

1-1-2014

# Interdependence Of Community Mental Health Care Providers In An Urban County: A Spatial Panel Approach

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## DEDICATION

To my lifetime partner, Albert Kim.

## ACKNOWLEDGMENTS

I would like to acknowledge and thank the following people who have witnessed and supported my work to make this project happen:

- Dr. Allen Goodman, for his generous support, intellectual guidance, and consistent encouragement.
- Dr. Xu Lin, for her willingness to share her expertise with me and for her patience as we tested the models again and again.
- Dr. Eugene Schoener, for his thoughtful suggestions and patient editing as well as opening the opportunity of having me work on the real-life data.
- Dr. Gail Jensen Summers, for her valuable comments on my study and stimulating discussion.
- Dr. Li Way Lee, who has supported my graduate study and other occasions.
- Cheri Miller and Delores Tennille, who have provided their support and assistance whenever I need.
- My colleagues and friends, who have been great treasure during my doctoral training years.
- My cousin, Shiyong Lu, who has made me an optimistic researcher and person.
- My parents-in-law, for having done anything possible to help me concentrate on my study and always cheered me up with great food and smiles.
- My brother and sister-in-law, who have done the best job in taking care of my parents and my nephew.
- My parents, who would be proud of me and understand my dream if they see my

work.

- My best friend and partner, Albert Kim, who deserves my greatest appreciation for his infinite love and belief in me. I owe him a lifetime of love for giving me new smile wrinkles and helping me to be the best version of myself.

I sincerely appreciate contributions from each of you to this work.

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## Chapter 1. INTRODUCTION

Mental health problems encompass a broad range of illnesses, such as anxiety disorders, mood disorders, schizophrenia, or substance abuse disorders. Nearly 20 percent of American adults meet diagnostic criteria for mental illness (Substance Abuse and Mental Health Services Administration, 2012). One out of eight children has had an emotional or behavioral health disorder in the previous year (Merikangas *et al.*, 2010).

The American economy bears a sizeable financial burden for mental health treatment. In fact, an estimated \$113 billion was spent during 2005 on mental health treatment in the United States, accounting for about 5.6 percent of total national health care spending (Mark *et al.*, 2011). Public funding represented 58 percent of these mental health care expenditures in 2005 (SAMHSA, 2012), 28 percent of which were paid by Medicaid. Over time, public funding has become increasingly important for funding mental health care in the country. It rose to 60 percent of all mental health spending by 2009, with Federal Medicaid serving as the critical safety net for mental illness during the recession (Levit *et al.*, 2013). With further implementation of the Patient Protection and Affordable Care Act over the next two years, there will be an even greater number of people covered by public funds. If all states follow the expansion path of Medicaid programs, as many as 2.7 million people with mental illness who are currently uninsured could be added to the Medicaid rolls, according to the Substance Abuse and Mental Health Service Administration (SAMHSA).

Community mental health (CMH) systems have played an important role in providing public mental health services to most people with mental illness since the 1960s. Community-based mental health care was designed to be a more humane and

effective means of service delivery than institutionalization. As indicated by the National Council for Behavioral Health,

“Community-based behavioral health services are delivered by a mix of government and county-operated organizations, as well as private nonprofit and for-profit organizations. These mental health and addiction services are funded by a patchwork of sources, including Medicaid; Medicare; county, state and federal programs; private insurance; and self-pays.”<sup>1</sup>

For the severely indigent and uninsured population with mental disorders, community-based care is the only real option today for treatment. Once an individual is deemed to be eligible for community mental health care, s/he can have access to an array of services including screening and assessment, case management, therapy, medication, peer support, and various intensive treatment services at community mental health (CMH) providers. Since deinstitutionalization occurred more than four decades ago, services for people with severe mental illness have shifted largely from inpatient to outpatient venues. These outpatient services are delivered by specialized as well as non-specialty mental health care providers. Specialty providers include both physicians (i.e., psychiatrists) and non-physician providers such as psychologists, social workers, counselors, and psychiatric nurses, all of whom practice in outpatient and inpatient mental health care settings and general medical settings. Non-specialty providers include schools, foster homes, clubhouses, and correctional facilities.

Public mental health care is funded 90 percent through state Medicaid and state mental health agency budgets (community mental health programs and state hospitals) (National Alliance on Mental Illness, NAMI, 2010). In the state of Michigan, individuals who are eligible for Supplemental Security Income are

<sup>1</sup> Community-based behavioral health services include mental health care services and substance abuse treatment. This study focuses on mental health services only.

automatically eligible for Medicaid. Children under age six from families with incomes below 133 percent of the federal poverty level and children ages 6-18 with family income below the federal poverty level are eligible for Medicaid. Basic services include psychiatrists, nursing home services, and home health care services. State mental health budgets are primarily funded by state general fund dollars to provide state hospital and inpatient care, crisis services and community mental health services for individuals with mental disorders. These budgets play a vital role in covering non-Medicaid eligible population. However, state general funds are not a dedicated and certain revenue source. The operating state budget varies from year to year, yielding periods of greater and lesser support for services. Recently, the general fund supports has been decreasing. In the face of Medicaid Expansion, Medicaid managed care will be replacing general funds.

Community Mental Health Services Programs (CMHSPs) of Michigan were formed under Act 258 of the Public Acts of 1974. A CMHSP manages mental health service resources locally and assures that providers comply with standards of care. It receives Medicaid funding and general funds and pays CMH providers based on contracting and capitated rates. Consumers can have a choice of providers once enrolled with a CMHSP.

This study examines strategic interaction among CMH providers in a publicly funded network. Generally, local CMHSPs are responsible for negotiating contract prices with providers and individualizing contracts to emphasize specialized services of providers. For example, a residential site is contracted to provide assisted daily living and follow up services for intensive treatment while an outpatient clinic is funded to provide counseling, medication and therapy. Providers may offer similar care as well as differentiated services to consumers. Consumers are assumed to have

homogeneous preferences in their consumption given their Medicaid eligibility and enrollment. In modern economics, agents make their intertemporal decisions between present and future market behaviors. Thus, a CMH provider is concerned with the public funding received from the local CMHSP in the present period as well as in the future. If the public funding of a strategic provider adjusts in response to that of its neighbor, the previous neighborhood funding is very likely to have the same effect as the current neighborhood spending. Also, the modern spillover model implies that an agent seeks to obtain a maximum level of public funding, but the amount an agent receives is also directly influenced by the funding level received by another agent. In a system, a provider's public funding may negatively impact the funding level of its neighbors with similar functions, while it can be positively related to that of its neighbors whose services are distinct and even complementary. As travel distance is one of the major concerns to both consumers and providers, a provider (as an agent) may affect another provider located nearby more than those who are further away. Because this study does not constitute human subject research according to the definition codified in the Common Rule at 45 CFR 46.102 (d) (f), it does not require Institutional Review Board oversight.

By focusing on the mental health care sector, the present study contributes to the literature in several aspects. Perhaps most noteworthy, this study is the first empirical application of strategic interaction concepts in a time-dynamic framework. Previous empirical spatial analysis ignores time dynamics for the most part. By employing a more general framework, this study clearly demonstrates that a provider follows a spatial autoregressive process in its revenue.

Secondly, a transformation approach is applied to overcome the incidental parameter problem and ensure consistency of estimation. Because the selected sample

covers only four time periods, the traditional direct approach will yield inconsistent estimation of the common parameters (Lee and Yu, 2010b). The data transformation is accomplished by applying the time mean operator to generate uncorrelated disturbances in the model, thus leading to consistent estimators.

Finally, this study explores the spending patterns in public mental health care at the provider level in a representative metropolitan area, with an understanding that delivery of mental health care is different from medical health care. It is imperative now to examine mental health care as a distinct market, even though similar research has been conducted in the general medical care industry at the provider level (Mobley, 2003), because care for severe persistent mental illness, characterized by a decentralized community mental health system, needs to be examined as a distinct market (Frank and McGuire, 2000). With unique access to the database that contains local Medicaid mental health care claims of Detroit-Wayne County (DWC), this investigation of its mental health care system promises to deliver practical policy implications.

Following the introductory chapter, the remainder of this dissertation is organized as below. Chapter 2 reviews the relevant literature on community mental health care and mental health care public funding support. It then reviews the existing literature on spatial analysis in health care systems and other related public funding systems. A review of recent studies on spatial econometrics is also presented.

Chapter 3 elaborates the background of this dissertation. Mental health care is one of the most expensive health conditions, and yet public funding for mental health services is shrinking. The chapter provides an introduction into community mental health services and then illustrates interaction among community mental health care providers in the neighborhood studied.

The statistical inference of the spatial model is presented in Chapter 4. The model incorporates spatial interdependency and dynamic consideration as well as exogenous factors. Two weightings are examined to ensure robustness of the results. As the time horizon is finite in this study, a data transformation approach is used to produce consistent estimators. The quasi-maximum likelihood approach help yields consistent estimates with properly centered distribution.

Chapter 5 presents the data, including the data source, selection of the sample, the variables considered and the limitations of the data. Investigation of providers' specialization is conducted to help understand the potential interdependency.

The results of the empirical analysis are presented in Chapters 6. The estimation starts with a simple fixed effect model, and then moves forward to the spatial panel dynamic data model with two different weights. Finally, a robustness check is conducted with a static spatial panel data model. All estimations are supportive of spatial interdependency. In Chapter 7, meanings of the empirical results are discussed.

The last chapter explicates the conclusions of the study. Implications for community mental health policy and programming are presented and the limitations of the study are discussed. Suggestions for future research are offered at the end of the chapter.



## Chapter 2. LITERATURE REVIEW

There has been insufficient health economics literature aimed at disentangling relationships among mental health care providers. Most existing studies on health care have only considered general health care: they have not included mental health care or simply treated it as a minor part of general health care. However, as noted by Frank and McGuire (2000), “mental health economics is like health economics only more so: uncertainty and variation in treatments are greater; the assumption of patient self-interested behavior is more dubious; response to financial incentives such as insurance is exacerbated; the social consequences and external costs of illness are more formidable”. Also, despite endeavors made through managed care and parity in mental health benefits, increased coverage and cost for mental illness has been seen as inefficient (Barry *et al.*, 2006).

Medicaid has become the most important health care safety net for people with mental disorders. Medicaid mental health policy has created incentives for expansion of community-based providers (Frank *et al.*, 2003). However, gaps still exist in services for indigent population with mental illnesses, as described in a recent study of twelve U.S. communities (Cunningham *et al.*, 2006). Residential services were consistently mentioned as short-supplied. Another important gap exists in shortage of psychiatric inpatient beds for acute care. In addition, shortages of key outpatient care staff, especially psychiatrists, resulted in longer waiting times. There is considerable interest among community providers and some states in addressing these issues of current care delivery.

Even though there is no apparent evidence supporting community-based mental health care as a more effective way to treat individuals with mental illness than institutional care, Healey and his coauthors present their insights of the effectiveness

of community mental health services (Healey et al, 2000). Using data from an Italian psychiatric case-register, their study endeavored to show how estimation of a patient health production function from longitudinal naturalistic data could test for the effectiveness of community mental health services. Under the community setting, all staff, including psychiatrists, psychologists, hospital nurses, community nurses, and social workers, work both inside and outside hospitals, ensuring continuity of care. Community-based contacts, such as visits made to patients' homes, visits to patients temporarily supported by other agencies, or visits by clinical staff, were found to be associated with improvements in the general functioning of patients.

The study by Mobley (2003) on hospital market pricing has inspired the present work by providing useful insights into interaction among health care providers. Her paper investigated how the slope of the reaction function reflects hospital specification and how equilibrium prices are affected by shifts in the reaction function. A spatial lag model characterizing the interdependencies helped to examine how hospital prices are explained by both observation-specific characteristics and characteristics of neighbors, with the impact of neighbors decreasing according to a pre-determined spatial weighting scheme. The estimation strategy involved running seemingly-unrelated regressions jointly for the cross-sectional data from 1993 and 1998 to observe whether the spatial effect was stable over time. Potential endogeneity of some explanatory variables was overcome by including their lags. Mobley considered spatial spillover effects across hospitals and their potential change over time in response to manage care penetration. Estimation results indicate that the spatial lag parameter estimate is significant with a positive sign and does not change significantly over time, meaning that the extent of specialization or differentiation among California hospitals did not change significantly over the period examined. A

hospital's response to market pricing is described under a static spatial framework; however, if a strategic provider adjusts its pricing in response to its neighbors' decision, the previous neighborhood pricing is very likely to be influential on the current hospital market pricing. This means that intertemporal dynamics is another important consideration in strategic interaction among different agents.

Deb and Holmes (1998) published another study concerned with mental health care providers from an economic point of view. It evaluated the extent to which patients may substitute physician (MD) and non-physician (PhD) outpatient mental health services in response to a change of insurance coverage. 1987 National Medical Expenditure Survey data were used to capture the variation in the coverage of physician and non-physician mental health care services. A semi-flexible two-stage demand specification was employed, where potential interactions between provider types were taken into consideration. The first stage examined the impact of price on the provider type sought. The second stage concentrated on the impact of pricing on the level of care demanded from the provider selected. The authors were interested in the physician-non-physician nexus, but they treat the provider types as heterogeneous by considering differences in their treatment styles. Their estimation found that physician and non-physician services were substitutes for patients who are seeking care from both provider types. While the results help improve understanding of how different types of outpatient care relate to one another, other possibly significant interaction effects were excluded. Since deinstitutionalization of mental health services in the 1960s, community-based care has become dominant in treating people with mental illness owing to its cost-effectiveness. Therefore, relationships between mental health care providers need to be studied in the community-based context.

Recent research in health economics has recognized that cross-section spillover is an important feature of health care spending. In a series of articles, Moscone and coauthors (2005, 2007a, 2007b) analyzed spatial patterns of spending decisions in the mental health care spending decisions between adjacent authorities on the municipal level in England. Moscone *et al* (2007a) employed a seemingly unrelated regression approach with a spatial interaction term to shed light on the degree of interdependence. The approach permitted them to explore the temporal evolution of policy interactions and examine whether local interaction is stable over time. The municipality-specific characteristics were controlled, including density of population, percentage of males, standardized mortality ratio, average house prices, and so on. The other two studies adopted a reduced form demand and supply model, extended to incorporate possible interaction among authorities. All three studies found that interdependence of spending decisions between neighboring municipalities potentially is an important feature of decision-making owing to information and knowledge spillover. Moscone *et al.* reported the demonstrative effect of a municipal neighbor from an authority with good performance and reputation. They estimated that that one percent increase in expenditure in neighboring localities could yield a rise of 0.16 percent in spending (Moscone *et al.* 2007b).

When investigating the relationship between health expenditure and income in the United States, Moscone and Tosetti (2010) controlled for two sources of interdependence. One arises from correlation across individuals when the responses are similar among individuals to common external forces or perturbations, such as innovations in diagnostic tools and therapies, regional epidemics, or sexual behaviors of a generational cohort. An alternative source of interdependence is spatial spillover

across neighboring US states, with respect to the geographical, economic, or social space in which they are embedded (Anselin, 2001).

