The Cost Savings of Tiered Care Coordination: Evidence from North Carolina

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ABSTRACT

This paper estimates the effect of Tiered Care Coordination (TCC) on the cost of care for system-involved youth with behavioral health needs. We use a difference-in-differences approach and a two-part model to estimate the effect of TCC on the probability of receiving a service and expenditures conditional on receiving a service. Estimation results find that referring youth involved with social services to TCC leads to average monthly savings of $2,824, or $33,888 annually. Descriptive evidence suggests that these savings are driven primarily by avoided inpatient claims. We also find that youth with a more serious and expensive service history are responsible for the largest savings, but there is evidence that TCC also lowers the cost of care for youth with a more modest service history. These results provide important insight on the benefits of interventions that successfully coordinate services for system-involved youth with behavioral health needs.

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1 Introduction

About two thirds of youth involved with the juvenile justice system have a mental health disorder and a majority of youth with one disorder suffer from at least one other substance use or mental health disorder (Meservey & Skowyra, n.d.; Shufelt & Cocozza, n.d.; Teplin et al., 2002). Providing youth with the necessary behavioral health services (BHS) is expensive and increasing in cost. Between 2005 and 2011, total annual Medicaid expenses increased from $19.3 billion to $30.2 billion (56%) for children receiving BHS (Pires et al., 2013). Youth receiving BHS via Medicaid who are involved with either the Department of Juvenile Justice (DJJ) or the Department of Social Services (DSS) account for a disproportionately large portion of total spending. Data within North Carolina Treatment Outcomes Program and Performance System (NC TOPPS) indicates that while justice-involved youth make up less than 1% of the overall adolescent population, they account for 20-60% of the high-level BHS. The alternatives to BHS are also costly – according to the Justice Policy Institute, the average price of youth incarceration in North Carolina is about $437 per day, or about $159,750 per year.

In 2017, a Tiered Care Coordination (TCC) pilot was implemented in Durham County of North Carolina, with the goal of better connecting system-involved youth with behavioral health needs to appropriate services. TCC has the potential to improve behavioral outcomes, address the growing need for BHS among system-involved youth, mitigate the increasing cost of serving youth with complex needs, and prevent the shifting of high costs across agencies.

This paper estimates the cost savings of TCC for system-involved youth using Medicaid claims and encounters data. We use a difference-in-differences approach where system-involved youth form a neighboring county served by the same provider and managed care organization are used as a comparison group. We use a two-part model to estimate the effect of TCC on the probability of receiving a service and the total cost of care for treated youth. We use an individual fixed effect to account for important youth-level and county-level differences, and we analyze results by referral source and service history.

We find evidence that TCC leads to significant cost savings and that results have important differences by referral source and service history. Youth referred to TCC from DSS lead to an average savings of about $38,000 in the year following referral, which is driven by avoiding costly inpatient services. We find descriptive evidence that DJJ-referred youth may lead to cost savings via fewer expenditures on BHS, but estimated effects are imprecise. Estimates of savings are largest in magnitude for youth with a history of residential services or therapeutic foster care, but there is evidence that savings may accrue for youth with a variety of pre-referral service histories. Across all estimates, cost savings are larger in magnitude than the per-youth cost of implementing TCC.

This paper contributes to our understanding of the cost savings of TCC by providing improved descriptive evidence and the first attempt at causal estimates in the literature. A growing body of research suggests that care coordination for youth with behavioral health needs is associated with cost savings via fewer inpatient services, fewer trips to the emergency room, and fewer interactions with Juvenile Justice and Social Services (*Evaluation Findings: Report to Congress 2011*, 2011; Grimes et al., 2011; Lin et al., 2017; Snyder et al., 2017; Stroul et al., 2014; Urdapilleta et al., 2012). However, most studies are purely descriptive and do not account for potentially important differences at the individual or provider level. Our study addresses these needs in the literature and finds evidence that TCC leads to significant cost savings to the state that far outweigh the cost required to implement TCC. These results provide new information that will help legislators make informed decisions about how to better serve system-involved youth with behavioral health needs.

2 Background

The 2016 Governor's Task Force for Mental Health and Substance Use made recommendations for TCC pilots. This allowed for funds through the NC Department of Health and Human Services (DHHS) to award grants to multiple entities, including UNC Greensboro, which is tasked with providing administrative, implementation, and evaluation support to Local Management Entities/Managed Care Organizations (LME/MCOs) and their providers. The LME/MCO Alliance Health contracted with DHHS to administer the first TCC pilot in Durham County. The goal of TCC is to better connect system-involved youth and their families to appropriate services. By coordinating services for youth involved with DSS or DJJ, TCC aims to successfully reunify youth with their families, improve behavioral outcomes at school and home, and reduce interactions with juvenile justice and crisis services.

Youth who receive TCC are assigned to one of three tiers based on their assessment. Tier 1 is for youth receiving outpatient BHS and provides access to embedded Liaisons and Family Navigators in DJJ and DSS offices. Tier 2 targets youth receiving enhanced BHS such as Day Treatment, Intensive In-Home, and Multisystemic Therapy in the community. This includes access to Liaisons, the Family Navigator, and Targeted case Management Services when needed. Tier 3 is aimed at youth returning from our-of-home placements or at risk for out-of-home placements. This allows access to a team of staff that provides High Fidelity Wraparound (HFW). HFW is an evidence-based service planning model that provides family and youth peer support. Moving up in tier provides an increasing level of attention and care coordination.

A successfully pilot may result in improved efficiency in navigating services, better outcomes, and reduced interactions with DJJ and DSS (Stroul et al., 2014). This could result in cost savings to the state via fewer expenditures on behavioral health and medical services, fewer interactions with juvenile justice, and fewer placements with social services. Estimates of the costs and cost savings of TCC will reveal whether TCC pilots provide a financial benefit to the state of NC, net of costs.

A growing literature finds that programs that target youth with behavioral health needs (e.g., Systems of Care, TCC, HFW, or Care Coordination) are associated with significant cost savings across several fronts. The Children's Mental Health Initiative (CMHI) conducted an analysis of 76 Systems of Care (SOC) communities for youth across the United States where they conducted interviews with youth at the time of intake and a year following intake. They compared outcomes and costs from the six months prior to intake to the six months prior to the second interview. They found that the number of days spent in inpatient psychiatric hospital care drop significantly, cutting average inpatient hospitalization costs by $1,433 (42%) per youth. Emergency room visits were also reduced, cutting emergency room costs by more than half . The average number of arrests for participating youth declined by 38%. Using an average cost per arrest, DJJ saves an estimated $718 per youth, which doesn't include savings accrued by reductions in detention or other services. Summed up for all participating youth, fewer inpatient psychiatric hospital care services, emergency room visits, and arrests were associated with a drop in spending of more than $62 million (*Evaluation Findings: Report to Congress 2011*, 2011).

