Assertive Community Treatment (ACT) and ACT-Like Services: Associations with primary care, general medical services, and rural areas.

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Abstract

Elizabeth Wiley-Exley, MPH: Assertive Community Treatment (ACT) and ACT-Like Services: Associations with primary care, general medical services, and rural areas.
(Under the direction of Marisa Domino, PhD)

Assertive Community Treatment (ACT) is a service delivery model designed to provide an integrated approach to care for persons with severe mental illness. The implementation of this model across North Carolina offers an opportunity to study this model at differing levels of fidelity in real-world, uncontrolled settings. We used Medicaid claims files from the years 2000-2002 to look at patterns of emergency room, general medical, primary care, and inpatient psychiatric costs and visits, as well as total costs, using cross-sectional and longitudinal models, including multivariate regression, propensity score analyses and Rosenbaum bounds. ACT significantly decreased inpatient psychiatric and emergency room costs and visits, but increased total costs. These successes were accomplished with what might have been very low or no fidelity ACT teams – and even greater successes at a lower cost were found in higher fidelity teams – and therefore suggest that there is a large potential for ACT to mature in North Carolina into a model that will fully reflect the cost-savings that have been found in ACT teams elsewhere.

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Chapter I: Introduction and Specific Aims

Assertive Community Treatment (ACT) is a service delivery model designed to provide an integrated approach to care for persons with severe mental illness, assisting with medication, housing, and everyday life challenges (Bond, Drake et al. 2001). The ACT model was developed as an alternative to hospitalization and to other community and outpatient treatments which are often insufficient and/or inappropriate because some severely mentally ill patients waver on the brink of rehospitalization and need time-unlimited services (Stein and Test 1980). After many years of research on this initial model, practice guidelines recommend ACT for individuals with severe mental illness who are at risk of repeated hospitalization or who have had difficulty staying in treatment (Lehman, Steinwachs et al. 1998), and organizations like the National Alliance for Mental Illness have pushed for implementation of this evidence-based treatment nationally (Burns 1998).

Yet there are still questions as to how ACT performs in every day, uncontrolled settings, as most of the previous research on ACT has been performed during randomized controlled trials. In addition, there is little evidence about whether low fidelity ACT teams can really produce results when rolled out at a state-wide level, even though this is of concern to researchers and policymakers. In North Carolina, ACT was implemented across the state in the mid-1990s and has been working to achieve outcomes found in the literature. Thus North Carolina offers us an opportunity to study some questions about what ACT and ACT-like models can and cannot do when rolled out on a state-wide level in an uncontrolled environment. For example, how much is Medicaid spending on health services other than ACT in this context? How much do individuals on ACT cost the state? Are there discrepancies between rural and urban areas in costs associated with ACT?

One main concern about ACT in an uncontrolled environment is related to how closely ACT follows the main principles which have made ACT so successful in the past. In this study, we are unable to discern whether or not the ACT teams follow all ACT principles; therefore "ACT teams" might be true ACT teams or teams that call themselves "ACT" but which are more like standard case management. As noted, there is little evidence about these "ACT-like" teams, even though they are of concern to researchers and policymakers, and therefore this study was designed to look specifically at whether or not these ACT-like teams of all levels of fidelity in North Carolina can really produce results when rolled out at a state-wide level. For this reason, all ACT teams are referred to interchangeably throughout as ACT or ACT-like teams.

This proposed study was designed to gain a better understanding of the questions proposed above from a program evaluation perspective. As the state was paying ACT teams at a standard "ACT team" rate, we need to better understand what health services these costs were paying for, whether or not they are in line with the literature on ACT, and whether or not ACT-like models across North Carolina are producing results. The specific aims were as follows: (1) The first looked at who is using ACT (Aim 1); and (2) and (3) the final two aims examined how ACT use affects use of other health services (Aims 2-3), as described here:

- **Aim 1: To describe the Medicaid population using and not using ACT and the ACT teams serving these individuals**. These analyses used longitudinal Medicaid claims files from 2000-2002 to examine binary associations of the main covariates and health service outcomes (total costs and emergency room, general medical, primary care and inpatient psychiatric care costs and visits) using t-tests and chi-square tests between ACT users and non-users and ACT users in urban, mixed and rural areas. Collapsed person-level LPM models controlling for heteroskedasticity were used to determine the correlates of ACT treatment during the study period in urban, mixed, and rural populations. A final collapsed person-level regression model which controlled for heteroskedasticity determined which observable characteristics affected the number of months on ACT for those on ACT based on these three place of residence groups (rural, mixed and urban based on Rural Urban Continuum Codes (RUCC) (Brown, Hines et al. 1975; Beale 2004)).

- **Aim 2: To examine whether ACT was associated with differences in patterns of primary and general medical care.** These analyses used longitudinal Medicaid claims files from 2000-2002 and person-level fixed effects regression models controlling for heteroskedasticity to look at the effect of the main independent variable of interest, percent of quarter on ACT, on the dependent variables, total costs and the number and costs of primary care and general medical care. Two-part models were used to examine differences in costs, and negative binomial regression models were used to examine differences in the number of visits.

- **Aim 3.1: To examine whether total costs and the number and costs of inpatient psychiatric and emergency room visits were different for Medicaid beneficiaries in ACT or ACT-like programs in *rural* areas than for ACT users on Medicaid in *urban or mixed areas*.**

- **Aim 3.2: To examine whether the number and costs of primary care and general medical visits were different for Medicaid beneficiaries in ACT or ACT-like programs in *rural* areas than for ACT users on Medicaid in *urban or mixed areas*.** The same data and models as in Aim 2 were used to examine the dependent variables of interest: number and costs of emergency room visits, general medical, primary care, inpatient psychiatric visits, and total costs. The independent variables of interest were involvement in ACT and percent of month on ACT. The models were run in three different samples: urban, mixed, and rural.

This study seeks to provide information about the effectiveness of ACT, especially ACT in rural areas, to payers, providers and consumers across the country. Decision-makers nationwide are implementing ACT, often with state-wide programs, and there is little evidence about how this will work on such a large scale, how it will affect general medical and primary care services use, whether or not it works in rural areas, and whether or not low-fidelity ACT-like models can produce results. Policymakers would benefit from increased evidence with which to inform their plans. A broad long-term goal of this work is to achieve a greater understanding of rural ACT, which will improve rural mental health service delivery and better allocate increasingly scarce resources.

Our analyses suggest that, even when rolled out in many different settings, including rural areas, with many different potential fidelity levels, ACT in North Carolina has had some important successes, such as decreasing the likelihood of emergency room and inpatient psychiatric care and costs. These successes were accomplished with what might have been very low or no fidelity ACT teams – and even greater successes at a lower cost were found in higher fidelity teams – and therefore suggest that there is a large potential for ACT to mature in North Carolina into a model that will fully reflect the cost-savings that have been found in ACT teams elsewhere.

Chapter II: Literature Review

What is ACT?

ACT is a service delivery model where treatment is provided by a team of professionals with services and duration determined by consumer needs. The ACT model was developed as an alternative to hospitalization and to other community and outpatient treatments for severely mentally ill patients who often waver on the brink of rehospitalization and need time-unlimited services; early research revealed that former models of care, including hospitalization, were often insufficient and/or inappropriate for this population (Stein and Test 1980).

ACT is based on several key principles, which help support the consumers in their own settings 24 hours a day, seven days a week: multidisciplinary staffing, integration of services, team approach, low patient-staff ratios, locus of contact in the community, medication management, focus on everyday problems in living, rapid access, assertive outreach, individualized services, and time-unlimited services (Bond, Drake et al. 2001). The ACT team is composed of individuals from the fields of psychiatry, nursing, and social work, as well as professionals with expertise in other areas, such as substance abuse treatment and vocational rehabilitation.

ACT teams generally target heavy users of inpatient psychiatric care with disabling mental disorders (Phillips, Burns et al. 2001; Thornicroft and Tansella 2004).

More specifically, ACT-eligible individuals are often identified based on (1) a diagnosis of a severe mental illness (schizophrenia, affective disorders except single-episode depression, delusional disorders, and psychotic disorders) with treatment for at least one year; (2) SSI/SSDI status for an individual who has two or more hospitalizations per year or had been in treatment for at least two years; and (3) three or more hospitalizations within one year (Cuddeback, Morrissey et al. 2006). These individuals often under use less-intensive services, or they might be placed on ACT because the less-intensive services are ineffective (Latimer 1999; Bond, Drake et al. 2001). Estimates suggest that between 0.06%-0.1% of adult populations will need ACT services (Bond, Drake et al. 2001; Cuddeback, Morrissey et al. 2006). However, these estimates vary based on the capacity of the mental health system; for example, if the system is deficient, more ACT teams may be required (Bond, Drake et al. 2001).

Although there are strict guidelines about how ACT should be provided (e.g., all services should be provided 24 hours a day, seven days a week by a team with a consumer to staff ratio of 10:1) (Lewin Group 2000), ACT teams often sacrifice fidelity to fit the needs – and resources – of the communities they serve (Meyer and Morrissey 2007). This results in a wide range of modifications, which sometimes depart from the defined ACT standards (George, Durbin et al. 2008). To determine how closely ACT teams adhere to these ACT standards, fidelity scales have been created to measure how closely ACT programs align with a list of critical components (Teague, Bond et al. 1998; Phillips, Burns et al. 2001). Research suggests that higher fidelity to the ACT model is associated with better outcomes, including reduced days in the hospital (Latimer 1999; Bond, Drake et al. 2001). However, it should be noted that higher fidelity to the ACT model is sometimes based on a comprehensive rating of the teams (i.e., teams are classified as high fidelity or low fidelity based on an arbitrary cutoff), rather than by using the different components of the fidelity scale to determine what aspects of fidelity are the most important (McHugo, Drake et al. 1999).

Much work has been put into the ACT model to ensure its success and the success of the consumers being served by the program; a short history of ACT explains how this model became so well-accepted and important in mental health services in the United States. Leonard Stein and MaryAnn Test developed the Training in Community Living model, which was later renamed the Program of Assertive Community Treatment (PACT, also known as ACT), over 30 years ago in Wisconsin (Stein and Test 1980). Diffusion of ACT in the United States was initially slow (Morrissey and Meyer 2005). But a much more rapid implementation of ACT was prompted after the National Alliance for Mental Illness embraced ACT by making it a national priority (Allness and Knoedler 1999; Morrissey and Meyer 2005) and following a push to implement evidence-based practices (Center for Mental Health Services 1999). Advocacy efforts pushed the agenda forward, creating a grassroots demand for ACT through packaging the practice for implementation, engaging the media, coordinating efforts and communicating progress (Torrey, Drake et al. 2001). The results of their efforts have been important for consumers, decreasing inpatient hospitalizations and improving housing stability (Burns and Santos 1995; Marshall and Lockwood 2000; Bond, Drake et al. 2001).

ACT in North Carolina

The North Carolina ACT program is designed to increase the ability of individuals with mental illness to function in work, social, and other areas of daily life and to reduce emergency and inpatient psychiatric care, severe psychiatric symptoms, and criminal justice involvement (North Carolina MH/DD/SAS 2006). In NC, there were precursors to ACT programs as early as the beginning of the 1990s (Brooks 2006), but by 2000, more teams were in start-up phases (Woodson 2006). By 2003, there were 42 teams in existence (Meyer and Morrissey 2004).

The primary source of funding for ACT is typically reimbursement through Medicaid as a cost-saving measure (i.e., to avoid expensive hospitalizations) under the rehabilitative services or targeted case management categories (Phillips, Burns et al. 2001). This is true in North Carolina, as well. Adults are eligible for Medicaid by membership in the traditional Medicaid categories (Aged, Blind, Disabled, or Pregnant Women), through program enrollment in Temporary Assistance for Needy Families, through spend-down provisions, or via other mechanisms. Many ACT consumers receive services via disability coverage, and individuals usually enter ACT through individual referral or referrals from state or local agencies. Sometimes these individuals will already be on Medicaid; other times this is not the case. In the sample used in this analysis, for example, 91 percent of the individuals who came onto ACT after the first quarter were on Medicaid in the preceding quarter. In NC, in 2000, the first year of the study period, there were 1.2 million Medicaid eligibles; 0.08 percent of those were on ACT in the same year.

The funding for ACT teams in NC has been based on a capitated monthly basis (i.e. one payment for every individual covered by the ACT team per month) since the study period of interest. Since the inception of the program, however, ACT has been funded in various ways: through local programs, via state funds based on non-unit cost reimbursement, and via state funds based on monthly unit costs (Woodson 2006).

This type of non-incentive based funding raises questions for researchers studying ACT teams. The main concern is related to fidelity, as there are no specific measures built into the payment system to help motivate high fidelity to the ACT model. Therefore, although a team is being paid an ACT team rate by Medicaid, they may not necessarily be providing true ACT services. Thus researchers are unable to discern whether or not these teams are really ACT teams or whether they function like community support teams—or some other model. In North Carolina, however, during the study period the state paid a specific rate for ACT-team services based on a service definition monitored by the local and state mental health agencies. This difference in payment should, in theory, indicate a fundamental difference in both the type of services provided by the ACT teams and the mentality of the treatment team; yet this may not be true. Therefore all teams in these analyses were referred to interchangeably ACT or ACT-like teams, and this consideration should be kept in mind in the interpretation of the results presented here.

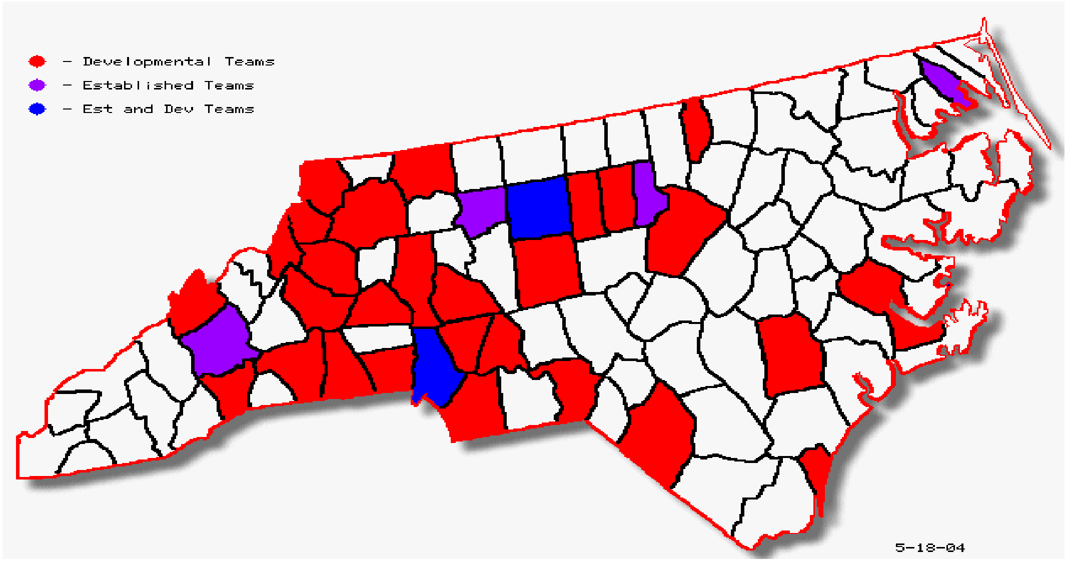
One example of how these differences in fidelity could affect services use is highlighted by the belief that ACT should, in theory, decrease the use of outpatient services (Latimer 1999), since many of those services should be provided by the ACT team. If a team is not providing a high level of intensive services to consumers, with gaps in services lasting more than a few days or possibly weeks, individuals on the teams could seek care outside of the ACT team – or fall through the cracks completely. Either way, however, we would not expect these low fidelity teams to be providing the same level of services to the ACT consumers as high fidelity teams might. Similar patterns might be expected for primary care, emergency room use, and inpatient psychiatric care, as well. In addition, there are many areas of the state, such as in the mountains, where it is difficult to deliver services, which makes it more difficult to create and sustain ACT teams (Siskind and Wiley-Exley 2008). This could potentially lead to adaptations of the ACT model which reduce fidelity.

These potential differences in fidelity were highlighted in a 2003 review of ACT teams in North Carolina (Meyer and Morrissey 2004). This review described how the program has been implemented throughout the state and provides ratings for multiple aspects of fidelity (based on the Dartmouth Assertive Community Treatment Scale (Teague, Bond et al. 1998)), which includes admission criteria, intake rates, team size, staffing, caseload size, community-based services, responsibility for treatment, crisis services, team approach, dropout policy, and program meetings (Meyer and Morrissey 2004). This was a one-time study conducted by the Program in Mental Health and Substance Abuse Services at the Cecil G. Sheps Center in Chapel Hill, North Carolina, and showed that there were 42 teams in NC during the time period, which means that ACT was not available in all 100 counties in North Carolina, although the teams were relatively widely dispersed (see Figure 1). The findings from the survey show that most ACT teams were small, and rural teams were smaller than urban teams and not as able to hire required staff due to shortages of professionals. They also had a more difficult time maintaining multidisciplinary staff. On a number of dimensions, however, the rural and urban ACT teams were similar, including intake rates, treatment responsibility, team approach, and admission criteria.

To address these fidelity concerns, ACT in North Carolina has changed significantly since its implementation in 2000-2002. As of 2006, 61 teams were functioning (Mahadevan 2006). These teams provide services to as many consumers as possible while still holding true to the small consumer to staff ratio (10:1), but there are not enough teams to respond to the demand (Brooks 2006). In addition, in 2006, new service definitions were created and many of the teams were restructured, as noted above. These new service definitions are important, as they have strengthened adherence (i.e., fidelity) to the ACT model, which should, in theory, improve services and outcomes and possibly decrease costs. More research will be necessary to determine if this will be true.

The ACT teams in NC were formerly integrated within the Local Management Entities (LMEs), groups of counties which manage mental health, developmental disability, and substance abuse services in North Carolina. However, most ACT teams are now composed of private providers who bill the LMEs for their services.

Figure 1. Map of Established and Developmental Assertive Community Treatment Teams in North Carolina in 2003



Footnote: Guilford County has 1 Established Team and 2 Developmental Teams

Does ACT work?

Evaluation shows that the ACT model has been beneficial in a variety of settings (Bond, Drake et al. 2001; Phillips, Burns et al. 2001). Multiple studies note that ACT decreases inpatient hospitalization, improves housing stability, and improves patient satisfaction when compared with other forms of case management (Burns and Santos 1995; Marshall and Lockwood 2000; Bond, Drake et al. 2001). Specifically, a review of 25 randomized controlled trials showed that ACT compared to control conditions such as intensive case management and progressive in-hospital treatment with community aftercare and psychiatric hospitalization, reduced psychiatric hospital use in 74% of the studies; improved housing stability in 67% of the studies; and improved patient satisfaction in 88% of the studies (Bond, Drake et al. 2001). Stein and Test's (1980) seminal publication on the ACT model showed similar findings. After 14 months, the need for hospitalizations was reduced and individuals spent more time in the community.

The literature on the relationship between ACT and primary care and other general medical services, however, is sparse. Although there are several studies that touched on issues of continuity of care (Lachance and Santos 1995; Marshall and Lockwood 2000; Crawford, de Jonge et al. 2004), few studies have looked directly at these areas. An extensive review of the ACT literature notes that many outpatient services should in theory be provided by ACT teams; and therefore ACT should decrease the use of these services in other domains (Latimer 1999). Yet those relationships were not found in this review. For example, the original ACT team in Wisconsin appeared to decrease the use of outpatient clinics (Stein and Test 1980; Test and Stein 1980; Weisbrod 1983), but studies of other teams and ACT-like programs found different results (Rosenheck, Neale et al. 1995; Chandler, Hu et al. 1997; Lehman, Dixon et al. 1997) . One study found site-level differences in use of outpatient clinics by ACT consumers (Chandler, Hu et al. 1997); another study found no difference in use of programs at a community mental health center between ACT team patients or standard care given at a community mental health center (Bond, Miller et al. 1988); a separate trial found significantly higher costs for mental health outpatient visits for individuals on ACT compared with standard aftercare at an outpatient clinic with no community care (Lehman, Dixon et al. 1997); and a final cost-effectiveness study found that outpatient costs (including day treatment, medication management, emergency intervention and residential services) were lower for ACT patients than for those in standard case management (Clark, Teague et al. 1998). A systematic review of research on ACT noted that these differences in reported outcomes might be a product of ACT teams not having high fidelity to the ACT model (Latimer 1999).

Previous research suggests that higher fidelity to the ACT model is correlated with better outcomes (Latimer 1999; Bond, Drake et al. 2001). This concept has been recognized since early in the ACT literature; adaptations of the ACT model showed fewer favorable results than did programs with a stricter reliance on the principles of ACT in a couple of early studies (Bond, Miller et al. 1988; Bond, Witheridge et al. 1990; Burns and Santos 1995). Therefore, there is a need for more research related to how many adaptations are adopted when ACT is implemented widely within a state or a region. For example, research suggests that widespread implementation is challenging, resulting in lower than expected team caseloads, drift from the target consumer group, and significant under-staffing within teams (George, Durbin et al. 2008). The expectation would be that these adaptations would negatively affect services use and outcomes, but more research in this area is necessary to determine the exact magnitude of these implementation challenges.

Other studies suggest that ACT is cost-effective for patients with extensive prior hospital use (Essock, Frisman et al. 1998; Latimer 1999; Phillips, Burns et al. 2001). For example, in one study consumers in ACT spent more days in the community than did patients in standard case management at no additional cost (Essock, Frisman et al. 1998). In addition, ACT was more cost-effective than standard case management for consumers hospitalized at study entry. Another study, however, found less positive results, noting that in 223 patients randomized to receive either ACT or standard case management, ACT was not more cost-effective than the control group, however, its efficiency did appear to improve over time (Clark, Teague et al. 1998).

Challenges to implementation of ACT in rural areas

ACT services seem optimal for rural areas because they are self-contained in terms of services delivered, and in rural areas, other services, such as housing programs, might not be available (Meyer and Morrissey 2007). Yet several challenges to the provision of care in rural areas are often associated with adaptations to the ACT model, resulting in less intensive services (Santos, Deci et al. 1993; Meyer and Morrissey 2004; Meyer and Morrissey 2007). The number and availability of mental health professionals and the distances ACT teams have to drive to see consumers are two main concerns. Primarily, mental health services and personnel are often limited in rural areas (Human and Wasem 1991). Many rural areas are classified as health professional shortage areas (Fraher, Swartz et al. 2006), and as ACT needs a small consumer to staff ratio (10:1), many rural areas are often left without the professional capacity to create ACT teams. For example, in 2004, there were 17 counties in North Carolina with no psychiatrists, and twenty-seven counties had a shortage (fewer than .33 psychiatrists per 10,000 population) of general psychiatrists (Fraher, Swartz et al. 2006). In addition, in rural areas individuals are more likely to lack public transportation, have longer driving distances, and often face shorter hours of operation for some mental health services (Fox, Merwin et al. 1995; Blank and Jodl 1996), which makes it more difficult for service providers and consumers to give and receive services. For example, practitioners often have to drive for hours to see an ACT consumer, which limits the caseload size and frequency of consumer contact, and increases the cost of the program. Similarly, the time spent traveling reduces the amount of time available for administrative responsibilities (Santos, Deci et al. 1993). In North Carolina these challenges were highlighted in a survey of ACT teams which showed that urban teams had fewer problems with regard to geographic distance, staff turnover, hiring qualified staff, and insufficient staff than did mixed or rural teams (Meyer and Morrissey 2004). Other recent publications have reported similar concerns (George, Durbin et al. 2008; Siskind and Wiley-Exley 2008). Another challenge in a diverse state like North Carolina is that rural communities throughout the state (from the mountains of Appalachia to the coastal plains) are extremely different with different needs, different resources, and different cultures.

In addition to these access and availability concerns, it has been argued that a *population approach* to rural health is necessary to truly understand the urban/rural differential (Hartley 2004). A population approach considers not only the access issues, but also the societal, environmental and similar factors which affect health. For example, rural incomes are generally lower than those in urban areas; rural workers are more likely to be unemployed than those in urban areas (U.S. Congress 2002; New Freedom Commission on Mental Health 2004); over 25% of rural workers over the age of 25 earn incomes below the poverty rate; and education levels are lower than in urban areas (U.S. Congress 2002). In addition, feelings about mental illness often differ in rural areas; thus feelings may change how services are provided or received (Fox, Blank et al. 1999). Stigma, low incomes and lack of information, for example, could affect the ability of rural dwellers to seek out -- and use -- appropriate services, like ACT.

In general, these aspects of rural areas could make service delivery, especially for a high intensity service like ACT, more difficult than in urban areas. Sometimes this leads rural ACT teams to alter their services, for example, by creating smaller teams that are less comprehensive in the services they provide, and therefore less faithful to the original ACT model (Siskind and Wiley-Exley 2008). Several studies show that fidelity to the original ACT model is important in order to get the desired outcomes (Latimer 1999; Bond, Drake et al. 2001), but little is known about how these changes to the ACT model affect services use in rural areas.

Although ACT has a large evidence base demonstrating its success in decreasing use and costs of hospitalization, less is known about ACT in rural areas. A recent review revealed only six studies of rural ACT, and the results were inconclusive as to related outcomes and use of health services (Drake, McHugo et al. 1993; Santos, Deci et al. 1993; Chandler, Meisel et al. 1996; Becker, Meisler et al. 1999; Dush, Ayres et al. 2001; Kane and Blank 2004; Meyer and Morrissey 2007). Three reported lower levels of hospitalization, one in a pre-post setting (Santos, Deci et al. 1993) and two when compared with usual care, including clinical mental health services, limited case management and rehabilitation services (Chandler, Meisel et al. 1996) and access to hospitals with follow-up with a psychiatrist and referral to the local community health center (Dush, Ayres et al. 2001). One found an increase in the number of individuals working, social support, satisfaction by family members and lower levels of family burden (Chandler, Meisel et al. 1996).

These studies on rural ACT are useful in providing preliminary evidence; however, there are several methodological limitations. For example, one study used a mid-sized city in an agricultural county as a definition of rural and did not discuss the population size, density, or other characteristics (Chandler, Meisel et al. 1996), which could mean that the access to care and driving distances, etc., for these individuals were similar to those in urban areas. In addition, most of the articles either fail to discuss fidelity to the ACT model (Chandler, Meisel et al. 1996) or use variations of the ACT model (Drake, McHugo et al. 1993; Santos, Deci et al. 1993; Becker, Meisler et al. 1999; Kane and Blank 2004), which could mean that they were measuring something other than ACT.

