity Survey Replication (NCS-R). *Psychological Medicine*, *41*, 1751–1761. http://doi.org/10.1017/S0033291710002291

Morgan, A. (2002). A national call to action: CDC's 2001 Urban and Rural Health Chartbook. *The Journal of Rural Health, 18*, 382-383. doi:10.1111/j.1748-0361.2002.tb00900.x

Morgan, M. (2008). What is the goal of access to health care? *Journal of Law and Medicine, 15*, 742–751.

Mueller, R. M., Lambert, M. J., & Burlingame, G. M. (1998). Construct validity of the Outcome Questionnaire: A confirmatory factor analysis. *Journal of Personality Assessment, 70*, 248-262. http://dx.doi.org/10.1207/s15327752jpa7002_5

Murray, D. R., Trudeau, R., & Schaller, M. (2011). On the origins of cultural differences in conformity: Four tests of the pathogen prevalence hypothesis. *Personality and Social Psychology Bulletin, 37*, 318-329. doi:10.1177/0146167210394451

Padgett, D. K., Patrick, C., Burns, B. J., & Schlesinger, H. J. (1994). Women and outpatient mental health services: Use by Black, Hispanic, and White women in a national insured population. *The Journal of Mental Health Administration, 21*, 347–360. https://doi.org/10.1007/BF02521354

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology, 49*, 1373-1379. doi:10.1016/s0895-4356(96)00236-3

Penchansky, R., & Thomas J. W. (1981). The concept of access: Definition and relationship to consumer satisfaction. *Medical Care, 19*, 127–140. doi:10.1097/00005650-198102000-00001

Peng, C.-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Educational Research, 96*, 3-14. http://dx.doi.org/10.1080/00220670209598786

Peng, C.-Y. J., So, T.-S. H., Stage, F. K., & St. John, E. P. (2002). The use and interpretation of logistic regression in higher education journals: 1988-1999. *Research in Higher Education, 43*(3), 259-293. https://doi.org/10.1023/A:1014858517172

Petterson, S. (2003). Metropolitan-nonmetropolitan differences in amount and type of mental health treatment. *Archives of Psychiatric Nursing, 17*, 12-19. doi:10.1053/apnu.2003.5

Petterson, S., Williams, I. C., Hauenstein, E. J., Rovnyak, V., & Merwin, E. (2009). Race and ethnicity and rural mental health treatment. *Journal of Health Care for the Poor and Underserved, 20*, 662-677. http://dx.doi.org/10.1353/hpu.0.0186

Phinney, J. S. (1996). When we talk about American ethnic groups, what do we mean? *American Psychologist, 51*, 918–927. http://dx.doi.org.srv-proxy1.library.tamu.edu/10.1037/0003-066X.51.9.918

Proctor, B. D., Semega, J. L., & Kollar, M. A. U.S. Census Bureau. (2016). *Income and Poverty in the United States: 2015* (Report No. P60-250). Washington, DC: U.S. Government Printing Office. Retrieved from https://www.census.gov/library/publications/2016/demo/p60-256.html/

Reis, B. F., & Brown, L. G. (2006). Preventing therapy dropout in the real world: The clinical utility of videotape preparation and client estimate of treatment duration. *Professional Psychology: Research and Practice, 37*(3), 311-316. http://dx.doi.org/10.1037/0735-7028.37.3.311

Ricketts, T. C. (1999). *Rural Health in the United States.* New York, NY: Oxford University Press.

Robbins, S. B., Mullison, D., Boggs, K., Riedesel, B., & Jacobson, B. (1985). Attrition behavior before career development workshops. *Journal of Counseling Psychology, 32*(2), 232-238.

Rodolfa, E. R., Rapaport, R., & Lee, V. E. (1983). Variables related to premature terminations in a university counseling service. *Journal of Counseling Psychology, 30*, 87-90. https://doi-org.srv-proxy1.library.tamu.edu/10.1037/0022-0167.30.1.87

Roongpiboonsopit D, Karimi H. (2010). Comparative evaluation and analysis of online geocoding services. *International Journal of Geographical Information Science, 24*, 1081-1100. https://doi-org.srv-proxy1.library.tamu.edu/10.1080/13658810903289478

Safran, M. A., Mays, R. A., Huang, L. N., McCuan, R., Pham, P. K., Fisher, S. K., McDuffie, K. Y., & Trachtenberg, A. (2009). Mental Health Disparities. *American Journal of Public Health*, *99*, 1962–1966. http://doi.org/10.2105/AJPH.2009.167346

Sarche, M., & Spicer, P. (2008). Poverty and health disparities for American Indian and Alaskan Native Children: Current knowledge and future prospects. *Annals of the New York Academy of Sciences, 1136*, 126-136. doi:10.1196/annals.1425.017

Sareen, J., Jaqdeo, A., Cox, B. J., Clara, I., Ten Have, M., Belik, S. L., de Graaf, R., & Stein, M. B. (2007). Perceived barriers to mental health service utilization in the United States, Ontario, and the Netherlands. *Psychiatric Services, 58*, 357-64. doi: 10.1176/ps.2007.58.3.357

Saurman, E. (2016). Improving access: Modifying Penchansky and Thomas's theory of access. *Journal of Health Services Research And Policy, 21*, 36-39. doi:10.1177/1355819615600001

Schneider, A., Hommel, G., & Blettner, M. (2010). Linear Regression Analysis: Part 14 of a Series on Evaluation of Scientific Publications. *Deutsches Ärzteblatt International*, *107*, 776–782. http://doi.org/10.3238/arztebl.2010.0776

Semega, J. L., Fontenot, K. R., & Kollar, M. A. U.S. Census Bureau. (2017). *Income and Poverty in the United States: 2016*. (Report No. P60-259). Washington, DC: U.S. Government Printing Office. Retrieved from https://www.census.gov/content/dam/Census/library/publications/2017/demo/P60-259.pdf

Slaunwhite, A. K. (2015). The Role of Gender and Income in Predicting Barriers to Mental Health Care in Canada. *Community Mental Health Journal, 51*, 621-627. doi:10.1007/s10597-014-9814-8

Sledge, W. H., Moras, K., Hartley, D., & Levine, M. (1990). Effect of time-limited psychotherapy on patient dropout rates. *American Journal of Psychiatry, 147*, 1341-1347. http://dx.doi.org/10.1176/ajp.147.10.1341

Smith, K. J., Subich, L. M., & Kalodner, C. R. (1995). The transtheoretical model's stages and processes of change and their relation to premature termination. *Journal of Counseling Psychology, 42*, 34-39. Retrieved from http://search.ebscohost.com.srvproxy1.library.tamu.edu/login.aspx?direct=true&db=edsovi&AN=edsovi.00001192.199501000.00005&site=eds-live

Snyder, T. D., Dillow, S. A., & Hoffman, C. M. (2009). *Digest of Education Statistics 2008* (NCES 2009-020). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. Retrieved from https://nces.ed.gov/pubs2009/2009020.pdf

Sorkin, D. H., Murphy, M., Nguyen, H., & Biegler, K. A. (2016). Barriers to Mental Health Care for an Ethnically and Racially Diverse Sample of Older Adults. *Journal of The American Geriatrics Society, 64*, 2138-2143. doi:10.1111/jgs.14420

Sorkin, D. H., Pham, E., Ngo-Metzger, Q. (2009). Racial and ethnic differences in the mental health needs and access to care of older adults in California. *Journal of the American Geriatrics Society, 57*, 2311–2317. Retrieved from http://proxy.library.tamu.edu.srv-proxy1.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=gnh&AN=EP45599064&site=eds-live

Stalker, C. A., Horton, S., & Cait, C. (2012). Single session therapy in walk-in counseling clinics: A pilot study of who attends and how they fare afterwards. *Journal of Systemic Therapies, 31*, 38-52. doi:10.1521/jsyt.2012.31.1.38.

Sterk, C. E., Theall, M. K. P., & Elifson, K. W. (2002). Health care utilization among drug-using and non-drug-using women. *Journal of Urban Health, 79*, 586–599. doi:10.1093/jurban/79.4.586

Strupp, H. H., Horowitz, L. M., & Lambert, M. J.(Eds.). (1997). *Measuring patient changes in mood, anxiety, and personality disorders: Toward a core battery*. Washington, DC: American Psychological Association. http://dx.doi.org/10.1037/10232-000

Swift, J., Goldberg, D., Wilson, J. (2008). *Geocoding best practices: Review of eight commonly used geocoding systems* (Report No. 10). Report prepared for Division of Cancer Prevention and Control, National Center for Chronic Disease, Prevention and Health Promotion, Center for Disease Control and Prevention. Los Angeles, CA: University of Southern California GIS Research Laboratory. Retrieved from https://spatial.usc.edu/wp-content/uploads/2014/03/gislabtr10.pdf

Trimble, J. E., & Dickson, R. (2005). Ethnic gloss. In *The Encyclopedia of Applied Developmental Science* (Vol. 2, pp. 412-415). Thousand Oaks, CA: Sage.