Urdapilleta et al. (2012) evaluates a waiver program started by the Centers for Medicare and Medicaid Services to provide home-based and community-based services for youth with serious needs. The program was intended to be a substitute for the use of Psychiatric Residential Treatment Facilities (PRTF) and was adopted by nine states. They found that home and community-based services are associated with an average cost reduction of 68% compared to PRTF and related services. Over the course of three years, the program was associated with an average annual savings of more than $35,000 per youth via reduced Medicaid costs.

HFW is associated with significant drops in expenditures on inpatient services and BHS following referral to services (Kamradt, 2000; Snyder et al., 2017; Yoe et al., 2011). Pullman et al. (2006) found that youth in juvenile justice receiving HFW had significantly fewer days in detention and reduced recidivism rates compared to youth not receiving HFW, resulting in avoided long-term costs to juvenile justice. Grimes et al. (2011) uses propensity score matching to compare youth receiving HFW to a comparison group of youth. They found that referral to HFW is associated with 32% drop in yearly emergency room expenditures and a 74% drop in yearly inpatient psychiatry expenses compared to the comparison group

There is also evidence that care coordination more broadly results in cost-savings. Lin et al. (2017) found in a randomized control trial that care coordinators for frequent emergency room visitors resulted in 35% fewer ER visits and a 15% drop in average costs. Xing et al. (105) found that care coordination for Medicaid beneficiaries in Washington state is associated with a $318 drop in inpatient costs per person per month. Care coordination for youth with a variety of chronic conditions is associated with fewer ED visits, fewer hospitalizations, and lower inpatient costs (Antonelli et al., 2008).

While there is strong descriptive evidence that programs targeting youth receiving BHS result in cost savings, evidence of the causal effects is limited. Quasi-experimental approaches that use comparison groups and regression techniques to estimate effects could provide improved estimates of causal effects. However, between-group differences in individual or provider characteristics could be biasing these estimates. For example, differences in demographics, home life, referral source, and previous involvement with government agencies could be driving estimates of savings if they are not addressed. No peer-reviewed study has used a causal framework to estimate the cost savings of care coordination. Estimates of cost savings that incorporate various agencies and account for individual-specific factors are needed to better inform legislatures of the cost implications of TCC.

3 Evaluation Design and the Cost of TCC

Youth are eligible to receive TCC if they qualify for Medicaid, have behavioral health needs, and are involved with either DJJ or DSS. The JJSAMHP spreadsheet tracks youth who meet these criteria specifically for Wake and Durham counties, two of the most populous counties in North Carolina. When system-involved youth are assessed internally, they can be referred to a local managed care organization and/or provider for BHS. After the TCC pilot was implemented, when youth on the JJSAMHP spreadsheet in Durham County were referred to BHS, they received TCC. When youth on the spreadsheet in Wake County were referred to BHS, they received services ‘as usual’. Therefore, we use the JJSAMHP spreadsheet to identify youth who received TCC in Durham County and a comparison group of youth in Wake County.

Both the treated and comparison youth qualify for Medicaid, have behavioral health needs, and are system-involved. Both counties are also served by the same BHS provider and managed care organization – youth do not have the option to receive these services elsewhere. This ensures that differences in the types of services provided or characteristics of the service providers are not driving differences in outcomes.

Our approach to both descriptive and causal methods will rely on using information about Wake County youth to inform us of what outcomes Durham County youth may have experienced if they had not received TCC.

Implementing TCC in Durham County required significant up-front investment. The award letter for the project funded the labor and benefits for several full-time and part-time staff to work exclusively on TCC. The award also funded training and administrative costs required for TCC staff and others involved at the provider and managed care organization to carry out TCC. In an evaluation of the investment of TCC funded by NC DHHS, we estimate that the average monthly cost of providing TCC to a youth was about $290, or about $3,483 annually. These estimates provide a rough baseline to compare against estimates of cost savings resulting from TCC.

4 Data

We received claims and encounters data paid for by the Department of Mental Health, Developmental Disabilities and Substance Abuse Services (DMHDDSAS) and the Department of Health Benefits (NC Medicaid) for youth on the JJSAMHP spreadsheet in Durham and Wake counties. Data captures the 12 months before and 12 months after each youth's referral to BHS.

Important measures in the original claims data include revenue code, procedural code, service start and end dates, and amount billed. We also observe the date of referral to services and the source of referral. We define four categories of service claims and encounters: outpatient, inpatient, behavioral health, and residential.[2] We collapse the data into per-youth, per-month observations that include measures of the total number of services received, number of services received by category, total expenditures, and expenditures by type of service. All analyses are done with respect to each youth's month of referral to services.

We also received data on monthly eligibility for Medicaid. Youth who are not eligible for Medicaid will not show up in our data and are not eligible for TCC. However, eligibility status can change over time. If youth are ineligible for Medicaid in a given month, we assign them missing values for outcomes variables. If youth are eligible but we do not observe claims or encounters, we assign zero values.

To measure pre-referral service needs, we place youth into one of three categories depending on the most 'intense' service received in the year before referral: (1) residential services or therapeutic foster care, (2) enhanced services, or (3) outpatient services. This approximates pre-referral tier and is used to evaluate TCC for youth with varying service histories.

[2] 'Residential' includes long-term residential care (>30 days), such as a residential treatment program. Inpatient includes short-term residential care such as inpatient psychiatric, PRTF, and emergency room claims, as well as all other inpatient claims. Behavioral health includes claims for outpatient therapy, trauma care, peer support, enhanced services, and crisis services. Outpatient services includes all other services provided.

5 Descriptive Results

Table 1 contains descriptive statistics of the full sample by county. Youth in Durham County are younger, less likely to be female, and more likely to be black than youth in Wake County. About two-thirds of youth in Durham County are referred from DSS, while only one-fifth of youth Wake County are referred from DSS. This difference in referral source could be driving differences in demographics across counties, as well as differences in costs and the impact of TCC. Durham and Wake Counties have similar numbers of youth in pre-referral service history groups – this could be another margin by which TCC has different impacts on service use and costs.

Figure 1 plots average monthly expenditures per youth by county. Average monthly expenditures for youth in Durham County are about $1,100 in the year prior to referral, compared to just $425 per month for youth in Wake. In the year after referral to TCC, average monthly expenditures for Durham youth increase by 40% to about $1,550. In contrast, youth in Wake County experience an increase of 250% to about $1,500 per month. The stark difference in the change in expenditures following referral implies that youth in Durham may have experienced a similar increase in expenditures if they had not received TCC. This suggests that TCC could be responsible for significant savings. However, the monthly averages plotted in Figure 1 are unconditional. Differences in monthly claims by county may also be due to differences in characteristics of the youth populations, such as age, referral source, gender, or service history.