Other reasons for the importance of spatial interdependence in health care have been drawn from recent literature in public economics. The expenditure behaviors of local governments (municipalities, regions, or states) are traditionally explored through three channels: yardstick competition, fiscal competition, and expenditure externality. Bivand and Szymanski (1997) proposed a model of yardstick competition in which local principals contract with local agents. Yardstick competition emerges when it is optimal to condition local contracts on the performance of neighboring agents. An externality arises when particular principals pursue unobservable policies which then distort neighbors' incentive contracts. The authors employ a spatial weights matrix to test the spatial dependence of English garbage collection contracts. The results supported a clear spatial dependence in distribution of garbage collection cost data in England. It was also found that such dependence decreases after the introduction of a law on compulsory competitive tendering.

Revelli (2006) also examined yardstick competition in welfare spending before and after an institutional change in the U.K. using spatial econometrics. Those findings are consistent with the expectation that the institutional change, adoption of Social Services Performance Rating, diminished the relevance of local information spillovers, and weakened the incentives for local authorities to mimic the policies of neighboring jurisdictions. Lundberg (2006) also identified spillover effects between municipalities in Sweden in terms of recreational and cultural services provided at the local government level. Most recently, Yu *et al.* (2013) used a spatial Durbin model with spatial and time fixed effects to examine determinants of expenditures on public

health in China. They found strong evidence for the influence of public expenditure externality effect. Specifically, a provincial government appears to decrease its own health spending as a response to the rise of health spending of its neighboring provinces.

Strategic interaction among state and local governments is also a focus of increasing empirical work in public finance in the United States. Brueckner (2003) provided an overview of theoretical work on strategic interaction among governments. There are three major categories of literature in this aspect: research on tax competition, studies on welfare competition and analysis on strategic interaction due to benefit spillovers. Case *et al.* (1993) found that a state government's level of per capita expenditure is positively and significantly affected by the expenditure levels of its neighbors. Specifically, a one dollar increase in a state's neighbors' expenditures increases its own expenditure by over 70 cents. Using the same methodology of Case *et al.*, Brueckner (1998) tested for strategic interaction among California cities in adopting growth control measures. Under the spatial lag specification, the growth control index depends on city characteristics and on a variable measuring the stringency of controls in competing cities. In another study, Brueckner and Saavedra (2001) investigated whether cities in the Boston metropolitan area engage in strategic property-tax competition. The results indicate that local governments do engage in strategic interaction. By focusing on mandated increases in medical spending, Baicker (2005) found that population mobility between states is the strongest spatial predictor for state spending.

Most existing studies on spatial interaction are based on a static spatial framework and overlook dynamics present in cross-agent strategic interaction. Intertemporal considerations are found to be an important feature in strategic dynamic

game. Tao (2005) was the first to study the decision of local school spending in a dynamic framework. His study formulated a dynamic game-theoretical framework that allows a strategic agent to make intertemporal optimization. In particular, in positive response to the current neighborhood spending and his own previous spending, a forward-looking local policymaker will react negatively to the previous neighborhood spending as a result of an intertemporal resources constraint.

Spatial econometrics started with a cross-sectional model by Cliff and Ord (1973) and later extended to panel data models (Anselin, 1988; Elhorst, 2003). The article by Anselin *et al.* (2008) provides a list of spatial panel data models and presents the corresponding likelihood functions. It points out fundamental aspects of the models and testing of spatial dependence via LM tests, Yu and Lee (2010a) reviewed some recent development in econometric specification and estimation of spatial panel data models for both static and dynamic cases and investigated asymptotic properties of estimators. A general framework was developed to investigate different spatial and time dynamics. An immediate way to include the dynamic features is to add the time lag term as an independent variable. The study offers meticulous discussions on fixed and random effects specification of the individual and time effects. It points out the incidental parameter problem for the case of the small time dimension. The incidental parameter problem arises when the introduction of fixed individual effects increases the number of parameters to be estimated, and the time dimension does not provide sufficient information to consistently estimate those individual parameters.

Lee and Yu (2010b) propose a transformation approach to overcome the incidental parameter problem for spatial panel data models with fixed effects and spatial autoregressive (SAR) disturbances. Fixed effects are often included to inspect

unobserved individual or time effects on outcome variables. The paper shows that when the time dimension is small, the estimate of the variance parameter given by the direct approach is not consistent in the SAR panel model with fixed effects. The solution is to transform the data by employing a time mean operator and further including the Helmert transformation to eliminate linear dependence of disturbances over the time dimension. Even though both approaches yield the same likelihood function of the estimates (except the variance parameter), the estimates are numerically different, and only the ones under the transformation approach are consistent despite the size of the sample or the time dimension. Monte Carlo results are provided to illustrate finite sample properties of the various estimators. The paper establishes asymptotic properties of quasi-maximum likelihood estimators for SAR panel data models with fixed effects and SAR disturbances.

Most previous applications of spatial econometrics are carried out for aggregate units of observations, such as municipalities, counties and states. When parameters and other characteristics of a distribution are estimated at an aggregate level, but behavioral and socio-economic relations are inferred for another, disaggregate level, the ecological fallacy, which pertains to cross-level inference or bias, arises (Anselin, 2002). This dissertation extends earlier work to strategic interdependence between individual community mental health providers in a publicly funded network. This individual-level study avoids the ecological regression problem as parameters and characteristics of individuals are used. It aims to identify spillover effects among CMH providers who are located in a geographic neighborhood and to draw policy implications for the mental health care system. It is also the first empirical study applying an SAR spatial model in a healthcare setting.



## Chapter 3. BACKGROUND

### 3.1 Mental Health Expenditures

Both direct and indirect costs of mental illness to individuals and societies are known to be considerable. According to data from the Agency for Healthcare Research and Quality (AHRQ), mental disorders led the five most costly conditions<sup>2</sup> for the U.S. population in terms of direct medical spending in 1996 and in 2006 (Soni, 2009). Mental health spending increased from 0.71 percent of GDP in 1986 to 0.89 percent in 2005 (Mark *et al.*, 2011). Projection results released by SAMHSA indicate that mental health expenditures are expected to reach \$203 billion in 2014 (Levit *et al.*, 2008). Even though the share of health care spending for mental health is predicted to shrink, from 6.2 percent in 2003 to 5.9 percent in 2014, public sources of funding for most (58 percent) of mental health services in 2003 are expected to remain at the same share in 2014 (Table A.1).

Regarding individuals with behavioral health disorders, the Center for Medicaid and CHIP Services have identified several factors for influencing their decision to develop new coverage and service designs for the population (Mann, 2012). The Center indicates that Medicaid is the largest payer for mental health services in the U.S., comprising over a quarter of all expenditures of mental health services. As a result, Medicaid coverage policy can have a significant impact on the income of mental health care providers and the delivery and quality of mental health services they provide. It is also shown that individuals with mental health disorders comprise almost 11 percent of the people enrolled in Medicaid and represent almost 30 percent of all Medicaid expenditures. Furthermore, almost a quarter of hospital

<sup>2</sup> The five most costly conditions were: heart disease, trauma-related disorders, cancer, asthma, and mental disorders. See Figure A.1 for the expenditure data for the five most costly conditions.

admissions are associated with mental or substance use disorders, and emergency departments (EDs) are also used frequently by this population. Utilization of hospitals and EDs, especially by the uninsured, is a considerable challenge to mental health financing.

Treatment for mental health problems is most frequently delivered today on an outpatient basis (Garfield, 2011). Of \$113 billion spent on mental health services in the U.S., the largest share went towards outpatient services in 2005, compared to the largest share for inpatient services in 1986 (See Figure A.2). In fact, people with serious mental illness not only receive common treatments like psychosocial services, but they require support services, such as income assistance, vocational training, or housing assistance, to help them manage day-to-day activities (See Figure A.3). Therefore, mental health services frequently combine specialty and non-specialty providers. Community-based care allows the inter-relationship between the component parts of the whole system of care and thus becomes particularly significant to both mental health providers and consumers. According to the National Association of State Mental Health Program Directors, the number of consumers receiving mental health services from the State Mental Health community-based systems alone increased from 5.5 million to 6.5 million from 2007 to 2010, a 10 percent increase (Glover *et al.*, 2012).

### **3.2 Community Mental Health Services**

Community mental health care is community-oriented and person-centered in that most services are provided in community settings close to the people served (Thornicroft *et al.*, 2010). Services are provided within a “balanced care model”, requiring coordination among providers. The initial plan for community care called for centrally located professional case managers, who would be responsible for

coordinating all of the services for individuals with severe and persistent mental disorders in the community. In their article about lessons in developing community mental health care systems in North America, Drake and Latimer report that many challenges to caring for people in the community became apparent in the 1970s and 1980s (Drake and Latimer, 2012). It was clearly indicated that there is a wide range of common concerns, including integration and continuity of services for those with the most complex needs, appropriate housing, family burden, substance abuse, and violence. They pointed out that all of these problems had been exacerbated by poverty, unemployment, crime and reductions in housing subsidies.

Many models of care were developed to address the special problems and needs of population with severe mental illnesses living in the community setting (Drake and Latimer, 2012). For integration and continuity of care, service models like assertive community treatment, intensive case management, and clinical case management appeared. To meet the need for housing, foster care, residential continuum, and supportive and supported housing models were also developed. Other models like family interventions and treatments for co-occurring disorders were widely used to address more concerns. All of these services require close cooperation and collaboration among a range of agencies in order to meet special needs of the population. Drake and Latimer proffered that team-based care is the most direct way to insure access, continuity, and integration of care. Within a system, providers also need to work in teams to make it possible to offer patients sustainable medical, psychiatric, housing, financial, vocational, family, and social services.

According to Thornicroft and his colleagues (Thornicroft et al., 2010), the “balanced care model” for community-oriented care can have different levels of priorities, given available resources. In low-resource settings community care is

essentially characterized by a focus on population and public health needs, locally accessible services, community participation and decision-making in the planning and provision of mental health care systems, and so on. In medium-resource settings, with more resources, there is an extra layer of general mental health services. It is developed in five categories: outpatient/ambulatory clinics; community mental health teams; acute inpatient services; community-based residential care; and work, occupation and rehabilitation services. In high-resource settings, it is expected that high-intensity services are provided. For instance, there are specialized outpatient and ambulatory clinics, assertive community treatment teams, intensive case management, and crisis resolution teams, and so on. Therefore, a wide range of practitioners, professional and non-professional care and supports are drawn together by community mental health care systems, even though different components may play greater or lesser roles in particular settings depending on the context and the resources.

Mental health care providers fall roughly into one of four categories depending on the care being provided. They may be highly trained providers, generalists, social service providers, or informal volunteers. Individuals with mental illnesses may receive social services and general health care services from various agencies or providers. According to the Office of the Surgeon General, effective functioning of the mental health service system requires connections and coordination among public and private sectors, various specialty services, and a range of institutions in housing, criminal justice, and education (United States Public Health Service Office of the Surgeon General, 1999). As a result, the lack of effective communication between these service providers could result in missed opportunities to ensure that individuals with mental illness receive the care they need.

### **3.3 Interaction among Community Mental Health Providers in the Detroit-Wayne County Neighborhood**

According to Buck (2003), the community model of financing public mental health services has several major features. One is that the planning and administration of public mental health services are centered in a state/county mental health authority. It is generally assumed to be an autonomous agency in state/county government, with independence in setting policies and exercising oversight of local providers. Also, mental health authorities are considered as the primary funders of public mental health services. This funding is accomplished either through direct provision of services, mainly in public psychiatric institutions, or equally important, expenditures for the support of community-based specialty providers. These psychiatric institutions and providers most often are nonprofit agencies that serve indigent populations or clients of publicly supported programs. Often these providers do not specialize in one type of treatment but offer services across the continuum of care.

State/county mental health authorities have used a system of grants or contracts to support this specialty provider network. Within parameters set by the authority, these providers are viewed as having some discretion in designing programs, choosing clinical staff, and setting treatment guidelines (Buck, 2003). Shifts in the sources and character of funding will change mission, characteristics, staffing and services of CMH providers. Especially, increased competition will require changes in business areas. In this context, services will be determined more by their ability to generate revenue than any assessment of community need.

Michigan has contracted with counties and groups of counties across the state for the management of Medicaid services to people with severe mental illness (SMI), serious emotional disturbance (SED) and developmental disabilities (DD). The county

organizes function as Prepaid Inpatient Health Plans (PHIPs) under Medicaid rules, and consumers are assigned to these plans when they meet clinical criteria (Dougherty, 2011). Partly because of its size, the Detroit-Wayne County's mental health plan services are contracted out to private provider networks to ensure competition locally. In this mental health network, cooperation and dependency between providers is more prevalent and prominent than competition. Interdependency, either competitive or cooperative, may lead to different levels of care delivery.

The Detroit-Wayne County Community Mental Health Agency<sup>3</sup> (D-WCCMHA or the Agency) receives funding from the state and the Federal governments. The funding types largely include Medicaid and General Funds.<sup>4</sup> The Agency has five contracts with Managers of Comprehensive Provider Networks (MCPNs) -- three are for individuals with DD and two are for adults with SMI as well as children and youth with SED. There are about 500 sites scattered around the county, with over one third in Detroit and about two thirds out-County but not in Detroit. Some providers have multiple locations serving patients with different needs, and others under the same name are regarded as different sites because of their various locations and specialties. Different providers/clinics may offer similar services to patients in the system. Most of them are either affiliated with one of the MCPNs or have partnership with MCPNs by contracting, and a few have direct contracts with the Agency. Patients may receive services from multiple providers at the same time, but they are all accessed through a unique MCPN. Nearly 30 percent of the sites are foster care homes, where the service population includes individuals with MI and DD who require minimal assistance in activities of daily living. Foster care sites are relatively smaller and have limited

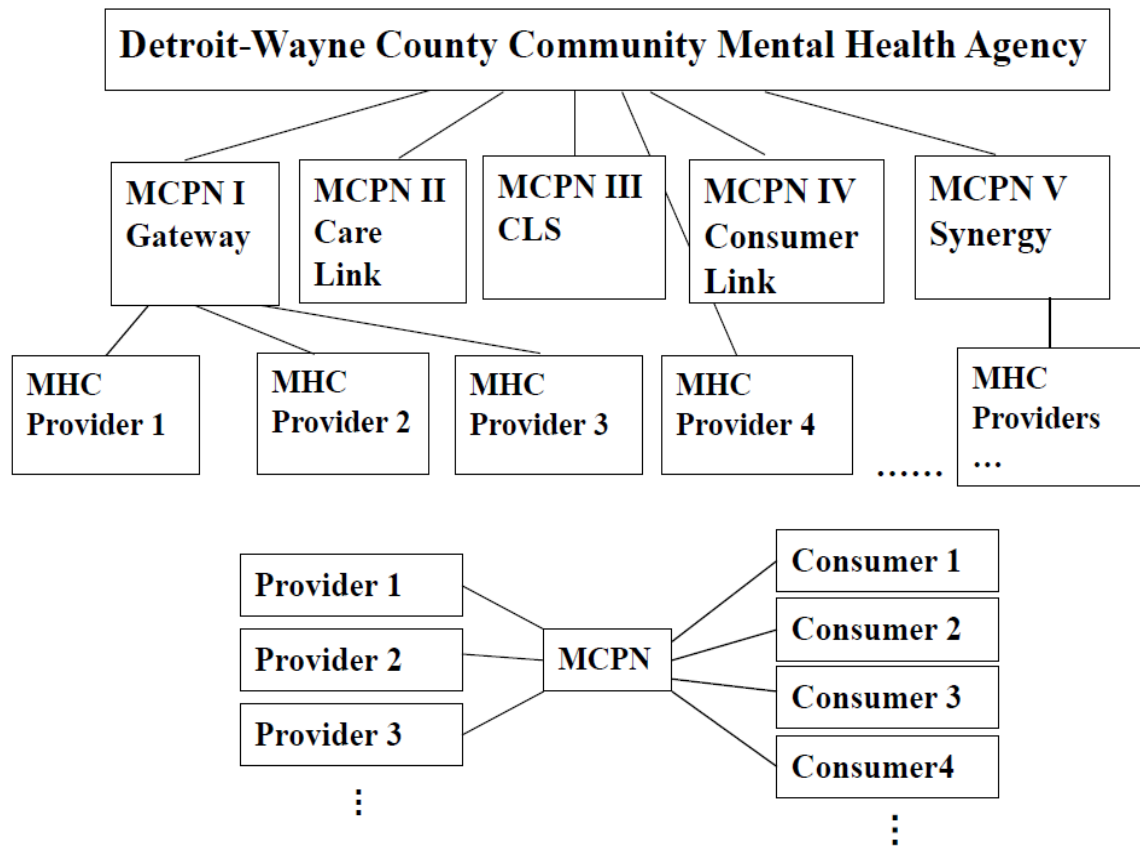
<sup>3</sup> Currently Detroit Wayne Mental Health Authority.