Challenges of defining rural

One of the challenges associated with studying rural areas is the definition of rural; many definitions have been developed to define the many variations within the rural/urban continuum (Hall, Kaufman et al. 2006). For example, the Census Bureau uses fewer than 2,500 residents and open territory, the Office of Management and Budget (OMB) uses metropolitan and nonmetropolitan areas based on county types, the Department of Agriculture (USDA) has several methodologies, such as a rural-urban continuum, urban influence codes, and rural county typology codes (New Freedom Commission on Mental Health 2004). There are also frontier rural areas, which are defined as having a low population density, usually fewer than 6 or 7 people per square mile (Ciarlo and Zelarney 2002; New Freedom Commission on Mental Health 2004). Researchers use a variety of these – and other – methods (Goldsmith, Holzer et al. 1999; Ellehoj, Tepper et al. 2006; Hauenstein, Petterson et al. 2006).

The NIMH Office of Rural Mental Health Research (2003) suggests that instead of relying on existing definitions of "rural," researchers should include eco-cultural characteristics such as community resources (e.g., rate and level of economic development, availability of economic resources, and social networks) and beliefs and values that influence community decisions. Rost and colleagues (2002) also suggest that studies should examine the multiple determinants of service use, quality, and outcomes. They suggest that this type of research will facilitate the identification of areas where policymakers and practitioners can intervene. More recently, a study relied on the social ecological perspective created by Bronfenbrenner (1979) in a literature review on rural and behavioral health services for children and adolescents (Heflinger and Christens 2006). This framework notes that ecological validity can be achieved by research that attends fully to the multiple levels of analysis over time. Bronfenbrenner's approach posits that the individual is always impacted by influences at the individual, familial, community, and social/global scale. Alternatively, Hartley suggested that the differences are not only based on an urban/rural split, but also that suburban areas should be considered separately, as well (Hartley 2004).

The New Freedom Commission on Mental Health (2004) states that the definition of rural does make a difference. As noted, there are few studies on ACT in rural areas, so determining an appropriate measure of rural would be ideal to ensure that the nuances of living outside of major metropolitan areas are fully captured. In our analyses, we borrowed from sociology and used a common definition of rural, the Rural Urban Continuum Code (RUCC) (Brown, Hines et al. 1975; Beale 2004), while also including several covariates that describe North Carolina counties. Although these characteristics provide some insight into differences associated with living in rural or urban areas, they oversimplify the nuances of the rural-urban continuum, as is noted in the limitations section.

Significance and Contribution

This study is important for a variety of reasons. First, persons with severe mental illness deserve quality care. If ACT is, for example, decreasing inpatient psychiatric hospitalization and emergency rooms costs when rolled out at the state level in multiple communities, then there is an even greater argument for its widespread implementation in other states. Most studies look at single or small groups of ACT teams. If ACT teams that are spread across a state -- with different fidelity levels, different qualifications, and different challenges -- are having successes, this is a good argument for even greater implementation of the model. However, if ACT is producing the same services use as usual care, there might be a need for a re-evaluation of the ACT program in order to more appropriately allocate valuable resources for the severely mentally ill. For example, it might signal a need for more flexibility in trying new policies and practices for ACT teams. Some ideas, such as step-down models or 'tiered' case management (Stein, Barry et al. 1999; Dixon 2000; Bond, Drake et al. 2001) or mechanisms for providing systematic feedback about ACT programs (George, Durbin et al. 2008), have been posed in the literature and by advocacy organizations, but are not often implemented in practice.

In addition, we need to know what is happening with ACT in rural areas. Program managers are concerned about how to implement ACT, especially in rural areas (Meyer and Morrissey, 2004), but there is little research evidence to suggest that ACT really does improve a variety of outcomes, especially in rural areas. In addition, it might be a stretch to believe that ACT will be implemented at full fidelity in rural communities across America. However, we may not need full fidelity models in all settings. This study looks at this issue by analyzing services use of individuals on ACT teams not operating at full fidelity in rural areas of NC between 2000 and 2002. If these teams produce positive outcomes, we may need future research to look more closely at the program elements they are including to better understand a "rural ACT model" that might be working for rural individuals.

Another issue is funding. We know enough about ACT to know that in most areas where it is implemented, it decreases costs of hospitalizations and provides some beneficial effects on outcomes, which is in itself an argument for broader implementation of the program. But as many states, like North Carolina, shift their priorities in favor of community-based care, the funds for these innovative community-based services, like ACT, often lag behind. Of course, the issue here is the same as it was 30 years ago when ACT was first conceptualized (Weisbrod 1983): who pays and who benefits. Local and state governments end up footing a large portion of the bill for ACT, while the beneficiaries are the state hospitals and sometimes local jails. Dealing with these complexities is an ongoing struggle.

Chapter III: Conceptual Model

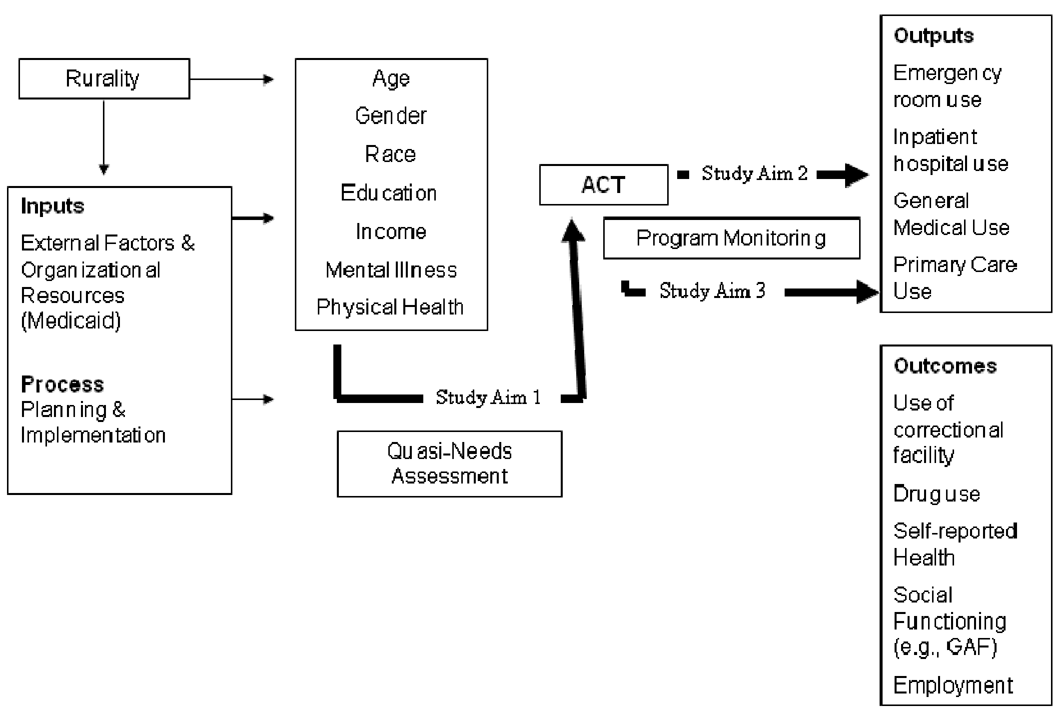
In program evaluation, results should inform program management, strategic planning and resource allocation (Bertrand, Magnani et al. 1996), yet many programs are implemented without this type of assessment. This leaves policymakers and practitioners without the knowledge they need to inform their decisions. This is especially important in a resource-intensive program such as ACT (George, Durbin et al. 2008).

Three main types of evaluation exist: needs assessment, program monitoring and impact assessment. Needs assessments answer the question of *what* the program should include; program monitoring is designed to identify *how* different aspects of programs are working; and impact assessments measure the *degree of change* in outcomes attributable to a given program (Bertrand, Magnani et al. 1996).

This study will look at two of these three components: needs assessment and program monitoring (Figure 2). Although we will be able to see the degree of change in the use of health services, the impact of the program on outcomes (i.e., impact assessment), such as social functioning and psychiatric symptoms, will not be measured here and is suggested as an area for future research. As described in the study aims and Figure 2, the study will first look at who is using ACT and who is not. This is not a formal needs assessment, but it will address the question of how broadly the ACT teams are covering cases of severe mental illness in NC. This type of information is typical of input provided into a needs assessment and will offer information useful for a broader, formal assessment which should be conducted in future research.

The next step of the process will be to determine how ACT use affects service utilization. The program evaluation framework shows that inputs into the program affect processes which in turn produce outputs and outcomes. Ideally, the Medicaid program and local governments cooperate to provide the inputs which then feed into the implementation and planning processes, producing outputs (service utilization). For example, in rural areas, there are fewer resources to begin with and implementation may be more difficult, which may alter the whole process.

Figure 2. Program Evaluation Framework to Study Assertive Community Treatment in North Carolina (Adapted from Bertrand, Magnan, and Rutenberg, 1996)



This evaluative process has rarely been used to look at the relationship between ACT and primary care. In this case, ACT is increasing resources available to the individual; however, it is unknown how this increase in resources (the process) affects the outputs (service utilization). On one hand, ACT could serve as a substitute for primary care since there is a psychiatrist on the team that can help with some general medical problems. On the other hand, however, ACT could increase the use of primary care since signs and symptoms might be detected more often, possibly increasing referrals to primary care and non-MH specialists. It is not clear a priori which effect is a stronger part of the process. This interplay is especially important in light of the fact that many payors (especially Medicaid and private payors) carve-out mental health services, which means if there are increased costs or savings in primary care, these are outside of the carve-out contract.

Although there are multiple aspects of program evaluation, only a few are tested in this study. The results here, however, will allow us to look at who ACT is serving and whether ACT is affecting outputs in North Carolina, and could be useful for Medicaid programs in other states. We will not, however, be able to determine the nuances of inputs and processes which might be affecting these outputs and outcomes (e.g., we will not be able to determine things like whether ACT team cohesiveness or having someone available 24 hours a day 7 days a week contributes more towards improving outcomes). These questions and other programmatic aspects, such as program costs, should be evaluated in future research.

Chapter IV: Data

Medicaid Claims and Enrollment Files

Administrative claims-based databases, such as the Medicaid claims files, have been used to study many aspects of health policy, including adherence to medications (Martin, Wiley-Exley et al. 2009; McIntyre and Jerrell 2009), appropriateness of care (Kosecoff, Chassin et al. 1987), pharmacoepidemiology (Ray and Griffin 1989), and quality of care (Samnaliev, Baxter et al. 2008). Administrative databases contain important information on diagnoses, procedures, services, drugs and costs for what can be very large portions of the population (Walkup, Boyer et al. 2000).

Medicaid claims files, in particular, are especially useful when trying to look at services use and costs for low-income patients. A major benefit is that, because of the low incomes of the recipients, Medicaid claims cover many of the diagnoses and health services used (Walkup, Boyer et al. 2000). Although free flu shots at a county health department would not be listed in the files, for example, we expected to have data for many mental health services. This is especially true for ACT services. Almost all ACT services are funded publicly rather than via private insurance, and Medicaid is often the funding mechanism of choice (Clark 1997).

However, there are concerns with these files, especially for defining outpatient use in psychiatric populations. For example, when Medicaid claims files were compared with medical records of 105 patients with an inpatient psychiatric stay (Walkup, Boyer et al. 2000), most of the transfers of these patients after they left the hospital were not recorded in the Medicaid claims files, although the medical records showed that 34.8% of the discharges were referred to other institutions, such as state mental hospitals, inpatient drug rehabilitation programs, and nursing homes. In addition, over a quarter of 46 discharges in the medical records were referred to other outpatient services that could not be identified in the Medicaid claims files. Another study which compared Medicaid claims files to medical records found slightly better results: ninety percent of the visits in the claims files were in the medical record, and total volume of visits in the medical records were 2.6% higher than in the claims files (Steinwachs, Stuart et al. 1998). However, for patients with low use rates, claims data reported 25% fewer visits than did the medical records.

Even though there are limitations to the use of these files, however, Medicaid claims files were reliable in the reporting of primary and secondary diagnoses (Walkup, Boyer et al. 2000), and offer a detailed, longitudinal record of utilization, diagnoses, procedures, and prescriptions across the full range of health care settings for a diverse individuals (Crystal, Akincigil et al. 2007). These aspects of the claims files were important for this study, as we needed to carefully define the control groups based on diagnoses and as we wanted to look at long-term patterns of use for a diverse group of individuals across the whole state of North Carolina. These files also help in achieving statistical power for low-prevalence events, such as use of ACT (Crystal, Akincigil et al. 2007).

For these reasons, this study drew from the population on Medicaid in North Carolina (NC). The NC Medicaid claims files were accessed from the Center for

Medicare and Medicaid Services for the calendar years 2000 through 2002. Medicaid claims files include anything reimbursed by Medicaid for people enrolled in the Medicaid system and are separated into two parts: enrollment data and services data. The enrollment data provided information about the individual, including race, age, whether the person is on Medicare or not, and enrollment dates. The services data gave information on every visit to a physician or hospital or other health service that is covered either partially or wholly by Medicaid, including diagnoses, procedures provided, total costs, and payments made by Medicaid, as well as a variety of other data.

ACT Team Survey

Claims data were merged to an ACT team survey which was conducted by phone in the Fall of 2003 (Meyer and Morrissey 2004), less than one year after the end of our study period; team-specific data on fidelity during the sample period was not available. The ACT team survey provides details on ACT team fidelity and was part of an evaluation component of the Substance Abuse and Mental Health Services Administration and the National Institute of Mental Health's Science to Service planning grant which was given to North Carolina to improve service delivery and implementation of evidence-based practices. The respondents were often the team leaders (n=28), but were sometimes administrators or supervisors (n=10). The survey provided ratings for the following aspects of fidelity to the ACT model based on the Dartmouth Assertive Community Treatment Scale (Teague, Bond et al. 1998): admission criteria, intake rate, team size, staffing, caseload size, community based services, responsibility for treatment, crisis services, team approach, dropout policy, and program meetings. These data were then used to classify whether teams were considered to be "established" (functioning with at least 60 consumers and a staff of 6 full-time mental health professionals) (n=7) or "developmental" (functioning with a range of between 8-56 consumers and 2-10 full time staff) (n=33). These classifications were defined by Meyer and Morrissey (2004), and the cutoff points were based on criteria which suggests that the optimal ratio of patients to clinicians is 10 to 1 (Phillips, Burns et al. 2001).

Merging Medicaid claims with Survey Data

The ACT survey variables were merged to the claims data for the individuals on ACT based on the provider identification number which was available in the claims data. Each Local Management Entity has one or more provider identification number(s) listed as billing providers on the ACT Medicaid claims. These provider identification numbers were used to link the ACT survey variables to the claims for those on ACT. It should be noted that a small number of individuals (3% of people on ACT) had claims from multiple LMEs within one quarter. For these individuals, the LME that was most often noted in the files was used.

County-level Factors

We employed county-level variables in our analysis in order to control for possible omitted variable bias. Because we believed that having an ACT team in a county was probably correlated with other county-level characteristics, such as mental health resources within the county, we included several variables that we believed might be correlated with other variables in the model and related to the outcomes of interest.

Had we not included these variables in the model, this could have biased our other coefficients. Specifically, we controlled for mental health services capacity in a county: the number of mental health professionals (Cecil G. Sheps Center for Health Services Research 2004) and Medicaid enrollees (North Carolina Division of Medical Assistance 2003). These variables allowed us to understand how many mental health practitioners were available, on average, per person, which served as an indicator of access to care, although this measure has not been validated. We hypothesized that if individuals did not have mental health professionals living in close proximity to them, they would be lower users of mental health care. The number of Medicaid enrollees is suggestive of the number of individuals in an area who might be eligible for a Medicaid-funded program like ACT.

For all of the county-level variables, we mapped individuals to their county of residence because we wanted to best reflect the service possibilities close to the individual's home. Because some people may cross county lines for service, we considered using the county where an individual received services. Although we have information in the claims data about the billing provider, these identification numbers are scrambled. Because we had the un-encrypted identifiers for ACT service providers only, we tested the sample to see whether individuals usually received services in their county or LME of residence. We found that individuals received care in the local management entity of residence over 80% of the time.

Chapter V: Methods and Measures

Sample

The sample was composed of adults over the age of 21 who were enrolled in NC Medicaid at some point during 2000-2002 and who had a qualifying mental health diagnosis as described below.

The intervention group included individuals who had at least one Medicaid claim for ACT services (based on procedure codes) between 2000-2002 (n=11,374 person-quarters; n=1,065 distinct individuals). Often these individuals went on and off of ACT over time; 37% of people had at least one gap in coverage (i.e., a month during which they did not receive ACT services after having been placed on ACT) during the three-year period of interest. Therefore, we used the percent of time someone was on ACT within a quarter (contingent on eligibility for Medicaid during that quarter) to better portray the amount of time someone spent on ACT. Therefore an individual could go in and out of the control group based on their ACT status within the quarter of interest.

Because looking at data in a non-experimental setting is subject to bias due to unobserved differences that cannot be or are not measured, the literature suggests using multiple control groups to determine how well the findings stack up when compared with different groups of people (Rosenbaum 2002). Therefore, we used three control groups in this study: a group of individuals who were eligible for ACT services based on diagnoses and history of hospital use (Cuddeback, Morrissey et al. 2006) but were not observed receiving ACT services, a group of individuals with a diagnosis of severe mental illness regardless of prior hospital use, and a group of matched individuals (matched on the following: the number of Medicaid eligibles per thousand per county, the number of mental health professionals per thousand per county, whether or not someone was on Medicare, SLMB status, mental illness diagnosis, and number of comorbidities and year quarter) created via propensity scores.

It should be noted that the three control groups are not mutually exclusive. The control group of individuals with a diagnosis of severe mental illness regardless of prior hospital use is the largest group. The other two groups are subsets of this control group.

Because 94% of people in the ACT group entered into Medicaid via the blind/disabled category, we limited all control groups to those who were eligible via the blind/disabled category. Each of these is described below. Less than 0.2% of the sample (i.e., individuals on ACT who were not in the Blind/Disabled category) came into the sample via the categories of aged or adult (not based on unemployment status, but based on poverty or former AFDC status).

Control Group 1: Potential ACT Consumers

The first control group was designed to compare individuals who were on ACT with Potential ACT Consumers (i.e., individuals who were not on ACT but who, in theory, should have been on ACT). According to the literature, an individual with two or more hospitalizations over a year's period for a severe mental illness should be part of the ACT target population (National Institute of Mental Health 1977), although other research uses three or more hospitalizations (Cuddeback, Morrissey et al. 2006). An individual was included in this group if s/he had ever had more than two hospitalizations with a DRG reflecting a mental health or substance abuse stay (424-427, 430, 432-437) over a single 12-month period during the three-year period of interest and also had a diagnoses of severe mental illness (e.g., schizophrenia (ICD-9=295), affective disorders (ICD-9=296, except 296.2), paranoia (ICD-9=297), and psychoses (ICD-9=298)). Although it would have been ideal to use SSI/SSDI status to create the Potential ACT group, as well, this information was not available in the Medicaid claims files, therefore we relied on the number of hospitalizations, diagnosis and Blind/Disabled status as a proxy. This issue is discussed in further detail in the limitations section.

There were 1,426 distinct individuals (15,043 person-quarters in our sample) who fit these criteria. When substance abuse DRGs were not included, there were 1,245 distinct individuals in the sample. We decided to include those with substance abuse DRGs as well as mental health DRGs because of the high rates of co-occurring disorders (Chwastiak, Rosenheck et al. 2006; Joukamma, Heliovaara et al. 2006). It should be noted that these individuals were never on ACT. If they met the criteria for this control group, but were on ACT for any period of time, they were considered to be in the intervention group, not in this or any other control group.

Since we based this control group on the use of inpatient services, the use of inpatient facilities were larger than the use by the ACT sample over the three-year period of interest. For example, the mean number of inpatient psychiatric visits and the mean total cost of inpatient psychiatric care were both significantly different between the intervention group and those who should have been on ACT (over the three-year period:

mean = Control Group: 1.2 versus ACT: 4.4 inpatient psychiatric visits, p=0.000; mean = Control Group: \$3,256 versus ACT: \$14,399 in inpatient psychiatric care costs, p=0.000).

Because we were drawing this control groups from a sample that looked different from ACT consumers, we also compared the ACT users to individuals who we expect to *under-use* services when compared with the ACT population, as defined below in Control Group 2. Using both of these control groups, we hoped to gain a better understanding of how ACT functions in real-world settings. For example, if ACT is associated with lower hospitalization costs in comparison with both control groups, then we can reasonably assume that ACT lowered hospital costs in NC during the study period. If, however, ACT is associated with higher costs in both comparisons, we could reasonably expect that ACT was not creating the cost-savings found in previous research (Essock, Frisman et al. 1998; Latimer 1999; Phillips, Burns et al. 2001).

Control Group 2: Individuals with Severe Mental Illness (SMI Group)

We also compared the individuals on ACT against a broader control group of individuals who did not receive ACT services but had any severe mental illness diagnosis in the outpatient or inpatient claims files: (e.g., schizophrenia (ICD-9=295), affective disorders (ICD-9=296, except 296.2), paranoia (ICD-9=297), and psychoses (ICD-9=298)). This sample was not restricted to individuals with hospitalizations, however, and was therefore much larger than the first control group (n=405,942 person-quarters; n=41,717 distinct individuals), although it included everyone in the first control group.

By including this larger sample, as well, we hoped to gain a better understanding of the relationship between ACT and health services use in North Carolina because, on average, we expected that the individuals in this larger control group would have lower services use than those on ACT, as individuals with SMI often have high unmet need (Salsberry, Chipps et al. 2005), or we expected them to live in areas where they did not have access to ACT. A priori, it is not clear whether this relationship is true, however. For example, ACT teams could be cherry-picking individuals who are less severe because they are easier to work with, although this would go against the principles of ACT. These questions point out the need for rigorous analyses, such as multivariate regression models, to parse out some of the direct influences of ACT on services use.

In our sample, however, we found that individuals in the ACT group, on average, were higher users of health services than other individuals with SMI. For example, the mean number of inpatient psychiatric visits and the mean total cost of inpatient psychiatric care were again significantly different between the ACT group and those in this control group (over the three-year period: mean = ACT: 1.2 versus Control Group: 0.5 inpatient psychiatric visits, p=0.000; mean = ACT: \$3,256 versus Control Group: \$1,302 in inpatient psychiatric care costs, p=0.000). Thus, we hypothesized that this control group would use fewer services over time when compared with the ACT users; therefore the ACT users should appear to be more expensive and should use more services when compared to this group.

The expected differences between the intervention group and the control group in both of the control groups listed above could cause problems. Because neither control group was perfect (i.e., randomized), there could be unobserved differences which would bias the coefficients in the model. However, as we expect one group to have higher costs than ACT and one group to have lower costs than ACT, we expect the results to be somewhere in between these two groups.

Control Group 3: Propensity Scores.

Our third control group was created using propensity scores (n=403,883) from a subset of Control Group 2 listed above. Propensity score methods simulate a comparable control group for the analyses and estimate the conditional probability of assignment to a treatment given a vector of observed covariates which ideally allows for unbiased estimates of program impact when selection of treatment exists (Rosenbaum and Rubin 1983). Propensity score methods allow for the creation of a comparable control group on the basis of observable characteristics so that we could conclude that it is more likely that ACT, rather than characteristics of other covariates, accounts for any observed outcome differences. Although propensity scores cannot deal with all of the biases inherent in observational studies, recent work (Aakvik 2001; Rosenbaum 2002; Rosenbaum 2002; Morgan and Winship 2007) has made it possible to determine how sensitive the propensity scores are to unobserved biases. This recent work, which is discussed in more detail below, provides an innovative overview of the accuracy of the analysis and was therefore employed here in conjunction with propensity scores.

There are many limitations to propensity score methods as described in the analyses and limitations sections below, which especially limit the method's robustness in observational studies. However, as noted above, we have a control group of individuals who are heavy users of health services and another group which uses lower services. The hope is that adding in a control group that has the aim of more closely matching those in the ACT group with those in a control group will smooth out some of the differences in the other two samples.

Measures

Dependent Variables.

Involvement in ACT. Involvement in ACT was created as a binary variable (yes/no related to whether or not an individual was ever involved in ACT during the study period or not) and was defined using procedure codes (Y2314) from the Medicaid data. ACT claims are made on a monthly basis; therefore all services provided within the month are considered one ACT unit for the month and paid accordingly.

Number of Months on ACT. We measured the number of months an individual was on ACT during the three-year period of interest, collapsed at the person-level.

Ever on ACT during Quarter. This binary variable was coded as one if the individual was on ACT for any percent of the quarter and zero otherwise. It was used only for the propensity score analyses.

Number and costs of emergency room, general medical, primary care, inpatient psychiatric care, and total costs. The service use outcomes were based on a variety of procedure, place of service, revenue and diagnostic related group categories applicable to outcome of interest. *Emergency care* was identified by procedure codes (99281-99285), revenue codes (450-459, 981), or place of service codes (23). *General Medical Services*, which indicate all outpatient based services, regardless of diagnosis type (e.g., mental health and non- mental health) were defined based on several type of service codes (physicians, other practitioners, outpatient hospitals, clinics, labs, x-rays, physical therapy, occupational therapy, speech therapy, hearing services, nurse midwives, nurse practitioners, private duty nursing, and a general category of other services). This category does not include ACT costs and is not limited by diagnoses. *Primary care* was defined based on procedure codes, which included office visits with physicians, in-home visits with physicians, chart reviews with family members and other doctors, physician case management, preventive medicine, and general evaluation and management (procedure codes 99201-99215, 99341-99350, 99354, 99355, 99358-99359, 99361-99373, 99381-99429, 99499). It should be noted that the primary care is a subset of general medical services. *Inpatient psychiatric care* included stays in psychiatric beds, psychiatric wards, and intensive care unit psychiatric beds and was identified through UB-92 revenue codes (114, 124, 134, 144, 154, and 204) and diagnostic-related group categories (424-432) (NC Department of Health and Human Services 2005). Individuals with inpatient stays due to substance abuse only were not specifically included (i.e., they are not treated differently from other, non-mental health comorbidities), although individuals with co-occurring drug abuse disorders could be included, if they have the aforementioned mental health codes. A final category of *total costs* was also included, which was the sum of all Medicaid payments over the time period of interest and includes costs of ACT services.