Referral source plays an important role in the needs of the youth, their service history, and the potential impact of TCC. In Figures 2 and 3, we split trends in expenditures by referral source, yielding notably different results. DJJ-referred youth in both counties see a similar spike in claims about 10 months prior to referral, followed by a downward trend in claims until referral. After referral, average claims jump significantly for both counties and remain at a higher cost through most of the year. Despite some noise eight months prior to referral, DSS-referred youth have similar average expenditures and trends in expenditures in the year prior to referral. Following referral, average claims for DSS-referred Wake County youth jump significantly, while claims for Durham County youth remain on a slow upward trend. These differences in trends and levels by referral group confirms the importance of pre-referral history and the potential for significant cost savings.

When a youth is referred from the system to behavioral health services, we expect service use and expenditures to increase in the short run. The cost savings of TCC are expected to arise through two avenues:

(1) Youth receiving TCC receive fewer services than they would have otherwise, ***and/or***

(2) Youth receiving TCC substitute costly services for less-costly services relative to what they would have received without TCC.

To explore these possible mechanisms, we also split trends apart by service type. Figure 4 plots service counts and claims expenditures by service type for DJJ-referred youth. Referral to TCC may lead to savings via fewer expenditures on behavioral health services for DJJ youth. Referral to services leads to sizable increases in the number of behavioral health services received in both counties. However, the increase in average behavioral health claims for Wake County youth is more dramatic following referral than the increase for Durham youth. The difference in trends between service counts and claims implies that while both counties may have seen an increase in number of services, TCC youth may have received less costly services, on average.

There is little evidence that referral to TCC has any impact on inpatient or outpatient service counts and expenditures for DJJ youth. Youth in both counties have noisy, flat trends in inpatient and outpatient service counts, and service counts appear to match closely to trends in claims expenditures. There is some evidence that referral to TCC increases the average cost of care through an increased number of residential services. However, residential services begin trending upward in the months prior to referral, suggesting that post-referral differences in expenditures could be driven by differences in pre-treatment trends. In any event, residential service counts and expenditures follow similar paths, implying that increases in residential services are responsible for increases in expenditures.

Figure 5 presents trends in service counts and claims by service type and county for DSS youth. There is strong evidence of cost savings due to avoided inpatient services. Aside from two outlier months, the average youth in both counties received less than one inpatient service per month prior to referral. Upon referral to TCC, Durham youth continue to rarely receive inpatient services, while youth in Wake County see an increase to 5-10 inpatient services per youth per month. These services are costly, resulting in an average increase in expenditures of several thousand dollars per youth per month. This suggests that referral to TCC for Durham youth avoided significant increases in the cost of care.

There is little evidence of cost savings due to TCC via changes in outpatient or behavioral health claims for DSS youth. It is unclear whether referral to TCC results in avoided expenditures on residential services for DSS youth. Wake County youth may not be a good comparison group in this case. While Wake youth see a sizable increase in service counts and cost following referral, this increase is similar in size to an increase experienced about six months prior to referral.

Splitting outcomes by referral source reveals important trends in service use and expenditures, but referral source may not tell the whole story. Figure 6 plots trends in service use and expenditures split apart by pre-referral service use. Youth in the ‘Outpatient’ category have similar trends in service use before and after referral in both counties, yet the cost of care nearly quadruples in Wake County for a few months following referral. It is unclear whether there is evidence of cost savings for youth in the ‘Enhanced Services’ category. Trends in services are similar across county, but both groups experience similar increases in expenditures following referral. The increase starts in Durham County prior to referral, complicating its interpretation. Youth with the highest needs (i.e., in the ‘residential and therapeutic foster care’ category) have similar trends in service counts over time between counties. However, the youth in Wake County see a large increase in expenditures following referral that youth in Durham County do not experience. The magnitude of this increase is much larger than in other groups, as residential and therapeutic foster care youth have significantly higher average expenditures over time.

Altogether, there is descriptive evidence that TCC may lead to cost savings across several populations and that savings may differ by referral source, service type, and pre-referral service needs. Youth referred to TCC from DJJ receive fewer behavioral health services than similar youth in Wake County, leading to lower average expenditures. Youth referred to TCC from DSS avoid a significant increase in inpatient services experienced by Wake County youth, which implies large savings. There is also evidence that TCC leads to cost savings for youth with a variety of service histories prior to referral, although youth with a history of residential services or therapeutic foster care are likely driving the most significant cost savings.

6 Empirical Approach

6.1 Identification

We turn to estimating the effect of TCC on service use and expenditures using a more formal difference-in-differences approach. We are interested in the average difference in the average monthly cost of care for youth receiving TCC and the average monthly cost of care for the same youth if they had not received TCC. We call this the Time-Averaged Average Treatment Effect on the Treated ($TAATT$). The average cost of care can be written as the product of the probability of receiving a service and the cost of services conditional on receiving a service. Let Y_t^1 be the monthly cost of care for time period *t* while receiving TCC and let Y_t^0 be the monthly cost of care for time period *t* while not receiving TCC. Let $\mathrm{D} = 1$ if a youth is in the treatment county and $D = 0$ if they are in the comparison county. The $TAATT$ is written as:

$$\begin{aligned} TAATT = \; & P(Y_t^1 > 0 | t \geq 0, D = 1) * E(Y_t^1 | Y_t^1 > 0, t \geq 0, D = 1) \\ & - P(Y_t^0 > 0 | t \geq 0, D = 1) * E(Y_t^0 | Y_t^0 > 0, t \geq 0, D = 1) \end{aligned} \quad (1)$$

We can decompose equation 1 into two separate $TAATT$s – the $TAATT$ of TCC on the probability of receiving a service (denoted $TAATT^1$), and the $TAATT$ of TCC on expenditures conditional on receiving a service (denoted $TAATT^2$).

$$TAATT^{\mathbf{1}} = P(Y_t^1 > 0 | t \geq 0, D = 1) - P(Y_t^0 > 0 | t \geq 0, D = 1) \quad (2)$$

$$TAATT^{\mathbf{2}} = E(Y_t^1 | Y_t^1 > 0, t \geq 0, D = 1) - E(Y_t^0 | Y_t^0 > 0, t \geq 0, D = 1) \quad (3)$$

Identification of the $TAATT$ relies on identifying the $TAATT^1$ and $TAATT^2$, which requires making two assumptions of the same form. We use nonlinear models to model the probability of receiving a service and conditional expenditures. To identify the $TAATT$ with a non-linear difference-in-differences model, we follow Lechner (2011) and use a counterfactual assumption based on the latent variable for Y_{it}, Y_{it}^*. We make the following identifying assumption:[3]

$$E(\bar{Y}_{t \geq 0}^{*0} - \bar{Y}_{t<0}^{*0} | \, D = 1) = (\bar{Y}_{t \geq 0}^{*0} - \bar{Y}_{t<0}^{*0} | \, D = 0) \quad (4)$$

The assumption in equation 4 is made twice: once when modeling the probability of receiving a service (to identify the $TAATT^1$), and once when modeling expenditures conditional on receiving a service (to identify the $TAATT^2$). When we model the probability of receiving a service, the latent variable Y_{it}^* is demand for services. The identifying assumption for $TAATT^1$ requires that, absent any group receiving treatment, youth in Wake County and Durham County would experience identical average monthly changes in demand for services from the year before referral to the year after referral. This is a reasonable assumption, as youth in both counties qualify for Medicaid, are involved in similar agencies, and are served by the same managed care organization and behavioral health provider.