<sup>4</sup> The two primary sources of public mental health funding are Medicaid and state general funds, accounting for 90 percent of the system on average. The rest 10 percent is funded by Medicare, federal block grant funds, which are not tracked under the Agency (NAMI, 2010)

service capacity. Because of the large number of foster care homes that coexist and their common nature, their entry and exit from the market is frequent. By contrast, twenty major providers are the most stable contractors with the Agency. Compared to the rest of providers, the major providers have closer relationships with the MCPNs and the Agency and offer more comprehensive services to consumers, so their service population and capacity are relatively constant.

The relationship between different service levels is described graphically in Figure 1. D-WCCMHA is on the top of the tier. Five MCPNs are affiliated directly with the Agency as they receive Medicaid and other public funding through the Agency, and they allocate the funding to local providers by contracts. Some providers sign direct contracts with the Agency, and some of them contract with two or three MCPNs. Each consumer is served through a distinct MCPN.

**Figure 1 Relationships among Detroit-Wayne County Mental Health Care Services**



Note: The DWCCMHA structure is composed by the author.

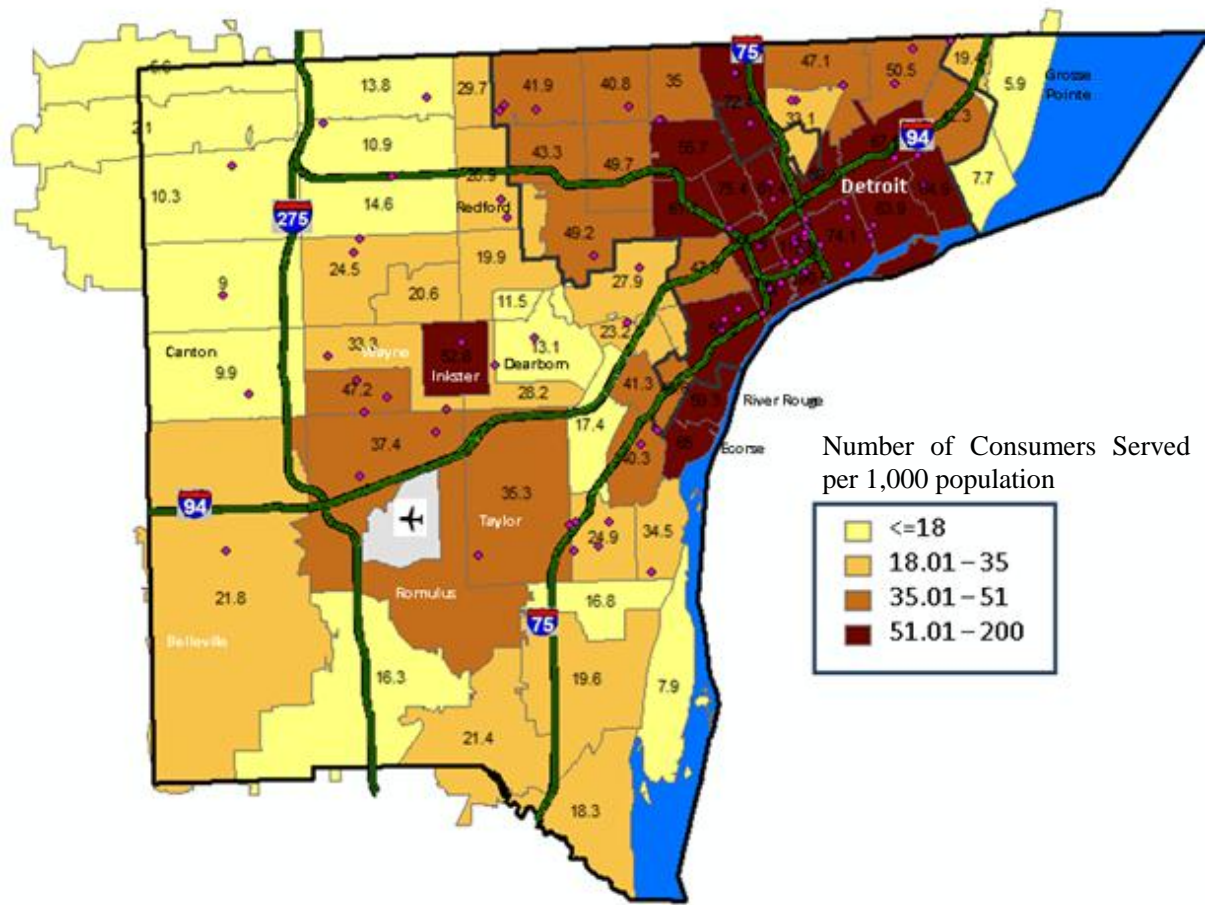


Providers are distributed roughly in accord with consumer concentrations, as illustrated in Figure 2 – Number of D-WCCMHA consumers served per 1,000 populations in FY2010 (the fiscal year 2010<sup>5</sup>) with provider locations. The density of consumers is highest in a few zip codes of Detroit, where sites are most highly concentrated. The concentration of consumers becomes lighter outside of Wayne County, and the locations of providers also become sparse. As many patients need to visit different sites to get treatment, coordination and cooperation across sites is necessary. Meanwhile, some providers offer identical services and have homogeneous functions in this system, so they act more like rivals.

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<sup>5</sup> Fiscal year (FY). A fiscal year is used because the funding budget is made by both the federal and state governments based on the calendar of a fiscal year which begins on October 1 of the previous calendar year and ends on September 30 of the year which is numbered.

**Figure 2 Number of DWCCMHA Consumers Served per 1,000 Population (FY2010) with Provider Locations**



Source: Map from “Need Assessment, FY 2011” by Project CARE, Wayne State University.

Note: Purple dots stand for locations of providers.

Conventional OLS regression models treat observations as independent of each other when analyzing different outcome variables. However, estimates will be biased when interdependence between observations is present but ignored. The annual revenue received by a strategic provider may respond to that of its neighbor, due to either competition or cooperation. Because distance/travel cost is taken into account by both consumers and providers, one provider may affect another provider located nearby, more than providers who are further away. Both the spillover model and the resource-flow model in Brueckner (2003) apply to this circumstance. In determining how much effort to devote to certain population and services, a CMH provider takes into account activities of the other providers in the system, this is termed the spillover effect. The resources available in the system (e.g., the total funding available) could shift a provider's decision about seeking and obtaining those resources in response to the extent that other providers are doing so. Despite different motivations that underlie provider interactions, the spillover and the resource flow models both lead to the same spatial econometric specification. If a provider's revenue is adjusted in response to his neighbor's, the previous neighborhood revenue is very likely to have the same impact as the current neighborhood incomes. Therefore, a provider is concerned with its revenue received in the future as well as in the current period.

## Chapter 4. THE MODEL

### 4.1 Model Specification

The dependence of providers' contracting values might induce endogeneity of spending choices. The spatial model allows inclusion and evaluation of interdependency of earnings among adjacent agents, where the value of the dependent variable for one agent is simultaneously determined with that of contiguous agents (Anselin, 2002). Following Lee and Yu (2010a), the model can be written as:

$$Y_{nt} = \lambda_0 W_n Y_{n,t} + \gamma_0 Y_{n,t-1} + \rho_0 W_n Y_{n,t-1} + X_{nt} \beta_0 + c_{n0} + V_{nt}, \quad (4-1)$$

$$n = 1, \dots, i, \quad t = 1, \dots, T,$$

where  $Y_{nt} = (y_{1t}, y_{2t}, \dots, y_{nt})'$  and  $V_{nt} = (v_{1t}, v_{2t}, \dots, v_{nt})'$  are  $n \times 1$  column vectors and  $v_{it}$  is independent and identically distributed (*i.i.d.*) across  $i$  and  $t$  with zero mean and variance  $\sigma_0^2$ . Also,  $W_n$  is an  $n \times n$  spatial weights matrix that is nonstochastic and generates the spatial dependence among across-sectional units  $y_{it}$ .

Empirically, the logarithm of the annual gross revenue of a provider,  $Y_{nt}$ , follows the spatial autoregressive (SAR) process and also depends on other exogenous factors.  $W_n$  is the spatial weight matrix which is nonstochastic and generates the spatial dependence among cross-sectional units  $y_{it}$ . It is row normalized from a symmetric matrix, which ensures that all the weights are between 0 and 1 and weighting operations can be interpreted as an average of the neighboring values. Also,  $W_n$  has the property that  $W_n l_n = l_n$ . Here, the weighting is based on the locations of providers and their geographic contiguity. The spatial autoregressive coefficient,  $\lambda_0$ , captures the cross-provider spatial effect.  $\gamma_0$  ( $-1 < \gamma_0 < 1$ ), the estimator on the lagged revenue term  $Y_{n,t-1}$ , gives the pure dynamic effect. Inclusion of the time lag allows dynamics in the model. The model also includes an observation time lag and

a contemporaneous spatial lag, namely, the ‘time-space simultaneous’ term in Anselin (2001). Its coefficient,  $\rho_0$ , contains the spatial-time simultaneous effect.  $X_{nt}$  is  $n \times k_x$  matrix of nonstochastic regressors. It refers to other exogenous variables, including providers’ own characteristics and demographic properties of the service population.  $c_{n0}$  is  $n \times 1$  column vector of individual fixed effects, which contains any time-invariant effect of observation-specific stable characteristics on the dependent variable.

Owing to the same baseline framework employed here, this paper follows the data generating process and the data transformation of Lee and Yu (2010c). Define  $S_n(\lambda) = I_n - \lambda W_n$  for any  $\lambda$ , and at the true parameter  $S_n \equiv S_n(\lambda_0) = I_n - \lambda W_n$ . Then presuming  $S_n$  is invertible and denoting  $A_n = S_n^{-1}(\gamma_0 I_n - \rho_0 W_n)$ , (4-1) can be rewritten as

$$Y_{nt} = A_0 Y_{n,t-1} + S_n^{-1} X_{nt} \beta_0 + S_n^{-1} c_{n0} + S_n^{-1} V_{nt}, \quad (4-2)$$

## 4.2 The Transformation Approach

As  $T$  is finite (up to four) in this study, a data transformation approach is used to produce consistent estimators with properly centered distributions (Lee and Yu, 2010b). Specifically, the transformation is accomplished by applying the time mean operator  $J_T$  to both sides of equation (4-1):

$$J_T = I_T - \frac{1}{T} l_T l_T' \quad (4-3)$$

where  $l_T$  is the  $T \times 1$  vector of ones. The variables in the deviation form would remain a SAR model as  $W_n$  is time invariant. Then,  $W_n l_T = l_T$ ,

and  $J_T W_n = J_T W_n \left( J_T + \frac{1}{T} l_T l_T' \right) = J_T W_n J_T$  because  $J_T W_n J_T = J_T l_T = 0$ .

Hence,

$$(J_T Y_{nt}) = \lambda_0 (J_T W_n) (J_T Y_{nt}) + \lambda_0 (J_T Y_{n,t-1}) + \rho_0 (J_T W_n) (J_T Y_{n,t-1}) + (J_T X_{nt}) \beta_0 + (J_T V_{nt}) \quad (4-4)$$

which does not involve the individual fixed effects as  $J_T c_{n0}$  is composed of zeros. Transformation in data leads to elimination of the individual effects, any time fixed elements will mimic the individual-specific constant term, which is captured by  $c_{n0}$  in equation (4-1).

However, the transformed equation (4-4) results in the variance matrix of  $J_T V_{nt}$  equal to  $\sigma^2 J_T$ , which means that the elements of  $J_T V_{nt}$  are correlated. Also,  $J_T$  is singular with rank  $(T-1)$  as  $J_T$  is an orthogonal projector with trace  $(T-1)$ . Therefore, there is a linear dependence among the elements of  $J_T V_{nt}$ . An effective way to eliminate such linear dependence is to include the Hermert transformation as a special case (Lee and Yu, 2010b). Specifically, it can be conducted with the eigenvalues and eigenvectors decomposition.

The eigenvalues of  $J_T$  are a single zero and  $(T-1)$  ones. An eigenvector corresponding to the zero eigenvalue is proportional to  $l_T$ . Let  $\left[ F_{T,T-1}, \frac{1}{\sqrt{T}} l_T \right]$  be the orthonormal matrix of eigenvectors of  $J_T$  where  $F_{T,T-1}$  is the submatrix corresponding to the eigenvalues of one and  $\frac{l_T}{\sqrt{T}}$  corresponds to the eigenvalue zero.

Then,

$$\begin{aligned} J_T F_{T,T-1} &= F_{T,T-1}, & F_{T,T-1}' F_{T,T-1} &= I_{T-1}, & J_T l_T &= \mathbf{0}, \\ F_{T,T-1}^{-1} l_T &= \mathbf{0}, & F_{T,T-1} F_{T,T-1}' + \frac{1}{T} l_T l_T' &= I_T, & F_{T,T-1} F_{T,T-1}^{-1} &= J_T. \end{aligned} \quad (4-5)$$

This gives the transformation of  $Y_{nt}$  to  $Y_{nt}^*$ , where  $Y_{nt}^* = F_{T,T-1}' Y_{nt}$  is a vector with dimension  $(T-1)$ . Hence,

$$Y_{nt}^* = \lambda_0 F'_{T,T-1} W_n Y_{nt}^* + \gamma_0 Y_{n,t-1}^* + \rho_0 F'_{T,T-1} W_n Y_{n,t-1}^* + X_{nt}^* \beta_0 + V_{nt}^* \quad (4-6)$$

where  $Y_{nt}^* = F'_{T,T-1} Y_{nt}$ ,  $X_{nt}^* = F'_{T,T-1} X_{nt}$ , and  $V_{nt}^* = F'_{T,T-1} V_{nt}$ . Because  $W_n l_T = l_T$  and  $F_{T,T-1}^{-1} l_T = \mathbf{0}$ ,

$$F'_{T,T-1} W_n = F'_{T,T-1} W_n \left( F_{T,T-1} F'_{T,T-1} + \frac{1}{T} l_T l_T' \right) = F'_{T,T-1} W_n F_{T,T-1} F'_{T,T-1}.$$

Let  $W_n^* = F'_{T,T-1} W_n F_{T,T-1}$ , then

$$Y_{nt}^* = \lambda_0 W_n^* Y_{nt}^* + \gamma_0 Y_{n,t-1}^* + \rho_0 W_n^* Y_{n,t-1}^* + X_{nt}^* \beta_0 + V_{nt}^* \quad (4-7)$$

where  $V_{nt}^*$  is an  $(T-1)$  –dimensional disturbance vector with zero mean and variance matrix  $\sigma_0^2 I_{T-1}$ . Equation (4-7) will provide the estimation of the structural parameters in the model. It is useful in motivating the derivation of the likelihood function for  $Y_{nt}^*$  in the transformation approach.