U.S. Department of Commerce. (1994). Census Blocks and Block Groups. In *Geographic Areas Reference Manual (GARM)*. Retrieved from: https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf

U.S. Census Bureau. (2011). *2007-2011 State and County Quick Facts*. Retrieved from https://www.census.gov/data/developers/data-sets/acs-5year.2011.html

U.S. Department of Health and Human Services. (1999). *Mental Health: A Report of the Surgeon General.* Rockville, MD: U.S. Dept of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services, National Institutes of Health, National Institute of Mental Health.

U.S. Department of Health and Human Services. (2001). *Mental Health: Culture, Race, and Ethnicity- A Supplement to Mental Health: A Report of the Surgeon General*. Rockville, MD: U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services. Retrieved from https://www.ncbi.nlm.nih.gov/books/NBK44243/pdf/Bookshelf_NBK44243.pdf

Vega, W. A., Kolody, B., Aquilar-Gaxiola, S., Alderete, E., Catalano, R., & Caraveo-Anduaga, J. (1999). Lifetime prevalence of DSM-III-R psychiatric disorders among urban and rural Mexican Americans in California. *Archives of General Psychiatry, 55*, 771-778. doi:10.1001/archpsyc.55.9.771

Vermeersch, D. A., Lambert, M. J., & Burlingame, G. M. (2000). Outcome Questionnaire: Item sensitivity to change. *Journal of Personality Assessment, 74*, 242-261. doi:10.1207/S15327752JPA7402_6

Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods*, *17*, 228-243. doi:10.1037/a0027127

Wierzbicki, M., & Pekarik, G. (1993). A meta-analysis of psychotherapy dropout. *Professional Psychology: Research and Practice, 24*, 190-195. http://dx.doi.org/10.1037/0735-7028.24.2.190

Wolgast, B. M., Rader, J., Roche, D., Thompson, C. P., Von Zuben, F. C. & Goldberg, A. (2005). Investigation of Clinically Significant Change by Severity Level in College Counseling Center Clients. *Journal of College Counseling, 8*, 140–152. doi:10.1002/j.2161-1882.2005.tb00081.x

Wrenn, G., & Fortney, J. (2015). *Core Set of Outcome Measures for Behavioral Health Across Service Settings.* Washington, D.C.: The Kennedy Forum. Retrieved from http://thekennedyforum-dotorg.s3.amazonaws.com/documents/MBC_supplement.pdf

Yu, J. J. (2011). *Predicting psychotherapy client dropout from in-treatment client reported outcome* (Doctoral dissertation). Retrieved from http://hdl.handle.net/1969.1/ETD-TAMU-2011-12-10356

Yu, Z., & Chen, L. (2016). Income and well-being: Relative income and absolute income weaken negative emotion, but only relative income improves positive emotion. *Frontiers in Psychology, 7*. http://doi.org/10.3389/fpsyg.2016.02012

Zandbergen, P. (2007). Influence of geocoding quality on environmental exposure assessment of children living near high traffic roads. *BMC Public Health, 7,* 7-37. https://doi-org.srv-proxy2.library.tamu.edu/10.1186/1471-2458-7-37

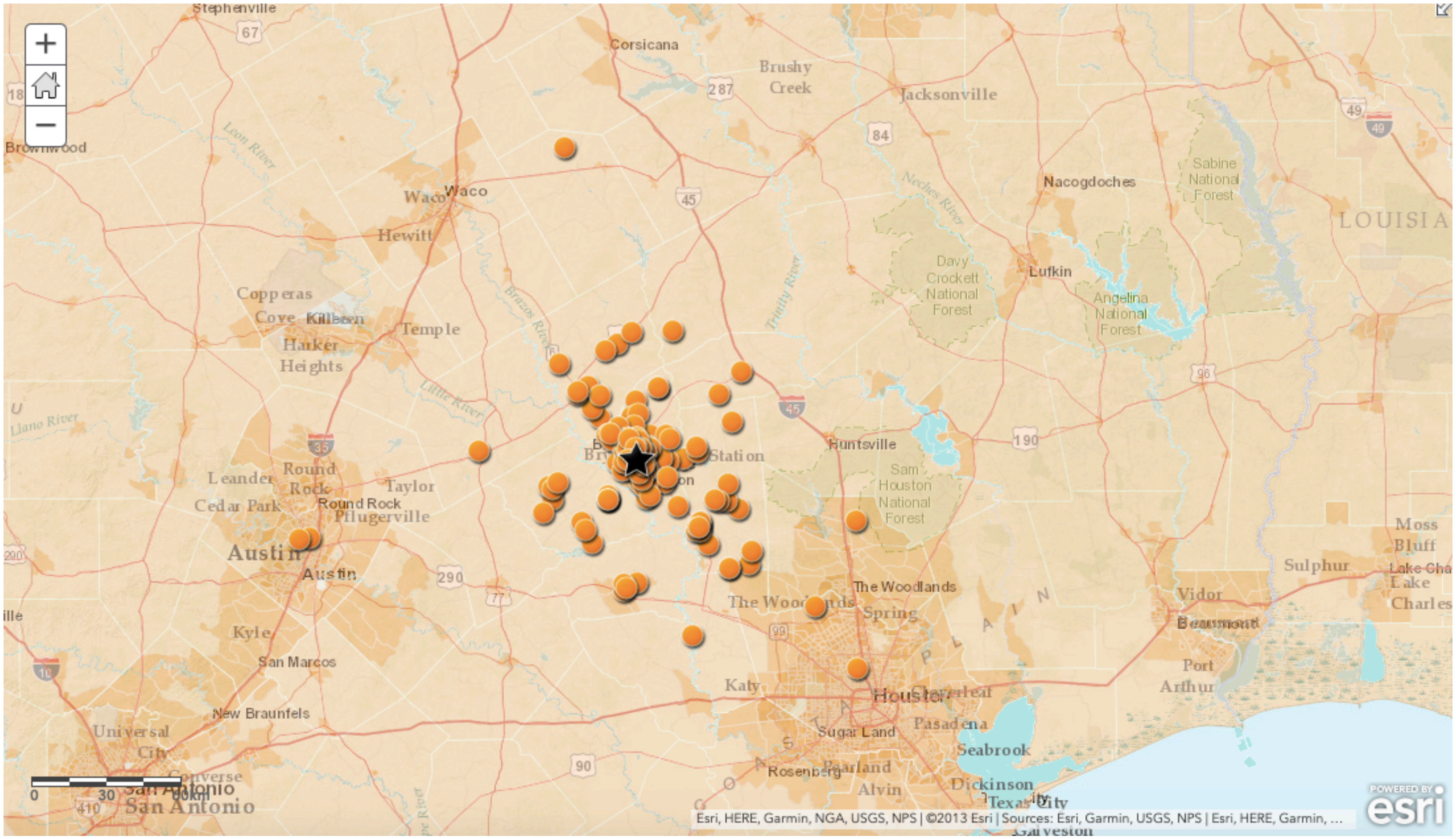
Zandbergen, P. A. (2008). A comparison of address point, parcel and street geocoding techniques. *Computers, Environment, and Urban Systems, 32*, 214- 232. https://doi.org/10.1016/j.compenvurbsys.2007.11.006

Zito, J. M., Safer, D. J., Zuckerman, I. H., Gardner, J. F., & Soeken, K. (2005). Effect of Medicaid eligibility category on racial disparities in the use of psychotropic medications among youths. *Psychiatric Services, 56*, 157–163. Retrieved from http://www.psychiatryonline.org.srv-proxy1.library.tamu.edu/doi/full/10.1176/appi.ps.56.2.157

Zuvekas, S. H., & Taliaferro, G. S. (2003). Pathways to access: Health insurance, the health care delivery system and racial/ethnic disparities, 1996-1999. *Health Affairs (Project Hope), 22*, 139-53. Retrieved from http://proxy.library.tamu.edu.srv-proxy1.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=mdc&AN=12674417&site=eds-live