[3] See Appendix B for a more thorough discussion of identification.

We model expenditures conditional on receiving a service using an exponential conditional mean function, which allows the identification assumption to be written in a convenient way. The identifying assumption for the $TAATT^2$ is that, conditional on receiving a service and absent either group receiving treatment, youth from Wake County and Durham County would have equivalent average *proportional* increases in expenditures from the year before referral to the year after referral. This is an assumption that we can visualize using observed outcomes. Without significant differences in pre-referral expenditures, this assumption is as reasonable as the traditional assumption of identical changes in the level of the outcome variable. For example, Figure 7 visualizes this identifying assumption for DJJ-referred youth.[4]

6.2 Estimation

We estimate results in two parts. First, we estimate the probability of receiving a service using an UFE Logit, as follows, where S_{it}^* is the latent variable for demand for services and S_{it} is a dichotomous variable for receiving a service:

$$S_{it}^* = TCC_i\alpha_1 + Post_t\alpha_2 + TCC_iPost_t\alpha_3 + c_i + \epsilon_{it} \tag{5}$$

$$S_{it} = \begin{cases} 1\ if\ S_{it}^* > 0 \\ 0\ if\ S_{it}^* \leq 0 \end{cases} \tag{6}$$

TCC_i is an indicator for being in Durham County, $Post_t$ is an indicator for being post-referral, and c_i is individual-level, time-invariant heterogeneity. We cluster standard errors at the individual-level. Including a fixed effect is essential to account for individual-level heterogeneity that may affect service use. We do not use a Conditional Fixed Effects Logit (CFE Logit) because of its inability to calculate predicted probabilities. We discuss the tradeoffs involved here in Appendix C.

We estimate expenditures using an Unconditional Fixed Effects (UFE) Poisson, where Y_{it} is expenditures and exp() is the exponential function:

$$Y_{it} = \exp(TCC_i\beta_1 + Post_t\beta_2 + TCC_iPost_t\beta_3 + c_i + \epsilon_{it}) \tag{7}$$

UFE Poisson does not suffer from incidental parameters bias, and we can calculate consistent estimates of marginal effects.[5] Poisson is advantageous because it models the non-negative nature of expenditure data and produces consistent estimates as long as the conditional mean is correctly specified (Wooldridge, 1999). We obtain correct standard errors in the case of overdispersion by using a standard error correction built into STATA.

We use estimates from equations 5 and 7 to calculate the $TAATT$, $TAATT^1$, and $TAATT^2$. Standard errors for treatment effects are calculated with a non-parametric bootstrap with 1,000 replications. The $TAATT$ can only be calculated for the sample that is eligible to be in both the

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[4] We assume homogeneity in the TAATT with respect to calendar time. We also index time relative to the month of referral, which ensures that no already-treated youth are used as comparison youth. Combined, these two steps avoid the recent pitfalls revealed of two-way fixed effects with variation in treatment timing (e.g., Sun & Abraham, 2020).

[5] We use UFE Poisson for estimating expenditures in the current draft of the paper, which could be infeasible with a larger sample size. In Appendix D, we discuss how we use an estimator developed by Martin (2017) to consistently estimate the AATT using CFE Poisson.

first and second parts of the two-part model. To avoid potential issues of sample selection, we do not estimate two-part models for subsets of services – we only estimate models including all services and service expenditures.

7 Estimation Results

Table 2 presents two-part model results split apart by referral source and tier. Column 1 estimates results for the DJJ-referred sample for all services with a fixed effect. TCC youth are about 7 percentage points less likely to receive a service after referral than their non-TCC counterparts, and they cost less after referral, conditional on receiving a service. The estimated $TAATT$ is -\$525, or about -\$6,300 annually, but is imprecisely estimated. While estimates of cost savings are imprecise for DJJ-youth, there is evidence that TCC leads to fewer services received in the year after referral. Estimates of the $TAATT$ point towards cost savings – additional pilot studies and a larger sample size could reveal cost savings in this group.

Column 2 estimates results for the DSS-referred sample. TCC youth are an average of 17 percentage points less likely to receive a service following referral, which is statistically significant at the 5% level. Conditional on receiving a service, TCC youth see average monthly reductions in behavioral health expenditures of \$4,829 per month, although this estimate is imprecise. While the estimate of the $TAATT^2$ is imprecise, the coefficient on Treat*Post in the second part is large and statistically significant at the 1% level. This implies that the semi-elasticity of the conditional mean of expenditures with respect to TCC is negative and different than zero. However, estimates of the $TAATT^2$ (in dollars) are likely imprecise due to high variance in the estimated fixed effects.

When both parts are combined, DSS-referred TCC youth see an average monthly drop in expenditures of \$2,824, or about \$33,888 per year, which is significant at the 10% level. The result of significant cost savings for DSS-referred youth is in line with the descriptive evidence or large relative drops in inpatient service use and expenditures following referral to TCC.

Column 3 estimates the two-part model for tier 1 youth and finds some evidence of cost savings. Youth are about six percentage points less likely to receive a service in a month following TCC, which is significant at the 10% level. TCC youth also cost \$1,226 less per month following referral, with an estimated $TAATT$ of -\$515 that is imprecisely estimated. Column 4 estimates results on tier 2 youth. We do not find any evidence of savings for tier 2 youth, which is consistent with descriptive evidence that suggests tier 2 youth in this sample may not be comparable due to diverging pre-trends in expenditures.

Column 5 finds evidence that tier 3 youth have especially large cost savings. Tier 3 youth are 7 percentage points less likely to receive a service following referral and cost about \$5,000 less per month conditional on receiving a service. The $TAATT$ is \$3,920, which is larger than any previous subsample, suggesting that tier 3 youth may be driving a majority of savings. However, all treatment effects in column 5 are imprecisely estimated.

Taken together, columns 3 and 5 imply that TCC has an economically and statistically significant impact on expenditures for youth with a variety of service histories. For tier 1 youth, the coefficients on Treat*Post in both parts are statistically significant; for tier 3 youth, the coefficient is large in magnitude and statistically significant in only the second part. The imprecise treatment effect estimates are the result of high variation and skewedness of the fixed effects. The coefficient in a UFE Poisson represents a semi-elasticity, which is a type of proportional effect. When used for prediction, fixed effects have a large say over the magnitude of the treatment effect.

8 Discussion

This study presents descriptive and causal evidence that referral to TCC leads to significant cost savings to the state of North Carolina. These savings are driven both by reducing the number of services received and fewer expenditures conditional on receiving a service. Estimates of savings are always notably larger than internal estimates of the average yearly cost of implementing TCC, which are about $3,500 per youth per year, implying that TCC has a positive return on investment to the state. Heterogeneities in savings by referral source and service history have important implications for policy makers.