All costs were based on the actual Medicaid payment amounts for the services in the defined categories and were summed to total payments per quarter. For the number of visits, we looked at distinct combinations of several variables. This was a straightforward process for inpatient stays because they were collapsed to the stay level, therefore we were able to use unique combinations of beginning date of service and individual patient identifier to determine the distinct number of stays. The same process was used for emergency room visits. The other outpatient visits were defined as unique combinations of date of service, individual patient identifier and individual provider identification numbers.

Independent Variables.

Percent of quarter on ACT. The percent of the quarter that an individual used ACT/ACT-like services was created as a censored continuous variable, based on the percent of time an individual was on ACT during the part of the quarter that they were also eligible for Medicaid. This variable was defined using the ACT procedure codes and Medicaid enrollment dates. This variable is important and is distinctly different from the Involvement in ACT variable. As stated above, ACT is billed on a monthly basis in North Carolina. Therefore, many individuals on ACT are not on it for the whole year, for even a whole quarter, or for a whole month. For example, someone could be on ACT for 3 of the 4 weeks in a month and still potentially be billed at the monthly rate. In addition, sometimes an individual was on ACT in one quarter but not in the next. The challenge here was that, although we had monthly status, we are unable to determine the "dose" of ACT that an individual received. The percentage variable was the closest approximation and gave us the percent of a *quarter* for which a team billed for ACT services for an individual, *not* the percent of a month. This obviously does not replace a dose-response interaction that would be available via a randomized trial or chart review, but does provide us with information about whether an individual stayed on ACT steadily over several quarters or years.

Established ACT team. The ACT teams were divided into two groups that defined the operational status of the ACT teams: established teams (functioning with at least 60 consumers and a staff of 6 full-time mental health professionals) (n=7) and developmental teams (functioning with a range of between 8-56 consumers and 2-10 full time staff) (n=33), as per the definitions used in the ACT survey described above (Meyer and Morrissey 2004). A binary indicator for being on an established team was included in the cross-sectional analyses looking at the number of months on ACT.

It should be noted here that established ACT teams are largely an urban phenomenon. As noted in the table below, seven of the nine established teams were in urban areas, and none of those teams were in rural areas. Problems with fidelity to the ACT model in rural areas have been found in previous research (Siskind and Wiley-Exley 2008), however the real implications of these differences on services use within uncontrolled settings are unknown.

	Rural	Mixed	Urban
Not established	3	12	16
Established	0	2	7

Place of Residence. One of the primary research questions examined here investigates whether there were differences in service use based on the place of residence (rural, mixed or urban areas). There are many different ways of defining rural that are subject to a variety of biases (Goldsmith, Holzer et al. 1999; Ciarlo and Zelarney 2002; NIMH Office of Rural Mental Health Research 2003; New Freedom Commission on Mental Health 2004; Hart, Larson et al. 2005; Ellehoj, Tepper et al. 2006; Hall, Kaufman et al. 2006; Hauenstein, Petterson et al. 2006). In our analyses, we employed one of the most commonly used definitions of rural (Rural Urban Continuum Code (RUCC) (Brown, Hines et al. 1975; Beale 2004) and included several covariates that describe North Carolina counties.

The Rural Urban Continuum Code (RUCC) (Brown, Hines et al. 1975; Beale 2004) defines metropolitan and nonmetropolitan areas based on several characteristics. The metropolitan counties are determined by the population size of the area, and the nonmetropolitan counties are determined by population size of the urban areas within the counties and the degree of urbanization and adjacency (at least 2 percent of the employed labor force commutes to the central metropolitan counties) to other metropolitan areas. These classifications are broken into nine groups: counties in metropolitan areas of 1 million population or more; counties in metropolitan areas of 250,000 to 1 million population; counties in metropolitan areas of fewer than 250,000 population; urban population of 20,000 or more, adjacent to a metropolitan area; urban population of 20,000 or more, not adjacent to a metropolitan area; urban population of 2,500 to 19,999, adjacent to a metropolitan area; urban population of 2,500 to 19,999, not adjacent to a metropolitan area; completely rural or less than 2,500 urban population, adjacent to a metropolitan area; completely rural or less than 2,500 urban population, not adjacent to a metropolitan area.

However, several of the categories in NC are too small to be meaningful and would not permit identification in the analyses. Therefore, we consolidated the nine categories into three based on classifications similar to those used in the literature (Baer, Johnson-Webb et al. 1997; Bennett, Skatrud et al. 1997): urban (all metropolitan areas), mixed (urban population not considered metropolitan of 2,500 or more people adjacent to a metropolitan area OR an urban population of 20,000 or more, not adjacent to a metropolitan area), and rural (a population of 19,999 or less that was not adjacent to a metropolitan area OR a completely rural area with less than 2,500 urban population, which was adjacent to a metropolitan area). These variables were used to split the sample into three distinct categories. These types of groupings have been used in previous research (Baer, Johnson-Webb et al. 1997; Bennett, Skatrud et al. 1997). Other options which we could have selected include the Urban Influence Codes (Ghelfi and Parker 1995) or the Rural-Urban Commuting Area Codes (USDA ERS). Both of these are similar to the RUCCs, although the RUCA can be used when census track detail is available, versus the county-level data necessary for the RUCC and the Urban Influence Codes. However, because we decided to group the categories, smaller (zip code level) categories would not have provided additional information because we would have had to group them as well.

Another way to control for issues related to place of residence is through inclusion of eco-cultural characteristics, such as community resources (NIMH Office of Rural Mental Health Research 2003). In order to control for some unobserved characteristics related to access to mental health services within different communities in rural, mixed and urban areas, we used variables which counted the number of mental health professionals and Medicaid enrollees within a county. The first variable noted the number of Medicaid enrollees per thousand people per county (North Carolina Division of Medical Assistance 2003). Other covariates focused on the number of psychiatrists, psychologists and psychological associates per thousand per county (Cecil G. Sheps Center for Health Services Research 2004). These indicators are suggestive of the level of government assistance and mental health services available within a county, which could increase the uptake rate and provision of ACT and other services.

Other Control Variables. The control variables included age, gender, race, comorbidities (including mental illness and substance abuse diagnoses), Medicaid eligibility status, Medicare status, and specified low-income Medicare beneficiary program/qualified Medicare beneficiary program (SLMB/QMB). These variables were included to control for hidden bias related to demographics, disease status, and other plan coverage (Medicare) that might affect service use. We expected each of these to be important, as each has either been important in previous studies on ACT – including age (Salkever, Domino et al. 1999), gender (Salkever, Domino et al. 1999), race (Siskind and Wiley-Exley 2008), and comorbidities (Cuddeback, Morrissey et al. 2006) – or are important in the funding streams of health services (Medicaid and Medicare status).

It should be noted that, as described in the analyses section below, we used person-level fixed effects to control for time-varying factors at the person-level in the analyses that were not collapsed to the person-level. This means that many of the control variables that do not vary over time, including age at baseline, gender, and race, are only included in models with person-level fixed effects as part the bundle of characteristics that identify the individual, called fixed effects. Therefore we will not get coefficient estimates on these variables for longitudinal models, although the cumulative effect of these variables is still a part of the estimation via the fixed effects.

Age was defined as the actual age on Jan 1, 2002. Gender was a binary variable (male = reference), and race was a mutually-exclusive categorical variable of non-Hispanic Caucasian, non-Hispanic African American, Hispanic, other and unknown, based on self-reported categories from individuals' Medicaid enrollment records. Comorbidities, defined on a yearly basis, were accounted for by employing a comorbidity index developed specifically for psychiatric research using administrative data (Ricci, Dorfman et al. 2001). We used this comorbidity index to create eight mental health comorbidity indicators and a single continuous count of all other comorbities. For the eight mental health indicators, we included binary variables in the model (including drug abuse, alcohol abuse, bipolar and manic depressive disorders, psychoses, personality disorders, depression and schizoaffective disorders, schizophrenia, and other mental disorders). For the continuous count of comorbities, we collapsed the index, which divides the ICD-9 codes into 45 categories (37 non-mental health and 8 mental health), into a single variable because only 5 of the 37 non-mental health disease categories were indicated annually in over 5 percent of the sample. This single variable was a count of the total number of comorbidities an individual had during each calendar year, which could be between 0 and 37; we did not include the eight mental health comorbidities in this count. We tested for the best fit between the continuous comorbidity variable and a categorical system (0 comorbidities, 1 comorbidity, and 2 or more comorbidities) by using the adjusted R^2 of various models. The R^2's for the models were very similar, although sometimes the continuous variable was slightly higher, therefore we used that variable in all the analyses, except for the propensity scores where the categorical variables improved balance.

Because a few of the individuals in the ACT team were not eligible via the blind/disabled category, we also included a non-disabled indicator to indicate whether someone qualified for Medicaid via a category other than the Blind/Disabled category, to differentiate them from others who might be in Medicaid due to poverty. This indicator suggests a fundamental difference between two groups of people: one group is severely disabled and needs assistance due to their disability; the other group lives in poverty but is not necessarily as sick. We included this indicator as a way to account for the fact that being blind and/or disabled is probably correlated with other variables in the models, including the percent time an individual is on ACT, as well as comorbidities. In addition, although some of the disabilities an individual has will be accounted for by including comorbities in the model, this does not account for severity of disease. The non-blind/disabled indicator suggests a level of severity that is less extreme than others in the Medicaid population, and therefore we wanted to control for some of the hidden bias related to these underlying differences. Because we include person-level fixed effects in the models as described in the analyses section, we were specifically concerned about individuals who change status during the three-year period of interest (e.g., those individuals who were not blind/disabled in 2000, but changed status in 2001). We expected that these individuals probably had some life event (e.g., a worsening of an illness, for example) that catapulted them into the blind/disabled category. Again, we wanted to control for this type of unobserved difference, and this variable allowed us to do that. It was collected on a yearly basis.

The models looking at the dependent variable length of time on ACT also controlled for the number of months an individual was on Medicaid. We needed to control for this because the number of months on Medicaid for any given individual could have been correlated with several other individual characteristics that were included in the model, such as comorbidities, Medicare status, and mental health diagnoses. We investigated whether the ACT teams started at different times in different places of residence (i.e., did the ACT teams in urban areas start in 2000, followed by ACT teams in rural areas in 2001?), however all places of residence had ACT teams in 2000, therefore we did not control for this in the study.

Other indicators which were also used for all models were related to Medicare status and were collected on a yearly basis. It is important to control for an individual's involvement in Medicare because individuals who were dually-eligible for both Medicaid and Medicare would not have had all costs (i.e., those paid for by Medicare) included in our analysis. However, this study was designed to look at Medicaid, not societal, resources and differences in Medicare costs are not expected to vary, on average, between the ACT and control groups. In addition, only about 6 percent of the sample began receiving Medicare during the three-year period of interest, therefore the individual-level fixed effects was picking up a large portion of the time-invariant unobserved differences which might have made Medicare costs differ between the ACT and control groups. Binary indicators were also used to determine whether or not an individual was on Medicare or whether or not an individual received Medicaid cost sharing for Medicare but was not eligible for Medicaid drug coverage (QMB/SLMB programs, a subset of those on Medicare). These indicators were used because Medicaid costs were expected to have mean differences across these three dual eligibility categories.

Ever and Always Variables. In the analyses section, we described the use of collapsed person-level models for several analyses. In order to collapse at the person level for time-varying characteristics, a choice has to be made as to whether one wants to look at, for example, “ever”, “always”, modal, or some other measurement of an individual’s time-varying characteristics. In our analyses, we coded the variables in several different ways in order to test the sensitivity of our models to the different assumptions inherent in this choice.

First, because almost 10% of individuals changed counties during the three-year period, we coded individuals who changed counties into county types based on the county-type they lived in for the longest period of time. Ties, which composed only 0.1% of the population, were coded as the most rural status (e.g., if a person lived in a rural county for 12 months and a mixed county for 12 months, they were collapsed into the rural group). For all time-invariant variables (except for the place of residence variable as noted above), we used the minimum or “always” value for the three-year period. We refer to these interchangeably as “minimum” or “always” models because they represent values for characteristics only if the individual always had those characteristics. This meant that we classified individuals who were only sometimes eligible (e.g., for one out of three years) for Medicaid due to the blind/disabled category as *not* being eligible via the blind/disabled category. This was also true for the Medicare and SLMB categories and the binary mental health comorbidity indicators (e.g., if someone was classified as having schizophrenia in the third year, they were considered to never have had schizophrenia). For the number of mental health professionals and psychiatrists per county, the smallest number that appeared over the three-year period was used. For the number of diagnoses per individual, the lowest number recorded over the three-year period was used.

Of course, using only the minimum values for the time-varying variables other than county of residence may not accurately represent the data, therefore we also conducted sensitivity analyses for all collapsed models by coding everyone with the most urban status (e.g., if an individual lived in an urban and a mixed area, they were considered to have an urban place of residence). In these models, all of the time-invariant variables were coded to the maximum values (e.g., people with schizophrenia in one year were coded as having schizophrenia). We refer to these as "ever" models, as they represent whether an individual ever had any of the characteristics of interest.

Analyses

For Aim 1, we first examined binary associations of the main covariates and outcomes defined above using t-tests and chi-squared statistics between ACT users and non-users and ACT users in urban, mixed and rural areas.

We then used a collapsed person-level linear probability model (LPM) model to determine the correlates of ACT treatment and the number of months on ACT during the study period, controlling for all covariates listed above; standard errors were adjusted for potential heteroskedasticity.

For binary outcomes, such as ACT treatment, there were several concerns to address. In particular, we examined the use of binary models, such as logit or probit models, in addition to the LPM. None of these models were perfectly suited to this type of analysis. Ordinary least squares regression models in this context are always heteroskedasticitic and may lead to out of range predictions. The problem of heteroskedasticity can be solved, however, by using robust standard errors, but the problem of out of range predictions is not preventable. To counteract the problems in these models, we could have employed a logit or probit model. However, these models look for time variation within variables that probably does not exist. In our case this meant that the models would have discarded individuals with no variation in outcomes over time. Therefore, many individuals would have dropped out of the model, because they either received ACT treatment for the whole period of interest or did not receive ACT treatment during the three-year time span.

Because each of these models had different problems and because we felt that out of range predictions were less of a concern than throwing out data, we decided to use LPM models and provide the reader with the percent of observations with out of range predictions as part of the results.

The models looking at the correlates of ACT treatment were split into three place of residence groups as described above: urban, mixed, and rural populations. Again, we used the “always” values combined with the longest residence to collapse these data. Analyses using OLS were conducted at the person-level since little variation in ACT participation was observed within individuals across the three-year study period.

Most of the rest of the analyses for all aims (Aims 1-3) were completed using some form of fixed effects models, as described below. We used these models because they allow for estimation of longitudinal data and have the ability to control for unobserved time-invariant variables through the use of "fixed effects".

There are a variety of other models that we could have used to analyze our longitudinal data, and a variety of beliefs about which is the best (Bertrand, Magnani et al. 1996; Rencher 2002; Rosenbaum 2002; Xie, McHugo et al. 2004; Austin, Grootendorst et al. 2007; Twomey and Kroll 2008). For example, we considered using a random effects model, which would model each individual as if s/he were drawn from a random population as part of the error term (Wooldridge 2003). Person-level fixed effects, on the other hand, consider each person to be a separate parameter which should be estimated (Wooldridge 2003). In addition, even if the individual level effects were drawn from a random population, they might be correlated with the explanatory variables, which causes endogeneity. If this were true, the random effects model is inappropriate. To test whether the random effects or the fixed effects model was the most appropriate, one can use a Hausman test (Hausman 1978). This enables a choice between the fixed effects estimator, which is always consistent (i.e., converges on the true value of the estimator) but may be inefficient (i.e., has a large variance), and the random effects estimator, which is more efficient. However, because we believe that each individual should be treated as a separate parameter and that individual effects are probably highly correlated with other explanatory variables, we used fixed effects models in all of our analyses. These models also have the additional bonus of always being consistent.

We controlled for potential heteroskedasticity in the fixed effects models using robust standard errors.

One important limitation of the fixed effects model is the models can still be biased if there are any time-varying omitted variables that are correlated with included variables and that are not at the same level as the fixed effects. For example, the number of months on Medicaid was most likely correlated with other variables in the model, including, for example, comorbidities since most individuals qualified through the blind/disabled category and therefore the comorbidities they had likely catapulted them into this category at some point in their Medicaid tenure. For example, a person might have entered into Medicaid via the disabled category because his or her doctor recognized a severe case of schizophrenia in 2002. This type of correlation would have changed the coefficients on both variables (e.g., the number of months on Medicaid and schizophrenia) in a regression model because they were both related to each other and the outcome of interest. If both of these variables were not included in the model, then the model would have suffered from omitted variable bias. This is a limitation of most statistical models, however, and was why we employed multiple control groups and sensitivity analyses around the propensity scores.

For all of the fixed effects models, we ran each of the models (the main model and any sensitivity analyses) for Control Groups 1 (Potential ACT Consumers) and 2 (SMI). Each of the sample sizes was different for the different models.

For integer-valued data, such as the number of medical visits in a quarter, we used count data models, specifically the negative binomial regression model. In our data, there were often a majority of individuals with only a few visits and only a small percentage of people with a large number of visits. To account for this, we employed the negative binomial regression model which allows the variance to be larger than the mean. It should be noted that these models drop all individuals who never had any visits, and that although they employ fixed effects, they report the coefficients on the fixed effect variables – such as involvement in ACT, age, gender, and race – that are time-invariant and that are not included in the fixed effect regression models used for costs. We also tested a Poisson model by examining goodness of fit tests and tests of over-dispersion. In our models, the Poisson was not a good fit based on the results of the likelihood ratio test, which tests whether the over-dispersion parameter is zero (i.e., whether the negative binomial distribution is equivalent to a Poisson distribution), therefore we employed the negative binomial regression model. Again, we controlled for heteroskedasticity with robust standard errors and employed person-level fixed effects.

For outcome variables with a large number of zeros reflecting non-use, we used two-part models. These models employ a binary model (the first part of the model) to determine the probability of any use, and then a continuous regression model (the second part of the model), which modeled the effect of the covariates on the level of use for only the individuals who had any expenses within the time period of interest. In our analyses, we used an LPM model for the first part and linear regression for the second. In both cases, we controlled for heteroskedasticity using robust standard errors and employed person-level fixed effects.

We used a Wooldrige test to test for the logged form of the continuous regression model (Wooldridge 1994). This test looked at how well two models explained the variation in the dependent variable by looking at the pseudo R^2 from the logged model compared with the R^2 from the unlogged model. In this test, the model with the highest R^2 (or simulated R^2 in the case of the logged model) is usually employed. In all of our analyses the models that were logged had smaller simulated R^2 values. We therefore employed non-logged models on all outcomes.

Additionally, in order to look at the difference between rural and other areas in the analyses where place of residence was of interest, the models were run in three separate samples: all individuals living in rural areas (based on the RUCC codes described below), all individuals living in mixed areas, and all individuals living in urban areas. Separating the models in this way essentially interacted all of the variables with the variable of interest (place of residence: rural, mixed or urban). This therefore provided us with a more complete picture of the differences between the effects of place of residence on the outcomes of interest.

Analyses for Propensity Score Models

Propensity scores model the conditional probability of receiving ACT treatment given the pre-treatment variables. Pre-treatment variables are characteristics of an individual which designate whether or not an individual will receive ACT and include, but are not limited to, mental illness diagnosis, county type (urban, rural, or mixed) and previous hospitalizations.

When using propensity scores, the "balance" between the treatment and simulated control groups is very important. A balanced dataset ensures that the distribution (e.g., similar means, variances, and percentiles) of the observed characteristics used in the analyses are similar in both groups (Gu and Rosenbaum 1993). The purpose of balancing is to eliminate as many baseline differences as possible, thereby making our study more closely resemble a randomized trial (Austin 2007).

A logit or probit model is usually used to estimate the probability that a person selected into the treatment condition. In general, the resulting predicted probabilities from these analyses are then either used as weights in the subsequent analyses (Imbens 2000; Foster 2003) or separate analyses are conducted for different propensity supports. Research has shown that greater balance between treated and untreated groups can be obtained by using the estimated propensity score directly in the analysis rather than stratifying the sample (Austin, Grootendorst et al. 2007), therefore this approach was employed in our analyses. The differences between matched groups in the outcomes were then analyzed using a test statistic that accounts for the matched design of propensity scores (Austin 2008), the Wilcoxon rank sum statistic.

There are, however, limitations to the use of propensity score analyses, as there are to multivariate models, as neither of these methods are able to estimate the effect of unobserved time-varying characteristics (Aakvik 2001; Rosenbaum 2002; Austin, Grootendorst et al. 2007; Austin, Grootendorst et al. 2007). In addition, there are limitations to the use of propensity scores in administrative Medicaid data since, for example, clinical outcomes are usually not available in these data, although using administrative data to develop propensity scores is becoming more common (Austin, Mamdani et al. 2005). Clinical outcomes could be useful in creating propensity scores because they would pick up some of the possible time-varying unobserved differences for individuals in the sample. These unobserved, time-varying variables are the variables which cause bias in any model, and although the lack of these data is important for propensity scores, it is also important in regular regression models. It is impossible to control for all of these differences outside of randomization, and this is again why we chose to use multiple control groups and sensitivity analyses to test the robustness of our findings.

Fortunately, recent work notes that there are also other ways to address some of the aforementioned problems inherent in propensity scores (Aakvik 2001; Rosenbaum 2002; Rosenbaum 2002; Morgan and Winship 2007; Foster, Wiley-Exley et al. 2008). Although a researcher may never be able to estimate *the effect* of an unobserved covariate on the outcome of interest, the researcher can systematically determine *the direction and size* of the unobserved bias via sensitivity analyses (Rosenbaum 2002; Morgan and Winship 2007).

One of the suggested ways to test the direction and size of the unobserved bias is to use sensitivity analyses around the sign rank test to measure the added uncertainty that is present when the groups are drawn from observational studies (as is true in this analysis) (Rosenbaum 2002; Rosenbaum 2002). After matched groups were created through the propensity score analyses, the sign rank test was used to determine whether there were differences between the two groups in the service outcomes of interest. This test first looks at the differences between the two groups for each person-quarter observations or collapsed person-level observations, depending on the model used, and ranks the absolute value of these differences. The ranks were then summed and tested for a statistically significant effect. Then, although it is not possible to calculate the magnitude of selection bias in these data, it is possible to calculate the upper and lower bounds of this test statistic (Aakvik 2001; Rosenbaum 2002), which allows estimation of how large the hidden bias or unobserved covariates would need to be in order to change the significance of research findings. This sensitivity procedure presents the p-value under an alternative set of assumptions about the link between the unobservables and the treatment status. The different possibilities are given by the odds ratio, called Γ. If the upper and lower bounds around Γ are significant, a hidden bias would have to increase the odds of changing outcomes by more than a factor of the stated Γ. For example, if the upper and lower bounds are significant between $\Gamma=0$ and $\Gamma=12$, a hidden bias would have to increase the odds of changing outcomes by more than a factor of 12; therefore the hidden bias would have to be quite large. On the other hand, if the upper and lower bounds are significant between $\Gamma=0$ and $\Gamma=1$, a hidden bias would have to increase the odds of changing outcomes by more than a factor of 1, which suggests that the model is highly sensitive to unobserved biases. Therefore, as Γ grows, and if the bounds around it stay significant, the likelihood of having hidden bias in a study decreases. If the upper and lower bounds are never significant, the likelihood of having hidden bias within a study is large.

For this study, the specific methods involved running person-level fixed-effects LPM (controlling for heteroskedasticity) which estimated the probability that an individual was on ACT during the person-quarter of interest. There were 5,787 person-quarters when individuals received ACT, which formed the intervention group for this part of the study. The independent variables for these models were composed of whether or not an individual was involved in Medicaid through a category other than the Blind/Disabled category, the number of Medicaid eligibles, psychologists, psychological associates, and psychiatrists per thousand per county, Medicare status, QMB/SLMB status, whether someone had zero, one, or two or more comorbidities (a categorical variable), the specific mental health diagnoses listed above, and indicators for each quarter of the study (quarter 1 through quarter 12). Because we were looking at person-level fixed effects, the time-invariant person-level variables of age, gender, race, and previous use of health services were not used in the model. Although not all of these variables were necessarily related to exposure to ACT, they could have been related to the outcomes of interest and to other variables in the model, and therefore should have been included in the model (Brookhart, Schneeweiss et al. 2006).

In order to achieve balance, especially with regard to the comorbidities in each group, we split the model into sixteen groups – one of each of the following diagnosis categories in either urban or non-urban areas: those with a diagnosis of schizophrenia and personality disorder and alcohol abuse; those with none of these diagnoses; those with only one of these diagnoses (so three separate models); those with schizophrenia and personality disorder (and no alcohol abuse); those with personality disorders and alcohol abuse (and no schizophrenia); and those with schizophrenia and alcohol abuse (no personality disorders). For each of these sixteen groups, we ran the LPM model described above. These groups were chosen based on the variables that were not balancing when the sample was pooled. Individuals with schizophrenia, personality disorders, and alcohol abuse were statistically different in the treatment and control groups, as were several of the place of residence variables. We hypothesized that the differences could be alleviated if the sample was split by some combination of mental health diagnoses and place of residence. After trying many variations on the above theme, we found that splitting the sample as described achieved balance at conventional levels of statistical significance ($p<0.05$), except for one of the twelve year-quarter dummy variables.

The predicted probabilities from these models were used to create a propensity score. We then used nearest-neighbor matching, which allows for replacement. Another option would have been to use greedy matching, which matches treatment and control cases on a first-come, first-serve basis (even though a better match may be found) and does not allow for replacement. Although there are multiple options available to match cases, there is relatively little evidence to determine which form of matching always performs the best (Baser 2006). We then tested the balance by running models of the propensity score on each of the covariates of interest as dependent variables to determine whether there were significant differences between the treatment and simulated control groups. Then we used the sign rank test to determine whether there were significant differences between the two groups for each of the services use variables. Finally, we tested the sensitivity of the groups by calculating the upper and lower bounds (Γ) of this test statistic (Aakvik 2001; Rosenbaum 2002).