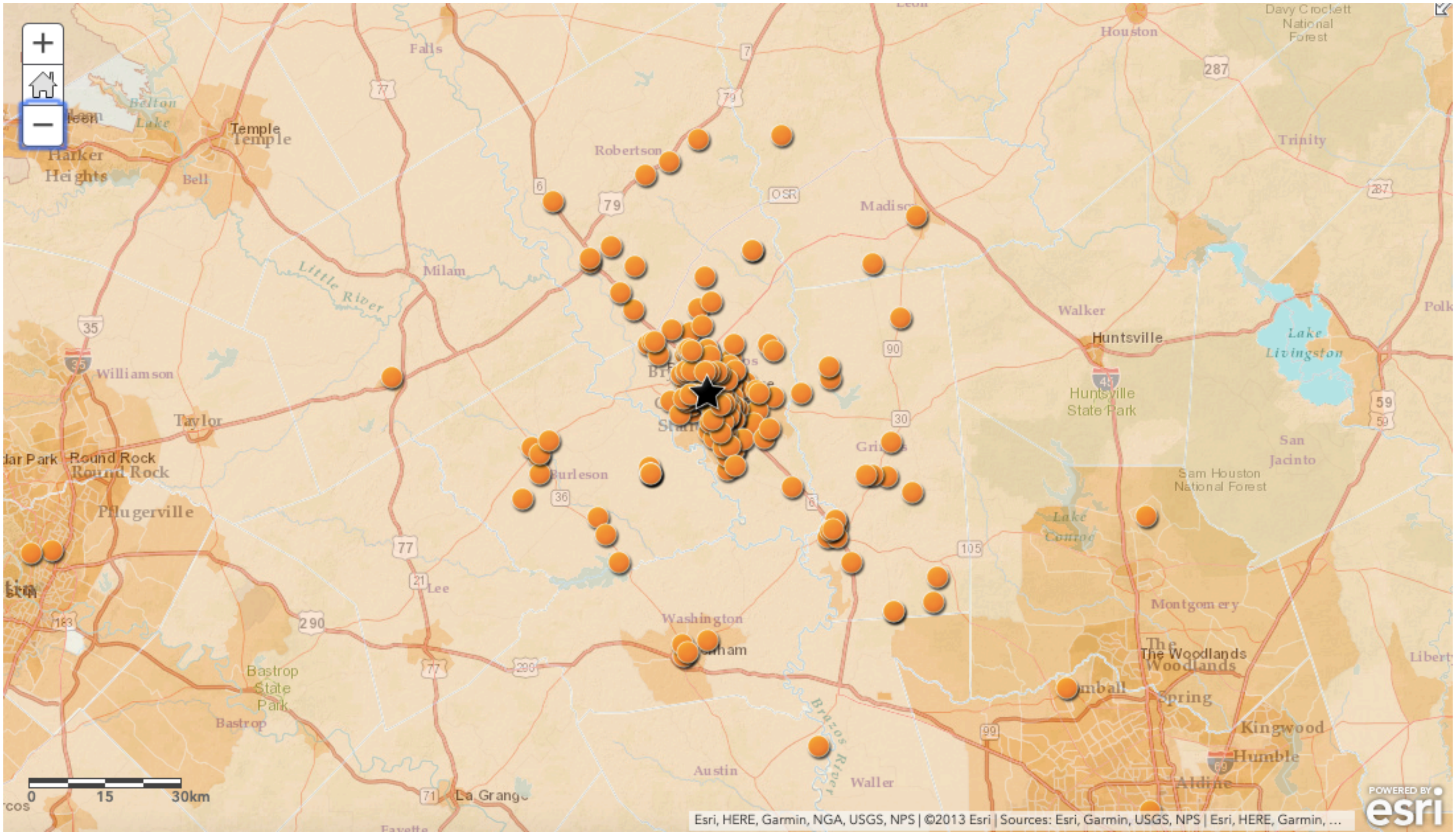
APPENDIX A

BRAZOS COUNTY POPULATION MAP (60KM SCALE)



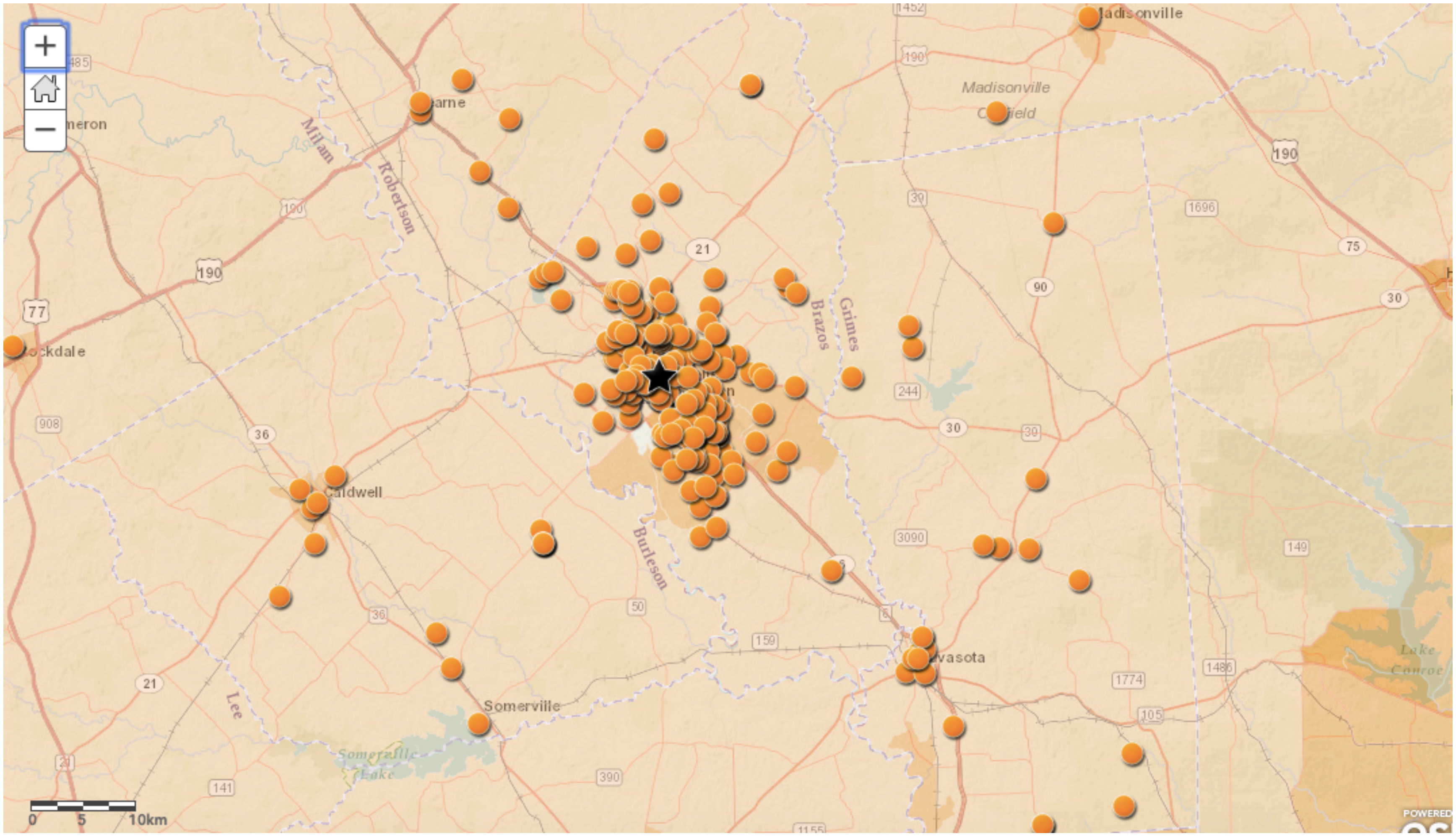
APPENDIX B

BRAZOS COUNTY POPULATION MAP (30KM SCALE)