The average youth referred to TCC from DSS leads to an average cost savings of $2,824 per month, or about $33,888 per year, in the year following referral. Descriptive evidence suggests that these savings are driven by avoiding costly inpatient services that similar youth in Wake County frequently use after referral. This highlights a key success of TCC – referred youth receive care coordination that diverts them away from expensive, unnecessary services. Without proper coordination, youth and their families may perceive inpatient services as the most appropriate course of action, leading to a higher cost of care. These large estimates of savings are similar in magnitude to some previous descriptive work (e.g., Urdapilleta et al., 2012), but they may not tell the whole story. If DSS-involved youth receiving TCC also saw a decrease in services received directly from DSS (which are not billed to Medicaid and do not show up in this study), then DSS may also see a reduction in their internal cost of care.

Descriptive evidence suggests that TCC youth referred from DJJ receive fewer behavioral health services, which could lead to cost savings. However, estimates of savings are imprecisely estimated, and we fail to find strong evidence of cost savings for DJJ-youth. The lack of savings here may be driven by the absence of DJJ cost data from this paper. If DJJ-referred youth had fewer interactions with DJJ and received fewer costly DJJ services, then we could be missing an important source of savings. Estimates of savings were always positive but more modest in magnitude – it is possible that a larger sample size would allow more precise estimates, revealing more evidence of cost savings in this population.

Across referral source, we estimate that youth with a history of residential services or therapeutic foster care lead to especially large savings when referred to TCC. These differences in savings by service history implies that the largest return on investment comes from better coordinating services for youth with an expensive service history. However, we caution that TCC and similar policies ought to not focus solely on youth with a history of these services. Descriptive evidence suggests that referral to TCC for youth with a less serious service history may still lead to cost savings. Youth across the spectrum of behavioral health needs could benefit from care coordination, and the state saves money as a result. Coordination of services for all system-involved youth with behavioral health needs may also be easier to practically implement than restricting coordination to youth who meet a service history threshold.

This paper has several limitations worth noting. First, our sample is restricted to one pilot county and one neighboring comparison county, which could limit the external validity of our results or have important effects on results if the comparison group is not adequate. Evaluating several pilot and comparison counties at once would provide us with information about how TCC generalizes to several settings, as well as give us more confidence in the comparison group used. Second, the sample size is relatively small, especially when looking at heterogeneities by referral source and service history. Evaluating multiple pilots would likely address this concern as well. Finally, we only have data for Medicaid claims and encounters, which does not include potentially important cost of care data collected by DJJ, DSS, or other state agencies. An evaluation of how TCC affects the cost of care to several state agencies would be an important contribution to our understanding of the effects of TCC that has not yet been seen in the literature.

Despite these drawbacks, this paper provides improved descriptive and causal evidence that TCC leads to significant cost savings to the state by avoiding costly services. These savings far outweigh the cost of implementing TCC. This evidence suggests that implementing TCC on a larger scale could lead to meaningful cost savings to state agencies and free up resources to be spent on important competing priorities.

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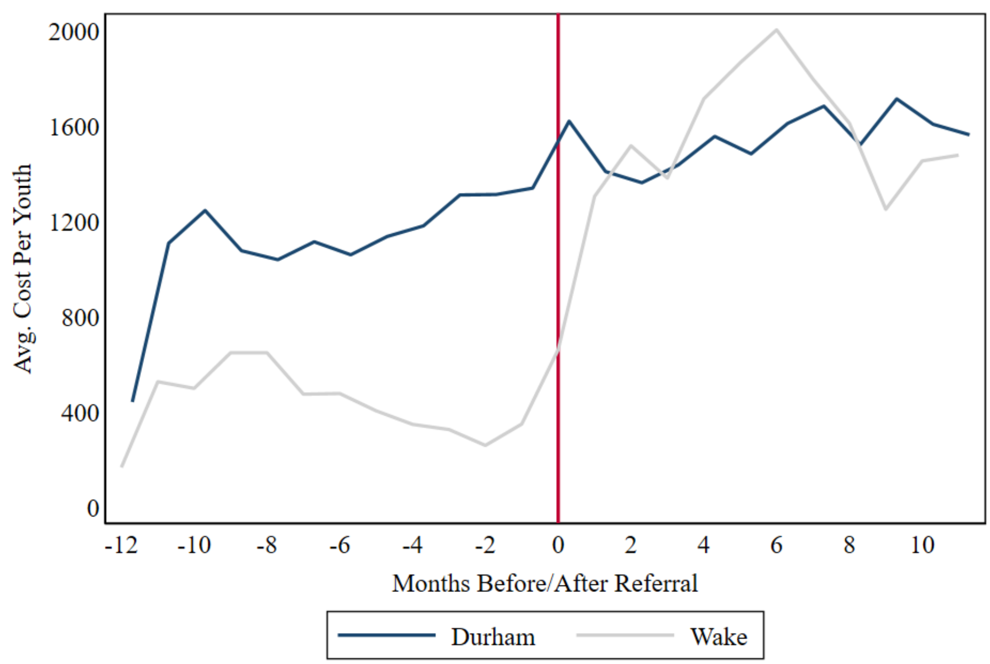
Appendix A – Tables and Figures

Table 1 – Descriptives by County

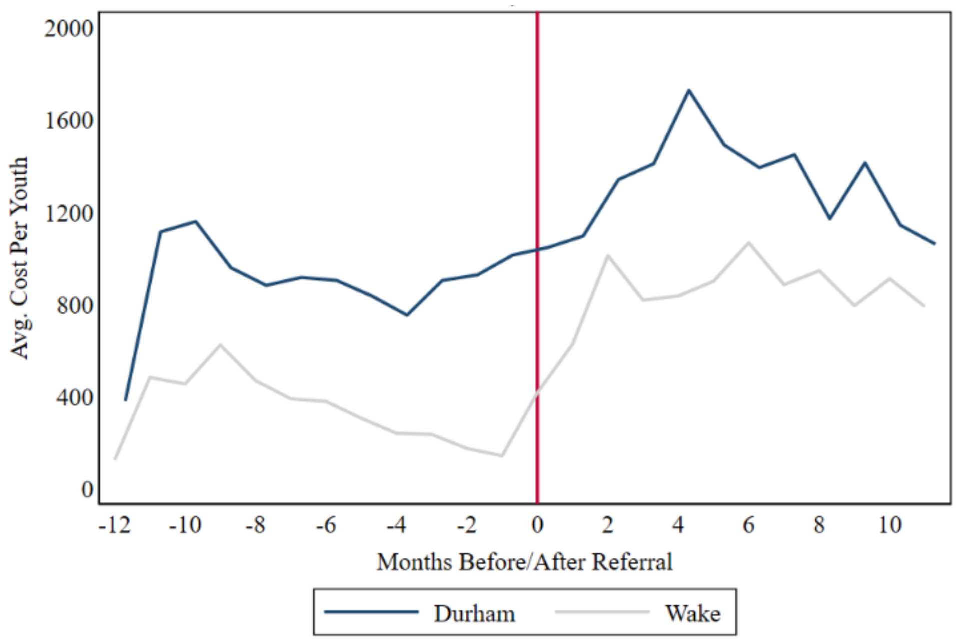
	Durham		Wake		T-Test
	Mean	SD	Mean	SD	P-Value
Male	0.56	0.50	0.66	0.47	(0.01)
White	0.17	0.38	0.28	0.45	(0.00)
Black	0.82	0.38	0.70	0.46	(0.00)
Hispanic	0.10	0.30	0.15	0.36	(0.03)
Age	12.20	3.83	14.72	2.12	(0.00)
DSS Referral	0.67	0.47	0.20	0.40	(0.00)
DJJ Referral	0.33	0.47	0.80	0.40	(0.00)
Outpatient Services	0.51	0.50	0.56	0.50	(0.27)
Enhanced Services	0.27	0.44	0.33	0.47	(0.06)
Residential / Therapeutic Foster Care	0.22	0.41	0.11	0.32	(0.00)
Observations	395		305		701