Predictions and Marginal Effects. For several of the main models of interest, we reported predictions, conditional on any use of the health service of interest, for a sample person defined as the following (except where noted): someone on ACT for the whole quarter, who was disabled, had one comorbidity of schizophrenia and lived in a county with 167, 0.15, 0.10, and 0.088 Medicaid eligibles, pscyhologists, pscyhological associates and psychiatrists per thousand per county, respectively, in year-quarter 12. We also reported marginal effects of several coefficient estimates based on the two-part models, reporting standard errors based on 100 bootstrap replications.

Sensitivity Analyses. We conducted sensitivity analyses of the cost variables by looking at whether percent time on ACT made a difference in spending when compared with a variable that smoothed over gaps in ACT of less than two months. We recoded each month that an individual was not on ACT as a 0 into a 1 if individuals had a gap of two months or less in services (e.g., if an individual was on ACT in month 1, but not in month 2, but reappeared on ACT in month 3, month 2 was re-coded as "having been on ACT"). We then recoded these findings into a single variable that defined the percent quarter someone was on ACT and on Medicaid. One concern with the data was that individuals who were on ACT but who had a gap during the quarter may have truly been on ACT for that month, but that there might have been a glitch in the billing.

We also used the established team variables to run a sensitivity analysis to determine whether being on an established ACT team or a non-established ACT team made a difference in the outcomes of interest. This variable was a categorical variable in the longitudinal analyses: percent time on an established ACT team, which was the percent of the quarter on an individual had received services from an established ACT team; percent time on an ACT team that was not established, which equaled the percent of quarter on an individual was on an ACT team that was not established; and not on an ACT team. We then used a t-test to determine whether there were significant differences between the coefficients of being on an established ACT team and being on an ACT team that was not established. The established team variable, as noted above, was based on a cross-sectional survey. This means that whether or not an ACT team was considered established did not change over time in our analyses, although it probably would have had we been able to measure this variable over time. This is a limitation of our analyses and is discussed further in the limitations section.

We also ran two sensitivity analyses using the propensity scores. The first model was cross-sectional, based on the collapsed person-level (without fixed effects and including the person-level characteristics of age, gender, and race in the creation of the propensity score) for Control Group 1 (Potential ACT). We dropped everyone who was Hispanic from this model (n=16 unique people) because we were unable to balance on this variable. In order to achieve balance in this sample, we had to split the sample into four groups (instead of the sixteen used in the first propensity score model): those with a diagnosis of schizophrenia and manic depression; those with only schizophrenia; those with only manic depression; and those with neither of these diagnoses. These results were more significant than the original models, and therefore we reported the results here.

The second sensitivity analysis for the propensity scores was also based on collapsed-person level data, but used a probit instead of LPM. The probit is the more traditional way of determining propensity scores; therefore we wanted to see if there were differences between this model and the LPM analyses. The probit models dropped observations that perfectly predicted the outcome of treatment, so the sample sizes were somewhat smaller than the LPM models.

In order to ensure that the collapsed person-level models were not sensitive to the collapsing mechanism of choice ("always" values combined with the longest place of residence), we ran two sensitivity models. The first was based on the "ever" values of the data, and the second was based on the "always" values without consideration of the longest place of residence.

Finally, several control variables defining previous use were considered for use in our sensitivity analyses. However, these variables, because they are time-invariant, could not be included as covariates in fixed effects models. We then looked at using these variables to define smaller samples for sensitivity analyses of individuals who had previous use (i.e., individuals who were on ACT in 2001 and/or 2002, but who were not on ACT in 2000). These smaller samples did not include anyone who was on ACT at the beginning of the study period (2000), but included all individuals who began ACT in 2001 or 2002, and used the indicators described here to measure their use of services in

2000. The variables included the total number of inpatient hospital stays for the year of 2000, the total number of days an individual was in a mental hospital for the aged (not including regular hospital psychiatric wards) in 2000, the total number of days an individual was covered by Medicaid for a stay in a long-term care facility (not including hospitals) in 2000, and the total amount of money paid by Medicaid for the recipient (fee-for-service and premium payments) during 2000 for all types of services and claims. However, we found that only about 10% of the sample entered ACT in 2001 or 2002, therefore the sample size was too small to be practically useful for analysis. This issue is discussed in more detail in the limitations section.

Chapter VI: Results

Descriptive Statistics and Predictors of Treatment and Time on ACT

Table 1 gives the means or proportions of all dependent and explanatory variables for individuals receiving ACT team services, and those in each of the first two control groups. During the three-year period, total costs were highest for those in the potential ACT group ($57,094; p-value<0.01), however costs in the SMI group were significantly lower ($32,672) than those on ACT teams ($40,672; p-value<0.01). These same patterns were true (potential ACT highest cost, SMI lowest cost) for emergency room costs, inpatient psychiatric care costs, emergency room visits, and inpatient psychiatric stays. ACT participants had significantly lower general medical costs, primary care costs, general medical visits, and primary care visits than did individuals in either control group (p-value<0.01).

ACT consumers were significantly younger (42 compared with 42.6 in the potential ACT group and 46 in the SMI group, p-value<0.05) and were more often male (53% compared with 42% in the potential ACT group and 41% in the SMI group, p-value<0.01), but there were no significant differences in race. Individuals on ACT teams lived in areas with fewer Medicaid eligibles per thousand population and more mental health professionals per thousand population, as well (p-value<0.01). Fewer individuals in the potential ACT group were on Medicare (33%, compared with 53% on ACT, p-value<0.01). ACT team consumers had higher rates of schizophrenia (57% compared with 39% in the potential ACT group and 38% of those with SMI, p-value<0.01), but had significantly lower rates of all other mental disorders than those in the potential ACT group (p-value<0.01).

Table 2 provides similar information as did Table 1 separated by place of residence: rural, mixed and areas. During the period of interest, Medicaid spending was lowest for individuals on ACT living in rural areas ($31,255 compared with $41,037 in urban areas;p<0.05). Everyone in the sample had at least some costs in the Medicaid claims files.

Spending on emergency room visits was not statistically different among place of residence categories (between $2,520 and $3,326 for everyone in the sample, between $4,071 and $4,357 for those who ever had any costs).

Individuals in mixed areas had the highest costs for general medical costs ($2,306), which was statistically different from those in urban areas ($1,662, p<0.05). The same pattern was true of primary care costs (mixed areas = $174; urban areas $126, p<0.05). Individuals in rural areas had the highest percentage of ever having any primary care costs (74% compared with 55% in mixed areas and 47% in urban areas, p<0.05).

Inpatient psychiatric costs did not differ significantly by place of residence ($3,105 for rural areas; $3,415 for mixed areas and $3,028 for urban areas).

People on ACT had between 3.8 and 5.9 emergency room visits over the three-year study period. Here again, mixed and urban areas have statistically significant differences in the number of ER visits (p<0.05). The same pattern was true for general medical visits, 39 for those living in mixed areas and 30 for those living in urban areas

($p<0.05$), and for primary care visits, 3.9 for those in mixed areas and 2.6 for those in urban areas ($p<0.01$).

The number of inpatient psychiatric visits did not differ by place of residence.

Individuals were on ACT in rural areas for the shortest amount of time (7.4 months compared to 16 for those in urban areas, $p<0.01$) (p=0.000). The average age of people on ACT was between 42 and 43, and a majority of the sample in rural and mixed areas was female, while a majority of the sample in urban areas was male. About half of the sample was white, and about one-third of the samples in mixed and urban areas were black, while only 10% of those in rural areas were black.

More than 90% of individuals in all places of residence qualified for Medicaid via the Blind/Disabled category.

Individuals in rural areas on ACT lived in counties with more Medicaid eligibles and fewer psychologists per thousand population than did individuals in mixed or urban areas ($p<0.01$); and they also had the fewest psychological associates and psychiatrists per thousand per county when compared with mixed and urban areas.

About half of all ACT participants were on Medicare, but only a small portion of the sample were in the SLMB category (<1%). Individuals on ACT had between 0.69 and 1.1 comorbidities, on average, over the three-year period of interest when measured using a comorbidity index developed specifically for psychiatric research using administrative data (Ricci, Dorfman et al. 2001). The most common diagnosis was schizophrenia (50% in rural areas compared with 59% in urban areas, $p<0.01$), and individuals in urban areas had significantly ($p<0.05$) fewer psychoses and other mental disorders than did individuals in mixed areas and significantly ($p<0.05$) fewer personality disorders than did individuals in rural areas. More individuals in urban areas (36%) were on established ACT teams when compared with individuals living in mixed (1.3%) and rural (0.0%) areas.

Individuals in the potential ACT control group had higher costs ($55,785-$60,388) than those in the SMI control group ($31,381-$32,086) (Table 3). Almost everyone in the sample had some costs (approaching 100% for all places of residence in both control groups).

Emergency room costs were lowest in rural areas, and a smaller proportion of individuals in rural areas ever had any emergency room costs. General medical costs were higher for those in the potential ACT consumer group ($4,789-$5,381) than those with SMI ($2,787-$3,025). The same was true for primary care costs and inpatient psychiatric care costs. Only about a quarter of the SMI sample ever had any inpatient psychiatric costs, while over 90% of the potential ACT consumer group did. The same patterns were true of the number of visits.

Individuals in both control groups were, on average, in their 40s, and about half of both samples were white. Because we only included individuals in either control group if they were eligible via the Blind/Disabled category of Medicaid, no one in either sample was eligible via any other category.

Controls living in rural areas also lived in counties with more Medicaid eligibles and fewer psychologists per thousand per county than those living in urban areas. About 30% of the potential ACT consumer group was on Medicare, while almost 50% of the SMI sample was. Individuals had, on average, had one comorbidity.

The number of Medicaid eligibles per thousand per county was negatively related to ACT receipt in all county types in multivariate analyses (Table 4). Schizophrenia is often positively associated with treatment, as well.

The number of the psychiatrists per thousand population did not significantly affect treatment receipt, except in rural areas when compared with those with SMI (β=7.6; se=3.4; p<0.05). The number of psychologists was positively related to treatment in mixed areas, and the same pattern was true of psychological associates in urban areas.

In the sensitivity analyses where we collapsed individuals using their maximum ("ever") values on all variables and where we collapsed everyone using their minimum ("always") values on variables but did not include the longest place of residence as a factor, we found similar results in relation to the magnitude and direction of the significant findings as compared with those presented in Table 4. A few exceptions existed, however. In the "ever" model of individuals in the potential ACT group, the relationships between ACT and black individuals as well as the relationship between ACT and the number of Medicaid eligibles per thousand population in the urban sample became insignificant, while drug abuse (β=-0.33, se=0.14; p<0.05), alcohol abuse (β=-0.44, se=0.14; p<0.01), and bipolar disorders (β=-0.38, se=0.13; p<0.01) became significant. The number of psychologists (β=-9.6, se=3.7; p<0.01), psychological associates (β=-8.5, se=3.5; p<0.05), and psychiatrists (β=25, se=5.5; p<0.01) per thousand per county was significant in rural counties, while the number of comorbidities per person was insignificant in the same area. The fewest changes occurred in mixed areas, where the number of psychological associates per thousand per county (β=-3.8, se=1.6; p<0.05), the number of comorbidities (β=-0.108 se=0.049; p<0.01), and the constant (β=2.07; se=0.79; p<0.01) was significant.

In the "ever" models for individuals with SMI, several of the variables in the urban models changed. The number of Medicaid eligibles per county, the number of comorbidities, and personality disorders was insignificant, while Black (β=-0.197; se=0.087; p<0.05), the number of psychologists per thousand population (β=1.39; se=0.63; p<0.05), Medicare (β=0.217 se=0.079; p<0.01), and other mental disorders were significant (β=0.191; se=0.082; p<0.05). In mixed areas, age was insignificant, and other mental disorders were significantly related to treatment (β=0.517; se=0.178; p<0.01). In rural areas, the only significant difference was that the number of psychologists per thousand per county was significant (β=-11.4; se=2.6; p<0.01). The coefficient on the number of psychiatrists per thousand was also much larger, although still significant (β=22.3; se=4.4; p<0.01).

The other "always" models (that did not account for longest place of residence) had significant findings that were similar in direction and magnitude for all variables, except for psychoses for those in urban areas on potential ACT teams, which were insignificant, and age in rural areas for those with SMI, which was significant (β=-0.039; se=0.020; p<0.05).

When looking at relationships between covariates and the number of months on ACT (Table 5), the number of Medicaid eligibles per thousand per county was always positively and significantly related to number of months on ACT. As shown in Table 4, although individuals living in counties with more Medicaid eligibles were less likely to receive treatment, here we found that individuals who lived in these counties stayed on

ACT for small, but significantly longer periods of time than do their counterparts in counties with lower numbers of Medicaid eligibles. This was true in the other sensitivity analyses, as well, except for those living in urban areas when we used the "ever" values to collapse all variables. There we found a coefficient of -0.0200, with a standard error of 0.0068 ($p<0.01$).

The relationships between the number of mental health professionals per thousand per county and the number of months on ACT suggest that having one more psychologist or psychological associate in urban and mixed areas per thousand, respectively, decreases the number of months an individual spends on ACT by 17 to 20 months (i.e., for a county of 10,000, hiring one more psychological associate would suggest that an individual would stay on ACT for two more months), respectively. However, more psychological associates or psychiatrist per county increases the number of months on ACT in urban areas. The numbers suggest that, for example, for a county of 10,000, hiring one more psychiatrist would increase the number of months on ACT by 4.1 months. These findings were true in the sensitivity analyses as well, with one exception—when looking at only the "always" values without considering longest residence, the number of psychological associates per thousand per county was insignificant.

Low-income dual eligibles (SLMB) spent about seven fewer months on ACT than those not in this category in urban areas, and being on an established ACT team in urban areas was associated with an increase in the time an individual spent on ACT (about 5 months), although being on an established team in a mixed area was associated with about 4 less months on ACT. The coefficients on the established team variables were similar in the sensitivity analyses, although one model suggested that the value for those living in mixed areas was not significantly related to number of months on ACT: in the "always" models, the coefficients were mixed (β=-3.5; se=1.8; $p<0.05$) and urban areas (β=4.85; se=0.43; $p<0.01$), and in the "ever" models, the coefficients were mixed (β=-2.3; se=2.7; $p>0.05$) and urban (β=2.66; se=0.96; $p<0.01$).

As noted, the findings from the sensitivity analyses were similar in relation to the direction and magnitude of significance as shown in Table 5, with the exceptions noted above and the following differences, although the other models were much less significant in general. In the "ever" models, several variables that were significant in Table 5 were insignificant: unknown race in rural areas; Black race, alcohol abuse and other mental disorders in mixed areas; Medicare in mixed and urban areas; and bipolar disorder, psychoses, and schizophrenia in urban areas. In the "always" models, the following variables became insignificant: the number of months on Medicaid in rural areas; Hispanic, the number of comorbidities, and other mental disorders in mixed areas; and psychological associates and psychoses in urban areas. The only variable that was more significant was the number of psychologists per thousand population in rural areas (β=89; se=33; $p<0.05$).

The predictions (not shown in Tables) suggest that individuals living in mixed areas stayed on ACT for the shortest periods of time, and those in urban areas were on ACT for the longest periods of time. For example, the models predicted that a 46-year old white female who qualified for Medicaid through the disabled category and who was on Medicaid for 10 months, had schizophrenia and lived in a county with 167, 0.15, 0.10, and 0.088 Medicaid eligibles, psychologists, psychological associates and psychiatrists per thousand population, respectively, would be on ACT in rural areas for about 7 (bsse=4.2) months, in mixed areas for about 6 months (bsse=1.3), and in urban areas for almost 13 (bsse=1.1) months.

Health Services Use and Costs

The percent of the quarter an individual was on ACT was associated with an increase in the likelihood that an individual would have any costs during the quarter and increased the total average costs, given any costs, for the quarter (β=1,754; se=85; *p*-value<0.01) (Table 6). Being on Medicare or SLMB was significantly associated with reduced total costs or the likelihood of any costs, respectively, but the number of comorbidities was associated with significant increases in costs and the likelihood of costs. All of the specific comorbidities shown here were significantly associated with increased total costs (given any costs), as well, with psychoses showing the largest magnitude (β=783; se=92; *p*-value<0.01). When using the larger control group of individuals with SMI (not shown here), the findings were similar in relation to the direction and magnitude of significant findings (including the coefficients on percent quarter on ACT for likelihood of total costs (β=0.0726; se=0.0049; *p*-value<0.01) and total costs (β=$1,836; se=81; *p*-value<0.01)), although the following exceptions apply. The number of psychological associates per thousand population was associated with decreased total costs (β=-$1,184; se=321; *p*-value<0.01), the number of psychiatrists per thousand per county was associated with the likelihood of costs (β=0.051; se=0.022; *p*-value<0.05) and increased total costs (β=1,086; se=464; *p*-value<0.01), Medicare was associated with the increased likelihood of total costs (β=0.0160; se=0.0024; *p*-value<0.01), and being on SLMB was associated with decreased total costs (β=-258;

se=90; *p*-value<0.01). All of the comorbidity values were associated with significant increases in the likelihood of total costs and total costs, as well.

ACT was associated with decreases in the likelihood of any ER costs (β=-0.020; se=0.010; *p*-value<0.05), although ER costs among ER users were unaffected by the time spent on ACT (Table 7). Being on Medicare or SLMB was associated with significant decreases in the likelihood of ER costs. As in total costs, all variables relating to comorobidities were almost always associated with increases in the likelihood of and total ER costs. Again, the sensitivity analyses from the larger (SMI) control group, which may be less ill, showed similar magnitudes and directions for significant variables, although the association between likelihood of ER costs and the percent quarter on ACT was insignificant, although it was a negative value (-0.017).

The only differences were that the number of psychological associates per county and being on Medicare were significantly associated with fewer ER costs; and the number of Medicaid eligibles was significantly associated the likelihood of any costs.

The percent of quarter an individual spent on ACT was associated with a decrease in the level of general medical costs among users of general medical services in the quarter, although the likelihood of any general medical costs and primary care costs were unaffected by the percent of quarter spent on ACT. Being on Medicare and qualifying as SLMB was associated with reduced costs and the likelihood of general medical costs, respectively. The number of comorbidities, bipolar disorder, and psychoses were positively and significantly related to general medical costs, as well; schizophrenia was associated with the likelihood of any general medical costs. For primary care costs, only the number of comorbidities had any affect at all on the likelihood of primary care costs or primary care costs.

When looking at the larger control group of anyone with SMI for general medical care, the coefficient on percent quarter on ACT was similar in direction and magnitude, but the following differences were found in other variables, as the models from this larger control group of SMI were generally more significant than those shown in Table 7. The coefficient on SLMB was negative and significant (β=-113; se=40; p=value<0.01), all of the comoribidities, except for drug abuse and schizoaffective disorders, were positively and significantly associated with the likelihood of any costs. Other mental disorders and personality disorders were significantly associated with general medical costs. For the likelihood of primary care in the larger SMI control group, the coefficients on percent quarter on ACT were similar in direction and magnitude to those shown in Table 7, but most other covariates were significantly related to the likelihood of any costs, except for the eligibility category, the number of Medicaid eligibles per thousand per county, the number of comorbidities, alcohol abuse, and other mental disorders. For primary care costs, Medicare was associated with a significant decrease in costs (β=-12.3; se=2.8; p=value<0.01) and several comorbidity variables were associated with significant increases: other mental disorders, personality disorders, and depression/schizoaffective disorders.

The percent quarter someone spends on ACT was negatively and significantly associated with the likelihood of any inpatient psychiatric costs, but not with inpatient costs. Being on Medicare was associated with a decrease in inpatient psychiatric costs. As in the other models, many of the comorbidities are highly significantly associated with increases in the likelihood of inpatient care costs and inpatient costs. The only difference in the sensitivity analyses using the larger control group of individuals with any mental illness was that the number of psychiatrists per thousand population and three of the comorbidities (personality, depression/schizoaffective disorders, and schizophrenia) were not significantly associated with inpatient psychiatric costs.

Predicted values (not shown in tables) indicate the magnitude of the result. For someone who was on ACT, we would expect total costs, ER costs, general medical costs, primary care costs and inpatient psychiatric costs to be $5,027(bsse=$168), $123 (bsse=$344), $898 (bsse=$105), $91 (bsse=$12), and $2,402 (bsse=$526), respectively, conditional on any use. For a similar person who was never on ACT (compared with the Potential ACT Consumer group), we would expect the same costs to equal $3,273 (bsse=$175), $334 (bsse=$302), $1,171 (bsse=$132), $102 (bsse=$9.20), and $2,592 (bsse=$448), respectively. This suggests that predicted total costs, given any use, for the sample person described above would be about $1,754 more for someone on ACT than for someone not on ACT. The marginal effect of being on ACT for a full quarter increases an individual's total costs by $2,177 (bootstrapped standard error = $93) over someone who was not on ACT for that quarter when compared with the potential ACT group. Other marginal effects were as follows: emergency room costs: -$51 (bsse=$48); general medical costs: -$111 (bsse=$24); primary care costs: -$2.30 (bsse=$2.45); and inpatient psychiatric care costs: -$51 (bsse=$38). As noted, no differences were found between ACT and the control group for ER, primary care and inpatient psychiatric costs.

Two other sensitivity analyses (Table 8) were run to determine whether different values for the independent variable of interest would change the relationships between that covariate and the outcomes of interest when compared with the relationships between the percent of quarter on ACT and the outcomes of interest. The first models examined whether there were differences between established and non-established ACT teams using the following categorical variables: percent time on an established ACT team, which was the percent of the quarter on an individual had received services from an established ACT team; percent time on an ACT team that was not established, which equaled the percent of quarter on an individual was on an ACT team that was not established; and not on an ACT team. We ran this for the control group of individuals with SMI. The second models examined whether percent time on ACT made a difference in spending when compared with a variable that smoothed over gaps of two months or less on ACT; here we recoded the Percent Quarter on ACT variable to equal one if individuals spent more than half of the month on ACT and zero otherwise. We ran this on the control group of individuals with SMI and the control group of those in the Potential ACT group.

Table 8 shows the coefficients on the established team variables, as well as the t-tests that indicate whether being on an established ACT team differs from being on a team that was not established. The coefficients on the percent of the quarter that an individual was on an established ACT team or on a team that was not established were very similar to the percent quarter on ACT variable presented in Tables 6 and 7. The direction and significance of the variables were all similar, although magnitudes were different, except in two cases. First, the established team variables were not related to the likelihood of ER costs. Second, being on an established ACT team was not associated with a significant decrease in general medical costs (β=-62; se=72; *p*-value>.05) although being on an ACT team that was not established was (β=-265; se=52; *p*-value<.01). The t-tests suggest that there are only significant differences between those on established ACT teams and those on ACT teams that are not established for the likelihood of any costs, total costs, the likelihood of any general medical costs, general medical costs, and the likelihood of any inpatient psychiatric care costs.

The sensitivity analysis which examine whether percent time on ACT made a difference in spending when compared with a variable that smoothed over gaps in ACT services produced similar results to the models shown in Tables 6 and 7. For both the sample of everyone with SMI and those in the potential ACT consumer group, all of the models suggest similar relationships (including magnitude, direction and significance) between the independent variable of interest and the outcomes as shown in Tables 6 and 7, although the likelihood of any ER costs was not significantly affected by the percent of time on ACT when compared to those with SMI.

The models in Table 9 show that being on ACT was always positively and significantly related to the likelihood of total costs and total costs, regardless of place of residence. The SMI control group, which is not shown here, reports similar magnitudes, direction and significance levels on the percent quarter on ACT variables for both parts of the model, although the percent quarter on ACT was not associated with any use in rural areas in this sample. In both control groups (SMI not shown here), the largest effects of ACT on total Medicaid costs were found in mixed areas, with rural areas having the smallest effects, although the likelihood of any costs was greater in urban areas in both control groups. The covariates show us other differences between places of residence, as well. Having more psychologists or psychiatrists per thousand per county was associated with decreases in total costs and increases in the likelihood of any costs, respectively, for those living in mixed areas. The number of comorbidities was associated with an increase in total costs in mixed and urban areas, as were many of the mental health comorbidities. The number of comorbidities and most of the different mental health diagnoses were significant in the SMI control group model (not shown here).

Predictions of the level of use, conditional on any use, from these models (not shown in tables) indicate that total spending for those on ACT in rural areas is usually less than that in other areas. Specifically, for the sample person who was not on ACT (compared with those in the potential ACT group), total costs were as follows: rural ($1,643; bsse=$2463), mixed ($3,009; bsse=$374) and urban ($3,152; bsse=$225). For a similar person on ACT, the following costs were predicted: rural ($3,161; bsse=$2,240), mixed ($4,952; bsse=$557), and urban ($4,917; bsse=$240).

Although the pooled samples indicated that the percent of quarter on ACT was associated with the likelihood of greater total costs, Table 10 suggests that this is only true in mixed and urban areas for those with SMI. In addition, we find that the significant associations between ACT and the likelihood of ER costs are being driven by the urban model. Urban areas also appear to be driving the significant decreases that were shown in other tables in the likelihood of inpatient psychiatric care. The table also suggests that individuals on ACT in rural areas, when compared with the SMI group, have a decreased likelihood of any general medical costs.

We find that percent quarter on ACT was significantly related to a decrease in the number of ER and general medical visits, but is not related to the number of primary care visits when compared with individuals with SMI (Table 11). None of the findings related to the percent of quarter on ACT were significant, however, in the potential ACT consumer group (not shown here). The number of comorbidities was significantly associated with increases of any ER and primary care visits. All of the mental health comorbidities used here were positively associated with increases in ER costs, although the same variables were often, but not always, significantly related to general medical or primary care visits.

When looking at the effect of ACT on ER visits (Table 12), we find that the differences found in Table 11 are being driven by urban ACT team. Again, the results, when compared with those in the potential ACT group, were not significant, although we were unable to determine if there were differences in ER costs for those in the potential ACT group in mixed areas because of a convergence complication. Mental health comorbidities are often positively associated with ER visits.