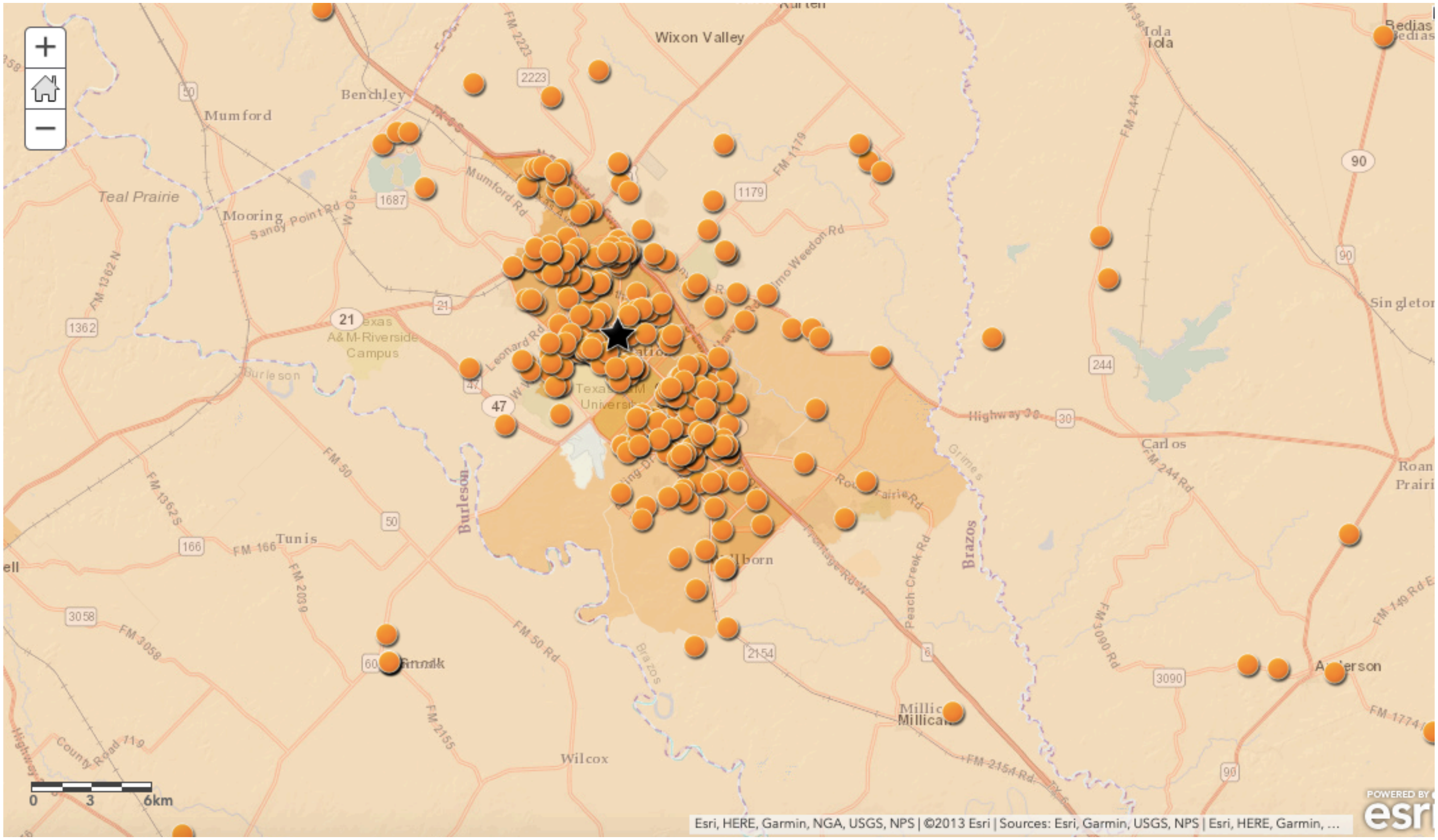
APPENDIX C

BRAZOS COUNTY POPULATION MAP (10KM SCALE)



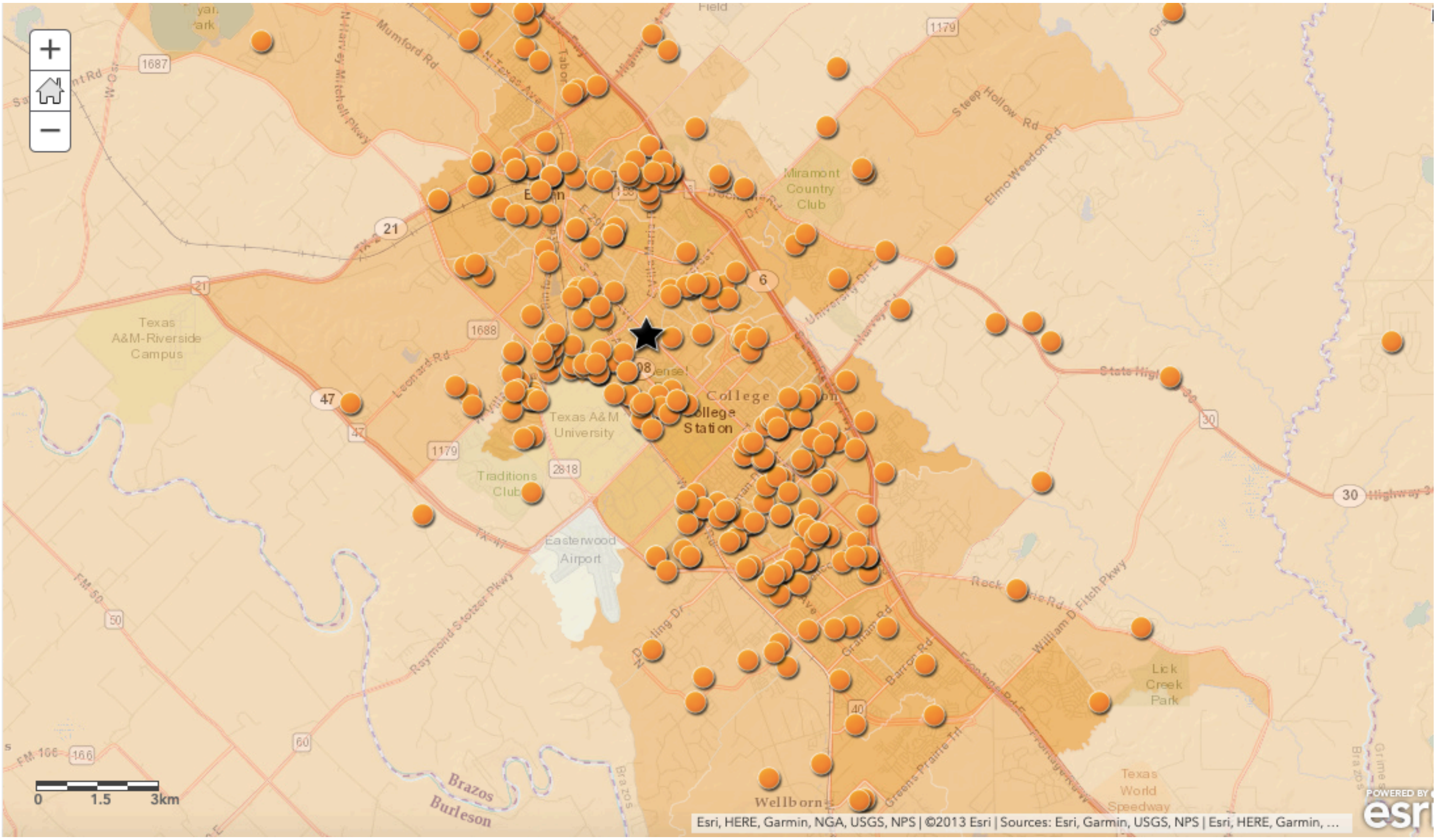
APPENDIX D

BRAZOS COUNTY POPULATION MAP (6KM SCALE)



APPENDIX E

BRAZOS COUNTY POPULATION MAP (3KM SCALE)



APPENDIX F

POPULATION DENSITY LEGEND AND MEDIAN INCOME LEGEND

USA Population Density

Persons per square mile by block group

- 100,001 or more people
- 25,001 to 100,000 people
- 10,001 to 25,000 people
- 1,001 to 10,000 people
- 101 to 1,000 people
- 100 or less people
- No population

USA Median Household Income

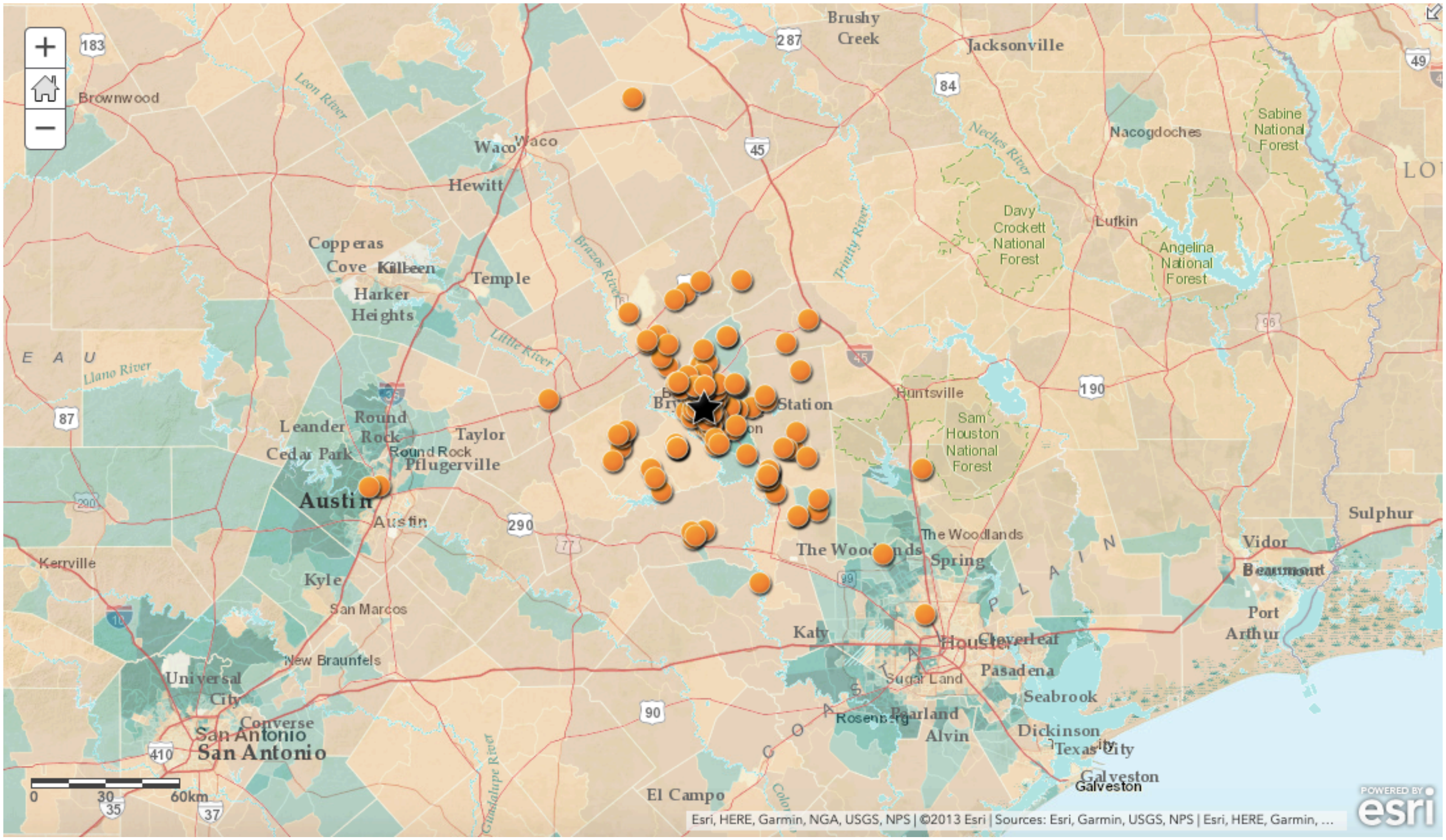
Median Household Income

Block Groups

- More than $82,000
- $68,001 to $82,000
- $53,001 to $68,000
- $39,001 to $53,000 (US median: $50,157)
- $24,001 to $39,000
- $24,000 or less
- No households