### 4.3 The Method of Maximum Likelihood Estimation

The transformed equation, equation (4-7), can be estimated by the quasi-maximum likelihood (QML) approach. Then the likelihood function of the parameters is conditional on the time average of the dependent variable,  $\bar{Y}_{nt}$ .

Denote  $\delta = (\gamma, \rho, \beta')'$  and  $\theta = (\delta', \lambda, \sigma^2)'$ . At the true value, and  $\delta_0 = (\gamma_0, \rho_0, \beta_0')'$  and  $\theta_0 = (\delta_0', \lambda_0, \sigma_0^2)'$ . If the disturbances are normally distributed, that is,  $V_{nt}$  follows the normal distribution  $N(0, \sigma_0^2 I_T)$ , and the transformed  $V_{nt}^*$  follows the normal distribution  $N(0, \sigma_0^2 I_{T-1})$ , the log likelihood function of equation (4-7) for  $Y_{nt}^*$  is

$$\begin{aligned} \ln \mathcal{L}_{n,T}(\theta) &= -\frac{n(T-1)}{2} \ln(2\pi\sigma^2) + (T-1) \ln |I_{T-1} - \lambda W_n^*| \\ &\quad - \frac{1}{2\sigma^2} \sum_{t=1}^{T-1} V_{nt}^{*\prime}(\theta) V_{nt}^*(\theta) \end{aligned} \quad (4-8)$$

where  $V_{nt}^*(\theta) = (I_{T-1} - \lambda W_n^*) Y_{nt}^* - Z_{nt}^* \delta$  with  $Z_{nt}^* = (Y_{n,t-1}^*, W_n Y_{n,t-1}^*, X_{nt}^*)$ .

To use the transformed equation (4-6) for effective estimation, the term  $(I_{T-1} - \lambda W_n^*)$  needs to be invertible. Note that  $(I_{T-1} - \lambda W_n^*) = F_{T,T-1}' (I_T - \lambda W_n) F_{T,T-1}$ , and the determinant of  $(I_{T-1} - \lambda W_n^*)$  can be solved through  $\left[ F_{T,T-1}, \frac{1}{\sqrt{T}} l_T \right]' (I_T - \lambda W_n) \left[ F_{T,T-1}, \frac{1}{\sqrt{T}} l_T \right]$  as

$$\begin{aligned} |I_{T-1} - \lambda W_n^*| &= \left| \left[ F_{T,T-1}, \frac{1}{\sqrt{T}} l_T \right]' (I_T - \lambda W_n) \left[ F_{T,T-1}, \frac{1}{\sqrt{T}} l_T \right] \right| \\ &= \frac{1}{1-\lambda} |I_T - \lambda W_n| \end{aligned} \quad (4-9)$$

And then the inverse of  $(I_{T-1} - \lambda W_n^*)$  is

$(I_{T-1} - \lambda W_n^*)^{-1} = F_{T,T-1}' (I_T - \lambda W_n)^{-1} F_{T,T-1}$ . This means that  $(I_{T-1} - \lambda W_n^*)$  is invertible as long as the original matrix  $(I_T - \lambda W_n)$  is invertible.

$$\begin{aligned} \text{Moreover, } V_{nt}^*(\theta) &= (I_{T-1} - \lambda W_n^*) Y_{nt}^* - Z_{nt}^* \delta \\ &= F_{T,T-1}' (I_T - \lambda W_n) F_{T,T-1} Y_{nt}^* - F_{T,T-1}' Z_{nt}^* \delta \\ &= F_{T,T-1}' (I_T - \lambda W_n) \left( I_T - \frac{1}{T} l_T l_T' \right) Y_{nt}^* - F_{T,T-1}' Z_{nt}^* \delta \\ &= F_{T,T-1}' [(I_T - \lambda W_n) Y_{nt}^* - Z_{nt}^* \delta], \end{aligned} \quad (4-10)$$

because  $F_{T,T-1}' W_n l_T = F_{T,T-1}' l_T = \mathbf{0}$ . It follows that

$$V_{nt}^{*\prime}(\theta) V_{nt}^*(\theta)$$



$$\begin{aligned}
&= [(I_{T-1} - \lambda W_n^*)Y_{nt}^* - Z_{nt}^* \delta]' [(I_{T-1} - \lambda W_n^*)Y_{nt}^* - Z_{nt}^* \delta] \\
&= [(I_T - \lambda W_n)Y_{nt} - Z_{nt} \delta]' F_{T,T-1} F_{T,T-1}' [(I_T - \lambda W_n)Y_{nt} - Z_{nt} \delta] \\
&= [(I_T - \lambda W_n)Y_{nt} - Z_{nt} \delta]' J_T [(I_T - \lambda W_n)Y_{nt} - Z_{nt} \delta] \tag{4-11}
\end{aligned}$$

since  $F_{T,T-1} F_{T,T-1}' = J_T$ . Therefore, the log likelihood function (4-4) for  $Y_{nt}^*$  can be expressed in terms of the original  $Y_{nt}$  as

$$\begin{aligned}
\ln \mathcal{L}_{n,T}(\theta) &= -\frac{n(T-1)}{2} \ln(2\pi\sigma^2) + (T-1) \ln |I_{T-1} - \lambda W_n| \\
&\quad - \frac{1}{2\sigma^2} \sum_{t=1}^{T-1} V_{nt}'(\theta) J_T V_{nt}(\theta) \tag{4-12}
\end{aligned}$$

where  $V_{nt}(\theta) = (I_T - \lambda W_n)Y_{nt} - Z_{nt} \delta$  and  $J_T$  can be read as the generalized inverse of  $\sigma^{-2} \text{Var}(J_T V_{nt})$ .

Denote  $\widetilde{\psi}_{nt} = \psi_{nt} - \overline{\psi}_{nt}$  for any  $n \times 1$  vector at time  $t$ , where  $\overline{\psi}_{nt} = \frac{1}{T} \sum_{t=1}^T \psi_{nt}$ . The concentrated likelihood function of (4-12) is written as

$$\begin{aligned}
\ln \mathcal{L}_{n,T}(\theta) &= -\frac{n(T-1)}{2} \ln(2\pi\sigma^2) + (T-1) \ln |I_{T-1} - \lambda W_n| \\
&\quad - \frac{1}{2\sigma^2} \sum_{t=1}^{T-1} \widetilde{V}_{nt}'(\theta) J_T \widetilde{V}_{nt}(\theta) \tag{4-13}
\end{aligned}$$

where  $\widetilde{V}_{nt}(\theta) = (I_T - \lambda W_n) \widetilde{Y}_{nt} - \widetilde{Z}_{nt} \delta$ .

For the first-order conditions, let  $G_n = W_n S_n^{-1}$ . The first-order derivatives are

$$\frac{\partial \ln \mathcal{L}_{n,T}(\theta)}{\partial \theta} = \begin{pmatrix} \frac{\partial \ln \mathcal{L}_{n,T}(\theta)}{\partial \delta} \\ \frac{\partial \ln \mathcal{L}_{n,T}(\theta)}{\partial \lambda} \\ \frac{\partial \ln \mathcal{L}_{n,T}(\theta)}{\partial \sigma^2} \end{pmatrix} = \begin{pmatrix} \frac{1}{\sigma^2} \sum_{i=1}^n ((J_T \tilde{Z}_{nt})' \tilde{V}_{nt}(\theta)) \\ \frac{1}{\sigma^2} \sum_{i=1}^n ((J_T W_n \tilde{Y}_{nt})' \tilde{V}_{nt}(\theta)) - (T-1) \text{tr} G_n(\lambda) \\ \frac{1}{2\sigma^4} \sum_{i=1}^n (\tilde{V}_{nt}'(\theta) J_T \tilde{V}_{nt}(\theta) - \frac{n}{T} (T-1) \sigma^2) \end{pmatrix}$$

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and the second-order derivatives are

$$\frac{\partial^2 \ln \mathcal{L}_{n,T}(\theta)}{\partial \theta \partial \theta'} = - \begin{pmatrix} \frac{1}{\sigma^2} \sum_{i=1}^n \tilde{Z}_{nt}' J_T \tilde{Z}_{nt} & \frac{1}{\sigma^2} \sum_{i=1}^n \tilde{Z}_{nt}' J_T W_n \tilde{Y}_{nt} & \frac{1}{\sigma^4} \sum_{i=1}^n \tilde{Z}_{nt}' J_T W_n \tilde{V}_{nt}(\theta) \\ * & \frac{1}{\sigma^2} \sum_{i=1}^n ((W_n \tilde{Y}_{nt})' J_T W_n \tilde{Y}_{nt}) + T \text{tr} G_n^2(\lambda) & \frac{1}{\sigma^4} \sum_{i=1}^n (W_n \tilde{Y}_{nt})' J_T \tilde{V}_{nt}(\theta) \\ * & * & -\frac{(T-1)n}{2\sigma^4} + \frac{1}{\sigma^6} \sum_{i=1}^n \tilde{V}_{nt}'(\theta) J_T \tilde{V}_{nt}(\theta) \end{pmatrix}$$

#### 4.4 Spatial Weighting

$W_n$  is the spatial weight matrix which is nonstochastic and generates the spatial dependence among cross-sectional units  $y_{it}$ . It is row normalized from a symmetric matrix, which ensures that all the weights are between 0 and 1 and weighting operations can be interpreted as an average of the neighboring values. Because of high concentration of consumers in the area, the geographic contiguity is first defined by the driving distance between a pair of zip codes where two sites are located. In this matrix each site is a neighbor of another site, and the driving distance is to measure to what extent neighboring is between pairs of sites. Greater driving distance means a smaller neighboring coefficient. The weighting matrix is constructed as below,

$$w_{ij} = \frac{1}{D_{ij}} = \frac{1}{P_i - P_j}$$

and

$$W = \{w_{ij}\}$$

where  $P_i - P_j$  measures the driving distance from the zip code where provider  $i$  is located to the zip code of provider  $j$ . This means that each provider is associated with every other provider geographically, but correlation decays with their distance. If provider  $i$  is over 100 miles away from provider  $j$  by car, correlation between these two providers is trivial.

It is worth noting that in the spatial context the influence across providers is not single-directed (Dubin, 1998). If provider  $i$  affects provider  $j$ , it is likely that the reverse is also true. The direction of influence is also multi-dimensional. Provider  $i$  can have impact on many other providers beside provider  $j$ , and those other providers may affect Provider  $i$ .

## Chapter 5. DATA AND VARIABLES

The dataset is mainly drawn from the Mental Health Wellness Information Network (MHWIN), the administrative database storing claims data since 2002, managed and maintained by Detroit-Wayne County Mental Health Agency. The database is used to track and manage mental health care services, access, and charges in the Detroit-Wayne mental health care system. Providers collect and report data related to the billable activities the system performs for its clients. Data sharing within the system is fully compliant with the Health Insurance Portability and Accountability Act (HIPAA). The claims data includes service information such as procedure codes, revenue codes and modifiers<sup>6</sup>, date of services, diagnosis codes<sup>7</sup> related to services, insurance status, and some demographic information for patients. There is also a table listing providers with their geographic location.

The sample selected covers the data of four fiscal years from FY2008 to FY2011. The reason to observe these four time periods is that the data are more complete than those of other years. The total number of sites in each fiscal year is not fixed. In order to be selected into the sample, a site, as an observation, needs to be actively serving population throughout the four time periods, and the time-varying factors considered in this study must contain sufficient variation per provider over time.

Table 1 lists all variables in consideration of this study and their detailed descriptions, and Table 2 presents the summary statistics of the four-year data. Over time the dependent variable, the annual gross revenue, has experienced a large variation, with the mean of nearly \$2.2 million. Taking the logarithm of the annual

<sup>6</sup> The service codes follow the Healthcare Common Procedure Coding System code set issued annually by the Centers for Medicare & Medicaid Services.

<sup>7</sup> ICD-9 codes.

gross revenue leads to a normal distribution of the variable. The number of patients served and the service scope index are containing large variations, which partly explains the large variation in the revenue factor.

**Table 1 Description of Variables**

<b>Variable</b>	<b>Description</b>
<i>Grossrev</i>	Gross revenue
<i>Npt</i>	Number of patients served at a site
<i>Scope</i>	Index of service scope, a proxy of service scope and intensity
<i>PctMale</i>	Percentage of male patients served by a provider
<i>PctAA</i>	Percentage of African American patients served
<i>PctDetr</i>	Percentage of Detroit residents served
<i>PctDepress</i>	Percentage of patients with depressive disorders served
<i>PctSchizo</i>	Percentage of patients with schizophrenia and other psychotic disorders served
<i>PctMedicaid</i>	Percentage of claims reimbursed through Medicaid

### 5.1 The Dependent Variable

To investigate differences in allocation of public mental health funding among providers in the system, the logarithm of the annual gross revenue (*Grossrev*) per provider is employed as the dependent variable. A provider's annual gross revenue is the total dollar amount reimbursed to the provider each fiscal year based on contracting as well as services provided to its patients, and thus it is an appropriate reflection of the funding distributed to the provider. The revenue variable is in the nominal value in each fiscal year, which is not adjusted by the Consumer Price

Index-Urban (CPI-U) because the time periods examined are finite and the expenses are not consumers' out-of-pocket spending. The mean annual gross revenue is over two million dollars in each of the four time periods. *Grossrev* contains large variation across sites, ranging from less than one thousand dollars to over one hundred million dollars. The logarithm form of *Grossrev* displays a normal distribution.

## 5.2 The Independent Variables

Besides the spatial weight and the individual effects, other independent variables mainly cover exogenous factors, including sites' characteristics and demographic properties of their service population. All variables per provider contain certain variation over time for the purpose of test significance of dynamics in the spatial model. The time variant factors are collected from the claims data. Other explanatory variables are time-invariant and collected from the provider table in the MHWIN and the Department of Licensing and Regulatory Affairs of the state of Michigan. The time invariant variables are only examined in the OLS regression. Table 1 gives a list of the variables and their detailed descriptions, and Table 2 displays the summary statistics of the four-year data.

### 5.2.1 The number of patients served

*Npt* gives the number of patients served at a site each year. Sites are appropriately distributed for concentration of consumers, and those located in the city of Detroit usually have higher service population than those outside of the city. Sites of small sizes also have lower service populations. Generally, several state psychiatric hospitals have greater annual revenue than others, and the providers who serve population with developmental disability have higher income because services for the population are more expensive than services for patients with mental illness only. The mean number of patients served varies from 492 in FY2008 to 539 in FY2009, and

the median is between 36 and 43. The statistics of the variable indicate that it is highly skewed to the left.

### 5.2.2 *The index of service scope*

Following case mix measures in previous studies, a service scope index (*Scope*) is developed to assign a possible proxy to describe the discrepancy in the service intensity across sites. It is expected to be influential on the public funding a provider receives. With the claims data available, the index is constructed using the billing codes submitted by providers.