The percent of time on ACT negatively affects general medical visits for those in ruraland urban areas when compared with those on SMI (Table 13), although percent of time on ACT positively affects general medical use for those on ACT when compared with potential ACT consumers in urban areas ($\beta=0.084$; se=0.040; $p<0.05$) (not shown here). Being Hispanic or of other race often increases the number of general medical visits, when compared with whites, when looking at everyone with SMI, as does having more psychiatrists per thousand per county.

In the models shown in Table 14 and in the models compared with the potential ACT consumer group (not shown), the independent variable of interest – percent quarter spent on ACT – is not significantly associated with primary care visits. The number of psychologists per thousand per county was negatively and significantly associated with primary care visits in rural areas, and positively associated with the same outcome for those in mixed areas when looking at everyone with SMI. Being on Medicare had a negative and significant impact on primary care visits in almost all of the models.

Propensity Score Analyses

The regression models that were used to create the propensity score are described in Tables 15 and 16. We separated the sample based on several mental health comorbidities and urban and non-urban place of residence in order to achieve balance in the covariates. As the tables show, the coefficients are relatively small; although the number of psychiatrists per thousand population seems to be one of the most highly significant indicators of treatment.

The findings from the propensity scores and the Wilcoxon rank sum tests (Tables 17 and 18) suggest that more of the outcome variables show significant differences between ACT and non-ACT teams than the other analyses were showing. When the sample was pooled across all counties of residence and compared to a group of individuals with SMI (Table 17), ACT was shown to increase total, general medical, primary care, and inpatient psychiatric costs and decrease ER costs; the same patterns were true of visits. In rural areas, the only significant ($p<0.05$) findings were associated with increases in total costs and decreases in inpatient psychiatric costs and visits. In mixed areas, ACT was associated with increases in total and ER costs, but decreases in inpatient psychiatric costs and visits. Finally, in urban areas, ACT was significantly associated with all variables with the same patterns noted in the full sample.

However, upon closer examination, we find that we find that many of these models are highly sensitive to even small amounts of unobserved heterogeneity as is shown by the results of the Rosenbaum bounds tests. The analysis suggests that a hidden bias would have to increase the odds of changing total costs by a factor of two in order to change the significance of this finding. The one exception in the full sample is related to emergency room use. A hidden bias here would have to increase the odds of changing ER costs or ER visits by a magnitude of greater than five or four, respectively, in order to change the significance of this finding. Small gammas were reported for most of the other outcomes in the full model, as well. This suggests, besides ER costs and visits, these analyses are all very sensitive to hidden bias, therefore the effects shown here may be related to some unobserved bias instead of ACT alone. Potential unobserved bias appears to be a challenge in the rural models and the mixed models, as well. The findings from the urban areas are a little more robust, suggesting again that the decreased ER costs and visits associated with ACT team treatment are insensitive to unobserved bias. The other findings, although similar to those in the full model, are significant when gamma=1 or gamma=2, which suggests these models might be more easily affected by unobserved bias.

Although the first propensity score model shown in Table 17 was run on quarterly data using fixed effects to determine the propensity score, we also ran two collapsed person-level models without fixed effects to test the sensitivity of our results to the chosen model specification: an LPM model based on the potential ACT consumer group and a probit model based on the potential ACT consumer group.

The findings from the sample not separated by place of residence (Table 18) suggests that, when individuals on ACT are collapsed at the person level and compared to a group of similar people without ACT, the total costs actually decrease ($p<0.01$), although it should be noted that the Rosenbaum bounds here are significant at gamma=1, which suggests a high level of potential unobserved bias which could be affecting this estimate. In the full sample, we also found that being on ACT decreases costs and visits in all other categories (except for primary care costs in rural areas), and most of these dependent variables are significant where gamma>=2, except for the total cost and primary care variables. The place of residence models suggest that most of the significant effects are being driven by the urban and mixed areas, as only ER costs, and inpatient psychiatric costs and visits are significant at $p<0.05$ in rural areas. Here, though, for ER costs, the Rosenbaum bounds are small, which suggests that these relationships may not be all that strong, but the case of inpatient psychiatric care is different and suggests a higher level of insensitivity to unobserved bias. These same patterns associated with inpatient psychiatric care emerge in mixed areas, as well. Although ACT is associated with other outcomes in mixed areas, these are all highly sensitive to unobserved bias. In urban areas, again ACT is negatively and significantly associated with all of the outcomes of interest, except total costs where $p=0.0625$, and the gamma is often greater than or equal to two for these variables.

The results from the Wilcoxon rank sum statistics for the probit model suggest the same patterns in terms of magnitude and direction of significance as were noted in Table 18 and are therefore not presented here. The only notable difference between the two models was that a few of the primary care probit models showed slightly more significant results in mixed and rural areas, with bounds increasing by one point from zero to one (e.g., primary care visits in mixed areas was associated with a Wilcoxon Rank Sum Z-statistic of -2.42, which is significant at p=0.0155, and the Rosenbaum bound was equal to gamma=1). In urban areas, Wilcoxon rank sum statistic for primary care costs became insignificant. It should be noted that these differences probably result from the fact that the Rosenbaum tests show that these models are highly sensitive to unobserved bias.

Chapter VII: Discussion and Policy Implications

To our knowledge, this is the first study that has looked at the costs of ACT or ACT-like models in a real-world, uncontrolled setting across tens of ACT teams throughout such a large geographic area. The findings from the main models shown here suggest that ACT increased total costs, but decreased the likelihood of emergency room use and inpatient psychiatric care – and costs associated with these services, which is in line with the literature as discussed below. Therefore, ACT in NC appears to be doing what it was designed to do with regard to health services use and costs as defined by previous research and theories about ACT, although it is more costly than other forms of care.

Methodology

In order to better understand what may seem like some conflicting results, however, we first should look more closely at the different methods used here to analyze these data.

As noted in the results section, there were differences found in the different models, especially between the propensity score models compared with all of the other models. First, it should be noted that in the collapsed person-level analyses, we are aggregating individuals with varying levels of ACT exposure, including months not on ACT, to a three-year total. This model is therefore distinct from the person-quarter analyses, where we are looking solely at the time spent on ACT as an indicator of health services use. Therefore, in the collapsed person-level models, the findings may not necessarily be associated with ACT, but with other individual level fixed effects, such as the months an individual spent while *not* on ACT. For example, it could be that individuals who are on ACT in some quarters have far lower costs in the months they are not on ACT than do the controls, and this could be driving the findings. This, in and of itself, could explain the differences in findings between these models. These findings could also be associated with other individual-level factors that affect selection into ACT treatment.

Another thing to note here is that the main differences that emerge are related to the total cost and general medical models. For example, most of the analyses suggest that ACT increases total costs, while the collapsed person-level propensity score analysis suggests that persons on ACT have lower total costs. However, for these models where there might be questions, it is important to look at the results of the Rosenbuam bounds; for total costs, for example, the collapsed person-level model (gamma=1) is more sensitive to unobserved bias than is the fixed effects model (gamma=2). These findings suggest what was stated above – the collapsed person-level models may suffer from unobserved biases. Therefore, for total costs, it is more likely that time spent on ACT is increasing total costs. All of these findings are discussed in more detail below.

Overview of Total Costs

In the multivariate regression analyses, ACT was associated with increases in total costs that were between $1,187 (from the propensity score analysis based on person-quarter estimates) and $2,177 (the difference between the predicted values of a sample person on ACT and not on ACT) per quarter. The final model, based on the collapsed person-level propensity scores, suggested an opposite trend – that the costs could be as much as $20,309 lower for those on ACT over the three-year period (about $1,692 per quarter) for individuals on ACT. However, as noted above, these findings were highly sensitive to unobserved bias and are measuring different things (percent of quarter on ACT versus having ever been on ACT). Therefore, it appears that ACT is significantly related to increased total costs.

However, these increased costs should be placed within the context of previous literature and the payments being made to ACT teams during the study period. The payments for ACT consumers during the study period started out in the beginning of 2000 at $590/per person/per month and increased every few months until it was $828 at the end of the study period. This suggests that, even at the most expensive point, ACT cost $2484 per quarter per person. With that in mind, even if the costs are as high as $2,177 per quarter more for ACT (the highest estimate we found in our data), ACT seems to be at least partially paying for itself.

In addition, previous research suggests that ACT should not necessarily increase total costs, but notes that this is true only if ACT is targeted to the correct consumer group (Latimer 2005). Latimer notes, for example, that ACT can offset total costs if an individual would otherwise spend a large amount of time in the hospital. Therefore, if costs are increasing here, as the data seems to suggest, better targeting of consumers could assist in making the program even more cost-effective.

Whether or not ACT costs are too high or too low or just right is a subject of ongoing concern. Some teams in North Carolina have suggested that it costs as much as $1,850 per month ($22,200 per year) to care for ACT patients (Bonner 2008) currently. However, these costs are not necessarily in line with previous research, which suggests that ACT should cost between $9,000 and $12,000 per consumer per year (Substance Abuse and Mental Health Services Administration 2003; Latimer 2005).

However, within this context it should be noted that higher expenses may be leveling the playing field for those with SMI and potentially decreasing longer-term costs. Previous research suggests that people with SMI often have higher rates of chronic conditions and poorer physical health (Chwastiak, Rosenheck et al. 2006; Joukamma, Heliovaara et al. 2006; Cuddeback, Scheyett et al. 2009) than those in the general population, and unfortunately these needs often go unmet (Salsberry, Chipps et al. 2005).

Although we cannot be certain that this type of increased need would be driving expenses noted in our analyses, it can be inferred from previous research that absent an ACT team, individuals with SMI in North Carolina are most likely underserved. In addition, this study did not look at societal costs, but when societal costs have been considered for ACT in previous research, findings suggest that ACT is no more expensive than standard treatment (Burns 1998; Clark, Teague et al. 1998; Drake, McHugo et al. 1998). Previous research suggests that ACT can even be cost-effective in a variety of settings (Clark, Teague et al. 1998; Essock, Frisman et al. 1998; Lehman, Dixon et al. 1999) and only a few studies have found higher total costs associated with ACT (Borland, McRae et al. 1989; Chandler, Hu et al. 1997; Latimer 1999). Therefore, even though the use of ACT teams in this study was associated with higher costs, ACT is likely promoting positive outcomes for some of the most underserved consumers and possibly reducing societal costs. A formal cost-effectiveness analysis based on these data combined with clinical data would provide a better picture of the cost versus the benefits and the potential long-term cost savings of this approach to care.

In addition, previous research has noted that many of the early findings on cost savings for ACT were noted when liberal state psychiatric hospitalization policies were in use (Burns 1998). Burns notes that in states where these high costs services have already been decreased and the base payments for individuals with severe mental illness is already low, payors should not expect to see the high savings seen in previous studies (Burns 1998; Essock, Frisman et al. 1998). Burns suggests that costs may be shifting from state-funded hospitals to jails and/or emergency rooms. The worst case scenario is that care for these individuals is being neglected completely (Burns 1998).

ACT and Other Services Use and Costs

Our analysis suggests that this cost-shifting hypothesis – at least for emergency rooms – may be happening in North Carolina. If individuals not on ACT were using emergency room services instead of inpatient care, we might expect ACT to decrease emergency room use and costs. We found that ACT in North Carolina did just that – ACT was associated with decreases in the likelihood of any emergency room use, as well as emergency room costs and visits. These findings are not unusual. In Latimer's (1999) extensive review of ACT studies, he found that several studies report a significant reduction in emergency room use due to ACT (Stein and Test 1980; Quinlivan, Hough et al. 1995).

ACT in our analyses also had the expected effect on hospital use – it reduced the likelihood of any inpatient psychiatric stay and inpatient psychiatric costs (when looking at the collapsed person-level models which were highly insensitive to unobserved bias). Reduction of time spent in the hospital is one of the most consistent findings in the literature (Burns and Santos 1995; Latimer 1999; Marshall and Lockwood 2000; Bond, Drake et al. 2001). It should be noted that studies where the comparison group is some form of case management report smaller reductions in hospital days when compared with ACT than do pre-post studies (Latimer 1999). In all control groups we probably have individuals receiving some form of case management for psychiatric symptoms; therefore it is interesting to see that even with what might be an important factor in decreasing the effect of ACT in this domain, ACT still performed as expected. Future research could look more closely at this issue by using the procedure codes available in these claim files to select a control group to compare with ACT.

The findings related to general medical costs were not necessarily in line with the literature, however. Latimer (1999) notes that ACT should in theory decrease the use of outpatient services, since many of those services should be provided by the ACT team, but his study, like our analyses, did not find those significant relationships in his literature review. When compared to those in the potential ACT consumer group, we found that percent of time on ACT was related to an increased number of general medical visits for individuals when compared with the potential ACT consumer group in urban areas, although we found that the costs per user decreased, which may mean that ACT consumers get more, but less intensive visits. When the ACT sample was compared with individuals with SMI, we find that ACT use was associated with a decrease in the number of general medical visits. The fixed effects propensity score analyses suggest that ACT was increasing general medical costs and visits, and the collapsed person-level model suggest that ACT decreased general medical costs and visits. However, it should be noted that the bounds around the person-level fixed effects are quite small (gamma=1), which suggests that this finding might be sensitive to unobserved bias. The bounds around the collapsed person level model are a little larger (gamma=2), but as noted above, this model is not necessarily measuring time spent on ACT; it is measuring having ever been on ACT, which includes the months an individual was not on ACT. Therefore, although we can say that having ever been on ACT may likely reduced general medical costs and visits, we are unable to make many definitive statements about the relationship between ACT and general medical costs.

The findings for primary care costs and visits were rather ambiguous, as well. The multivariate regression models suggest that ACT does not significantly affect these outcomes, yet when matched in the propensity score models, the relationships between ACT and these variables become more significant. In the first propensity score model which matched ACT individuals to those with SMI, the findings suggested that ACT significantly increased primary care costs and visits when compared with the control group, yet these findings were highly sensitive to unobserved bias, even when separated by place of residence. The findings from the collapsed person-level model, however, tell a different story; in these models, ACT was associated with significant decreases in primary care costs and visits, but the findings are still highly sensitive to unobserved bias. Therefore it is difficult to make any definitive statements about how ACT in North Carolina relates to use of primary care during this time-period.

Rural/Urban Differences

In our analyses, we found that there were definite differences based on place of residence, although the mechanism driving differences between urban and rural areas was unexplored. More specifically, individuals in rural and mixed areas spend the least amount of time on ACT; people on ACT in rural areas live in counties with fewer mental health professionals and more Medicaid eligibles; and 74 percent of those in the potential ACT consumer group live in rural or mixed areas compared to 26 percent in the ACT sample. This final statistic suggests that individuals living in rural or mixed areas may need ACT but are not getting access to these services. Similarly, individuals in the potential ACT consumer groups live in counties with more Medicaid eligibles and fewer mental health professionals than those on ACT, and the number of Medicaid eligibles per thousand per county was negatively and significantly related to ACT treatment for all places of residence, suggesting that the more people on public assistance in a county, the less likely they are to receive ACT.

These differences suggest that ACT is being provided in well-resourced counties, and the counties that may need these services the most (i.e., the counties with the fewest mental health professionals and those with the most Medicaid eligibles) are not always getting them. Although this was expected, it underscores the challenges in care for rural and mixed areas. Yet, interestingly, once an individual was on ACT in a county with more Medicaid eligibles, she stayed on ACT for a longer period of time than her counterparts in counties with fewer Medicaid eligibles.

When looking at the multivariate regression models, we found that being on ACT in urban areas was associated with a significant decrease in the likelihood of any emergency room and inpatient psychiatric costs, although this was not true in the other places of residence. When looking at the propensity score models, high levels of potential unobserved bias were observed when compared with the SMI group for mixed and rural areas on the number of emergency room and inpatient psychiatric visits and for urban areas on the number of inpatient psychiatric visits. In the urban model, ACT appears to decrease emergency room uses and costs. The final model, the collapsed person-level propensity score analysis, suggests that, in all places of residence, ACT appears to decrease inpatient psychiatric visits even when subject to a high level of unobserved bias. Together these findings suggest that ACT has little or no effect on emergency room use in rural and mixed areas, but can decrease inpatient psychiatric care in these areas, and that in urban areas, ACT is associated with decreases in emergency room use and inpatient psychiatric care.

This finding represents a success for ACT in decreasing high cost inpatient psychiatric care in rural, mixed, and urban areas, but the finding related to emergency room use (i.e., rural and mixed areas see no effect while ACT decrease ER use in urban areas) deserves more research because, as noted above, individuals in rural areas are often living in areas with fewer resources (i.e., counties with fewer mental health professionals), and therefore may suffer from differences in access to care (and therefore may use the emergency room more often). ACT provides one opportunity to eliminate at least some of these differences in access, yet our study suggests that, during 2000-2002, ACT teams were not yet able to achieve this goal with regard to emergency room use.

With the aforementioned changes in the new service definitions for ACT teams in North Carolina, however, there is the possibility that these differences may now be eliminated; more research is needed.

Established ACT Teams

Yet all of these findings beg a question that is at the core of this analysis and any analysis on ACT: are these really ACT teams? Or, in other words, what exactly are we studying? During the study period, Medicaid was paying service providers at a stated ACT team rate, but what type of care were the individuals actually receiving?

This question is not new in the literature. As Morrissey and colleagues (Morrissey, Meyer et al. 2007) noted recently, the concept of ACT has diffused much more rapidly than the practice of ACT. After pressure by national and state governments and publications in the 1990s, “ACT” programs were implemented all over the country, but often lacked many of the necessary ingredients, including specific structure and staffing requirements (Morrissey, Meyer et al. 2007).

This is where fidelity comes in. Fidelity scales can show whether ACT programs are true ACT programs or some form of case management (Teague, Bond et al. 1998), but even with these scales, it is difficult to parse out which elements of ACT are precisely linked to positive outcomes (Morrissey, Meyer et al. 2007). Thus, the implication is that ACT-like models often produce diminished outcomes or no effects at all (Morrissey, Meyer et al. 2007).

In our analysis, the main finding of interest related to fidelity was that being on an established ACT team seemed to significantly increase the number of months individuals in urban areas stay on ACT, although those effects were not seen in mixed areas. Individuals on established teams incurred significantly fewer general medical costs than did those on non-established teams, and established teams were more likely to have any total costs, but lower costs given any costs, and a lower likelihood of any inpatient psychiatric care than those on non-established teams.

As noted above, Latimer (1999) suggests that ACT should in theory decrease the use of outpatient services, but we would expect any significant findings in this area to be related to established teams. However, as noted above, ACT in North Carolina may be operating in a resource-poor setting where other forms of psychiatric care are less available. In this situation, we might expect ACT to increase general medical care. Therefore, non-established ACT teams might not be as proficient in this area, which could lead to lower general medical costs. However, as noted above, the findings associated with general medical care are highly sensitive to unobserved bias; therefore this finding may be attributable to something else entirely.

Whether these discrepancies are attributable to some unknown factor – such as the possibility that even the established ACT team models did not have high fidelity to the model, or the possibility that these data on fidelity, which were cross-sectional, were not able to pick up differences over time – is unknown. Unfortunately we are unable to answer that question in these analyses, however, these questions point to the need for future research on whether ACT teams can have high fidelity to the ACT model even when widely implemented across a state like North Carolina and what these differences to fidelity mean.

The other findings related to established ACT teams (e.g., being on an established ACT team decreases total costs given any costs and lowers the likelihood of any inpatient psychiatric care when compared with non-established teams), however, suggest that these larger, higher fidelity teams may be saving the state money, while also promoting better outcomes than non-established teams. Therefore, although the results overall suggest that even ACT-like teams in North Carolina are having successes, it should be noted that higher fidelity models are having even more successes – at a lower cost.

Other findings

Several other findings also deserve attention. First, hiring one more psychologist or psychological associate in mixed areas decreased the number of months on ACT by a magnitude of around two months in a county of 10,000, for example. Although there is little literature to help explain this finding, it could be that these individuals are serving as substitutes for ACT services. Again, the Medicaid claims files contain codes that could easily flesh out the answer to this question.

Another finding is that individuals did not stay on ACT continually throughout the three-year period. In fact, the number of months on ACT ranged from 7.4 in rural areas to 16 in urban areas, on average, out of a total of 36 months. ACT is supposed to be a time-unlimited service, and therefore these gaps in service receipt could be negatively affecting the ACT consumers. More research in this area is needed to determine how these gaps affected services use and outcomes.

The upside of this finding, however, is that even though ACT was not always provided continuously, ACT in North Carolina was still creating the results we would expect to see from the literature. This suggests that a model that was more focused on providing continuous care to consumers might substantially improve care and costs. This is why a focus on how ACT is being implemented is so critical, as is discussed below.

Finally, all of the mental health comorbidities used here were positively associated with increases in the likelihood of emergency room use, although the same variables were less often significantly related to general medical or primary care. As has been noted, research suggests that people with SMI often have higher rates of chronic conditions and poorer physical health (Chwastiak, Rosenheck et al. 2006; Joukamma, Heliovaara et al. 2006) than those in the general population, and these needs often go unmet (Salsberry, Chipps et al. 2005). It appears that in our data, these needs are most likely being met in the emergency room, not in primary care clinics or through other outpatient services. This is again an indication that ACT in North Carolina may be operating in a treatment-poor environment and stresses the need for more ACT teams, which can decrease emergency room visits, as was shown in this analysis.

Policy Implications: Fidelity, Implementation and Financing

Even though the findings here suggest that ACT teams (whether or not they were high fidelity or low fidelity) in North Carolina were performing as expected, it is still important to examine what could make these teams better, especially in rural areas, and especially in light of the fact that we found lower costs in more established teams. Are there ways that ACT could significantly decrease total costs while still preserving important outcomes like decreases in emergency room use and inpatient psychiatric visits? Are there alternatives to full-fidelity ACT teams in rural areas with fewer resources?

One answer that has been proposed to the final question comes out of the Netherlands where they have suggested a variation on the ACT model, which allows a sort of stepped-down approach to the high intensity of ACT services (Bak, van Os et al. 2007; van Veldhuizen 2007). This model, called F-ACT (Function ACT), allows for a mix of patients with intensive and less intensive treatment needs within the same team. In this model, case management techniques used in psychiatric rehab are combined with ACT. While patients are high functioning, they remain in the team and case managers provide care based on rehabilitation principles. When care needs to be intensified, ACT is reactivated. This model was actually prompted by the needs of rural communities, as well as the large group of more stable long-term mentally ill individuals that live in the community.

Of course, another answer is to pay more attention to the fidelity levels of the ACT teams in the current system, through either regular monitoring of fidelity or other similar quality mechanisms. Much of the recent research on ACT has looked at this area, suggesting ways to improve and sustain quality implementation of ACT programming (Moser, Deluca et al. 2004; Isett, Burnam et al. 2007; George, Durbin et al. 2008; Bjorklund, Monroe-Devita et al. 2009).

In the late 1990s, for example, Ontario took on a similar challenge of dealing with the proper implementation of high fidelity ACT models that North Carolina has faced in recent years. The government of Ontario implemented ACT teams throughout the province, totaling 59 teams within six years. In a large evaluation of the new system of care, researchers identified three areas of underperformance: lower than expected team caseloads, drift from the target consumer group, and significant under-staffing (George, Durbin et al. 2008). In order to deal directly with these challenges, George and colleagues (George, Durbin et al. 2008) focus on the need for continuous feedback cycles and for infrastructure and mechanisms for providing this type of systematic feedback. The government has responded to this need by setting up a monitoring and evaluation subcommittee for the implementation of ACT (George, Durbin et al. 2008). The Ontario system has also adopted technical support and accreditation strategies, which have helped in the implementation process.

Moser and colleagues (Moser, Deluca et al. 2004) describe similar challenges in the implementation of ACT in Indiana, with a slight spin on the story. When comparing ACT to integrated dual diagnosis treatment programs, the researchers noted a greater level of implementation success in the ACT teams due to a number of factors, which included wide stakeholder familiarity with ACT and receptivity to its implementation; establishment of detailed, prescriptive standards tied to certification and reimbursement; availability of an adequate ongoing funding stream, along with incentive funding tied to certification; and a comprehensive program of training and technical support provided through a well-funded, university-based technical assistance center. However, even with these successes, the teams still had to deal with staffing and enrolling consumers that met the service criteria. These authors also focus on the need for mechanisms to promote a feedback loop for continuous improvement of the ACT teams.

A similar story unfolded in the state of Washington (Bjorklund, Monroe-Devita et al. 2009). Here again, the state decided to implement several high-fidelity ACT teams, and the findings from the first year of implementation suggest that several strategies were integral parts of the program's success: strong administrative support, evidence-based training and consultation with experts, and fidelity review items which were tied to contract requirements. However, these teams also experienced problems with staff turnover and recruitment in rural areas.

These case studies provide some important lessons for North Carolina policymakers regarding implementation of ACT, while also answering some of the questions regarding ways of monitoring the fidelity of teams to the ACT model. Our study shows that ACT has had some important success in North Carolina. Building on these and expanding their reach is the next step – implementation in this context will be crucial.

Chapter VIII: Limitations

One of the largest concerns in this study is related to the fidelity of ACT teams to the original ACT model. Because of the nature of administrative claims files, we were unable to look at this aspect of the ACT programs in depth. If the fidelity of the ACT team to the ACT model is unknown, researchers are unable to discern whether or not these teams are really ACT teams or whether they function like community support teams.

In our administrative files from North Carolina, the state was paying a specific ACT-team rate for the services studied here based on a service definition monitored by the local and state mental health agencies. We wanted to determine whether or not these ACT and ACT-like teams were producing the desired results. Therefore, all teams in this paper were referred to as ACT teams, but this does not necessarily mean that they were providing services that had high fidelity to the ACT model.

Although we tried to better define the fidelity levels through the use of the Established Team variables via the ACT Team Survey, there were challenges with this strategy as well. First, the survey was conducted in 2003, which was after the period of our study, and it was a point-in-time estimate; therefore we were unable to look at time variations within the data. In addition, the fidelity survey was based on self-reported information from the team leader gathered over the phone (Meyer and Morrissey 2004).

Another concern within this analysis was related to place of residence. For example, the visibility of the ACT program in rural areas may lead to self-selection into the program because families with more information about the program may find ways to opt in. Another example is that rural communities throughout North Carolina are extremely different; the mountains of Appalachia have challenges that are very different from the coastal plains. The definition of rural used here covers several important elements of life in rural areas, such as degree of urbanization and adjacency to urban areas. However, other things, such as eco-cultural characteristics, are not used. This limits the ability of the study to be able to state what aspects of rural contribute to any observed differences, which in turn limits policy changes which could improve any discrepancies. Determining which components of place of residence drive the differences between urban, mixed and rural areas is an important area for future research. It would also be interesting to try to define these types of unobservable variables to use in future analyses and/or in the definition of place of residence.