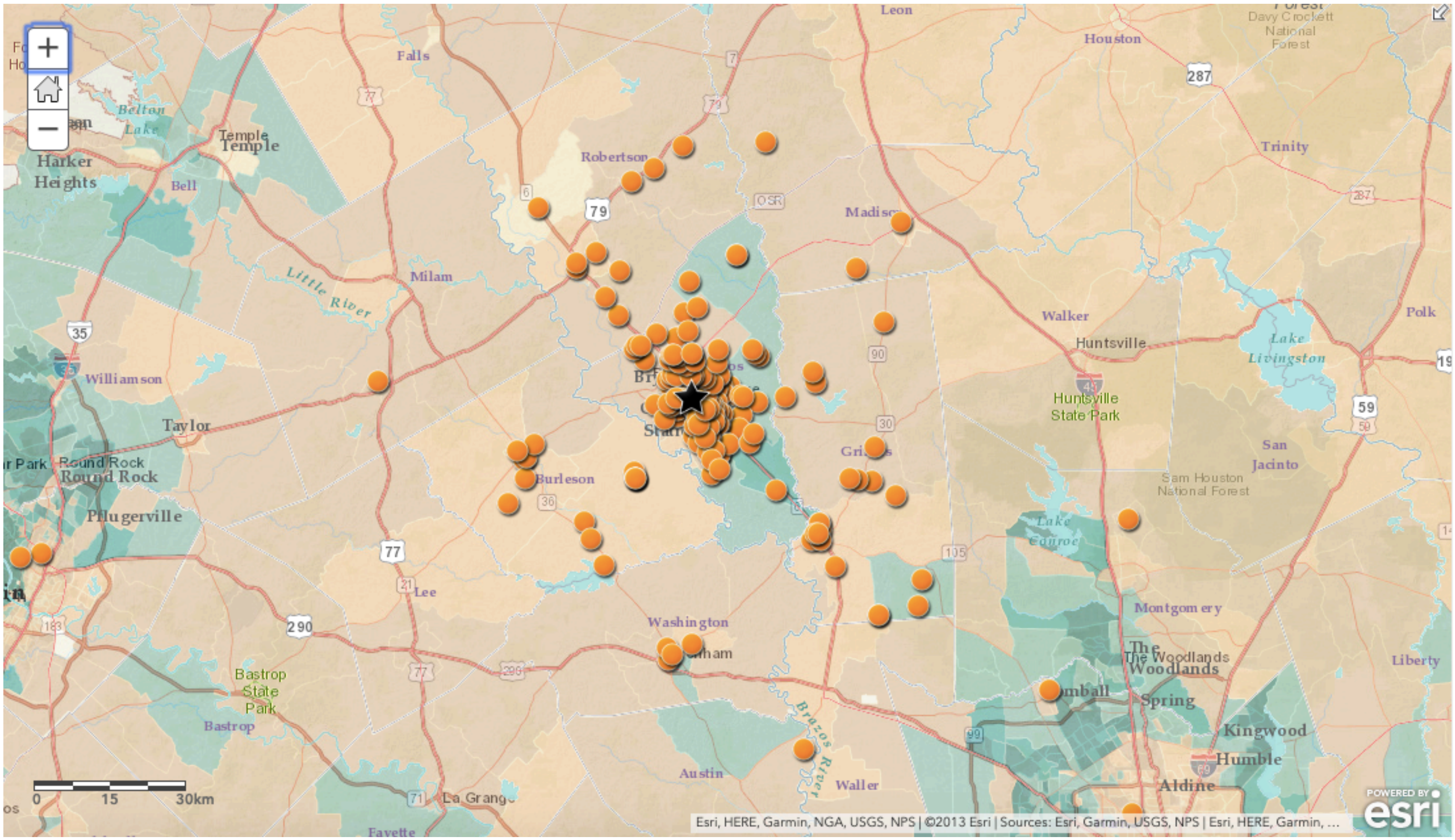
APPENDIX G

MEDIAN HOUSEHOLD INCOME MAP (60KM SCALE)



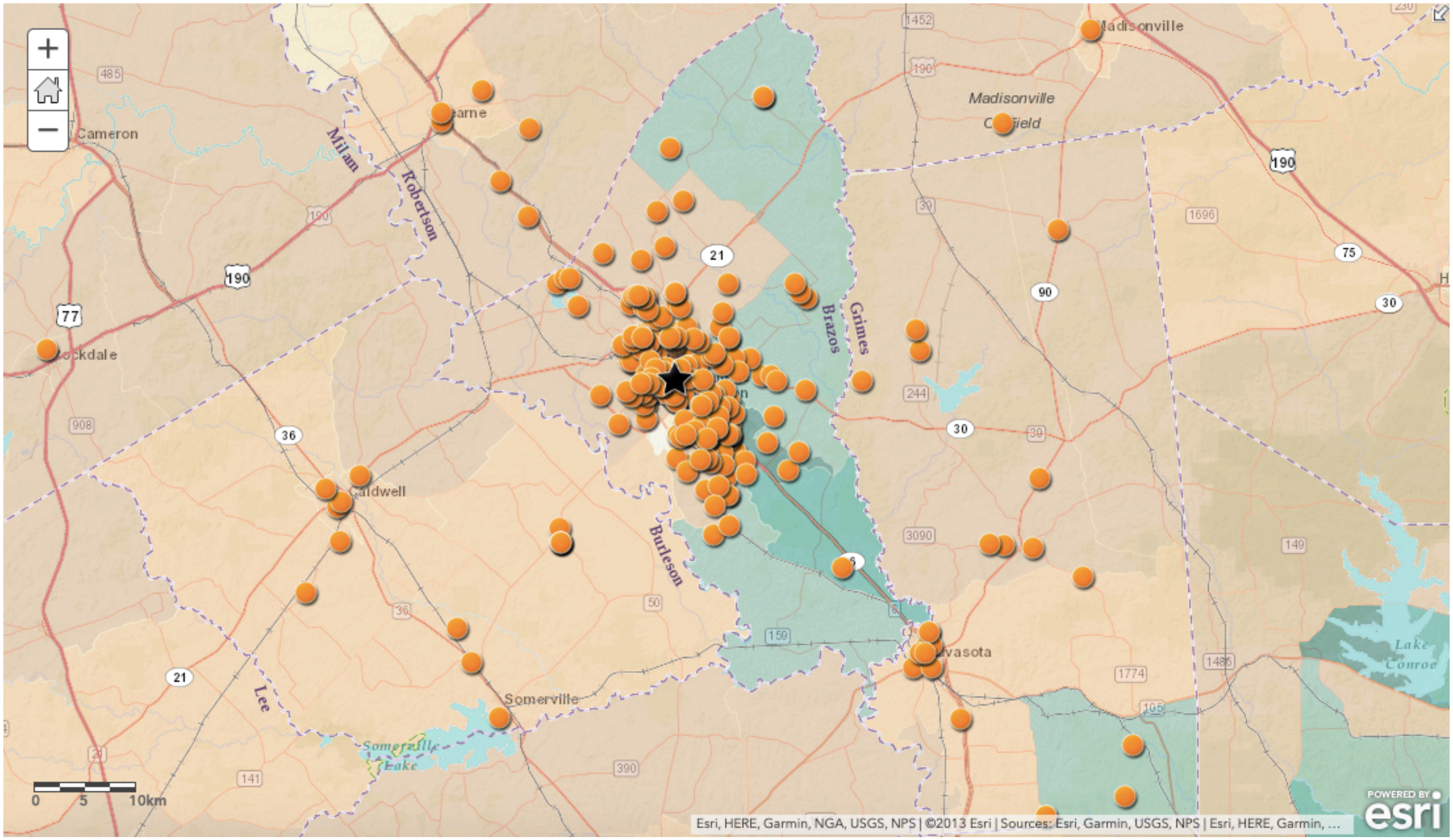
APPENDIX H

MEDIAN HOUSEHOLD INCOME MAP (30KM SCALE)