Figure 1 – Trends in Expenditures by County, All Youth



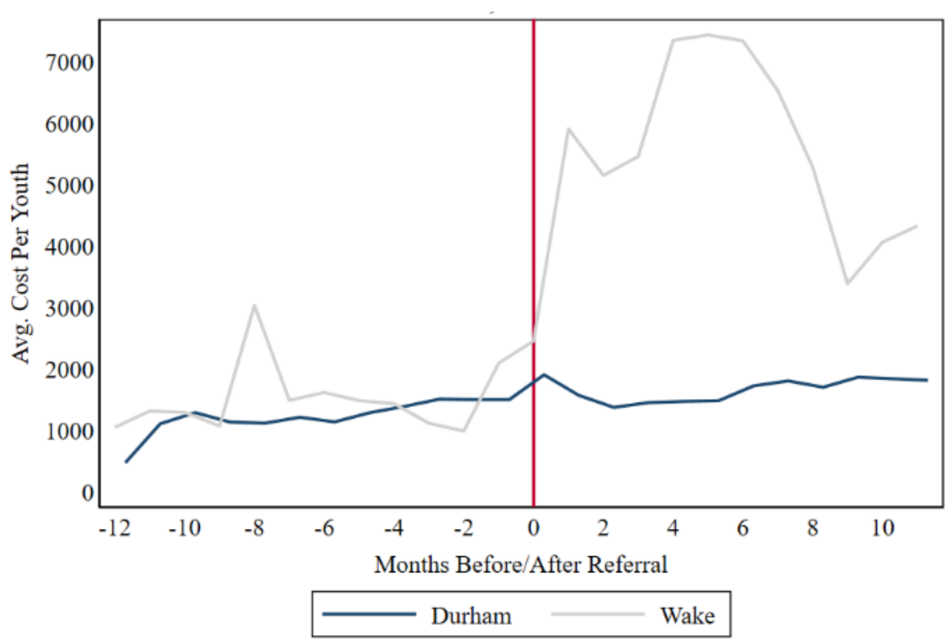
Note: This figure plots average monthly expenditures by county for all youth. The red line is the month of referral to services – Durham youth (N = 395) are referred to TCC, while Wake youth (N = 305) are referred to other services.

Figure 2 – Trends in Claims by County, DJJ-Referred Youth



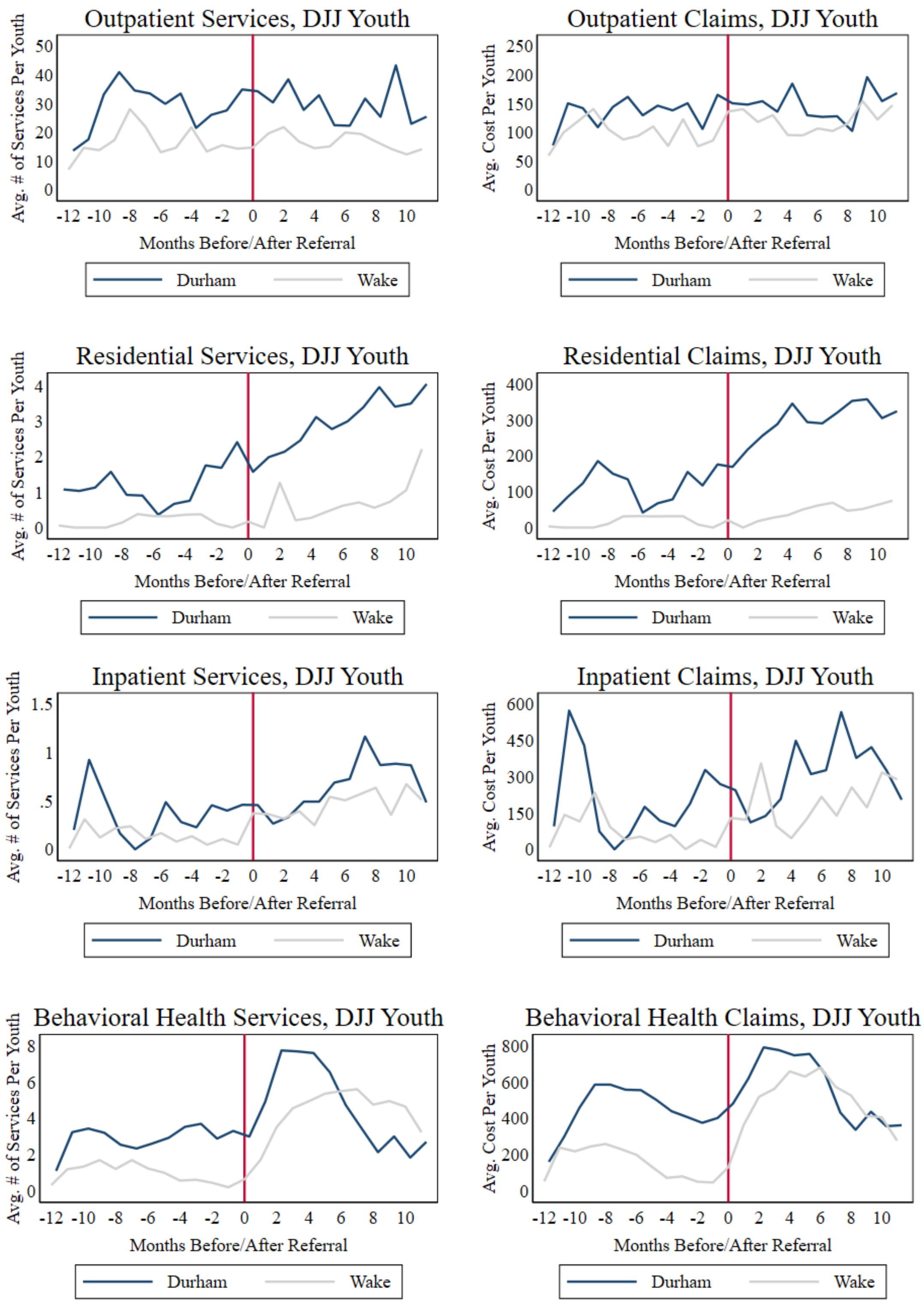
Note: This figure plots average monthly expenditures by county for all DJJ-referred youth. The red line is the month of referral to services – Durham youth (N = 132) are referred to TCC, while Wake youth (N = 244) are referred to other services.