When using Medicaid claims files, as noted above, all outpatient claims and transfers from Medicaid-funded psychiatric hospitals, including stays in state psychiatric hospitals are not captured for certain individuals (Walkup, Boyer et al. 2000). For example, federal rules preclude the funding of stays in state psychiatric hospitals for individuals aged 21-64 in the Medicaid program. We are currently in the process of trying to obtain the state psychiatric hospital files so that we will be able to look at all psychiatric hospitalizations within North Carolina for this population. Although this is an issue that will be dealt with in future research, previous research has shown that having these claims may not significantly change the outcomes because often individuals, if placed in state hospitals and on Medicaid, are quickly transferred into non-state hospitals (Salkever, Domino et al. 1999).

The use of Medicaid claims files calls into questions other concerns as well. Claims files do not include some important clinical or social outcomes, which are important in ACT because these factors predict involvement and outcomes in ACT (Burns and Santos 1995; Marshall and Lockwood 2000; Bond, Drake et al. 2001; Phillips, Burns et al. 2001). Because we used individual-level fixed effect models, we controlled for time-invariant differences (including time-invariant clinical and social factors) between individuals (e.g., number of hospitalizations before entering ACT).

Another concern with the administrative data is that we were not able to observe individual contacts between the ACT teams and the consumers, since the payments are made on a monthly basis. Therefore we are not able to assess how many visits per month teams were making. A sort of “dose” variable of this type would have been valuable in assessing the true impact of service over time. We tried to account for this by looking at the percent of the quarter that an individual was on ACT. However, if a team billed Medicaid for ACT for a person for a month, had a gap in billing, and then they billed the state again in the third month, in the data, it looks as though the person spent one month off of ACT. Thirty-seven percent of people on ACT had this type of gap in coverage. Although it may be true that the individual did not receive services during that gap, it could also be due to a billing error. It is unknown, therefore, whether these “missing” months are truly “missing.” Therefore, we also ran sensitivity analyses to determine whether someone who ever had a gap of less than 2 months was considered the same as someone who had never had a gap. As noted above, these analyses did not suggest many significant differences from the main analyses, which suggests that these missings were most likely not affecting the main outcomes of interest whether or not they were billing errors or true missings.

As is true of most effectiveness studies, external validity may be limited. However, North Carolina is one of the larger Medicaid programs in the US and has a diverse population, which may increase the generalizability of these results. This study will also contribute to a growing work of literature on the topic, which can then be analyzed in concert to determine cumulative effects of ACT programs.

There are also limitations to the use of the models presented in this analysis. One concern is related to the models used in these analyses is related to the fixed effects estimators. Although the fixed effects models allow us to control for time-invariant unobserved covariates and they are always consistent (i.e., converges on the true value of the estimator), they may not always be as efficient (i.e., have the smallest variance) as other estimators, such as random effects models. This could mean there might be more significant findings than what we are reporting here. Although we are giving the most conservative estimates, this should be considered when looking at the results.

Also, as noted above, ordinary least squares regression models when using a binary dependent variable (called Linear Probability Models, or LPM) are always heteroskedasticitic and may lead to out of range predictions. Although we are able to solve the problem of heteroskedasticity by using robust standard errors, the problem of out of range predictions is not preventable. In order to deal with this issue in our analyses, we report the out of range predictions when using LPM models, and we ran sensitivity analyses for the collapsed person-level propensity analysis using probit models.

There are also concerns with using propensity score models to tighten up a control group when the control groups have already been limited to the most significant variables for the analysis. In our study, we limited all control groups to those with SMI who were eligible via the blind/disabled category of Medicaid. In the potential ACT group, we added in the limitation of high inpatient use. There are few other criteria which could highly predict ACT treatment in administrative claims files (e.g., we do not have data about whether someone has been hard to engage in traditional forms of treatment). Therefore, although there are conceptual arguments for including the covariates used here to predict ACT treatment to create a propensity score, it could also be argued that this method would only add significantly more additional value if more clinical or social information were available in the claims files.

In addition, the sample sizes of those in the rural analyses were quite small. Although they did show some significant results, this needs to be considered when interpreting these findings. Similarly, the results related to place of residence suggest that there might be differences in rural, mixed and urban areas. Because we controlled for number of mental health professionals and Medicaid eligibles in these areas, we can assume that these place of residence findings are picking up other intangibles related to residence in rural, mixed and urban areas, such as cultural characteristics or driving distance, although we are unable to determine what these specific differences are.

Also, for individuals who are dually eligible for Medicare and Medicaid, Medicare costs were not incorporated, although about 50% of the ACT and SMI samples were on Medicare during the study period. However, this study was designed to look at Medicaid, not societal resources, and differences in Medicare costs are not expected to vary between the ACT and control groups.

Another limitation is that we were unable to use SSI/SSDI status to create the Potential ACT group. Although we can assume that individuals are eligible for this group based on their illness and the time they spent in hospitals, the administrative files cannot tell us whether someone was eligible for SSI/SSDI but not yet placed in that category. We limited the control groups to those that were in the blind/disabled category of Medicaid, however, which should give us a large majority of the individuals which would be eligible for SSDI.

There were also a variety of changes that happened within Medicaid during the study period which could have caused omitted variable bias had they affected the ACT group more than the controls (or vice versa) and if they had been related to other variables in the models. One of the changes, for example, happened in the fall of 2000, and ended the need for primary care physician authorization for payment of professional services provided in the emergency room. Another couple of changes, which increased the copayment for brand name drugs and changed the allowable days supply on prescriptions from 100-days to 34-days, occurred in mid-to-late 2001. However, it should be noted that we would not necessarily expect these changes to affect the control group more than the treatment group, therefore we doubt that these exclusions are causing bias within the study.

As noted throughout the paper, there is also a concern that none of the control groups used was perfect for the situation at hand. Control Group 1 (Potential ACT) were high users of services, and Control Group 2 (SMI) were lower users of services. We expected ACT users to be somewhere in the middle, which means the estimates given represent a likely range of actual effects. Matching via propensity scores helped to deal with some of these issues, but as noted, one can never completely rule out unobserved differences within observational studies, which was also why we used the Rosenbaum bounds (Rosenbaum 2002). Controlling for person-level fixed effects can deal with some of these issues related to time-invariant characteristics. However, as is true in many observational studies, we are still at risk of picking up people who are at risk of being sicker in ways that are not time-invariant. For example, if someone goes into a crisis that makes them a better candidate for ACT, we would not necessarily be able to quantify what made that person more ill. In addition, although person-level fixed effects in the analysis control for time-invariant propensity to use inpatient services, this propensity for use could be higher in the ACT group. Again, we are unable to fully control for this possible situation.

Finally, for most of the main analyses, we used all three years of data to look at the outcomes of interest. Another way to model the outcomes of interest would have been to separate the sample into two time periods (2000 and 2001-02); this would have allowed us to use the earlier period to provide a baseline of health services use. Most of the individuals on ACT, however, did not have pre-ACT data in the claims files, as 90% of the people on ACT had at least one ACT claim in each of the three years (90%). This is a limitation of the data and was therefore why we used individual-level fixed effects in most of the models; this allowed us to control for individual-level time-invariant characteristics, such as previous use.

Chapter IX: Conclusions

The results shown suggest that, even when rolled out in many different settings with many different potential fidelity levels, ACT or ACT-like models in North Carolina had some important successes during 2000-2002, such as decreasing the likelihood of inpatient psychiatric and emergency room care. These successes were accomplished with what might have been very low or no fidelity ACT teams – and even greater successes at a lower cost were found in higher fidelity teams – and therefore suggest that there is a large potential for ACT to mature in North Carolina into a model that will fully reflect the cost-savings that have been found in ACT teams elsewhere.

Tables

Table 1. Differences between individuals on ACT and Control Groups 1 and 2 in the 2000-2002 North Carolina Medicaid Claims Files at the Collapsed Person-Level*

	ACT (n=1,065) Mean (sd) or Percent	Potential ACT (n=1,426) Mean (sd) or Percent	SMI (n=41,717) Mean (sd) or Percent
Costs			
Total Costs	40,672 (28,813)	57,094** (47,477)	32,672** (43,530)
% people with any costs	100	99.9	100
Total Costs|Use	40,672 (28,813)	57,174** (47,462)	32,721** (43,544)
ER Costs	3,013 (7,630)	11,262** (14,992)	2,801 (9,445)
% people with any use	69	95**	63**
ER Costs|Use	4,349 (8,845)	11,896** (15,161)	4,413** (11,551)
General Medical Costs	1,880 (4,135)	5,048** (9,630)	2,959** (6,688)
% people with any use	94	98**	94
General Medical Costs|Use	2,006 (4,242)	5,127** (9,684)	3,143** (6,850)
Primary Care Costs	137 (267)	281** (399)	173** (314)
% people with any use	50	71**	55**
Primary Care Costs|Use	272 (324)	397** (424)	313* (367)
Inpatient Psychiatric Costs	3,256 (7,536)	14,399** (14,708)	1,303** (4,570)
% people with any use	53	96**	27**
Inpatient Psychiatric Costs|Use	6,191 (9,480)	14,933** (14,710)	4,899** (7,805)
Visits/Stays			
Number of ER Visits	4.6 (8.5)	14** (19)	3.9** (8.4)
% people with any use	69	95**	64**
ER Visits|Use	6.7 (9.5)	15** (19)	6.1 (9.8)
Number of General Medical Visits	32 (48)	63** (70)	43** (70)
% people with any use	94	98**	94
General Medical Visits|Use	35 (49)	64** (70)	45* (71)
Number of Primary Care Visits	2.9 (5.6)	6.0** (8.0)	3.9** (6.7)
% people with any use	50	71**	55**
Primary Care Visits|Use	5.8 (6.7)	8.4** (8.3)	7.0* (7.7)
Number of Inpatient Psychiatric Stays	1.2 (1.8)	4.4** (2.5)	0.5** (1.1)
% people with any use	53	96**	27**

Inpatient Psychiatric Visits|Use	2.3 (1.9)	4.6** (2.3)	1.8** (1.5)
Number of Months on ACT	14 (11)	0**	0**
Age in 2002	42 (11)	42.6* (9.9)	46** (11)
Male	53	42**	41**
Race			
Black	36	29	35
Hispanic	0.8	0.42	0.56
Other Race	0.8	1.6	1.4
Unknown Race	11	12	12
Eligibility Category: Non-Blind/Disabled	5.2	0	0**
Medicaid Eligibles per 1000 per County	145 (32)	169** (59)	168** (59)
Psychologists per 1000 per County	0.23 (0.27)	0.14** (0.20)	0.15** (0.20)
Psychological Associates per 1000 per County	0.14 (0.12)	0.100** (0.075)	0.10** (0.08)
Psychiatrists per 1000 per County	0.13 (0.16)	0.08** (0.11)	0.09** (0.12)
Medicare	53	33**	51
SLMB	0.47	0.28	0.58
Number of Medical Comorbidities	0.8 (1.2)	1.7** (1.8)	1.2** (1.6)
Psychiatric Diagnostic Groups			
Drug Abuse (%)	11	18**	4.5**
Alcohol Abuse (%)	8.8	18**	4.9**
Bipolar and Manic Depressive Disorders (%)	15	20**	11**
Psychoses (%)	20	37**	25**
Personality Disorder (%)	5.6	17**	8.8**
Depression and Schizoaffective Disorders (%)	7.0	25**	8.9*
Schizophrenia (%)	57	39**	28**
Other Mental Disorders (%)	6.9	18**	5.8

*For all time-invariant variables (except for the place of residence variable as noted above), we used the "always" value for the three-year period. This meant that we classified individuals who were only sometimes eligible (e.g., for one out of three years) for Medicaid due to the blind/disabled category as not being eligible via the blind/disabled category. This was also true for the Medicare and SLMB categories and the binary mental health comorbidity indicators (e.g., if someone was classified as having schizophrenia in the third year, they were considered to never have had schizophrenia). For the number of mental health professionals and psychiatrists per county, the smallest number that appeared over the three-year period was used. For the number of diagnoses per individual, the lowest number recorded over the three-year period was used.

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^P-values based on t-tests between two groups (either ACT versus Potential ACT or ACT versus SMI), only significant results are reported; * Significant at 5%; ** Significant at 1%

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Table 2. Differences between individuals on ACT in Rural, Mixed and Urban Areas in the 2000-2002 North Carolina Medicaid Claims Files at the Collapsed Person-Level* and individuals in the Potential ACT Consumer Group

	ACT		
	Rural (n=42) Mean (sd) or Percent	**Mixed (n=169) Mean (sd) or Percent**	**Urban (n=806) Mean (sd) or Percent**
Costs			
Total Costs	31,255 (22,138)	38,443 (25,358)	41,037[aru] (28,326)
% people with any costs	100	100	100
Total Costs|Use	31,255 (22,138)	38,443 (25,358)	41,037 [aru] (28,326)
ER Costs	2,520 (5,424)	3,326 (8,879)	2,771 (6,993)
% people with any use	62	76	67[amu]
ER Costs|Use	4,071 (6,456)	4,357 (9,947)	4,143 (8,215))
General Medical Costs	1,874 (2,815)	2,306 (3,963)	1,662[amu] (3,689)
% people with any use	95	96	93
General Medical Costs|Use	1,968 (2,853)	2,391 (4,010)	1,790 (3,800)
Primary Care Costs	146 (204)	174 (281)	126[amu] (268)
% people with any use	74	55[arm]	47[bru]
Primary Care Costs|Use	198 (215)	317 (314)	267 (339)
Inpatient Psychiatric Costs	3,105 (7,526)	3,415 (7,161)	3,028 (7,306)
% people with any use	48	60	50[amu]
Inpatient Psychiatric Costs|Use	6,521 (9,939)	5,568 (8,513)	6,040 (9,401)
Visits/Stays			
Number of ER Visits	3.8 (4.7)	5.9 (11.2)	4.2[amu] (7.6)
% people with any use	62	76	67[amu]
ER Visits|Use	6.2 (4.6)	7.7 (12.3)	6.3 (8.6)
Number of General Medical Visits	37 (45)	39 (60)	30[amu] (45)
% people with any use	95	96	93
General Medical Visits|Use	38 (46)	40 (60)	32 (46)
Number of Primary Care Visits	3.8 (4.5)	3.9 (6.3)	2.6[bmu] (5.5)
% people with any use	74	55[arm]	47[bru]
Primary Care Visits|Use	5.1 (4.5)	7.1 (7.0)	5.6 (6.9)
Number of Inpatient Psychiatric Stays	0.83 (1.23)	1.4 (1.8)	1.1 (1.7)

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% people with any use	48	60	50[amu]
Inpatient Psychiatric Visits|Use	1.8 (1.3)	2.3 (1.9)	2.3[bmu,bru] (1.9)
Number of Months on ACT	7.4 (6.3)	8.7 (7.3)	16[bmu,bru] (12)
Age in 2002	43 (13)	43 (11)	42 (11)
Male	40	44	55[amu]
Race			[bmu,bru,bru]
Black	10	34	38
Hispanic	24	0	0.87
Other Race	0	0.59	0.87
Unknown Race	12	8.9	11
Eligibility Category: Non-Blind/Disabled	7.1	9.5	4.1[bmu]
Medicaid Eligibles per 1000 per County	185 (32)	165[brm] (47)	138[bmu,bru] (22)
Psychologists per 1000 per County	0.085 (0.036)	0.15[brm] (0.17)	0.27[bmu,bru] (0.29)
Psychological Associates per 1000 per County	0.089 (0.042)	0.11 (0.11)	0.15[bmu,bru] (0.12)
Psychiatrists per 1000 per County	0.047 (0.036)	0.052 (0.099)	0.15[bmu,bru] (0.17)
Medicare	48	49	55
SLMB	0	0	0.62
Number of Medical Comorbidities	0.69 (1.0)	1.1 (1.4)	0.77[bmu] (1.2)
Psychiatric Diagnostic Groups			
Drug Abuse (%)	7.1	7.7	11
Alcohol Abuse (%)	2.4	11	8.6
Bipolar and Manic Depressive Disorders (%)	14	18	14
Psychoses (%)	24	25	18[amu]
Personality Disorder (%)	12	7.1	4.7[aru]
Depression and Schizoaffective Disorders (%)	12	8.3	6.6
Schizophrenia (%)	50	50	59[bru]
Other Mental Disorders (%)	9.5	10	5.7 [amu]
Established ACT Team	0	1.3	36[amu]

*For all time-invariant variables (except for the place of residence variable as noted above), we used the "always" value for the three-year period. This meant that we classified individuals who were only sometimes eligible (e.g., for one out of three years) for Medicaid due to the blind/disabled category as not being eligible via the blind/disabled category. This was also true for the Medicare and SLMB categories and the binary mental health comorbidity indicators (e.g., if someone was classified as having schizophrenia in the third year, they were considered to never have had schizophrenia).

For the number of mental health professionals and psychiatrists per county, the smallest number that appeared over the three-year period was used. For the number of diagnoses per individual, the lowest number recorded over the three-year period was used.
^P-values based on t-tests between two groups (aru=rural versus urban significant at 0.05; bru=rural versus urban significant at 0.01; arm=rural versus mixed significant at 0.05; brm=rural versus mixed significant at 0.01; amu=mixed versus urban significant at 0.05; bmu=mixed versus urban significant at 0.01)

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Table 3. Differences between individuals in the Potential ACT Consumers Group and the SMI Control Group in the 2000-2002 North Carolina Medicaid Claims Files at the Collapsed Person-Level by Place of Residence*

	Potential ACT			SMI		
	Rural (n=71) Mean (sd) or Percent	Mixed (n=491) Mean (sd) or Percent	Urban (n=756) Mean (sd) or Percent	Rural (n=2,514) Mean (sd) or Percent	Mixed (n=12,277) Mean (sd) or Percent	Urban (n=24,178) Mean (sd) or Percent
Costs						
Total Costs	60,388 (57,651)	57,398 (48,303)	55,785 (46,038)	31,381 (40,187)	32,086 (42,682)	31,885 (44,046)
% people with any costs	100	100	100	100	100	100
Total Costs|Use	60,388 (57,651)	57,515 (48,282)	55,859 (46,024)	31,431 (40,200)	32,146 (42,700)	31,898 (44,060)
ER Costs	6,674 (9,161)	10,356 (13,843)	11,882 (15,438)	1,695 (5,953)	2,136 (7,292)	2,740 (10,020)
% people with any use	87	95	95	58	62	62
ER Costs| Use	7,643 (9,422)	10,911 (13,995)	12,493 (15,587)	2,901 (7,561)	3,425 (8,991)	4,417 (12,428)
General Medical Costs	5,274 (9,926)	5,381 (12,227)	4,789 (7,779)	2,896 (6,287)	3,025 (6,984)	2,787 (6,405)
% people with any use	96	99	98	95	95	94
General Medical Costs|Use	5,507 (10,081)	5,447 (12,288)	4,873 (7,821)	3,145 (6,422)	3,201 (7,145)	2,980 (6,580)
Primary Care Costs	257 (345)	303 (429)	260 (368)	183 (308)	175 (313)	162 (305)
% people with any use	65	75	68	60	56	53
Primary Care Costs|Use	396 (356)	404 (453)	383 (390)	305 (348)	310 (364)	305 (363)
Inpatient Psychiatric Costs	16,908 (22,342)	13,820 (12,758)	14,137 (14,667)	870 (2,730)	758 (2321)	850 (2,949)
% people with any use	96	97	96	23	25	23
Inpatient Psychiatric Costs|Use	17,654 (22,542)	14,255 (12,716)	14,661 (14,677)	3,714 (4,613)	3,081 (3,838)	3,657 (5,212)
Visits/Stays						
Number of ER Visits	9.2 (11.7)	15 (20)	14 (19)	2.8 (5.4)	3.5 (7.8)	3.4 (7.3)
% people with any use	87	95	95	58	62	62
ER Visits|Use	11 (12)	16 (21)	15 (19)	4.8 (6.3)	5.6 (9.2)	5.5 (8.6)
Number of General Medical	62 (76)	67 (72)	61 (69)	47 (77)	44 (71)	40 (69)

Visits						
% people with any use	96	99	98	95	95	94
General Medical Visits|Use	64 (77)	68 (72)	62 (69)	49 (77)	47 (73)	43 (71)
Number of Primary Care Visits	6.0 (7.9)	6.5 (8.5)	5.5 (7.4)	4.4 (7.1)	3.9 (6.7)	3.6 (6.5)
% people with any use	96	75	68	60	56	53
Primary Care Visits|Use	9.2 (8.1)	8.7 (8.9)	8.0 (7.8)	7.4 (7.9)	3.9 (7.7)	6.8 (7.6)
Number of Inpatient Psychiatric Stays	4.3 (2.3)	4.5 (2.3)	4.4 (2.5)	0.32 (0.66)	0.35 (0.72)	0.33 (0.69)
% people with any use	96	97	96	23	25	23
Inpatient Psychiatric Visits|Use	4.4 (2.2)	4.6 (2.2)	4.5 (2.4)	1.4 (0.7)	1.4 (0.7)	1.4 (0.7)
Number of Months on ACT	n/a	n/a	n/a	n/a	n/a	n/a
Age in 2002	43 (11)	42 (10)	41 (10)	47 (11)	46 (11)	46 (11)
Male	44	41	42	41	41	41
Race						
Black	27	30	28	38	32	36
Hispanic	0	0.41	0.53	0.24	0.37	0.68
Other Race	1.4	3.1	0.79	1.0	2.5	0.94
Unknown Race	14	12	11	12	12	11
Eligibility Category: Non-Blind/Disabled	0	0	0	0	0	0
Medicaid Eligibles per 1000 per County	227 (68)	203 (66)	142 (34)	225 (61)	206 (66)	144 (39)
Psychologists per 1000 per County	0.046 (0.079)	0.061 (0.083)	0.206 (0.240)	0.05 (0.079)	0.068 (0.096)	0.21 (0.23)
Psychological Associates per 1000 per County	0.080 (0.079)	0.078 (0.054)	0.12 (0.08)	0.069 (0.074)	0.076 (0.068)	0.12 (0.08)
Psychiatrists per 1000 per County	0.037 (0.048)	0.037 (0.039)	0.12 (0.14)	0.034 (0.045)	0.039 (0.053)	0.12 (0.14)
Medicare	39	30	35	48	52	51
SLMB	0	0.41	0.13	0.91	0.66	0.53
Number of Medical Comorbidities	1.3 (1.9)	1.7 (1.7)	1.7 (1.9)	1.2 (1.6)	1.3 (1.7)	1.1 (1.6)
Comorbidities						
Drug Abuse	7.0	15	19	3.8	3.6	4.3

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Alcohol Abuse	9.9	18	17	5.5	4.5	4.3
Bipolar and Manic Depressive Disorders	14	16	22	9.8	9.9	11
Psychoses	31	40	37	26	26	24
Personality Disorder	17	16	18	9.4	9.1	4.3
Depression and Schizoaffective Disorders	15	25	26	8.5	8.6	8.2
Schizophrenia	42	38	38	29	27	28
Other Mental Disorders	21	15	20	5.4	5.2	5.4

*For all time-invariant variables (except for the place of residence variable as noted above), we used the "always" value for the three-year period. This meant that we classified individuals who were only sometimes eligible (e.g., for one out of three years) for Medicaid due to the blind/disabled category as not being eligible via the blind/disabled category. This was also true for the Medicare and SLMB categories and the binary mental health comorbidity indicators (e.g., if someone was classified as having schizophrenia in the third year, they were considered to never have had schizophrenia). For the number of mental health professionals and psychiatrists per county, the smallest number that appeared over the three-year period was used. For the number of diagnoses per individual, the lowest number recorded over the three-year period was used.