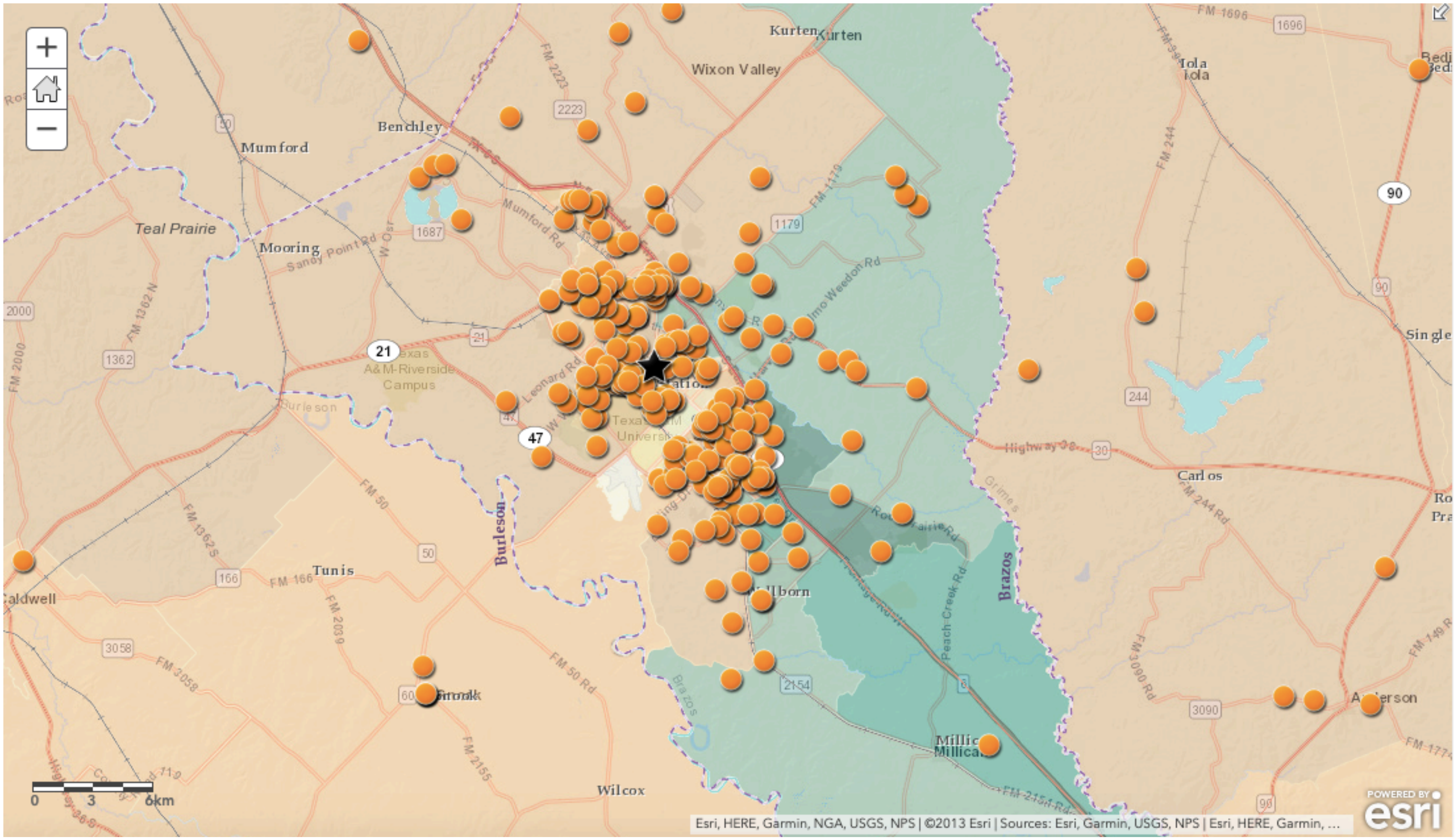
APPENDIX I

MEDIAN HOUSEHOLD INCOME MAP (10KM SCALE)



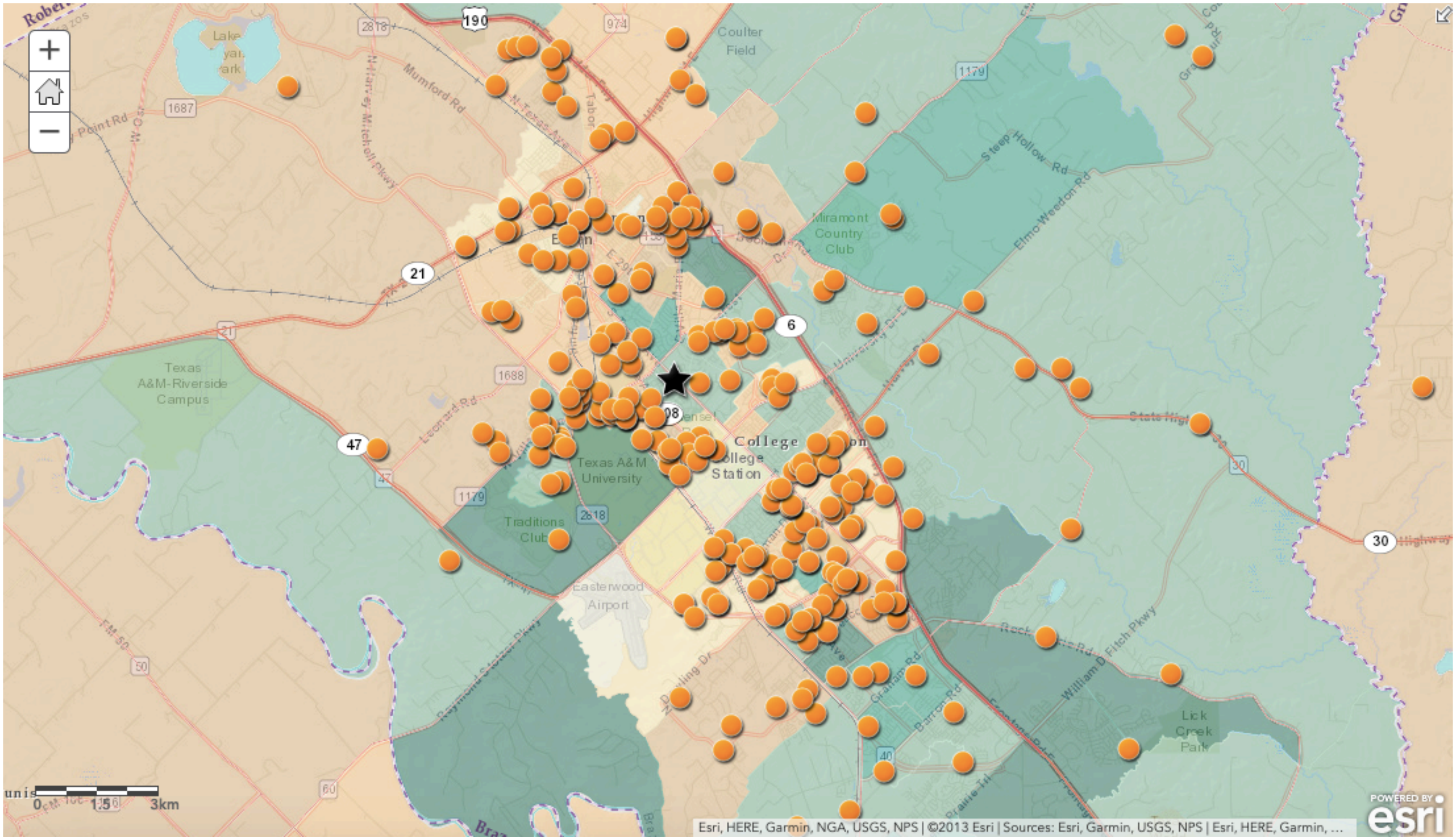
APPENDIX J

MEDIAN HOUSEHOLD INCOME MAP (6KM SCALE)



APPENDIX K

MEDIAN HOUSEHOLD INCOME MAP (3KM SCALE)



APPENDIX L

COUNSELING AND ASSESSMENT CLINIC SLIDING FEE SCALE

Sliding Fee Schedule
Effective 9/1/17

All services provided by the CAC are billed at $90.00 per hour. Part of this fee may be absorbed by the Clinic based on the client's financial status. Our sliding fee scale for therapy is based on ability to pay and is correlated to the Federal poverty guidelines and correlated with the current copay rate for services in the Community Health Center. All family income is calculated at an annual rate.