Figure 3 – Trends in Claims by County, DSS-Referred Youth



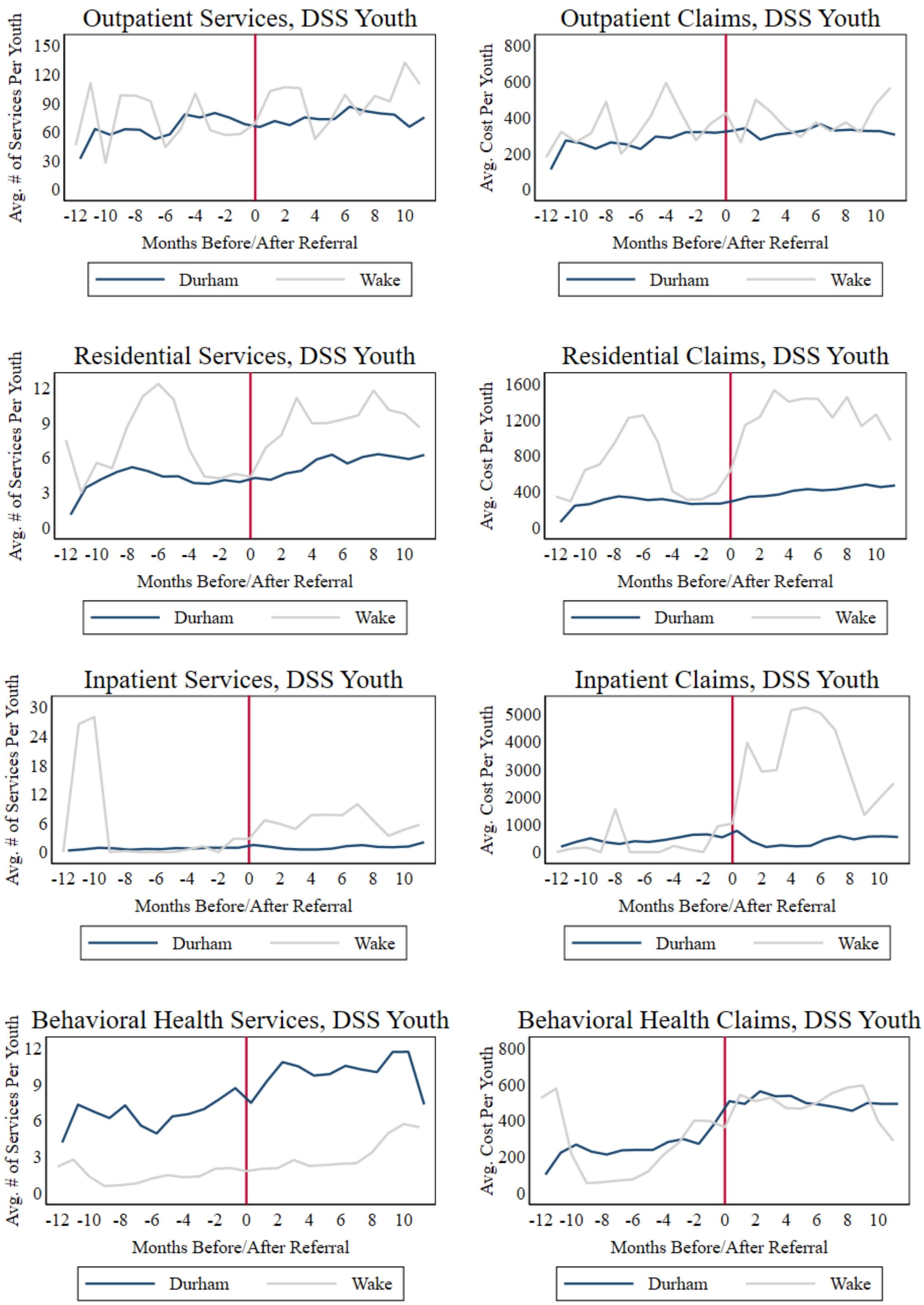
Note: This figure plots average monthly expenditures by county for all DSS-referred youth. The red line is the month of referral to services – Durham youth (N = 264) are referred to TCC, while Wake youth (N = 61) are referred to other services.