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Table 4. Linear Probability Model of Covariates on ACT Treatment at the Collapsed Person-Level by Place of Residence on Medicaid in North Carolina between 2000-2002 (Aim 1)

	Control Group 1: Potential ACT Consumers			Control Group 2: Individuals with SMI		
	Rural	**Mixed**	**Urban**	**Rural**	**Mixed**	**Urban**
Age in 2002	-0.029	-0.003	0.0149*	-0.032	-0.0266**	-0.0239**
	(0.027)	(0.010)	(0.0060)	(0.017)	(0.0080)	(0.0038)
Male	0.04	0.09	0.27*	-0.00	0.043	0.241**
	(0.51)	(0.21)	(0.12)	(0.32)	(0.167)	(0.078)
Black	-0.59	0.37	0.29*	-1.27**	0.29	-0.082
	(0.72)	(0.24)	(0.13)	(0.46)	(0.18)	(0.084)
Hispanic			0.76	0.9		0.20
			(0.51)	(1.2)		(0.38)
Other Race		-1.20	-0.13		-0.6	-0.06
		(0.98)	(0.57)		(1.0)	(0.39)
Race Unknown	-0.34	-0.28	0.15	-0.28	-0.06	0.19
	(0.70)	(0.36)	(0.18)	(0.51)	(0.27)	(0.12)
Medicaid Enrollees per Thousand in County	-0.0219**	-0.0071**	-0.0060*	-0.0112**	-0.0088**	-0.0038**
	(0.0053)	(0.0017)	(0.0023)	(0.0028)	(0.0015)	(0.0010)
Psychologists per Thousand per County	-4.3	6.8**	-0.30	-1.6	3.11**	-0.12
	(5.8)	(2.0)	(0.89)	(1.1)	(0.62)	(0.62)
Psychological Associates per Thousand per County	-4.3	-3.4	3.16**	2.8	-1.3	4.05**
	(4.3)	(2.3)	(0.63)	(2.0)	(1.5)	(0.45)
Psychiatrists per Thousand per County	17.0	-4.2	0.6	7.6*	-1.3	0.23
	(8.9)	(2.3)	(1.5)	(3.4)	(1.4)	(0.98)
Medicare	0.02	0.80**	0.67**	-0.00	-0.04	0.131
	(0.54)	(0.21)	(0.12)	(0.31)	(0.16)	(0.076)
SLMB			0.58			0.487
			(1.051)			(0.524)
Number of Comorbidities	-0.69**	-0.154	-0.272**	-0.24	-0.003	-0.114**
	(0.26)	(0.085)	(0.048)	(0.14)	(0.056)	(0.032)

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Drug Abuse	-0.35	-0.11	-0.26	0.58	0.34	0.75**
	(1.12)	(0.35)	(0.17)	(0.67)	(0.33)	(0.14)
Alcohol Abuse	-1.2	-0.56	-0.45*	-1.0	0.73*	0.62**
	(1.2)	(0.35)	(0.18)	(1.1)	(0.29)	(0.15)
Bipolar and Manic Depressive Disorders	0.60	0.44	-0.10	0.38	0.82**	0.49**
	(0.76)	(0.27)	(0.16)	(0.50)	(0.22)	(0.12)
Psychoses	-0.63	-0.43	-0.31*	0.22	0.16	0.11
	(0.62)	(0.25)	(0.14)	(0.47)	(0.21)	(0.11)
Other Mental Disorders	-1.35	-0.13	-0.60**	0.21	0.29	-0.12
	(0.84)	(0.41)	(0.21)	(0.65)	(0.31)	(0.17)
Personality Disorder	0.52	-0.38	-0.64**	0.05	-0.19	-0.40*
	(0.78)	(0.38)	(0.22)	(0.49)	(0.31)	(0.19)
Depression and Schizoaffective Disorders	-0.35	-0.94*	-0.68**	0.14	-0.12	-0.13
	(0.74)	(0.38)	(0.19)	(0.58)	(0.31)	(0.17)
Schizophrenia	0.26	0.24	0.48**	1.25**	1.19**	1.354**
	(0.62)	(0.21)	(0.12)	(0.33)	(0.17)	(0.081)
Constant	6.0**	0.17	-0.29	-0.75	-2.41**	-3.07**
	(1.8)	(0.57)	(0.45)	(0.97)	(0.49)	(0.23)
Observations	126	699	1,604	2,722	13,461	26,348
Pseudo R-squared	0.24	0.19	0.18	0.13	0.10	0.093

Standard errors in parentheses; * Significant at 5%; ** Significant at 1%

Table 5. Regressions by Place of Residence on the Number of Months on ACT for individuals on Medicaid and on ACT in North Carolina during 2000-2002 (Aim 1)

	Rural	**Mixed**	**Urban**
Age in 2002	0.043	-0.040	0.073*
	(0.046)	(0.057)	(0.037)
Male	-0.1	0.6	0.60
	(1.3)	(1.1)	(0.78)
Black	-0.5	3.2*	1.36
	(2.3)	(1.4)	(0.89)
Hispanic	2.3	29.2**	4.1
	(2.2)	(1.9)	(3.8)
Other Race		0.9	7.7**
		(2.1)	(2.4)
Race Unknown	-3.4*	2.4	-1.3
	(1.6)	(1.9)	(1.2)
Eligibility Category: Non-Blind/Disabled	-0.4	-2.3	-0.8
	(1.7)	(1.8)	(1.6)
Medicaid Eligibles per Thousand per County	0.058*	0.040**	0.067**
	(0.026)	(0.015)	(0.022)
Psychologists per Thousand per County	-8	3.6	-16.5**
	(33)	(5.7)	(5.9)
Psychological Associates per Thousand per County	-75*	-20.0**	7.7*
	(31)	(7.0)	(3.6)
Psychiatrists per Thousand per County	26	6.1	41**
	(22)	(6.5)	(10)
Medicare	1.3	2.7*	2.01**
	(1.6)	(1.0)	(0.75)

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SLMB			-7.4**
			(2.4)
Number of Months on Medicaid	0.57**	0.76**	2.00**
	(0.19)	(0.16)	(0.10)
Number of Comorbidities	0.12	-0.85*	-1.14**
	(0.58)	(0.40)	(0.34)
Drug Abuse	3.1	1.5	0.5
	(1.6)	(1.5)	(1.1)
Alcohol Abuse	-2.1	-3.1*	0.7
	(2.6)	(1.3)	(1.3)
Bipolar and Manic Depressive Disorders	0.0	1.1	2.6*
	(1.5)	(1.2)	(1.1)
Psychoses	1.8	0.2	2.0*
	(1.5)	(1.2)	(1.0)
Other Mental Disorders	-0.5	3.1*	-2.1
	(2.0)	(1.4)	(1.7)
Personality Disorder	-1.7	-1.7	-0.6
	(2.1)	(1.1)	(1.6)
Depression and Schizoaffective Disorders	-0.23	-1.2	1.0
	(2.2)	(1.9)	(1.4)
Schizophrenia	1.8	0.6	4.32**
	(1.9)	(1.2)	(0.81)
Established ACT Team		-3.5*	5.15**
		(1.7)	(0.92)
Constant	-6.2	-5.3	-26.3**
	(5.9)	(3.2)	(4.0)
Observations	50	169	811
R-squared	0.87	0.42	0.29

Standard errors in parentheses; * Significant at 5%; ** Significant at 1%

Table 6. Regression of the Effect of ACT on Total Costs per Quarter of Health Services for individuals in the Potential ACT Consumer Group (Control Group 1) in North Carolina during 2000-2002 (Aim 2)

	Total Costs	
	Likelihood of Costs LPM	Costs|Any Costs
Percent quarter on ACT	0.0797**	1,754**
	(0.0050)	(85)
Eligibility Category: Non-Blind/Disabled	-0.028	272
	(0.020)	(316)
Medicaid Eligibles per Thousand per County	0.000130	0.3
	(0.000070)	(1.9)
Psychologists per Thousand per County	0.038	1,297
	(0.034)	(1,059)
Psychological Associates per Thousand per County	-0.039	-1,383
	(0.039)	(1,136)
Psychiatrists per Thousand per County	-0.052	-122
	(0.055)	(1,769)
Medicare	0.0128	-623**
	(0.0081)	(192)
SLMB	-0.485**	314
	(0.043)	(614)
Number of Comorbidities	0.00626**	519**
	(0.00069)	(34)
Drug Abuse	0.0204**	368**
	(0.0043)	(109)
Alcohol Abuse	0.0187**	505**
	(0.0046)	(114)
Bipolar and Manic Depressive Disorders	0.0051	522**
	(0.0037)	(123)
Psychoses	0.0116**	783**
	(0.0032)	(92)
Other Mental Disorders	0.0078**	368**
	(0.0027)	(83)
Personality Disorder	0.0020	304**
	(0.0031)	(105)

Depression and Schizoaffective Disorders	0.0038	603**
	(0.0031)	(93)
Schizophrenia	0.0539**	647**
	(0.0053)	(124)
Constant	0.854**	2,003**
	(0.016)	(432)
Observations	26,402	25606
R-squared	0.37	0.4981
Number of individuals	2,491	2489
Percent of observations outside prediction	42	
Range of predictions	-.04, 1.24	

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Table 7. Regression of the Effect of ACT on Costs per Quarter of Health Services for individuals in the Potential ACT Consumer Group (Control Group 1) in North Carolina during 2000-2002 (Aim 2)

	ER Costs		**General Medical Costs**		**Primary Care Costs**		**Inpatient Psychiatric Costs**	
	Likelihood of Costs LPM	Costs|Any Costs	Likelihood of Costs LPM	Costs|Any Costs	Likelihood of Costs LPM	Costs|Any Costs	Likelihood of Costs LPM	Costs|Any Costs
Percent quarter on ACT	-0.020*	-211	-0.006	-274**	0.0030	-10.5	-0.0258**	-190
	(0.010)	(189)	(0.013)	(53)	(0.0085)	(9.4)	(0.0083)	(367)
Eligibility Category: Non-Blind/Disabled	-0.013	106	-0.042	-140	-0.035	-24	0.0153	4,474
	(0.039)	(375)	(0.057)	(136)	(0.039)	(39)	(0.028)	(2,921)
Medicaid Eligibles per Thousand per County	-0.00008	2.0	-0.00019	-0.2	0.00013	0.11	0.00002	-1.8
	(0.00018)	(3.0)	(0.00023)	(1.3)	(0.00016)	(0.17)	(0.00017)	(4.2)
Psychologists per Thousand per County	-0.096	592	-0.16	300	0.021	-26	-0.021	3,114
	(0.092)	(2,042)	(0.11)	(559)	(0.084)	(75)	(0.090)	(2,270)
Psychological Associates per Thousand per County	-0.102	511	0.10	-938	0.085	-8	-0.0431	2,210
	(0.090)	(1,719)	(0.11)	(806)	(0.080)	(97)	(0.087)	(2,183)
Psychiatrists per Thousand per County	0.24	866	0.24	128	-0.04	209	0.11	-5,071
	(0.15)	(3,465)	(0.18)	(915)	(0.14)	(138)	(0.15)	(3,805)
Medicare	-0.064**	-243	0.006	-224*	-0.034	-10	0.006	-1,044*
	(0.018)	(314)	(0.021)	(90)	(0.018)	(12)	(0.017)	(477)
SLMB	-0.097**	-535	-0.191**	-58	-0.036	100	-0.005	-97
	(0.036)	(745)	(0.043)	(513)	(0.027)	(64)	(0.036)	(1,078)
Number of Comorbidities	0.0362**	292**	0.0086**	54**	0.0076**	6.2**	0.0206**	173**
	(0.0023)	(47)	(0.0027)	(13)	(0.0021)	(1.5)	(0.0022)	(45)

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Drug Abuse	0.046**	504**	0.007	-23	-0.0141	-1.5	0.078**	277
	(0.011)	(153)	(0.013)	(59)	(0.0092)	(8.1)	(0.011)	(199)
Alcohol Abuse	0.048**	477**	0.021	-35	-0.0035	-9.4	0.080**	152
	(0.011)	(174)	(0.014)	(55)	(0.0095)	(8.7)	(0.011)	(193)
Bipolar and Manic Depressive Disorders	0.026*	122	0.010	169**	0.0022	-1.6	0.081**	272
	(0.011)	(166)	(0.013)	(55)	(0.0095)	(6.9)	(0.011)	(236)
Psychoses	0.0758**	432**	0.004	114*	0.0011	-10.1	0.1171**	534**
	(0.0089)	(148)	(0.010)	(46)	(0.0075)	(6.3)	(0.0086)	(180)
Other Mental Disorders	0.0813**	327**	0.0164	47	-0.0048	7.9	0.0913**	246
	(0.0082)	(120)	(0.0097)	(41)	(0.0072)	(5.2)	(0.0080)	(166)
Personality Disorder	0.0477**	-89	0.002	-69	0.0053	7.2	0.0635**	525*
	(0.0098)	(140)	(0.011)	(58)	(0.0087)	(6.6)	(0.0096)	(210)
Depression and Schizoaffective Disorders	0.0560**	411**	-0.000	1	0.0143	-2.2	0.0785**	419*
	(0.0093)	(140)	(0.011)	(46)	(0.0080)	(5.9)	(0.0090)	(182)
Schizophrenia	0.043**	410	0.038**	-6	-0.0005	-5.4	0.092**	732**
	(0.011)	(217)	(0.013)	(78)	(0.0098)	(8.4)	(0.011)	(280)
Constant	0.188**	-911	0.367**	1,200**	0.205**	68	-0.151**	1,748
	(0.042)	(658)	(0.051)	(351)	(0.037)	(39)	(0.038)	(914)
Observations	26,402	9,149	26,402	11,097	26,402	4,612	26,402	5,986
R-squared	0.39	0.36	0.13	0.64	0.25	0.52	0.26	0.63
Number of individuals	2,491	2,087	2,491	2,402	2,491	1,545	2,491	1,935
Percent of observations outside prediction	12		1		21		15	
Range of predictions	-0.31, 1.23		-0.14, 1.04		-0.08, 1.05		-0.42, 1.07	

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Table 8. Sensitivity Analyses for Regression Models Examining Costs of Health Services for Individuals on ACT in North Carolina Medicaid during 2000-2002 compared with Potential ACT Consumers and Individuals with SMI (Aim 2)

	Results from Tables 6 and 7: ACT compared with Potential ACT Consumer Group (Control Group 1)	Percent quarter spent on Established ACT Team for everyone with SMI (Control Group 2))	Percent quarter spent on an ACT Team that was not established for everyone with SMI (Control Group 2)	F-test between Percent Quarter spent on Established and Percent Quarter Not Established: F-statistic	F-test between Percent Quarter spent on Established and Percent Quarter Not Established: P-value	Smoothing Over Gaps in ACT for everyone with SMI (Control Group 2)	Smoothing Over Gaps in ACT for Potential ACT Consumer Group (Control Group 1)
Total Costs							
Likelihood of Costs (LPM)	0.0797** (0.0050)	0.107 ** (0.010)	0.0624** (0.0048)	113	0.0000	0.0732** (0.0048)	0.0802** (0.0050)
Costs|Any Costs	1,753** (85)	1712** (145)	1871** (86)	261	0.0000	1717** (419)	1625** (115)
ER Costs							
Likelihood of Costs (LPM)	-0.020* (0.010)	-0.032 (0.018)	-0.012 (0.011)	1.92	0.146	-0.0153 (0.0096)	-0.019* (0.098)
Costs|Any Costs	-210 (189)	-304 (438)	-73 (207)	0.27	0.7645	-113 (284)	-211 (191)
General Medical Costs							
Likelihood of Costs (LPM)	-0.006 (0.013)	0.036 (0.024)	-0.028 (0.015)	3.37	0.0344	-0.015 (0.013)	-0.0083 (0.0131)
Costs|Any Costs	-274** (53)	-62 (72)	-265** (52)	13	0.0000	-230** (59)	-276** (66)
Primary Care Costs							
Likelihood of Costs (LPM)	0.0030 (0.0085)	0.006 (0.014)	-0.0065 (0.0093)	0.36	0.6966	-0.0072 (0.0081)	-0.0011 (0.0083)
Costs|Any Costs	-10.5 (9.4)	-5 (24)	-8.9 (9.9)	0.43	0.6599	-8.5 (8.3)	-10.9 (9.2)
Inpatient Psychiatric Costs							
Likelihood of Costs (LPM)	-0.0258* (0.0083)	-0.030* (0.014)	-0.0209* (0.0089)	4.4	0.0122	-0.0156* (0.0080)	-0.019* (0.082)
Costs|Any Costs	-190 (367)	-639 (807)	-96 (546)	0.32	0.7266	-353 (321)	-329 (386)

Table 9. Two-part regression of the Effect of ACT on the likelihood of Total Costs and Total Costs per Quarter of Health Services for individuals in the Potential ACT Consumer Group (Control Group 1) in North Carolina during 2000-2002 (Aim 3)

	Potential ACT Consumers (Control Group 1)					
	Rural LPM (Any Use)	**Rural OLS (Costs|Any Use)**	**Mixed LPM (Any Use)**	**Mixed OLS (Costs|Any Use)**	**Urban LPM (Any Use)**	**Urban OLS (Costs|Any Use)**
Percent quarter on ACT	0.035*	1,517**	0.059**	1,943**	0.0880**	1,765**
	(0.016)	(521)	(0.010)	(193)	(0.0061)	(98)
Eligibility Category: Non-Blind/Disabled	0.0082	1,581	-0.035	-431	-0.034	351
	(0.020)	(978)	(0.027)	(842)	(0.027)	(307)
Medicaid Eligibles per Thousand per County	-0.00053	49	0.00025	-6.2	0.00016	-0.4
	(0.00038)	(30)	(0.00015)	(6.9)	(0.00010)	(2.1)
Psychologists per Thousand per County	0.03	1,070	0.03	-8,946*	0.01	1,746
	(0.17)	(6,720)	(0.13)	(4,108)	(0.05)	(1,339)
Psychological Associates per Thousand per County	0.11	6,087	-0.017	-2,236	-0.015	-1,651
	(0.18)	(7,555)	(0.097)	(2,942)	(0.057)	(1,247)
Psychiatrists per Thousand per County	-0.14	186	0.28*	1,231	-0.025	-753
	(0.23)	(6,040)	(0.12)	(4,410)	(0.095)	(2,267)
Medicare	0.021	-1,736	0.005	-358	0.018	-682**
	(0.036)	(1,189)	(0.014)	(439)	(0.010)	(233)
SLMB			-0.522**	1,251	-0.46**	687
			(0.074)	(1,534)	(0.056)	(593)
Number of Comorbidities	0.0003	110	0.0056**	538**	0.00780**	537**
	(0.0026)	(126)	(0.0011)	(59)	(0.00095)	(41)
Drug Abuse	-0.021	245	0.0049	569**	0.0303**	312*
	(0.013)	(583)	(0.0063)	(194)	(0.0059)	(130)
Alcohol Abuse	0.025	483	0.0040	522*	0.0212**	437**
	(0.021)	(612)	(0.0072)	(234)	(0.0061)	(127)

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Bipolar and Manic Depressive Disorders	-0.010	680	0.0011	665**	0.0091	487**
	(0.011)	(614)	(0.0055)	(223)	(0.0054)	(156)
Psychoses	0.010	2,133**	0.0134*	661**	0.0094*	762**
	(0.011)	(507)	(0.0057)	(171)	(0.0041)	(110)
Other Mental Disorders	0.0019	884	0.0111*	388**	0.0089*	273**
	(0.0077)	(527)	(0.0046)	(151)	(0.0036)	(100)
Personality Disorder	-0.011	-272	-0.0121*	574**	0.0079	238
	(0.011)	(511)	(0.0048)	(190)	(0.0045)	(130)
Depression and Schizoaffective Disorders	0.017	459	0.0107*	701**	-0.0009	573**
	(0.013)	(433)	(0.0054)	(161)	(0.0042)	(116)
Schizophrenia	0.043	683	0.0311**	693**	0.0679**	570**
	(0.025)	(660)	(0.0072)	(211)	(0.0075)	(166)
Constant	1.038**	-8,227	0.850**	4,286*	0.821**	2,075**
	(0.067)	(6,698)	(0.038)	(1,680)	(0.021)	(477)
Observations	1,380	1,351	7,795	7596	17,227	16,659
Number of individuals	158	158	789	789	1,697	1,695
R-squared	0.32	0.56	0.44	0.5135	0.3782	0.4959
Percent of observations outside prediction	8		44		41	
Range of predictions	0.32, 1.07		-0.05, 1.25		0.00, 1.24	

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Table 10. Coefficients on the Percent Quarter on ACT Variable from the Regressions of the Effect of ACT on Costs of Health Services for individuals with SMI (Control Group 2) and by Place of Residence for Control Groups 1 and 2 on Medicaid in North Carolina during 2000-2002 (Aims 2 & 3)

	Potential ACT Consumers (Control Group 1)			Individuals with SMI (Control Group 2)		
Percent quarter on ACT	Rural Areas	Mixed Areas	Urban Areas	Rural Areas	Mixed Areas	Urban Areas
Total Costs						
	0.035**	0.059**	0.0880**	0.0083	0.0518**	0.0818**
LPM	(0.016)	(0.010)	(0.0061)	(0.0093)	(0.0010)	(0.0059)
Observations (LPM)	1,380	7,795	17,227	26,733	133,910	255,933
OLS	1,517** (521)	1,943** (193)	1,765** (98)	1,218** (354)	1,968** (168)	1,851** (96)
Observations (OLS))	1,351	7,596	16,659	25,770	128,863	245,186
ER Costs						
LPM	0.065	0.022	-0.035**	0.048	0.018	-0.028*
	(0.056)	(0.026)	(0.011)	(0.046)	(0.024)	(0.011)
Observations (LPM)	1,380	7,795	17,227	26,733	133,910	255,933
OLS	-1,637 (1,953)	114 (341)	-272 (222)	-1477 (1,792)	318 (361)	-164 (237)
Observations (OLS)	445	3,188	5,516	4,599	26,570	48,432
General Medical Costs						
	-0.118	-0.008	0.004	-0.129*	-0.021	-0.002
LPM	(0.076)	(0.032)	(0.015)	(0.064)	(0.030)	(0.015)
Observations (LPM)	1,380	7,795	17,227	26,733	133,910	255,933
OLS	-788* (316)	-486** (132)	-203** (62)	-497** (187)	-387** (114)	-172** (52)
Observations (OLS)	600	3,488	7,009	11,577	57,161	106,050
Primary Care Costs						
	-0.012	-0.002	0.0073	-0.042	-0.009	0.0034
LPM	(0.055)	(0.021)	(0.0096)	(0.048)	(0.019)	(0.0094)
Observations (LPM)	1,380	7,795	17,227	26,733	133,910	255,933
OLS	11 (29)	-13 (18)	-12 (12)	25 (28)	-5 (17)	-12 (12)
Observations (OLS)	295	1,651	2,666	4,883	22,092	38,769
Inpatient Psychiatric Costs						
	0.045	-0.016	-0.0289**	-0.029	-0.009	-0.0273**
LPM	(0.045)	(0.021)	(0.0095)	(0.033)	(0.019)	(0.0093)

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Observations (LPM)	1380	7,795	17,227	26,733	133,910	255,933
OLS	-5,668 (7,677)	-453 (741)	17 (392)	-5360 (10,294)	-499 (935)	-5 (498)
Observations (OLS)	331	2091	3564	1156	6,548	11,551

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Table 11. Negative Binomial Regression Models of the Effect of ACT on Number of Health Services Visits for Individuals with SMI compared with those on ACT on Medicaid in North Carolina during 2000-2002 (Aim 2)

	Individuals with SMI (Control Group 2)		
	ER Visits	**General Medical Visits**	**Primary Care Visits**
Percent quarter on ACT	-0.112*	-0.105**	-0.117
	(0.050)	(0.032)	(0.064)
Age in 2002	-0.0205**	0.00013	0.00016
	(0.0011)	(0.00035)	(0.00081)
Male	-0.277**	0.0145	0.055**
	(0.024)	(0.0076)	(0.019)
Black	0.0927**	0.0203*	0.094**
	(0.026)	(0.0081)	(0.019)
Hispanic	0.33	0.139**	0.33**
	(0.19)	(0.053)	(0.11)
Other Race	-0.020	0.119**	0.172**
	(0.086)	(0.030)	(0.066)
Race Unknown	0.066	0.007	0.099**
	(0.036)	(0.011)	(0.025)
Eligibility Category: Non-Blind/Disabled	-0.15	-0.026	-0.12
	(0.18)	(0.081)	(0.16)
Medicaid Eligibles per Thousand per County	0.00038*	-0.000140*	0.00058**
	(0.00018)	(0.000060)	(0.00015)
Psychologists per Thousand per County	-0.00	-0.198**	-0.015
	(0.11)	(0.046)	(0.095)
Psychological Associates per Thousand per County	-0.07	-0.028	0.122
	(0.10)	(0.042)	(0.092)
Psychiatrists per Thousand per County	-0.11	0.331**	0.13
	(0.18)	(0.076)	(0.16)
Medicare	-0.243**	0.0027	-0.825**
	(0.018)	(0.0070)	(0.017)

SLMB	-0.742**	-0.946**	-0.89**
	(0.084)	(0.038)	(0.10)
Number of Comorbidities	0.1479**	0.0005	0.0269**
	(0.0023)	(0.0014)	(0.0026)
Drug Abuse	0.145**	0.010	-0.089
	(0.014)	(0.010)	(0.019)
Alcohol Abuse	0.244**	0.043**	0.011
	(0.015)	(0.010)	(0.020)
Bipolar and Manic Depressive Disorders	0.104**	0.0798**	0.034*
	(0.014)	(0.0082)	(0.016)
Psychoses	0.2008**	0.0667**	0.040**
	(0.0098)	(0.0062)	(0.011)
Other Mental Disorders	0.216**	0.0252**	0.022
	(0.010)	(0.0071)	(0.012)
Personality Disorder	0.204**	-0.0098	0.028*
	(0.011)	(0.0075)	(0.013)
Depression and Schizoaffective Disorders	0.218**	0.0187*	0.038**
	(0.011)	(0.0073)	(0.012)
Schizophrenia	0.167**	0.1408**	0.130**
	(0.015)	(0.0070)	(0.015)
Constant	0.325**	-1.652**	-0.710**
	(0.066)	(0.024)	(0.051)
Observations	272,409	404,243	240,820
Number of individuals	27,070	39,965	23,490

Table 12. Negative Binomial Regression Models of the Effect of ACT on ER Visits for Individuals with SMI compared with those on ACT on Medicaid in North Carolina during 2000-2002 by Place of Residence (Aim 3)

	Individuals with SMI (Control Group 2)		
	Rural	Mixed	Urban
Percent quarter on ACT	-0.06	-0.07	-0.114*
	(0.24)	(0.12)	(0.058)
Age in 2002	-0.0272**	-0.0187**	-0.0217**
	(0.0053)	(0.0020)	(0.0014)
Male	-0.15	-0.212**	-0.320**
	(0.12)	(0.043)	(0.031)
Black	-0.08	0.073	0.110**
	(0.13)	(0.047)	(0.033)
Hispanic	-1.1	-0.29	0.56*
	(1.2)	(0.32)	(0.24)
Other Race	-0.32	0.06	-0.18
	(0.34)	(0.12)	(0.14)
Race Unknown	0.15	0.077	0.049
	(0.18)	(0.064)	(0.046)
Eligibility Category: Non-Blind/Disabled	-0.75	-0.76**	0.24
	(0.96)	(0.28)	(0.24)
Medicaid Eligibles per Thousand per County	0.00158	0.00040	0.00052
	(0.00088)	(0.00032)	(0.00033)
Psychologists per Thousand per County	0.49	0.17	0.0704
	(0.49)	(0.25)	(0.1650)
Psychological Associates per Thousand per County	0.48	-1.07**	-0.02
	(0.41)	(0.28)	(0.13)
Psychiatrists per Thousand per County	-0.86	0.53	-0.29
	(0.71)	(0.34)	(0.27)
Medicare	-0.127	-0.176**	-0.287**