Family Size	$6.00 Copay 100%	$10.00 Copay 150%	$12.00 Copay 185%	$14.00 Copay 200%	$18.00 Copay 300%	$20.00 Copay 400%	$30.00 Copay	$50.00 Copay	$70.00 Copay	$90.00 Copay
1 *Up to*	12,060	18,090	22,310	24,120	36,180	48,240	60,000	90,000	130,000	160,001+
2 *Up to*	16,240	24,360	30,045	32,480	48,720	64,960	75,000	100,000	140,000	180,001+
3 *Up to*	20,420	30,630	37,780	40,840	61,260	81,680	95,000	120,000	160,000	190,001+
4 *Up to*	24,600	36,900	45,510	49,200	73,800	98,400	115,000	145,000	185,000	220,001+
5 *Up to*	28,780	43,170	53,245	57,560	86,340	115,120	135,000	160,000	200,000	240,001+
6 *Up to*	32,960	49,440	60,975	65,920	98,880	131,840	155,000	185,000	220,000	250,001+
7 *Up to*	37,140	55,710	68,710	74,280	111,420	148,560	175,000	210,000	250,000	280,001+
8+ *Up to*	41,320	61,980	76,440	82,640	123,960	165,280	190,000	250,000	280,000	300,001+

APPENDIX M

COUNSELING AND ASSESSMENT SCREENING EVALUATION

TELEPHONE SCREENING EVALUATION Billing Code:________________

Date: ___________ Referral Source: ____________________________ Client #: __________________
(Telephone intake date)

Name: ____ Age: ____________ Gender: M / F

DOB: _______________ # Family Members: ______ Annual Family Income: $___________________

Self-reported Ethnicity:______________________ Circle Ethnicity: 1 White-NH; 2 White Hispanic; 3 Black-NH; 4 Asian-NH; 5 AmIndian-NH; 6 Am Indian & White-NH; 7 Asian & White-NH; 8 Am Indian & Black-NH; 9 Black & White-NH; 12 AmIndian & White Hispanic; 13 AmIndian & Hispanic; 14 Black & Hispanic; 15 Pacific Islander; 10 Other Race Combination; 11 Not Available

Parent's name: ________________________________ ❒ Counseling: $______ per hour

❒ Assessment: __ hours at $ ___ per hour = $____

Address: ____

HM#: ________________WK#: ________________ Cell #:_________________ OK to leave msg? YES / NO

Occupation: ____ Legal Referral? YES / NO

Presenting Problem:____

____

____

____

____

____

____

____

____

____

____

Assessment of suicidal risk: (Hx previous therapy)____

____

Health and medications: (Hx meds for psych; hospitalization; Hx of family members) ____________________________

____

Interviewer recommendations (include type of case): Routine Emergent Urgent

____

____

Phone intake done by: **Ginger** **Jason** Client informed about videotaping and supervision? YES / NO

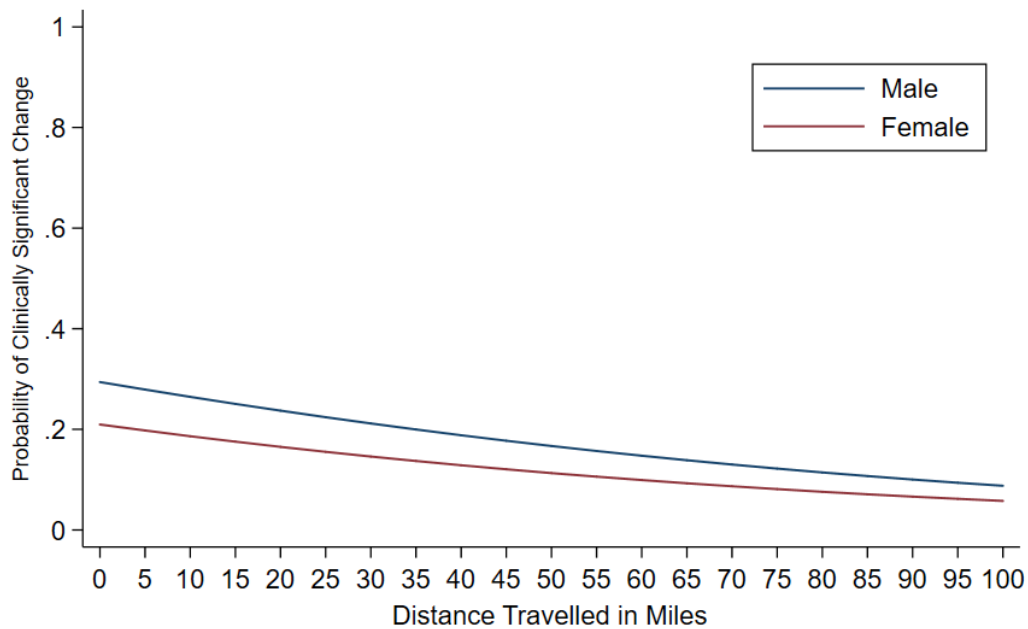
Intake scheduled for: ________________________________ ______________________

Intake Student Assignment Date

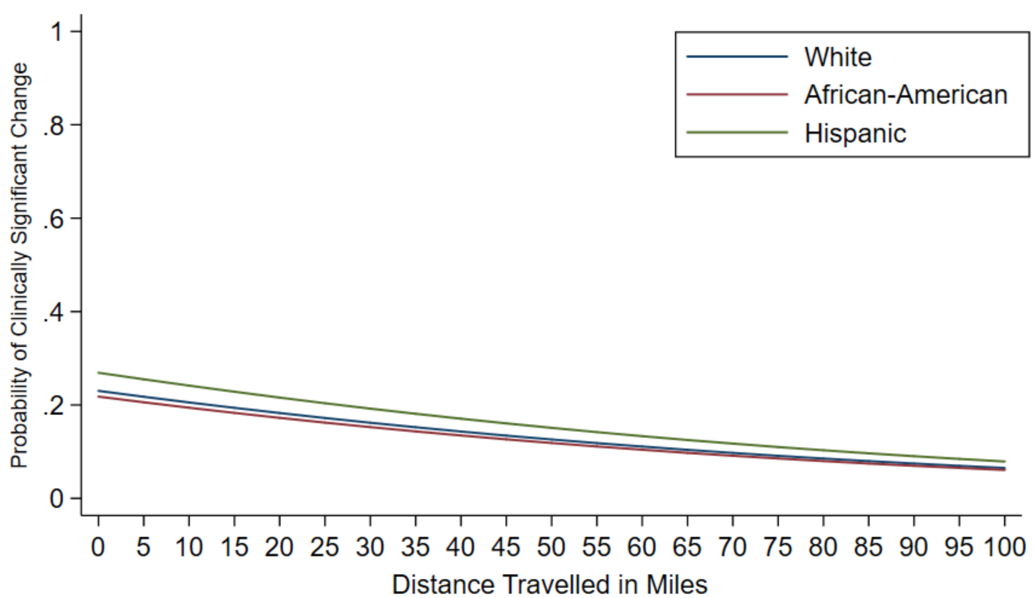
DO NOT REMOVE THIS SHEET FROM THE CLINIC!!!

If not seen for intake, please indicate phone contact attempts and disposition on the reverse using modified Progress Note format.

APPENDIX N
GRAPHS OF SIGNFICIANT INDIVIDUAL REGRESSIONS OF MODEL 5 - DISTANCE TRAVELLED PREDICTING CSC



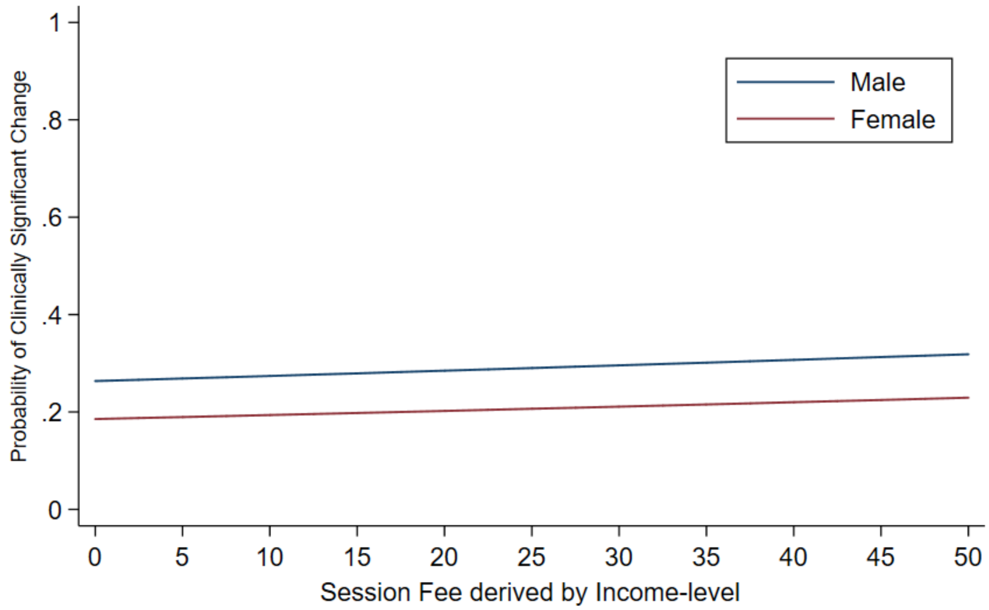
Probability for the Clinical Sample separated by Gender to Achieve CSC expressed over Distance Travelled, n=240