Case mix measures are commonly used in a study of health care agents. A case mix reimbursement system measures the intensity of care and services required for each resident in the nursing facility, and it translates those measures into groupings. Those groupings are used in the calculation of facility payment. A case mix index in the nursing facility is expressed in minutes of staff time required for the care of the residents based on levels of dysfunctions and procedures needed (Cohen and Spector, 1996). In the study of mental health care, case mix classification is also investigated, but it is considered as different from case mix measures in the general care. By conceptualizing services as “episodes of care”, two groups of researchers in Australia and New Zealand developed case mix classification based on characteristics of domestic mental health service users (Buckingham *et al.*, 1998; Eagar *et al.*, 2004). Mental health service users with similar clinical conditions and resource use needs were categorized into different groups. The site case mix index is a measure of the case complexity of patients treated at the site, and it is based on total volume adjusted for case mix.

However, there is no consensus on how to measure case mix in mental health care literature. Greenwood *et al.* (2000) considers case-loads and diagnoses as

instruments to construct case mix measures. In the setting of substance abuse treatment, Koenig *et al.* (2000) ranks providers in the case mix adjustment and non-adjustment models. In their study, case mix adjustment factors include clients' demographics, severity and treatment readiness. It is found that the adjustment model provides consistent ranking results.

With the actual claims available, the study is retrospective. There is no standardized management system other than the Community Mental Health Service Programs (CMHSPs) reporting procedure codes regulated by the Michigan state. Each year CMHSPs submit a report on all services and support activities provided to or on behalf of all consumers receiving services from a CMHSP regardless of funding stream. CMHSPs provide a separate report for each population group<sup>8</sup> - adults with mental illness, children with an SED and individuals with a DD. The CMHSP coding system is well-accepted. Table A.2 lists the service codes used by CMH providers in the DWCCMHA system.

Following Buckingham *et al.* (1998) on the site casemix index, the formula for the index of service scope of provider  $i$  in the fiscal year  $t$  is

$$Index_{it} = \sum_{k=1}^n (\%Code_k * UnitCost_k) \quad (5-1)$$

where  $\%Code_k$  is the proportion of service units submitted with code  $k$  by a provider over total service units in a fiscal year, and  $UnitCost_k$  is the unit cost of code  $k$  in the state cost report. The service units are collected from the claims data. The unit cost in the state cost report is conducted by the state, and it is expected not to be directly associated with the unit cost reimbursed to a provider. The variable also contains a

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<sup>8</sup> CMHSP Sub-element Cost Reports for Section 404, available at <http://www.michigan.gov/mdch>.



large variation in each fiscal year, meaning that there exists a large discrepancy in the services across providers in this system. This is related to specialization of providers in the community-based setting; this differs from the setting of pre-1960s state inpatient hospitals where every psychiatric hospital host patients and provide them relatively uniform care.

### 5.2.3 Patients' demographics

Consumers' basic demographics, such as gender, race and residency, are available, and they are aggregated by site to abstract features of the service population at each site. Other demographics such as median income, education and marriage status are also listed in the database, but they are available in the MHWIN database. Many literatures have shown geographic, racial and gender disparities in mental health utilization and cost (Schulz *et al.*, 2000a, 2000b; Well *et al.*, 2001; McGuire and Miranda, 2008). For example, in the study examining gender differences in the use of mental health-related services, Kessler and his colleagues (1981) found that women are more likely than men to consult a general physician about mental health-related problems. Compared to whites, African Americans have significantly lower rates of access to alcoholism, drug abuse, or mental health care (Well *et al.*, 2001), but they are more likely to use crisis services (Maynard *et al.*, 1997). Schulz *et al.* shows that African American women living in the city of Detroit report a higher level of unfair treatment and stressful life events than white women living outside the city (Schulz *et al.*, 2000).

Different utilization levels are expected to be correlated with variances in costs. Therefore, gender, race and residency are inspected to identify potential effects of demographics of service population on the cost based on the previous findings and their availability in the database. All three variables are in the percentage form:

*PctMale* gives the percentage of male patients served by a site, *PctAA* means the proportion of African American population served, and *PctDetr* abstracts the rate of Detroit service recipients at a site. All these three demographics variables exhibit normal distributions. On average there are 58 percent of male clients per provider, the mean percentage of African American patients (versus other racial groups including the white, Asians, Arabic population, and so on) is nearly 53 percent, and patients who live in Detroit other than out-Wayne County account for over 46 percent of the service population per provider on average.

#### 5.2.4 Clinic diagnoses

Two clinic factors, *PctDepress* and *PctSchizo*, are based on the diagnosis categories from the Clinical Classification Software for ICD-9-CM by the Agency for HealthCare Research and Quality.<sup>9</sup> Diagnoses codes are one part of service descriptions submitted for each patient by a provider. Each encounter can have at least one and up to four diagnosis codes for patients with comorbidities. Diagnosis codes of depressive disorders are found to be the most prevalent among service population across the system while schizophrenia and other psychotic disorders are identified to be most frequently submitted by providers in the annual claims data (see Table A.3 for diagnosis category listing). Each year 22 to 24 percent individuals of the service population in Detroit-Wayne County are diagnosed at least once to have certain depressive disorders, and the next most prevalent mental illness is schizophrenia and other psychotic disorders (19 to 21 percent). Thirty-two to 35 percent of claims data submitted by providers contain diagnosis codes of schizophrenia and other psychotic disorders. Therefore, *PctDepress* is employed to account for the proportion of patients with depressive disorders<sup>10</sup> who are treated at a site, and *PctSchizo* is the percentage

<sup>9</sup> Available at <http://www.hcup-us.ahrq.gov/toolsoftware/ccs/ccs.jsp>.

<sup>10</sup> ICD-9 codes 293.83, 296.2x, 296.3x, 300.40, 311.00.

of those with schizophrenia and other psychotic disorders<sup>11</sup>. When observed at the provider level, schizophrenia and other psychotic disorders turn to be more prevalent among individuals than depressive disorders. Per site, over 58 percent of individuals on average have schizophrenia and other psychotic disorders, about 23 percent have depressive disorders. The rates fluctuate largely from site to site.

#### 5.2.5 Funding sources

The last factor investigated is *PctMedicaid*, the percentage of claims paid through Medicaid (versus general funds) at a site. Medicaid and state general fund dollars are two primary sources of funding for public mental health services, accounting for around 90 percent of the funding across the national public mental health system (NAMI, 2010). Medicaid is a combined federal and state program that provides funding for health and long-term care services for certain categories of low-income Americans. As a significant payer of services, Medicaid has played a substantial role in shaping public mental health systems (Shirk, 2008). For example, Medicaid dollars are not used to pay for inpatient psychiatric treatment for people aged 22 to 64 in facilities that primarily serve individuals with mental illnesses. Meanwhile, this Medicaid regulation has also helped drive the trend to downsize state psychiatric hospitals (Aron *et al.*, 2009). The Medicaid program allows providers a great deal of freedom in determining plan design for patients. For instance, providers can offer patients a range of important community-based services, such as case management, assertive community treatment, psychiatric rehabilitation, peer supports, etc.

General funds<sup>12</sup> are the last resort for individuals who are not qualified for Medicaid. For mental health care purpose, general fund dollars are used to serve

<sup>11</sup> ICD-9 codes 293.81, 293.82, 295.xx, 297.00, 297.10, 297.20, 297.30, 297.80, 297.90, 298.00, 298.10, 298.20, 298.30, 298.40, 298.80, 298.90.

<sup>12</sup> According to the Michigan State Budget Office, the General Fund, by statute, covers all state appropriation, expenditure and receipt transactions, except those for which special constitutional or

persons of SMI who are not insured, who have exhausted private coverage, or who are not eligible or are awaiting eligibility for Medicaid. The Medicaid program is limited in scope, and its requirements and burdensome processes can make it difficult for providers to bill and get sufficiently reimbursed for effective services. For example, some psychiatric services, such as inpatient services in public psychiatric hospitals, cannot be reimbursed with Medicaid dollars for those aged 22 to 64, which are generally paid through general funds. Medicaid becomes the largest source of funding of public mental health services for youth and adults with mental illness. Moreover, the relative flexibility in general fund reimbursement processes gives providers the incentive of using this comprehensive supports. The NAMI (National Alliance on Mental Illness) funding report indicates that 44 percent of state mental health funding came from Medicaid in FY2006 in the country (National Alliance on Mental Illness, 2010). In this system, only the claims billed through Medicaid and general funds are recorded, and Medicare claims are not captured. Because of a higher poverty rate than the national average in the Detroit metropolitan area, Medicaid covers around 68 percent of treatment for the mentally ill in the system (Wayne State University Project CARE, 2011). Table 2 indicates that the mean number of claims reimbursed through Medicaid is about 67.3 percent of all claims submitted by a site, close to the system-wise proportion.

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statutory requirements demand separate fund accounting. Most of the traditional state services are included in the General Fund.

The accounts of the General Fund reflect the major share of the state's fiscal transactions. It is the predominant element in the annual budget review and enactment from the viewpoints of both appropriations and taxes. This is evidenced by the frequent identification of the "General" Fund with the State of Michigan as a whole.

The General Fund is financed by what are defined as general purpose and restricted revenues. General purposes are self-explanatory. Restricted revenues are those resources that, by constitution, statute, contract or agreement, are reserved to specific purposes, and expenditures that are limited by the amount of revenue realized.

**Table 2 Descriptive Statistics**

<b>Fiscal Year</b>	<b>Variable</b>	<b>Mean</b>	<b>S. D.</b>	<b>Min</b>	<b>Max</b>
FY2008 (N=182)	Grossrev	\$2,229,913	\$7,890,427	\$1,467	\$100,825,325
	Npt	492	1,013	1	5,154
	Scope	2.0159	5.6025	0.0000	35.3368
	PctMale	58.3%	19.0%	0.0%	100.0%
	PctAA	54.7%	21.9%	0.0%	100.0%
	PctDetr	46.7%	29.2%	0.0%	100.0%
	PctDepress	24.5%	21.0%	0.0%	100.0%
	PctSchizo	55.5%	37.7%	0.0%	100.0%
PctMedicclaim	62.8%	23.2%	0.0%	100.0%	
FY2009 (N=182)	Grossrev	\$2,208,647	\$7,920,515	\$627	\$101,127,456
	Npt	539	1,100	2	5,778
	Scope	2.8160	7.5154	0.0004	53.0027
	PctMale	58.2%	18.2%	0.0%	100.0%
	PctAA	52.9%	21.8%	0.0%	100.0%
	PctDetr	46.6%	28.2%	0.0%	100.0%
	PctDepress	24.5%	19.3%	0.0%	100.0%
	PctSchizo	58.1%	35.6%	0.0%	100.0%
PctMedicclaim	61.7%	23.0%	0.0%	100.0%	

<b>Fiscal Year</b>	<b>Variable</b>	<b>Mean</b>	<b>S. D.</b>	<b>Min</b>	<b>Max</b>
FY2010 (N=182)	Grossrev	\$2,156,138	\$8,057,870	\$656	\$103,036,252
	Npt	531	1,092	2	5,179
	Scope	3.6079	8.6057	0.0013	64.8355
	PctMale	57.6%	18.7%	0.0%	100.0%
	PctAA	51.8%	22.4%	0.0%	100.0%
	PctDetr	45.9%	28.8%	0.0%	100.0%
	PctDepress	21.5%	17.9%	0.0%	100.0%
	PctSchizo	59.2%	35.2%	0.0%	100.0%
	PctMedicaid	66.5%	23.5%	0.0%	100.0%
FY2011 (N=182)	Grossrev	\$2,087,471	\$7,762,272	\$28	\$98,513,117
	Npt	528	1,135	1	5,922
	Scope	2.4864	6.4362	0.0000	49.9393
	PctMale	57.9%	20.1%	0.0%	100.0%
	PctAA	51.0%	22.7%	0.0%	100.0%
	PctDetr	46.1%	30.1%	0.0%	100.0%
	PctDepress	20.3%	19.5%	0.0%	100.0%
	PctSchizo	59.5%	35.9%	0.0%	100.0%
	PctMedicaid	78.1%	20.3%	7.6%	100.0%

Note: Data source is the MHWIN database monitored and managed by Detroit-Wayne County Mental Health Care Agency.

### 5.3 Providers' Specialization

As mentioned above, provider's specialization is an important factor in influencing relationships among CMH providers. When Provider  $i$  plays a similar role in the system as Provider  $j$ , they are more likely to act like competitors in supplying substitute services. However, if two providers offer distinct services, it is quite possible that there is collaborative relationship among them.

To compare functions of CMH providers in this community-based environment, it is worthwhile to look into their specialties. Based on the service codes submitted by providers, Table 2 describes the sample by breaking providers into eight categories. Some categories are not exclusive because a provider specialized in one category may offer services of other categories. Specifically, the service categories have overlapped services provided at different sites except those focusing on emergency services and partial and inpatient hospitalization services.

Foster care homes account for nearly half (48%) of the overall sample, where service population are individuals with mental illnesses (MI) and developmental disabilities (DD) who require minimal assistance in activities of daily living. Foster care sites are in relatively smaller sizes and with limited service capacity. The services offered at foster homes mainly cover community living services and personal care. Eleven providers are specialized in community living services only, representing six percent of the sample. As productivity restoration is an important part of mental health treatment, supported employment services, skill building assistance and vocational training are provided in the system. Seventeen providers, nine percent of the sample, have supported patients with their productivity recovery.

There are only three providers designated for emergency transportation and crisis intervention. Twenty-one providers are either state psychiatric hospitals,

free-standing hospitals with psychiatric units or community psychiatric hospitals where patients can be partially or completely hospitalized. Patients in four state psychiatric hospitals are the most costly to serve because their disability is so severe that they need to put into those state facilities for a long time up to the whole fiscal year. A preliminary examination shows that sites with partial and inpatient hospitalization have higher annual revenue than any other providers in the system, *ceteris paribus*<sup>13</sup>.

This data also show that there are thirty-one sites in support of comprehensive care except emergency or inpatient services. Comprehensive care includes assessment, community living support, employment assistance, professional psychiatric consultation, therapy, etc.. Among the thirty-one providers, twenty-four are the major providers in the system and have long-term contracts with the local mental health care agency. Compared to the rest of the providers in the overall sample, these major providers are capable to serve more individuals with mental disorders and offer a variety of professional and non-professional psychiatric services. The other seven providers with comprehensive services have relatively small service capabilities.

Other mental health services include any other services that are not distinctly specified in the categories listed above, including assertive community treatment (ACT), case management, treatment planning, medication review, peer supports, etc.. Only twelve providers are included in this category.

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<sup>13</sup> The results are not presented as they are not the primary interest of this dissertation.



**Table 3 Distribution of Providers by Specialization**

Category of Providers	N	%	Subcategory	N	%
Foster care homes	87	48%			
Community living services	11	6%			
Employment support	17	9%			
Emergency services	3	2%			
Partial hospitalization and inpatient service	21	12%	State psychiatric hospital	4	2%
			Free-standing hospital with a psychiatric unit	13	8%
			Community psychiatric hospitals	4	2%
Comprehensive services	31	17%	Major	24	13%
			Minor	7	4%
Other mental health services	12	7%			
Total	182	100%			

Note: Data source is the MHWIN database monitored and managed by Detroit-Wayne County Mental Health Care Agency. The categories are constructed and combined using the services codes submitted by each provider.