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	(0.078)	(0.031)	(0.023)
SLMB	-0.53	-0.77**	-0.76**
	(0.38)	(0.14)	(0.11)
Number of Comorbidities	0.164**	0.1439**	0.1507**
	(0.011)	(0.0039)	(0.0030)
Drug Abuse	0.159*	0.131**	0.155**
	(0.074)	(0.025)	(0.019)
Alcohol Abuse	0.173*	0.222**	0.263**
	(0.079)	(0.028)	(0.020)
Bipolar and Manic Depressive Disorders	0.224**	0.079**	0.106**
	(0.071)	(0.026)	(0.018)
Psychoses	0.286**	0.188**	0.198**
	(0.044)	(0.017)	(0.013)
Other Mental Disorders	0.184**	0.202**	0.232**
	(0.047)	(0.018)	(0.014)
Personality Disorder	0.093	0.238**	0.197**
	(0.051)	(0.019)	(0.015)
Depression and Schizoaffective Disorders	0.155**	0.224**	0.211**
	(0.048)	(0.020)	(0.014)
Schizophrenia	0.236**	0.155**	0.175**
	(0.072)	(0.026)	(0.019)
Constant	0.22	0.27*	0.374**
	(0.32)	(0.12)	(0.091)
Observations	16,255	87,721	166,351
Number of individuals	1,708	8,993	17,015

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Table 13. Negative Binomial Regression Models of the Effect of ACT on General Medical Visits for Individuals with SMI compared with those on ACT on Medicaid in North Carolina during 2000-2002 by Place of Residence (Aim 3)

	Individuals with SMI (Control Group 2)		
	Rural	**Mixed**	**Urban**
Percent quarter on ACT	-0.49**	-0.117	-0.082*
	(0.19)	(0.086)	(0.035)
Age in 2002	0.00042	-0.00098	0.00067
	(0.0014)	(0.00061)	(0.00046)
Male	0.0201	0.020	0.0130
	(0.030)	(0.013)	(0.0098)
Black	0.0362	0.015	0.020*
	(0.035)	(0.015)	(0.010)
Hispanic	0.790*	-0.04	0.165**
	(0.35)	(0.11)	(0.061)
Other Race	0.34*	0.097*	0.109*
	(0.13)	(0.041)	(0.051)
Race Unknown	0.023	-0.001	0.007
	(0.045)	(0.019)	(0.015)
Eligibility Category: Non-Blind/Disabled	-0.19	0.21	-0.14
	(0.40)	(0.14)	(0.10)
Medicaid Eligibles per Thousand per County	-0.00067*	0.00003	-0.00005
	(0.00027)	(0.00010)	(0.00013)
Psychologists per Thousand per County	-0.24	-0.013	-0.298**
	(0.21)	(0.087)	(0.068)
Psychological Associates per Thousand per County	-0.38*	-0.03	-0.055
	(0.17)	(0.11)	(0.053)
Psychiatrists per Thousand per County	0.35	0.35**	0.49**
	(0.33)	(0.13)	(0.11)
Medicare	0.101**	-0.0028	-0.0069

	(0.028)	(0.012)	(0.0090)
SLMB	-1.04**	-0.810**	-1.010**
	(0.16)	(0.063)	(0.052)
Number of Comorbidities	-0.0073	-0.0048	0.0032
	(0.0059)	(0.0024)	(0.0018)
Drug Abuse	0.029	-0.011	0.015
	(0.047)	(0.019)	(0.013)
Alcohol Abuse	0.007	0.042*	0.046**
	(0.043)	(0.019)	(0.013)
Bipolar and Manic Depressive Disorders	0.167**	0.072**	0.071**
	(0.035)	(0.015)	(0.010)
Psychoses	0.033	0.062**	0.0732**
	(0.025)	(0.011)	(0.0080)
Other Mental Disorders	0.019	0.017	0.0280**
	(0.029)	(0.013)	(0.0092)
Personality Disorder	-0.013	0.026*	-0.0330**
	(0.031)	(0.013)	(0.0098)
Depression and Schizoaffective Disorders	-0.032	0.026*	0.0171
	(0.029)	(0.013)	(0.0094)
Schizophrenia	0.204**	0.132**	0.1380**
	(0.028)	(0.012)	(0.0090)
Constant	-1.50**	-1.623**	-1.695**
	(0.10)	(0.043)	(0.034)
Observations	26,010	129,757	247,276
Number of individuals	2,709	13,271	25,055

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Table 14. Negative Binomial Regression Models of the Effect of ACT on Primary Care Visits for Individuals with SMI compared with those on ACT on Medicaid in North Carolina during 2000-2002 by Place of Residence (Aim 3)

	Individuals with SMI (Control Group 2)		
	Rural	**Mixed**	**Urban**
Percent quarter on ACT	-0.16	-0.18	-0.082
	(0.28)	(0.15)	(0.075)
Age in 2002	0.0017	-0.0003	-0.0005
	(0.0031)	(0.0014)	(0.0011)
Male	0.075	0.092**	0.033
	(0.072)	(0.033)	(0.024)
Black	0.010	0.189**	0.064**
	(0.082)	(0.035)	(0.024)
Hispanic	0.75	0.60	0.22
	(0.52)	(0.32)	(0.12)
Other Race	0.08	0.256**	0.081
	(0.27)	(0.097)	(0.097)
Race Unknown	0.144	0.062	0.114**
	(0.094)	(0.042)	(0.032)
Eligibility Category: Non-Blind/Disabled	0.63	0.06	-0.37
	(0.79)	(0.24)	(0.23)
Medicaid Eligibles per Thousand per County	-0.00080	0.00053*	0.00043
	(0.00060)	(0.00023)	(0.00029)
Psychologists per Thousand per County	-0.94*	0.38*	-0.08
	(0.40)	(0.18)	(0.15)
Psychological Associates per Thousand per County	0.55	-0.53*	0.21
	(0.33)	(0.24)	(0.12)
Psychiatrists per Thousand per County	-0.24	0.42	0.25
	(0.61)	(0.30)	(0.25)
Medicare	-0.647**	-0.862**	-0.829**

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	(0.064)	(0.030)	(0.023)
SLMB	-1.24**	-0.60**	-1.08**
	(0.46)	(0.16)	(0.15)
Number of Comorbidities	0.029**	0.0150**	0.0319**
	(0.010)	(0.0046)	(0.0034)
Drug Abuse	-0.201*	-0.098**	-0.077**
	(0.086)	(0.034)	(0.025)
Alcohol Abuse	-0.064	0.057	-0.007
	(0.082)	(0.035)	(0.025)
Bipolar and Manic Depressive Disorders	0.199*	0.018	0.017
	(0.064)	(0.028)	(0.020)
Psychoses	-0.027	0.036	0.052**
	(0.043)	(0.020)	(0.014)
Other Mental Disorders	0.069	0.005	0.025
	(0.048)	(0.022)	(0.016)
Personality Disorder	0.009	0.038	0.022
	(0.052)	(0.023)	(0.017)
Depression and Schizoaffective Disorders	0.020	0.064**	0.021
	(0.048)	(0.022)	(0.016)
Schizophrenia	0.212**	0.123**	0.128**
	(0.056)	(0.025)	(0.019)
Constant	-0.53**	-0.605**	-0.684**
	(0.20)	(0.091)	(0.073)
Observations	16,651	79,243	142,779
Number of individuals	1,695	7,928	14,280

Table 15. Linear Probability Regression Results which were used to Create the Propensity Score Control Group (Control Group 3) of Time-Variant Covariates on the Likelihood of Any ACT Treatment within a Single Quarter in North Carolina between 2000-2002

	Schizophrenia/ No personality disorders/ Urban/ No Alcohol Abuse	No schizophrenia /Personality disorders/ Urban/ No Alcohol Abuse	No schizophrenia/ No personality disorders/ Urban/ No Alcohol Abuse	Schizophrenia/ Personality disorders/ Urban/ No Alcohol Abuse	Schizophrenia/ No personality disorders/ No Urban/ No Alcohol Abuse	No schizophrenia/ Personality disorders/ No Urban/ No Alcohol Abuse	No schizophrenia/ No personality disorders/ No Urban/ No Alcohol Abuse	Schizophrenia/ Personality disorders/ No Urban/ No Alcohol Abuse
Eligibility Category: Blind/Disabled	0.342**		0.118	0.22	-0.476*	0.33	0.31*	
	(0.097)		(0.085)	(0.23)	(0.188)	(0.30)	(0.12)	
Medicaid Enrollees per Thousand in County	-0.00025*	0.000008	-0.000317**	-0.00215*	0.000279**	0.000043	0.000000	0.00002
	(0.00010)	(.000026)	(0.000055)	(0.00095)	(0.000053)	(0.000048)	(0.000015)	(0.00010)
Psychologists per Thousand per County	0.085**	-0.029	0.022	-0.159	0.032	-0.032	-0.042**	-0.54**
	(0.027)	(0.031)	(0.011)	(0.089)	(0.028)	(0.032)	(0.016)	(0.21)
Psychological Associates per Thousand per County	0.15**	0.097	-0.031	0.013	-0.131**	-0.030	-0.047**	-0.24
	(0.026)	(0.077)	(0.017)	(0.068)	(0.016)	(0.020)	(0.012)	(0.13)
Psychiatrists per Thousand per County	-0.123**	0.024	-0.050**	0.12	0.235**	0.087	0.102**	0.97*
	(0.044)	(0.052)	(0.016)	(0.14)	(0.057)	(0.069)	(0.030)	(0.38)
Medicare	-0.0043	0.0064	0.0005	0.037	-0.0002	0.0075	-0.00314**	0.006
	(0.0046)	(0.0033)	(0.0014)	(0.024)	(0.0025)	(0.0040)	(0.00053)	(0.020)
SLMB	0.0018	-0.0007	-0.0083**	0.000	-0.0100	-0.0051*	0.00003	0.014
	(0.0054)	(0.0010)	(0.0027)	(0.016)	(0.0072)	(0.0020)	(0.00037)	(0.021)
Zero Comorbidities	0.0010	0.0044**	0.00133*	-0.0087	0.0006	-0.0034	0.00006	-0.0110*
	(0.0015)	(0.0015)	(0.00058)	(0.0062)	(0.0014)	(0.0020)	(0.00077)	(0.0055)

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One Comorbidity	0.0022	0.0035**	0.00172**	-0.0087	0.0043**	0.0012	-0.00065	0.0053
	(0.0014)	(0.0012)	(0.00058)	(0.0045)	(0.0012)	(0.0011)	(0.00054)	(0.0029)
Drug Abuse	0.0022	0.0094**	0.0042**	0.000	-0.0030	0.0058	0.0077**	0.0082**
	(0.0043)	(0.0030)	(0.0014)	(0.012)	(0.0040)	(0.0034)	(0.0022)	(0.0030)
Bipolar Disorder	-0.0042	0.0060*	0.0024	-0.0051	-0.0004	0.0006	0.0003	0.0174*
	(0.0030)	(0.0024)	(0.0013)	(0.0047)	(0.0029)	(0.0017)	(0.0012)	(0.0084)
Psychoses	-0.0037*	-0.0080	0.00242**	0.0082	0.0026	-0.0025*	0.00026	0.0008
	(0.0019)	(0.00072)	(0.00049)	(0.0055)	(0.0018)	(0.0012)	(0.00026)	(0.0037)
Other Mental Disorders	-0.0007	0.0003	0.0078	-0.0107	-0.0005	0.0018	-0.00097	-0.0039
	(0.0017)	(0.0014)	(0.00066)	(0.0066)	(0.0017)	(0.0098)	(0.00086)	(0.0054)
Depression and Schizoaffective Disorders	-0.0009	-0.0028	0.00083	-0.0033	-0.0077**	0.0017	-0.00023	-0.0059
	(0.0025)	(0.0010)	(0.00064)	(0.0065)	(0.0029)	(0.0012)	(0.00067)	(0.0040)
Constant	-0.280**	-0.010	-0.056	0.19	0.43*	-0.31	-0.30*	0.027
	(0.099)	(0.012)	(0.086)	(0.28)	(0.19)	(0.30)	(0.12)	(0.027)
Observations	81,154	32,981	106,639	9,514	47,859	22,458	66,895	6,948
Number of individuals	10,275	5,677	15,879	1,870	6,013	3,829	9,910	1,368
R-squared	0.80	0.77	0.81	0.81	0.58	0.39	0.53	0.66
Range of predictions	-.15, 1.13	-.02, 1.00	-.09, 1.01	-.08, 1.02	-.04, 1.01	-.02, 1.00	-.25, 1.00	-.05, 1.00
% of predictions outside 0-1	48	46	48	50	51	55	52	50

Standard errors in parentheses. *Significant at 5%; **Significant at 1%. Models also included indicators to control for year-quarter 1-12.

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Table 16. Linear Probability Regression Results which were used to Create the Propensity Score Control Group (Control Group 3) of Time-Variant Covariates on the Likelihood of Any ACT Treatment within a Single Quarter in North Carolina between 2000-2002

	Schizophrenia/ No personality disorders/ Urban/ No Alcohol Abuse	No schizophrenia /Personality disorders/ Urban/ No Alcohol Abuse	No schizophrenia/ No personality disorders/ Urban/ No Alcohol Abuse	Schizophrenia/ Personality disorders/ Urban/ No Alcohol Abuse	Schizophrenia/ No personality disorders/ No Urban/ No Alcohol Abuse	No schizophrenia/ Personality disorders/ No Urban/ No Alcohol Abuse	No schizophrenia/ No personality disorders/ No Urban/ No Alcohol Abuse	Schizophrenia/ Personality disorders/ No Urban/ No Alcohol Abuse
Eligibility Category: Blind/Disabled	-0.016		0.23				1.007**	
	(0.012)		(0.24)				(0.0030)	
Medicaid Enrollees per Thousand in County	0.000097	0.00047	0.000006	0.00044	0.00072*	-0.00021	-0.000198*	0.00119
	(0.000096)	(0.00024)	(0.000045)	(0.00023)	(0.00034)	(0.00014)	(0.000079)	(0.00076)
Psychologists per Thousand per County	0.07	0.144*	-0.134**	0.32	0.084	0.054	0.058	7.5**
	(0.12)	(0.057)	(0.052)	(0.17)	(0.064)	(0.041)	(0.030)	(2.9)
Psychological Associates per Thousand per County	0.08	-0.10	0.103	-0.184	-0.126	0.092	-0.004	1.61*
	(0.11)	(0.15)	(0.060)	(0.095)	(0.069)	(0.065)	(0.027)	(0.77)
Psychiatrists per Thousand per County	-0.20	0.34*	0.254*	-0.38	0.28	0.014	-0.212*	-4.1**
	(0.21)	(0.15)	(0.099)	(0.20)	(0.18)	(0.024)	(0.090)	(1.4)
Medicare	0.052	0.0002	0.023*	0.032	-0.0074	-0.0043	-0.0056**	
	(0.033)	(0.0026)	(0.010)	(0.020)	(0.0039)	(0.0041)	(0.0019)	
SLMB	-0.005	0.006	0.0000		-0.0194*	0.0081	-0.0029	
	(0.012)	(0.010)	(0.0038)		(0.0081)	(0.0066)	(0.0028)	
Zero Comorbidities	-0.0007	0.0000	0.0020	-0.014	0.0122	-0.0131	-0.0014	0.004
	(0.0094)	(0.0029)	(0.0051)	(0.012)	(0.0083)	(0.0091)	(0.0011)	(0.045)

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One Comorbidity	0.0030	-0.0019	-0.0010	0.0049	0.0074	-0.022	-0.0023	-0.021
	(0.0092)	(0.0065)	(0.0041)	(0.0073)	(0.0062)	(0.015)	(0.0027)	(0.041)
Drug Abuse	0.014	-0.0014	-0.0015	-0.051*	0.0100	-0.0011	0.0090*	0.019
	(0.012)	(0.0010)	(0.0050)	(0.026)	(0.0062)	(0.0014)	(0.0038)	(0.014)
Bipolar Disorder	-0.012	0.0060*	-0.0026	-0.056*	-0.021	-0.0032	0.00128*	0.016
	(0.014)	(0.0024)	(0.0050)	(0.027)	(0.013)	(0.0025)	(0.00062)	(0.022)
Psychoses	0.0005	0.00060	0.0034	0.0126	-0.0151*	0.0008	-0.00052	-0.017
	(0.0088)	(0.00087)	(0.0021)	(0.0087)	(0.0075)	(0.0009)	(0.00041)	(0.026)
Other Mental Disorders	-0.0036	0.0038	-0.0017	0.040*	0.0116	0.0011	-0.00019	0.005
	(0.0096)	(0.0012)	(0.0021)	(0.020)	(0.0069)	(0.0013)	(0.00040)	(0.010)
Depression and Schizoaffective Disorders	0.000	-0.0033	-0.0060*	-0.0115	-0.0167*	-0.0128	-0.0082**	-0.014
	(0.010)	(0.0019)	(0.0029)	(0.0084)	(0.0073)	(0.0086)	(0.0030)	(0.014)
Constant	0.089*	0.025	-0.24	0.001	-0.148	0.063	-0.939**	-0.82*
	(0.039)	(0.050)	(0.24)	(0.028)	(0.088)	(0.035)	(0.021)	(0.37)
Observations	7,933	4,375	11,629	1,708	5,358	2,875	7,163	1,087
Number of individuals	1,499	927	2,210	394	925	602	1,349	245
R-squared	0.77	0.81	0.79	0.75	0.65	0.42	0.57	0.68
Range of predictions	-.05, 1.0	-.09, 1.01	-.04, 1.0	-.07, 1.04	-.04, 1.01	-.02, .76	-.03, 1.00	-.15, 1.00
% of predictions outside 0-1	40	55	49	48	52	56	47	41

Standard errors in parentheses. *Significant at 5%; **Significant at 1%. Models also included indicators to control for year-quarter 1-12.

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Table 17. Results from the Propensity Score Analysis, Wilcoxon Rank Sum, and Rosenbaum Bounds Tests of the Effect of ACT on Costs and Services for Everyone with SMI (Control Group 2) in North Carolina Medicaid claims files between 2000-2002

	Average Effect of Treatment on the Treated					Wilcoxon Rank Sum*		Rosenbaum Bounds
	On ACT	**SMI**	**Difference**	**S.E.**	**T-stat***	**z=**	**Prob > |z|**	**Significant at Gamma=**
Full Sample (n=416,576 for ATT; n=5,787 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	4,619	3,432	1,187	1,942	0.61	27.5	0.0000	2
ER Costs	231	1,867	-1,637	776	-2.11	-44.0	0.0000	>5
General Medical Costs	137	119	18	421	0.04	17.4	0.0000	1
Primary Care Costs	11	5.5	5.6	19.5	0.28	8.9	0.0000	1
Inpatient Psychiatric Costs	252	216	37	866	0.04	6.2	0.0000	1
ER Visits	0.35	1.1	-0.75	0.58	-1.30	-39.6	0.0000	4
Inpatient Psychiatric Visits	0.10	0.068	0.033	0.18	0.18	6.2	0.0000	1
General Medical Visits	2.6	1.6	0.95	3.8	0.25	17.1	0.0000	0
Primary Care Visits	0.23	0.12	0.11	0.45	0.24	9.1	0.0000	1
Rural (n=26,733 for ATT; n=160 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	4,979	3,355	1,623	931	1.74	4.0	0.0001	1
ER Costs	522	155	367	279	1.31	-1.1	0.2607	0
General Medical Costs	372	112	260	227	1.15	1.9	0.0563	1
Primary Care Costs	11	4.4	6.7	8.0	0.84	0.3	0.7864	0
Inpatient Psychiatric Costs	393	1,028	-635	512	-1.24	-3.8	0.0002	1
ER Visits	0.48	0.98	-0.5	0.30	-1.66	-1.8	0.0697	1
Inpatient Psychiatric Visits	0.09	0.26	-0.17	0.097	-1.74	-3.6	0.0003	1
General Medical Visits	4.6	2.3	2.28	2.8	0.81	1.9	0.0516	1
Primary Care Visits	0.27	0.21	0.0625	0.26	0.24	0.4	0.7145	0
Mixed (n=133,910 for ATT; n=648 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	4,760	3,186	1,574	745	2.11	11.4	0.0000	2

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ER Costs	379	285	94	267	0.35	2.0	0.0448	0
General Medical Costs	155	225	-70	161	-0.44	1.4	0.1525	0
Primary Care Costs	14	15	-1.4	11.2	-0.13	-1.6	0.1017	0
Inpatient Psychiatric Costs	342	353	-11	308	-0.04	-2.7	0.0060	1
ER Visits	0.51	0.39	0.12	0.33	0.37	1.8	0.0645	1
Inpatient Psychiatric Visits	0.14	0.19	-0.051	0.097	-0.05	-2.7	0.0073	1
General Medical Visits	2.9	3.0	-0.066	2.6	-0.03	1.3	0.1815	0
Primary Care Visits	0.31	0.35	-0.035	0.22	-0.16	-1.5	0.1297	0
Urban (n=255,933 for ATT; n=4,979 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	4,590	3,421	1,169	2,157	0.54	25.6	0.0000	2
ER Costs	202	2,009	-1,807	900	-2.01	-43.5	0.0000	>5
General Medical Costs	128	108	20	453	0.04	18.1	0.0000	2
Primary Care Costs	11	4.2	6.4	18.6	0.35	10.4	0.0000	2
Inpatient Psychiatric Costs	236	188	48	1,009	0.05	7.3	0.0000	1
ER Visits	0.33	1.14	-0.81	0.62	-1.32	-39.3	0.0000	>5
Inpatient Psychiatric Visits	0.10	0.055	0.41	0.19	0.22	7.4	0.0000	1
General Medical Visits	2.5	1.5	0.98	4.2	0.23	18.3	0.0000	2
Primary Care Visits	0.21	0.092	0.12	0.46	0.27	10.6	0.0000	2

*The t-statistics signify the difference between those on ACT and those from the control group who were on support (i.e., people who were similar but who may not have been a match in the one-to-one matching algorithm) in the propensity score analysis. This is a larger group and does not take into account the matching used in the Wilcoxon Rank Sum statistic.

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Table 18. Results from the Sensitivity Analyses for the Propensity Score Analysis, Wilcoxon Rank Sum, and Rosenbaum Bounds Tests of the Effect of ACT on Costs and Services for Potential ACT Consumers in North Carolina between 2000-2002

	Average Effect of Treatment on the Treated							Rosenbaum Bounds
	On ACT	**Potential ACT**	**Difference**	**S.E.**	**T-stat***	**Wilcoxon Rank Sum***		**Significant at Gamma=**
Full Sample (n=2,730 for ATT; n=1,056 matched pairs for Wilcoxon and Rosenbaum)						**z=**	**Prob > |z|**	
Total Costs	40,783	52,682	-11,899	3,125	-3.81	-5.5	0.0000	1
ER Costs	3,031	7,298	-4,265	834	-5.11	-14.8	0.0000	2
General Medical Costs	1,888	3,909	-2,021	818	-2.47	-12.2	**0.0000**	2
Primary Care Costs	137	156	-18	23	-0.88	-3.3	**0.0010**	1
Inpatient Psychiatric Costs	3,273	11,471	-8,197	865	-9.48	-20.6	0.0000	>5
ER Visits	4.6	9.0	-4.3	1.0	-4.15	-14.1	0.0000	2
Inpatient Psychiatric Visits	1.2	4.2	-3.01	0.14	-21.99	-25.6	0.0000	>5
General Medical Visits	32	59	-27	4.7	-5.70	-14.3	0.0000	2
Primary Care Visits	2.9	3.5	-0.60	0.49	-1.23	-3.5	0.0005	1
Rural (n=120 for ATT; n=41 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	31,974	52,283	-20,309	14,210	-1.43	-1.8	0.0791	1
ER Costs	2,582	3,764	-1,182	1,906	-0.62	-2.0	0.0489	1
General Medical Costs	1,920	4,994	-3,074	2,875	-1.07	-1.6	0.1154	0
Primary Care Costs	150	196	-46	76	-0.60	0.2	0.8815	0
Inpatient Psychiatric Costs	3,181	18,829	-15,648	5,827	-2.69	-4.6	0.0000	3
ER Visits	3.9	4.8	-0.85	1.7	-0.51	-0.6	0.5243	0
Inpatient Psychiatric Visits	0.85	4.2	-3.3	0.43	-7.65	-5.4	0.0000	>5
General Medical Visits	37	71	-34	25	-1.34	-1.7	0.0836	1
Primary Care Visits	3.9	4.8	-0.98	1.6	-0.60	-0.2	0.8607	0
Mixed (n=747 for ATT; n=169 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	38,443	52,784	-14,340	6,666	-2.15	-2.8	0.0058	1
ER Costs	3,326	5,754	-2,428	1,089	-2.23	-4.2	0.0000	1

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General Medical Costs	2,306	5,509	-3,203	2,461	-1.30	-4.0	0.0001	1
Primary Care Costs	174	202	-28	43	-0.65	-1.1	0.2934	0
Inpatient Psychiatric Costs	3,415	10,611	-7,196	1,278	-5.63	-7.6	0.0000	3
ER Visits	5.9	8.4	-2.5	1.4	-1.77	-3.9	0.0001	1
Inpatient Psychiatric Visits	1.4	4.2	-2.8	0.247	-11.34	-9.9	0.0000	>5
General Medical Visits	39	69	-30	9.0	-3.34	-5.1	0.0000	1
Primary Care Visits	3.9	4.7	-0.75	0.90	-0.83	-1.2	0.2452	0
Urban (n=1683 for ATT; n=799 matched pairs for Wilcoxon and Rosenbaum)								
Total Costs	41,156	46,056	-4,900	3,190	-1.54	-1.9	0.0625	1
ER Costs	2,787	7,011	-4,224	1,121	-3.77	-13.3	0.0000	2
General Medical Costs	1,668	2,792	-1,124	454	-2.48	-9.7	0.0000	1
Primary Care Costs	126	137	-11	28	-0.41	-2.5	0.0136	1
Inpatient Psychiatric Costs	3,041	10,569	-7,528	1,146	-6.57	-18.2	0.0000	>5
ER Visits	4.2	8.0	-3.8	1.2	-3.19	-11.8	0.0000	2
Inpatient Psychiatric Visits	1.1	4.1	-2.9	0.17	-17.37	-22.2	0.0000	>5
General Medical Visits	30	50	-20	4.4	-4.57	-12.6	0.0000	2
Primary Care Visits	2.6	2.9	-0.35	0.57	-0.61	-3.1	0.0019	1

*The t-statistics signify the difference between those on ACT and those from the control group who were on support (i.e., people who were similar but who may not have been a match in the one-to-one matching algorithm) in the propensity score analysis. This is a larger group and does not take into account the matching used in the Wilcoxon Rank Sum statistic.

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