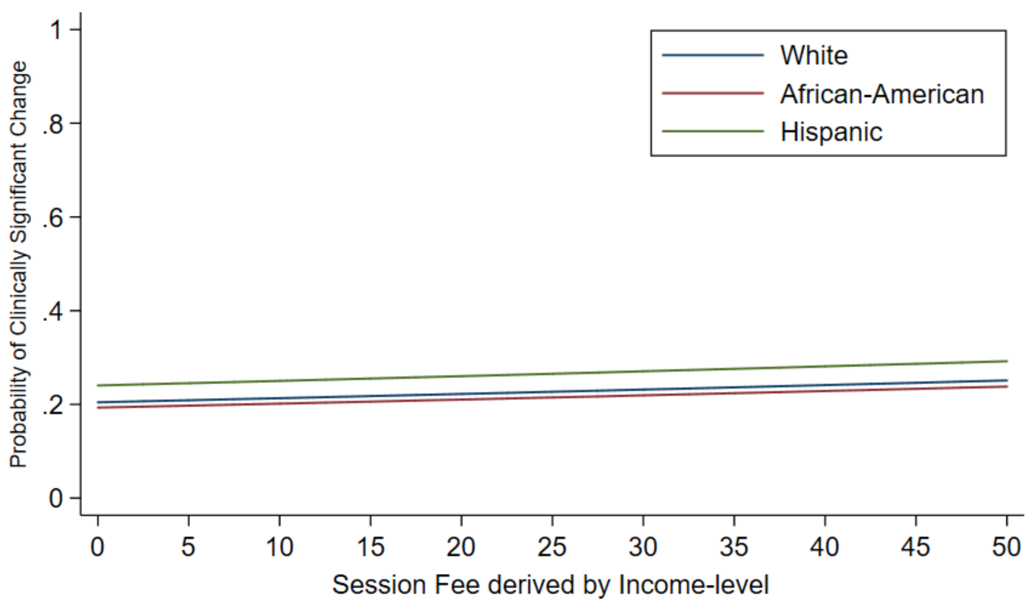
Probability for the Clinical Sample separated by Ethnicity to Achieve CSC expressed over Distance Travelled, n=240

APPENDIX O

GRAPHS OF SIGNIFICANT INDIVIDUAL REGRESSIONS OF MODEL 5- SESSION FEE PREDICTING CSC



Probability of the Clinical Sample separated by Gender to Achieve CSC expressed over Session Fee, n=240



Probability of the Clinical Sample separated by Ethnicity to Achieve CSC expressed over Session Fee, n=240

APPENDIX P
TABLE OF MARGINAL EFFECTS FOR SIGNIFICANT INDIVIDUAL REGRESSIONS IN MODEL 5

Table 9

Marginal Effects for Distance Travelled in Miles and Session Fee in US dollars

	Distance Travelled										Session Fee									
	Marginal Effect					*p*					*Marginal Effect*					*p*				
	M	*F*	*W*	*H*	*AA*	*M*	*F*	*W*	*H*	*AA*	*M*	*F*	*W*	*H*	*AA*	*M*	*F*	*W*	*H*	*AA*
Margin 1	*.27*	*.20*	*.23*	*.27*	*.22*	*.00*	*.00*	*.00*	*.00*	*.03*	*.26*	*.19*	*.20*	*.24*	*.19*	*.00*	*.00*	*.00*	*.00*	*.03*
Margin 2	*.26*	*.19*	*.22*	*.26*	*.21*	*.00*	*.00*	*.00*	*.00*	*.03*	*.27*	*.19*	*.21*	*.24*	*.20*	*.00*	*.00*	*.00*	*.00*	*.03*
Margin 3	*.25*	*.18*	*.21*	*.24*	*.19*	*.00*	*.00*	*.00*	*.00*	*.03*	*.27*	*.19*	*.21*	*.25*	*.20*	*.00*	*.00*	*.00*	*.00*	*.03*
Margin 4	*.24*	*.17*	*.19*	*.23*	*.18*	*.00*	*.00*	*.00*	*.00*	*.03*	*.27*	*.19*	*.21*	*.25*	*.20*	*.00*	*.00*	*.00*	*.00*	*.03*
Margin 5	*.22*	*.16*	*.18*	*.22*	*.17*	*.00*	*.00*	*.00*	*.00*	*.04*	*.27*	*.19*	*.21*	*.25*	*.20*	*.00*	*.00*	*.00*	*.00*	*.04*
Margin 6	*.21*	*.15*	*.17*	*.20*	*.16*	*.00*	*.00*	*.00*	*.00*	*.05*	*.28*	*.20*	*.22*	*.25*	*.20*	*.00*	*.00*	*.00*	*.00*	*.05*
Margin 7	*.20*	*.14*	*.16*	*.19*	*.15*	*.01*	*.01*	*.00*	*.01*	*.07*	*.28*	*.20*	*.22*	*.26*	*.21*	*.00*	*.00*	*.00*	*.00*	*.06*
Margin 8	*.19*	*.13*	*.15*	*.18*	*.14*	*.03*	*.02*	*.01*	*.03*	*.09*	*.28*	*.20*	*.22*	*.26*	*.21*	*.00*	*.01*	*.00*	*.01*	*.08*
Margin 9	*.18*	*.12*	*.14*	*.17*	*.13*	*.05*	*.04*	*.03*	*.05*	*.12*	*.28*	*.20*	*.22*	*.26*	*.21*	*.01*	*.02*	*.01*	*.02*	*.11*
Margin 10	*.17*	*.11*	*.13*	*.16*	*.13*	*.08*	*.07*	*.06*	*.08*	*.15*	*.29*	*.20*	*.22*	*.26*	*.21*	*.02*	*.05*	*.03*	*.04*	*.14*
Margin 11	*.16*	*.11*	*.13*	*.15*	*.12*	*.12*	*.11*	*.10*	*.11*	*.18*	*.29*	*.21*	*.23*	*.27*	*.21*	*.04*	*.08*	*.06*	*.07*	*.17*
Margin 12	*.15*	*.10*	*.12*	*.14*	*.11*	*.16*	*.15*	*.14*	*.15*	*.21*	*.29*	*.21*	*.23*	*.27*	*.22*	*.07*	*.12*	*.09*	*.10*	*.20*
Margin 13	*.14*	*.09*	*.11*	*.13*	*.10*	*.20*	*.20*	*.18*	*.19*	*.24*	*.30*	*.21*	*.23*	*.27*	*.22*	*.10*	*.16*	*.13*	*.14*	*.23*
Margin 14	*.13*	*.09*	*.10*	*.13*	*.10*	*.24*	*.24*	*.22*	*.23*	*.28*	*.30*	*.21*	*.23*	*.27*	*.22*	*.13*	*.20*	*.17*	*.17*	*.27*
Margin 15	*.12*	*.08*	*.10*	*.12*	*.09*	*.28*	*.28*	*.26*	*.27*	*.31*	*.30*	*.22*	*.24*	*.28*	*.22*	*.17*	*.24*	*.21*	*.21*	*.30*
Margin 16	*.11*	*.08*	*.09*	*.11*	*.09*	*.32*	*.32*	*.30*	*.31*	*.34*	*.30*	*.22*	*.24*	*.28*	*.23*	*.20*	*.28*	*.24*	*.24*	*.33*
Margin 17	*.11*	*.07*	*.09*	*.10*	*.08*	*.35*	*.35*	*.34*	*.34*	*.37*	*.31*	*.22*	*.24*	*.28*	*.23*	*.23*	*.31*	*.28*	*.27*	*.35*
Margin 18	*.10*	*.07*	*.08*	*.10*	*.07*	*.39*	*.38*	*.37*	*.38*	*.40*	*.31*	*.22*	*.24*	*.28*	*.23*	*.27*	*.34*	*.31*	*.30*	*.38*
Margin 19	*.09*	*.06*	*.07*	*.09*	*.07*	*.42*	*.41*	*.40*	*.41*	*.43*	*.31*	*.22*	*.25*	*.29*	*.23*	*.30*	*.37*	*.34*	*.33*	*.40*
Margin 20	*.09*	*.06*	*.07*	*.08*	*.07*	*.46*	*.44*	*.43*	*.44*	*.45*	*.32*	*.23*	*.25*	*.29*	*.24*	*.32*	*.40*	*.37*	*.36*	*.43*

Margins for Distance Travelled occurred in 5-mile margins from 0 to 100 miles.
Margins for Session Fee consisted of $2.50 margins from $0 to $50.

VITA

DONALD KLEINE-KRACHT

Address:	Department of Educational Psychology College of Education and Human Development Texas A&M University 704 Harrington Tower MS 4225 College Station, Texas 77843-4225
E-Mail Address:	daklei3@tamu.edu

Education:	Bachelor of Arts, Psychology, University of Kentucky, Kentucky, December 2012 Bachelor of Arts, Sociology, University of Kentucky, Kentucky, December 2012 Master of Education, Counseling Psychology, Texas A&M University, College Station, Texas, December 2015 Doctor of Philosophy, Counseling Psychology, Texas A&M University, College Station, Texas, December 2019
Professional Internship:	University of Kentucky – Lexington, Kentucky Counseling Services
Professional Affiliations:	American Psychological Association Texas Psychological Association