## Chapter 6. EMPIRICAL ANALYSIS AND MAIN FINDINGS

### 6.1 Empirical estimation of the fixed effect model

Preliminary analysis starts with the fixed effect model without spatial and dynamic terms, and the results are shown in Table 4. Both individual effects and time effects are included in the initial regression. However, time effects are tested to be statistically insignificant, so they are dropped from the fixed effect regression.

As presented in Table 4, only three variables are statistically significant in the results of the fixed effect model with individual effects, including the number of population served, the percentage of patients with schizophrenia and other psychotic disorders, and the Medicaid penetration proxy. With individual effects, the overall *R-squared* is high but does not provide interesting implication. Hence, *R-squared* is not reported in the table, and it is not specified in the results of other models either. The reported *intercept*, 5.93, is simply the average of the provider-specific effects. The substantial magnitude of the intercept suggests that there exist considerable fixed effects that are not observable in the current fixed effect model.

The coefficient on the number of population served is positive with a value of 0.0005, suggesting that serving one more client with mental illness can bring a provider around 0.05 percent more income every year. There is a negative sign on the coefficient of *PctSchizo*, meaning that a higher proportion of patients with schizophrenia and other psychotic disorders served at a site can be associated with its lower gross revenue, which can be explained by the significant and negative correlation of the number of patients served and the percentage of patients with schizophrenia. The predictor,

*Medicclaim*, also displays a negative coefficient, and it is significant at the five percent significance level, which means that providers with a higher percentage of claims paid through Medicaid, instead of general fund dollars, receive fewer revenues each year. The negative impact of Medicaid penetration is due to patients with no insurance coverage and paid through general fund that are using costly inpatient and crisis services.

**Table 4 Estimation Results of the Fixed Effect Model**

Independent Variable	Fixed Effect
<i>Npt</i>	0.0005*** (0.0000)
<i>Scope</i>	0.0054 (0.0046)
<i>PctMale</i>	-0.0361 (0.1146)
<i>PctAA</i>	0.1389 (0.1211)
<i>PctDetr</i>	-0.0805 (0.0850)
<i>PctDepress</i>	-0.0989 (0.1062)
<i>PctSchizo</i>	-0.3448*** (0.1104)
<i>Medicclaim</i>	-0.1550* (0.0810)
<i>Intercept</i>	5.9336*** (0.1920)

Note: 1. The dependent variable is the logarithm of the annual gross revenue per site.

2. The sample size is 182, with four time periods.

3. Standard errors are in parentheses.

4. \*\*\* significant at 1% level, \*\* significant at 5% level, \* significant at 10% level.

## 6.2 Empirical estimation of the SDPD model

### 6.2.1 Estimation results of the SDPD model with the zip code-based weighting

Given the preliminary results of the fixed effect model, the study next considers spatial and dynamic effects. The SDPD model is estimated with the zip code-based weight first, as shown in the first column, ZC-based, on Table 5. Again, time effects are not significant while individual effects are highly significant in the model. Inclusion of individual effects allows the model to capture unobserved individual fixed effects. As the transformation approach is used, any time invariant factors are eliminated and absorbed by individual effects  $c_{no}$ . Provider fixed effects are transformed out of the equation through the further transformation. Hence, no intercept is present. Both the spatial term and the dynamic terms are statistically significant. The signs of other factors all remain the same as in the fixed effect model. However, the magnitudes of estimates on other factors experience some change, and the Medicaid penetration proxy becomes insignificant with the negative sign. This means that the spatial effect and the dynamic effect are significant, and they absorb some impact of other factors on the dependent variable.

The coefficient on the spatial term is 0.45, which supports the hypothesis that there exists spatial interdependence among the local mental health care sites in the DWC area. It implies that 45 percent of the variation of a provider's gross revenue can be accounted for by its neighbor's same-year income, which arises from either the spillover effect or the resource flow across providers. The zip code-based weight indicates that such interdependency is associated with providers' strategic

consideration of travel distance to other sites, which essentially originates from patients' consideration of the travel cost.

The pure dynamic effect, the coefficient on  $Y_{n,t-1}$ , is positive and significant with an estimate of 0.65, implying significant time dynamics in the network. The magnitude of the estimate also indicates some degree of persistence in the gross income of a CMH provider as the current income can be partly explained by its income in the last period. The coefficient on the spatial-dynamic term,  $W_n Y_{n,t-1}$ , is negative and insignificant, suggesting that there exists no time-space simultaneous effects despite presence of the dynamic effect in this setting.

The number of consumers served at a site has a positive and significant coefficient. The estimate of 0.001 implies that serving one additional patient can on average bring a provider one percentage point more gross revenue every year, with other factors constant, a higher impact than in the fixed effect model. The estimate also indicates that elasticity of demand for community mental health care fluctuates with a change in the number of patients served. The positive coefficient estimate suggests that the lower elasticity of demand is related to fewer patients served at a CMH site, and conversely.

One would expect that a larger service capacity could bring more revenues. However, as in the preliminary investigation, the coefficient on the service scope index is insignificant with a positive sign, implying that the service capacity does not significantly predict providers' income. This is related to possible excess capacity at some sites where gross revenues may be offset by oversized staffing and an excess of

provision of various services. Moreover, since the community care and deinstitutionalization movements in the 1960s, services have shifted from being largely based on inpatient facilities to being delivered on an outpatient basis (Garfield, 2011). A CMH provider with an intention to provide one-stop shopping may not be able to serve patients with mental illnesses efficiently due to difficulties of management. Moreover, a provider with an excess of volume of services is not favorable in the current community-based model of services.

Similar to the fixed effect model, the coefficients on three demographic factors are all statistically insignificant in the SDPD model with the zip code-based weighting. The percentage of male clients served per site has a negative sign while the coefficient on the ratio of African Americans is positive. The negative sign on the coefficient of *PctMale* is consistent with the historic finding that men have been thought to have less mental health needs than women (Kessler *et al.*, 1981). Also, African Americans are found to be more likely to use crisis services and less likely to use individual or group treatment in utilization of public mental health services in Washington State (Maynard *et al.*, 1997). High utilization of crisis services and other intensive services can lead to much higher mental health care expenditures per capita among African Americans than other races. The last demographic factor is the percentage of Detroit clients served at a site, which is negative but insignificant. This means that demographics of service population do not influentially shift income of the sites that provide treatments for them, despite existence of evidence for gender, racial and geographic disparities in utilization and treatment spending at the individual level.

As for the clinical diagnoses indicators, both coefficients on *PctDepress* and *PctSchizo* display a negative sign, but only the latter is statistically significant. Therefore, percentage of patients with depressive disorders does not significantly affect treatment costs at the provider level. By contrast, rates of patients with schizophrenia and other psychotic disorders are an influential predictor. The negative sign of the coefficient on *PctSchizo* implies that the lower proportion of service population with schizophrenia and other psychotic disorders is related to higher revenues a provider can receive each year.

The last explanatory variable, Medicaid coverage, does not significantly predict the gross income of a provider, despite its negative coefficient. It means that whether a site treats a patient eligible for Medicaid or general funds does not make significant difference to its annual revenue. As mentioned above, being “a last straw”, general funds are used to pay for state inpatient and crisis services for those without private insurance or access to Medicaid. Meanwhile, state inpatient services and crisis intervention are the most costly among all community mental health services. Therefore, even though the publicly funded community mental health care system offers sufficient incentive to providers to treat “insured” individuals, Medicaid beneficiaries here, the sites specialized in treating “uninsured” with high severity and in need of emergency interference absorb a great amount of funding. In this way the effect of Medicaid penetration on a provider’s annual income appears ambiguous.



**Table 5 Estimation Results of the SDPD Model**

Independent Variable	ZC-Based (1)	Location-Based (2)
$W_n Y_{n,t}$	0.4549*** (0.1152)	0.4049*** (0.1007)
$Y_{n,t-1}$	0.6529*** (0.1142)	0.6486*** (0.1153)
$W_n Y_{n,t-1}$	-0.2478 (0.2992)	-0.1852 (0.3140)
$N_{pt}$	0.0010*** (0.0001)	0.0010*** (0.0001)
$Scope$	0.0047 (0.0052)	0.0046 (0.0051)
$PctMale$	-0.3369 (0.4666)	-0.3258 (0.4787)
$PctAA$	0.1906 (0.2537)	0.2111 (0.2527)
$PctDetr$	-0.2594 (0.2138)	-0.2554 (0.2128)
$PctDepress$	-0.2894 (0.1782)	-0.2659 (0.1762)
$PctSchizo$	-0.4820*** (0.1655)	-0.5060*** (0.1674)
$Medicclaim$	-0.1140 (0.2961)	-0.1562 (0.2380)

Note: 1. The dependent variable is the logarithm of the annual gross revenue per site.

2. The sample size is 182, with four time periods.

3. Standard errors are in parentheses.

4. \*\*\* significant at 1% level, \*\* significant at 5% level, \* significant at 10% level.

### 6.2.2 Estimation results of the SDPD model with the location-based weighting

The distance between zip codes of providers is approximate measure between two points, which may not allow testing for the precise relationship among providers. To confirm the estimation results given by the zip code-based weight, the location-based weighting is used to examine the model. The results are listed in the second column, Location-Based, on Table 5. As discussed in Chapter 4, the weight is based on the distance between detailed locations of any pair of sites. Compared to the results using the zip code-based weight, the signs of all coefficients remain the same, and their magnitudes are very close to those in the results with the ZC-based weight. The estimates on the spatial term and the pure dynamic term are relatively smaller than in the model with the zip code-based weight, suggesting that providers value the contiguity with approximate location, such as the neighborhood measured by zip code, of their counterparts more than their specific locations. The smaller magnitude of the coefficients on the spatial term and the dynamic term here also imply that the model with the specific-location-based weighting does not provide the results as robust as that with the zip code-based weighting. Therefore, distance between zip codes of two sites is the stronger spatial predictor for public mental health care funding within a geographic area.

### 6.2.3 Robustness check

To check the robustness of the results generated by the “ZC-based” SDPD model, particularly the spatial interaction effect, the static spatial panel data (SPD) model is exploited. The pure dynamic term  $Y_{n,t-1}$  in the dynamic model is excluded

from the static model while all other factors remain. The SPD model specification is then generalized as follows,

$$Y_{nt} = \lambda_0 W_n Y_{nt} + X_{nt} \beta_0 + c_{n0} + U_{nt}, \quad (6-1)$$

$$U_{nt} = \rho_0 M_n U_{nt} + V_{nt}, \quad (6-2)$$

$$t = 1, 2, \dots, T.$$

where all terms are identical to those specified in the SDPD model. The second equation indicates that the disturbance component  $U_{nt}$  follows a SAR process as the dependent variable  $Y_{nt}$  does.  $M_n$  may or may not be  $W_n$ , and it is an  $n \times n$  spatial weights matrix for the disturbances.

Due to finite  $T$ , the estimation follows the same transformation strategy as the SDPD model with individual effects and the zip code-based weighting. The results of the robustness check are shown in Table 6. The estimate of the spatial effect is 0.67, greater than those in the dynamic model. This is because the dynamic effect is not present in this model and the spatial effect abstracts some of the dynamic effect. All variables have the same signs as in two sets of estimations of the SDPD model, with some variation in their magnitudes. The coefficient on the number of service population is 0.0011, approximately as great as that in the dynamic model. Another statistically significant control variable, *PctSchizo*, has a larger absolute value in its coefficient, suggesting that there exists adequate dynamics in the correlation between *PctSchizo* and providers' annual income so that the magnitude of the coefficient changes tremendously without the dynamic term. The estimate of  $\rho_0$  is -0.6819, significant at the 10 percent confidence level. The estimation results of the SPD

model reassure us that spatial interdependence between providers is significant and not trivial.

**Table 6 Robustness Check**

Independent Variable	SPD
$W_n Y_{n,t}$	0.6695 *** (0.142)
$M_n U_{nt}$	-0.6819* (0.3705)
$N_{pt}$	0.0011 *** (0.0001)
$Scope$	0.0043 (0.0099)
$PctMale$	-0.0988 (0.2546)
$PctAA$	0.3262 (0.2619)
$PctDetr$	-0.1979 (0.1913)
$PctDepress$	-0.3081 (0.2345)
$PctSchizo$	-0.8428 *** (0.2433)
$Medicclaim$	-0.1355 (0.1568)

Note: 1. The dependent variable is the logarithm of the annual gross revenue per site.

2. The sample size is 182, with four time periods.

3. Standard errors are in parentheses.

4. \*\*\* significant at 1% level, \*\* significant at 5% level, \* significant at 10% level.

## Chapter 7. DISCUSSION

The major purpose of this empirical study is to better understand the delivery of community-based mental health care and gain insight into the interdependence of community mental health provider agencies in a publicly funded system. Spatial econometrics enables examination of inter-entity relationships via economic factors in this particular setting. The empirical findings derived with the spatial dynamic panel data model clearly show that CMH providers are spatially dependent on each other. The findings also lead to several important policy implications.

### 7.1 Spatial Interdependence

As hypothesized, significant spatial interdependence exists among CMH providers, and such interdependence may arise from either the spillover effect or the resource flow across provider agencies consistent with findings of Brueckner (2003). Strategic interdependence among providers appears to play an important role in their decision-making processes. Two measures of “neighborliness” in the same spatial model confirm the significance of spatial interdependence and dynamics, and they also reveal the differences in the regression results. ZIP code-based neighborliness generates a slightly stronger spatial interaction effect and a greater dynamic effect than specific location-based neighborliness. The comparison can be interpreted as supportive of stronger prediction by the ZIP code-based weighting for distribution of public funding among CMH providers. It also means that approximate neighborliness is valued more than accurate contiguity by providers for their strategic response to

their counterparts' behaviors. Such interdependence is associated with providers' strategic consideration of approximate travel distance to other sites, which essentially originates from patients' consideration of the travel cost. As shown in Table 5, the coefficient on the spatial term indicates that a one dollar increase in neighbors' gross annual revenue leads to a 0.40~0.45 dollar increase in their own gross annual revenue.

Significant spatial interdependence raises important implications for mental health care providers and policy makers in locating special service provisions. Provider agencies within a geographic area, either competitive or cooperative, interact with each other. No single provider has complete control over a single mental health service recipient. In particular, since deinstitutionalization in the 1960s, the initial plan for community care, developed by the National Institute of Mental Health and termed the Community Support Program, has been promulgated by systems care managers, who coordinate all of the services for people with mental illness in the community (Drake and Latimer, 2012). Currently, CMH providers are the main resources to address the special multi-level needs of individuals with mental illness. As delivery of services has shifted to community-based organizations, these providers have coordinated the new model of service delivery; the decisions of providers with different functions are not isolated. This array of service may include specialized outpatient and ambulatory clinics, assertive community treatment groups, case management, therapy, housing supports, and so on. In the context of a community mental health system, each service provider agency is compelled to be a part of the community system, and providers must adjust their strategies accordingly.

A second important finding of this study is that providers' strategic decisions are not static. The SAR lag coefficients are positive and statistically significant in the dynamic model, implying that a forward-looking local provider considers the previous revenue, and that its revenue in the last period is affecting the revenue of the present period. The coefficient estimate of 0.65 indicates a relatively persistent intertemporal impact. However, the spatial-time simultaneous term is insignificant. This means that the revenue of a provider in the present is not significantly influenced by that of its neighbors in the last period.

## **7.2 CMH Providers' Service Capacity**

As expected, the greater the number of patients served at a given site, the more revenue generated at the site. In terms of elasticity, price elasticity depends on how many individuals are served by a CMH provider. Given the positive estimate coefficient, a smaller service population signifies lower price elasticity, while a larger service population means high price elasticity.

One result of regression analyses in the present study, consistent implication with current public policies and findings from existing literature on community-based care and managed care, is that: the service capacity itself does not act as a significant predictor for local providers' revenue. Since community care replaced the hospital-dominated model of care, most service delivery organizations cannot provide "one-stop shopping" to mentally ill patients. That is, a patient can neither stay in a psychiatric institution for a long period of time nor receive all services required for his mental health care from one provider in the community. Moreover, under managed



care, more volume means less profit (Shortell *et al.*, 1994). Even though the consumer population in the system is encouraged to utilize services, the providers' revenue is not necessarily positively affected by an increase in the service volume. Hence, community mental health care is different from general health care where hospitals tend to be sizeable, and are able to provide comprehensive care on-site.

### **7.3 Demographic Composition of Service population**

Most of previous studies have considered demographic characteristics as risk factors for utilization of services. Scarce evidence exists to indicate that demographics substantially affect treatment costs at the individual level among persons with mental disorders. Evidence of the impact of such demographics on providers' revenues is more rare.

The present analysis has found no evidence that demographics play a significant role in distribution of public funding at the provider level, even though such characteristics have been considered important risk factors in individual-level psychiatric care. This observation should be invoked to avoid discrimination in access to and delivery of services based on demographic risk factors. If public funding received by a provider depended on its patients' demographics, the provider could "dump" or "cream" patients in order to boost its revenue.

### **7.4 Clinical Diagnosis**

Investigation of clinical diagnosis in this study reveals that the proportion of patients with schizophrenia and other psychotic disorders treated has a negative

impact on the total reimbursement of a provider by public programs. Conversely, the proportion of patients with depressive disorders, the most common diagnostic group, is not a significant factor in predicting public funding received by a CMH provider. Schizophrenia is markedly different from anxiety and depression, the more common forms of mental illness. Persons with schizophrenia and other psychotic disorders are far more disabled and require more extensive clinical and support services. The negative effect may arise from greater array and intensity of services these patients receive and length of time they stay with a provider in the system.

The study conducted by Healey and colleagues found inpatient care to be more effective for those with schizophrenia than other diagnostic groups including personality disorder, substance misuse and mental retardation (Healey *et al.*, 2000). Evidence also shows that marginal returns to inpatient and outpatient care for patients with different diagnoses and severity vary across groups (Knapp *et al.*, 1998). Specifically, cost-effectiveness advantages are different among patients with different diagnoses as well as over different intervention time horizons, given the same mode of care. In other cases, however, there is evidence that people with schizophrenia experience less improvement in mental health status under a carve-out arrangement for mental health care compared to traditional fee-for-service through Medicaid (Manning *et al.*, 1999; Morrissey *et al.*, 2002). These findings imply that providers need to consider specific appropriate venues for treating patients with different diagnoses, e.g., patients with schizophrenia and other psychotic disorders would be

placed in inpatient facilities to ensure continuity of care, most effective outcomes and greatest efficiency.

## 7.5 Medicaid penetration

Medicaid penetration is the last but not least important factor in the present analysis which examines how different funding streams affect a provider's income. The proxy, *Medicclaim*, is negative and significant at the five percent level in the fixed effect regression, which arises from less costly Medicaid services (compared to state inpatient and crisis services through general funds). The negative coefficient implies that, on average, providers with a higher proportion of claims reimbursed by Medicaid earn relatively less than those with a lower rate of Medicaid services. The finding counters the intuitive (but incorrect) supposition that higher rates of Medicaid-compensated services would help generate more income, given incentives allocated to Medicaid coverage. However, it underscores the common clinical observation that treating uninsured people with severe mental illness is more expensive than treating those who have insurance coverage, in particular when the uninsured receive emergency services and hospitalization.

As shown by McAlpine and Mechanic, barriers to care, including lack of insurance, are substantial (McAlpine and Mechanic, 2000). Individuals covered by public programs like Medicaid and Medicare are over six times more likely to have access to specialty care than the uninsured. Public programs are the major points of leverage for improving access, and policy interventions should be targeted to these programs.

However, as the SDPD model yields the insignificant estimate of the Medicaid penetration proxy when the spatial and dynamic terms are added, to some extent, preferences for Medicaid services counteract the impact of expensive services reimbursed through general fund resources. The change in statistical significance of the estimate is also related to fluctuations over time in the availability of Medicaid versus general funds. The finding in this study emphasizes the importance of Medicaid expansion to increase enrollment and reduce utilization of such services as crisis and inpatient hospitalization. More importantly, given Medicaid's prominent role in funding mental health care, a well-designed Medicaid plan is advocated with policies and services that benefit population living with DD, SED and SMI.

## Chapter 8. CONCLUSION

Mental health spending attracts the attention of policymakers and researchers today because of the growing awareness of the need for more effective and efficient delivery of services. Historically, the public sector has paid the greatest share of mental health costs. Among all sources of public funding, Medicaid pays for more mental health services than any other. Community mental health care allows provision of specialty and non-specialty services and addresses multi-level problems and needs of people with DD, SED and SMI; it has become the prevalent model of mental health care over the past five decades. Within the ideal community mental health care system, providers collaborate to provide comprehensive care for people with mental/behavioral disorders who are in need of many different services. However, as an economic entity, each publicly funded provider also aims to maximize their revenues and thereby competes for funding with other providers in the system with similar functions/service arrays.

Recent research has largely overlooked behavioral health care as a critical component of general medical care. The present study has examined a public mental health care system, exploring the nature and distribution of public funding across the system. The spatial econometric approach allowed examination of possible interaction among the agents that are funded in this system. In particular, the study investigated potential spatial interdependency between the mental health care sites in the Detroit-Wayne County area, using the spatial dynamic panel data model with individual effects. To conquer the incidental parameter problem, the transformation

approach was applied, and quasi-maximum likelihood estimation ensures consistency of estimates.

With unique access to the local Medicaid mental health care database, the model has also considered a variety of controls in the models used, including service scopes, characteristics of service population at various sites, clinical diagnoses, and Medicaid penetration. The analysis began with a simple fixed effect model, and then added the spatial and dynamic terms to the presence/nature of interdependency and dynamics in the dependent variable -- the amount of the public funding that a mental health provider receives each fiscal year. A robustness check was conducted with a static spatial model.

All estimation results support the existence of significant spatial interdependence among publicly funded mental health care providers in the DWC area. The preliminary investigation by the fixed effect (FE) model presents consistent results with that given by the SDPD models. The slight shift in the coefficients suggests that the spatial effect and the dynamic effects are present in the predictors. Two different neighborhood measurements in the spatial models not only confirm the significance of spatial interdependency and dynamics in the system, but also imply that approximate contiguity, instead of accurate neighborliness, is more critical to providers in their strategic interaction. This implies that mental health care providers/agents place great value on travel distance for clients, as do the clients themselves. Serving more patients helps increase a site's revenue; however, a great service capacity does not necessarily lead to commensurately greater income.

Some patient demographic/diagnostic characteristics are related to their utilization of services, but they do not seem to influence the expenditures or income at the clinic level. This implies that there is no apparent “dumping” or “creaming” among providers in this publicly funded mental health care system based on patients’ demographics. However, a greater proportion of clients covered by Medicaid at a particular site does not necessarily mean that the provider can receive greater reimbursement income; this seeming paradox occurs because Medicaid coverage pays for regular outpatient services which are less costly than inpatient and crisis services.

Strategic interaction affects the geographic expansion of heterogeneous firms across time and markets (Alcacer *et al.*, 2014). Location decisions are not static, isolated decisions related to specific geographic markets, rather they are events linked across time and geography. The results of this study may help state and federal governments to better understand some of the factors that influence local mental health care spending, including variations over time and interaction patterns between clinics. It is clear that some degree of competition may be as important as collaboration among providers.

Effective mental health services, like any other services, require resources and a high-quality system of service delivery. Funding design for public mental health systems plays a vital role in delivery and efficiency of services. Given the scarcity of resources for public mental health services, it is particularly important that state reimbursement policies and incentive structures employ the feature of interdependency among mental health care providers to improve mental health care

systems. As noted by NAMI, “. . . the failure to fund mental health services adequately results in significantly greater funding being required in other systems, such as child welfare, jails and prisons, and emergency rooms, to address the consequences of untreated mental illness” (Aeon *et al.*, 2009).

A disadvantage of the spatial specification with transformation approach and the fixed-effect model is that all observable provider-specific effects<sup>14</sup> are removed from the models. If these variables are of importance for policy making, then the value of the specification is discounted. However, given that the primary interest of this research is in estimating the spatial interdependence and dynamics among providers, the issue of eliminating observable individual-fixed effects is not considered to be a major drawback in this instance.

This study has several limitations, the first of which is its limited sample size. As a result, a large proportion of the predictors are not significant. Increasing the sample size ought to help improve predictive capability of the model. Secondly, certain provider-specific characteristics, such as percentage of different professionals, staffing levels, and patients’ outcome measurements, could be important predictors and controls for revenue and spatial effects. It might be beneficial to extend the analysis using different measures of neighborliness; it is possible that geographic contiguity may not be the only source of the spatial interaction effects. Indeed, Baicker (2005) finds that population mobility between states is the strongest spatial predictor for state spending. The Detroit-Wayne County area has experienced higher

<sup>14</sup> See Table A.4 in the appendix for a list of the observable provider-specific factors.



poverty rates and the crime rates than the national average, and there has been a high rate of population loss in the past few years.

Factors that may be very important for further analysis include measures of quality of care and client outcomes across mental health care providers. These variables are not standardized across the DWC system nor documented in the Agency/Authority database used in this study. To be cost effective, public funding needs to be transferred into utilization and recovery of individuals with mental disorders. Many studies have demonstrated discrepancies between ideal/effective mental health care and care that is actually delivered. Given significant interdependence among community mental health providers, their quality of care is expected to follow predictable interactive patterns. Owing to data limitations, however, examination of mental health care quality is beyond the scope of the current study.

Mental health care is one of the most critical, yet often neglected areas in the healthcare world. To the author's knowledge, this is the first study that considered spatial interdependence among mental health care providers in the community-based setting. In the face of Medicaid expansion and parity legislation, the study intends to elucidate how public funds are distributed among community mental health providers in Detroit-Wayne County. With access to the administrative database storing local mental health claims data, the study considers a spatial dynamic panel data model, in which a CMH provider's gross revenue follows a spatial and temporal autoregressive process. A transformation approach is applied to conquer the incidental parameter

problem and ensure consistency of the estimators. With individual effects only, the gross revenue among local CMH providers is strategically interdependent, but including both individual and time effects makes interdependence statistically insignificant. The finding of strategic interdependence is consistent with the empirical results of the literature on primary health providers. As the first study to consider this feature of the mental health care system, the results provide theoretical insights to policy makers.

## APPENDIX

**Table A.1 Percent Distribution of Mental Health and All-health Expenditures by Payor: 1986, 2003 and 2014**

Type of Payer	Year		
	Historical		Projection
	1986	2003	2014
<b>Mental Health Expenditure</b>	100	100	<b>100</b>
Private	46	42	<b>42</b>
Public	54	58	<b>58</b>
Medicaid	16	26	<b>27</b>
Medicare	6	7	11
Other Federal, State and Local	32	25	19
All Federal	21	26	30
All State	33	32	28
<b>All Health Expenditure</b>	100	100	100
Private	59	55	51
Public	41	45	49
Medicaid	10	17	18
Medicare	17	18	22
Other Federal, State and Local	13	10	9
All Federal	28	31	35
All State	13	13	14
<b>Mental Health as Share of All Health Expenditures</b>	7.5	6.2	5.9

Source: Data compiled by the author using data from Substance Abuse and Mental Health Services Administration

<http://beta.samhsa.gov/health-reform/financing-research-data/samhsa-spending-estimates>

**Table A.2 Service Codes Submitted by DWCCMHA Providers, FY2008-FY2012**

<b>Service Code</b>	<b>Service Description</b>
0100, 0101, 0114, 0124, 0134, 0154 -inpatient PT22 (revenue code)	State Psychiatric Hospital - Inpatient PT22
0100, 0101, 0114, 0124, 0134, 0154 -inpatient PT65 (revenue code)	State Mental Retardation Facility - Inpatient (ICF/MR) PT65
0100, 0101, 0114, 0124, 0134, 0154 -inpatient PT68 (revenue code)	Local Psychiatric Hospital/IMD PT68
0100, 0101, 0114, 0124, 0134, 0154 -inpatient PT73 (revenue code)	Local Psychiatric Hospital - Acute Community PT73
0450 (revenue code)	Inpatient Hospital Ancillary Services - Emergency Room
0901 (revenue code)	ECT Facility Charge
0912 (revenue code)	Outpatient Partial Hospitalization
0913 (revenue code)	Outpatient Partial Hospitalization
80100	Drug Screen for Methadone Clients Only
82075	Alcohol Breath Test for Methadone Clients Only
90801, 90802	Assessment-Psychiatric Assessment
90804-90810, 90812, 90814, 90815, 90817, 90819, 90821, 90824	Therapy-Individual Therapy
90846, 90847	Therapy-Family Therapy
90853, 90857	Therapy-Group Therapy
90862, M0064	Medication Review
90870 with revenue code 0901	ECT Physician
90887, 96105, 96110, 96111	Assessments-Other
92506-92808, 92526, 92610	Speech & Language Therapy
96101	Psychological Testing PSYCH/PHYS
96102	Psychological Testing by Technician
96116	Neurobehavioral Status Exam (Children's Waiver)
96120	Neuropsych test Admin w/Comp

Service Code	Service Description
96372, 99506	Medication Administration
97001, 97002	Physical Therapy
97003, 97004	Occupational Therapy
97110, 97150, 97530, 97533, S8990	Occupational or Physical Therapy
97802, 97803	Assessment or Health Services
99211	Physician Services Medication Administration
99221-99223, 99231-99233, 99242, 99243, 99251-99255	Physician Services
A0120, A130, T2001, T2002, T2003	Transportation
A0425, A0427	Transportation
E1399, T2028, T2029	Enhanced Medical Equipment-Supplies
G0177	Family Training/Support EBP only
H0001	Substance Abuse: Individual Assessment
H0002, H0031, T1001, T1023	Assessment
H0018	Crisis Residential Services
H0023	Peer Directed and Operated Support Services
H0025	Prevention Services - Direct Model
H003 with modifier TS	Monitoring of Treatment - Clinician
H0032	Treatment Planning
H0034, S9445, S9446, S9470, T1002	Health Services
H0036	Home Based Services
H0038	Peer Directed and Operated Support Services
H0039	Assertive Community Treatment (ACT)
H0043	Community Living Supports in Independent living/own home
H0045, S5150	Respite

<b>Service Code</b>	<b>Service Description</b>
H2000	Behavior Treatment Plan Review
H2000 with modifier TS	Behavior Treatment Plan Review - Monitoring Activities
H2011	Crisis Intervention
H2014	Skill-Building and Out of Home Non Vocational Habilitation
H2015, H2016 (modifier: TF, TG)	Community Living Supports
H2021, H2022	Wraparound
H2023 (modifier: TT)	Supported Employment Services
H2030	Clubhouse Psychosocial Rehabilitation Programs
S5110	Family Training - EBP
S5111	Family Training
S5116	Home Care Training, Non-Family (Children's Waiver)
S5120	Chore Services
S5140, S5145	Foster Care
S5165	Environmental Modification
S9123, S9124 with revenue code 0582, T1000	Private Duty Nursing
S9484	Intensive Crisis Stabilization-Enrolled Program
T1005 (modifier: TE), T2036	Respite Care
T1015	Family Psycho-Education - EBP
T1016	Supports Coordination
T1017	Targeted Case Management
T1020 (modifier: TF, TG)	Personal Care in Licensed Specialized Residential Setting
T1999	Enhanced Medical Supplies or Pharmacy
T2015	Out of Home Prevocational Service
T2023	Targeted Case Management (Children's Waiver)

<b>Service Code</b>	<b>Service Description</b>
T2025	Fiscal Intermediary Services
T2038	Housing Assistance

Note: 1. The list of procedure codes is illustrative, but is not a comprehensive list of community mental health services. The codes are not limited to a particular population group (adults with mental illness, children with a serious emotional disturbance or individuals with a developmental disability).

2. Service descriptions are provided in the Mental Health HCPCS/CPT Code list.

**Table A.3 Diagnosis Categories Present in the Claims Data**

Mental Health Diagnosis Categories		ICD-9-CM Diagnosis Codes
<b>Top 10 most Frequent Diagnosis Categories</b>		
1	Depressive disorders	3010 3011x 3012x 3014 3015x 3016 3017 3018x 3019
2	Schizophrenia	2938x 295xx 297x 298x
3	Bipolar	2960x 2961x 2964x 2965x 2966x 2968x 2969x
4	Intellectual disabilities	317 318x 319
5	Substance dependence	304xx 292x 2921x 2922 2928x 2929 304xx 3052x 3053x 3054x 3055x 3056x 3057x 3058x 3059x 6483x 6555x 76072 76073 76075 7795 96500 96501 96502 96509 V6542
6	Conduct disorder & Oppositional Defiant Disorder	3120x 3121x 3122x 3128x 3129 31381
7	Attention Deficit Hyperactivity Disorder	3140x 3141 3142 3148 3149
8	Anxiety disorders	29384 3000x 30009 30010 3002x 3003 3005 30089 3009 308x 30981 313x 31382 31383
9	Adjustment disorders	3090 3091 30922 30923 30924 30928 30929 3093 3094 30982 30983 30989 3099
10	Pervasive developmental disorders	29900 29901 2991x 2998x 2999x



**Other Diagnosis Categories (no ranking)**

	Alcohol dependence	2910-2915	2918x	2919	3030x	3039x	3050x	76071	9800																				
	Personality disorders	3010	3011x	3012x	3013	3014	3015x	3016	3017	3018x	3019																		
	Disorders of Infancy, childhood or adolescence	3073	30921	31323	31389	3139																							
Others	Delirium, dementia, and amnesic and other cognitive disorder	2900	2901x	2902x	2903	2904x	2908	2909	2930	2931	2940	2941	2941x	2942x	2948	2949	3100	3102	3108	3108x	3109	3310	3311	33111	33119	3312	33182	797	
	Impulse control disorders	3123x	31235	31239																									
	Dissociative disorders	30012	30013	30014	30015	3006																							
	Learning disorders	31500	3151	3152	3159	V400																							
	Communication disorders	3070	3079	31531	31534	31535	31539	V401																					

Note: Categorization by the author using the diagnosis categories from the Clinical Classification Software for ICD-9-CM by the Agency for HealthCare Research and Quality.

**Table A.4 Observable Provider-Specific Factors**

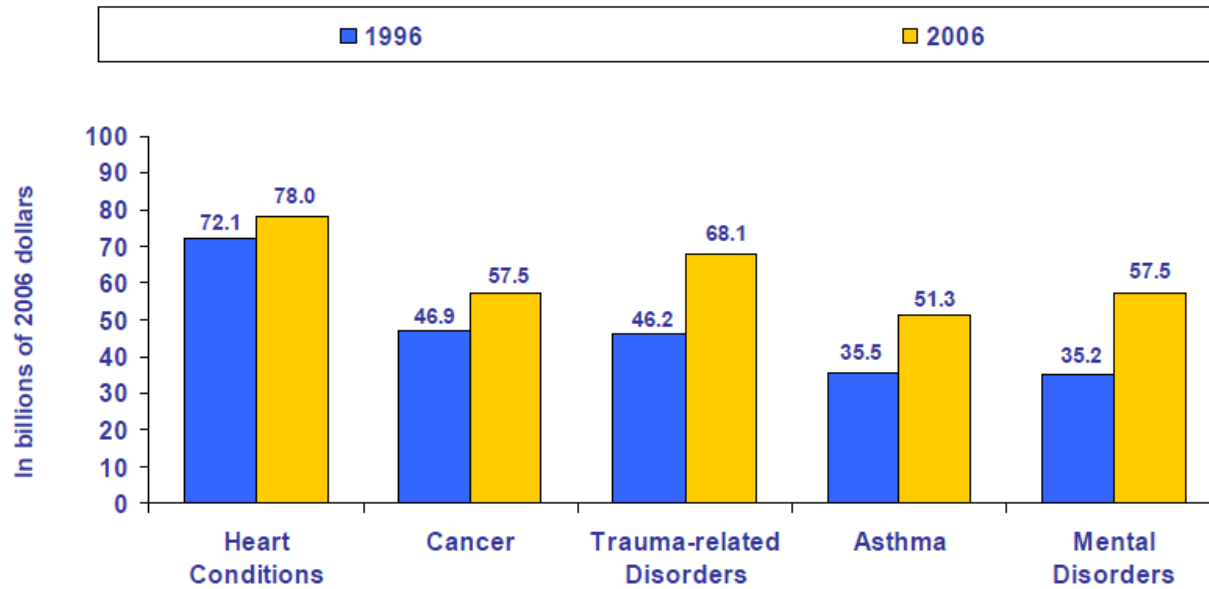
Observable Provider-Specific Factor	Description	Number of observations	
		Yes	No
Main providers*	if a provider is the main contractor in the system	24	158
Psychiatric hospitals*	if a provider is a psychiatric hospital and a medical hospital with a psychiatric unit	21	161
Foster care home*	if a provider is a foster care site	87	95
Developmental Disability*	if a provider serves population with disability designation only	32	150
Youth*	if a serves youth only	7	175
For-Profit**	if a provider is for-profit	70	112
Dissolved**	if a provider has been dissolved after FY12	15	167

Note:

\* Indicators are abstracted from the MHWIN database.

\*\* The ownership (For-Profit) and the corporate status (Dissolved) are collected from the Department of Licensing and Regulatory Affairs of the state of Michigan.

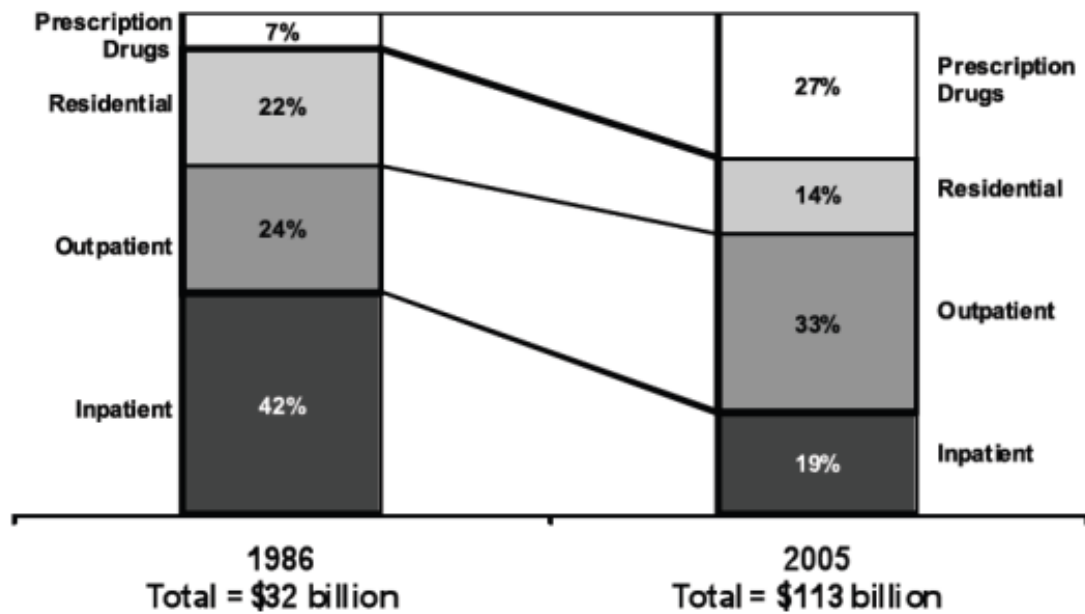
**Figure A.1 Expenditures for the Five Most Costly Conditions, 1996 and 2006**



Source: Center for Financing, Access, and Cost Trends, AHRQ, Household Component of the Medical Expenditure Panel Survey, 1996 and 2006,

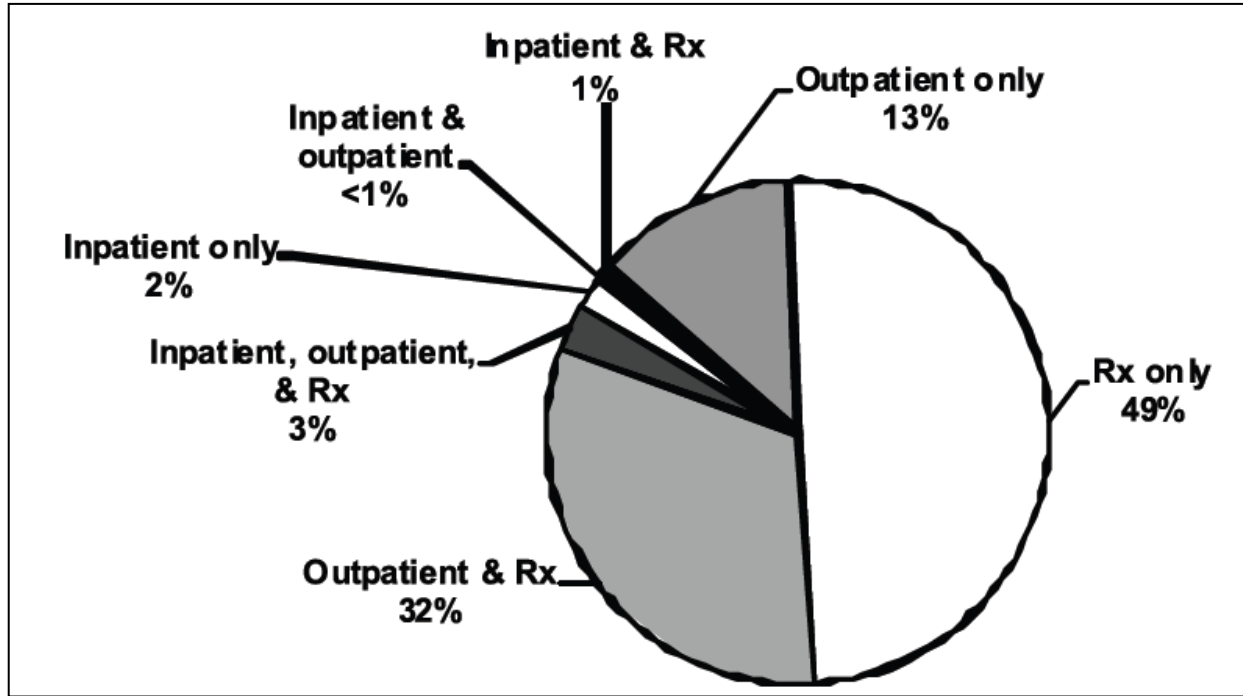
[http://meps.ahrq.gov/mepsweb/data\\_files/publications/st248/stat248.pdf](http://meps.ahrq.gov/mepsweb/data_files/publications/st248/stat248.pdf)

**Figure A.2 Distribution of Mental Health Expenditures by Type of Service, 1986 & 2005**



Note: Exclude spending on insurance administration. Data not adjusted for inflation.  
Source: SAMHSA spending Estimates Project, 2010.

**Figure A.3 Types of Mental Health Services Used Among Adults Receiving Treatment in 2009**



Source: Kaiser Commission on Medicaid and the Uninsured calculations using results from National Survey on Drug Use and Health by Substance Abuse and Mental Health Administration  
<http://kaiserfamilyfoundation.files.wordpress.com/2013/01/8182.pdf>

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presented to Detroit-Wayne County Community Mental Health Agency.

**ABSTRACT****INTERDEPENDENCE OF COMMUNITY MENTAL HEALTH CARE PROVIDERS IN  
AN URBAN COUNTY: A SPATIAL PANEL APPROACH**

by

**LIZI WU****May 2014****Advisor:** Dr. Allen Goodman**Major:** Economics**Degree:** Doctor of Philosophy

This study applies spatial econometrics into the mental health care sector. Previous studies have described interaction effects among health care providers under a static spatial framework. However, in modern economics, agents make their intertemporal decisions between present and future market behaviors. This study encompasses the intertemporal dynamics in the spatial panel data model, in which the gross revenue of a community mental health care provider is considered to follow a spatial and temporal autoregressive process. A transformation approach is employed to conquer the incidental parameter problem and ensure consistency of the estimators.

By focusing on the mental health care sector, the present study contributes to the literature in several aspects. Firstly, this study is the first empirical application of strategic interaction concepts in a time-dynamic framework. By employing a more general framework, this study clearly demonstrates that a provider follows a spatial autoregressive process in its revenue. Secondly, due to the limited time horizons, a



transformation approach is applied to overcome the incidental parameter problem and ensure consistency of estimation. It is accomplished by applying the time mean operator to generate uncorrelated disturbances in the model, thus leading to consistent estimators. Finally, this study explores the spending patterns in public mental health care at the provider level in a representative metropolitan area, with an understanding that delivery of mental health care is different from medical health care.

The findings suggest that strategic interdependence among providers play an important role in their decision-making process and that providers' strategic decisions are not static. However, the spatial-time simultaneous effect is not significant. Given the scarcity of resources for public mental health services, it is particularly important that state reimbursement policies and incentive structures employ the feature of interdependency among mental health care providers and consider intertemporal significance to improve mental health care systems.

## AUTOBIOGRAPHICAL STATEMENT

### EDUCATION

<b>Ph.D. in Economics</b> , Wayne State University, Detroit, MI	2014
<b>M.A. in Economics</b> , Bowling Green State University, Bowling Green, OH	2009
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### RESEARCH INTERESTS

Health Economics, Spatial Econometrics, Labor Economics

### PROFESSIONAL EXPERIENCE

**Research Assistant**, Wayne State University School of Medicine *May 2012-present*

- Providing economic analysis oriented towards improving policy and program development, analysis of service utilization costs, assistance on the integrated care and needs assessment.

**Data Manager**, Karmanos Cancer Institute, *September 2011-present*

- Working with a health research study team to manage detailed study information; development of the research database; import/export of data into different platforms; producing reports; running queries; performing data entry and mail merges

**Instructor**, Department of Economics, Wayne State University *July 2010-May 2012*

- Taught Principles of Microeconomics

**Project Assistant**, Air Liquide (Hangzhou) Co., Ltd., China, *November 2004- July 2007*

- Worked with project managers and engineers in establishing project budgets, master schedules, monthly project reports; corresponded with other departments, subsidiaries, and customers

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