Figure 4 - Service Counts and Claims by Service Type, DJJ Youth



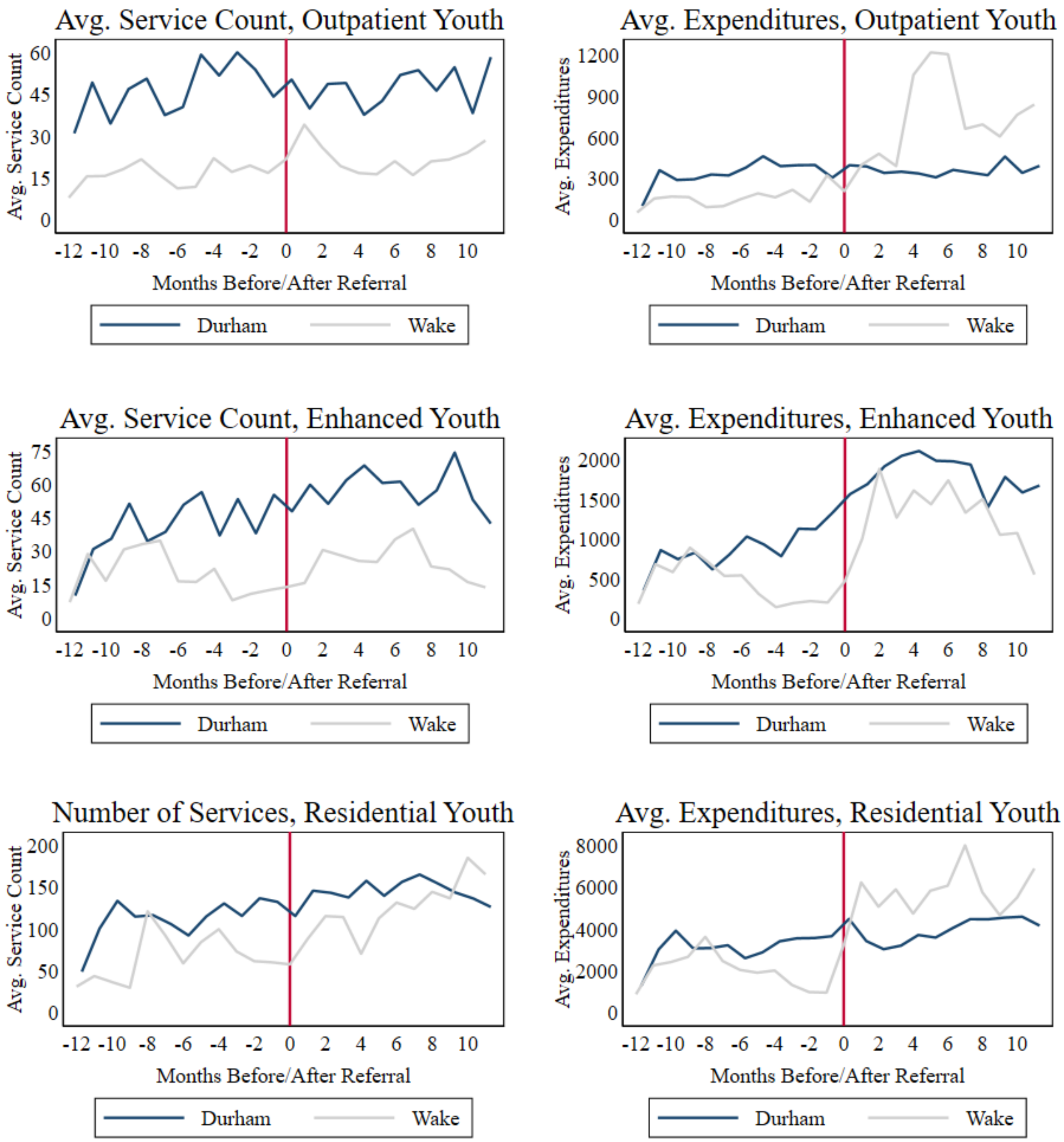
Note: This set of figures plots average service counts and monthly expenditures by county and service type for all DJJ-referred youth. The red line is the month of referral (i.e., referral to TCC for Durham youth). N = 132 for Durham, N = 244 for Wake.

Figure 5 - Service Counts and Claims by Service Type, DSS Youth



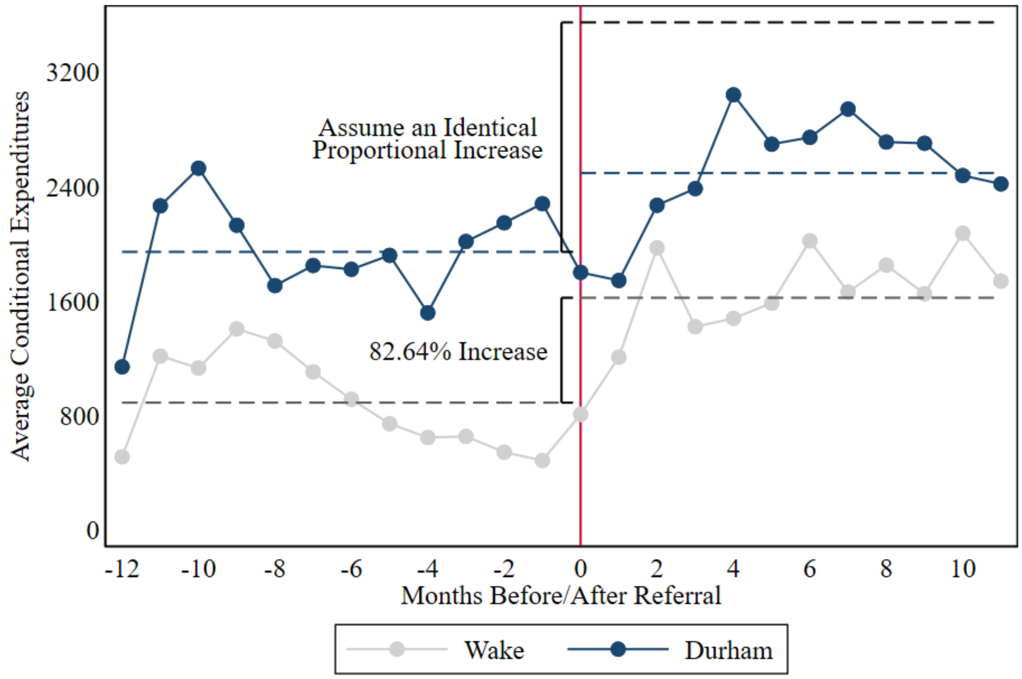
Note: This set of figures plots average service counts and monthly expenditures by county and service type for all DSS-referred youth. The red line is the month of referral (i.e., referral to TCC for Durham youth). N = 264 for Durham, N = 61 for Wake.

Figure 6 – Trends in Services and Expenditures by Pre-Referral Service History



Note: This set of figures plots average service counts and monthly expenditures by county and service type for all youth, split by pre-referral 'tier'. The red line is the month of referral to services (i.e., referral to TCC for Durham youth). Youth are placed into one of three categories based on their 'highest' level of service in the year before referral: 'residential or therapeutic foster care (N=87 for Durham, N=34 for Wake) is the highest level, followed by 'enhanced services' (N=105 for Durham, N=101 for Wake). 'Outpatient services' (N=204 for Durham, N=170 for Wake) includes all other youth.

Figure 7 – Visualizing the Identifying Assumption, DJJ-Referred Youth and All Services



Note: This figure only plots averages for observations that received a service (i.e., conditional on receiving a service). The gray dashed lines represent average monthly expenditures in Wake, while the navy dashed lines represent average monthly expenditures in Durham.

Table 2 – Two-Part Model Results

	(1)	(2)	(3)	(4)	(5)
Logit – Receives a Service					
Treat*Post	-0.37*	-1.18*	-0.31*	-0.37	-0.80
	(0.21)	(0.63)	(0.18)	(0.28)	(0.68)
$\boldsymbol{TAATT^1}$	**-0.07***	**-0.17****	**-0.06***	**-0.06**	**-0.07**
	(0.04)	(0.08)	0.03	0.05	0.05
Observations	8,447	5,543	7,635	4,593	1,762
Poisson – Conditional Expenditures					
Treat*Post	-0.26	-1.29***	-1.22**	-0.09	-0.78**
	(0.22)	(0.39)	(0.53)	(0.22)	(0.33)
$\boldsymbol{TAATT^2}$	**-573**	**-4,829**	**-1,226**	**-249**	**-5,019**
	(530)	(3,090)	(886)	(627)	(3,680)
Observations	3,932	4,707	3,609	2,746	2,268
$\boldsymbol{TAATT}$	**-525**	**-2,824***	**-515**	**-351**	**-3,920**
	(396)	(1,682)	(350)	(510)	(2,794)
Sample	DJJ	DSS	Tier 1	Tier 2	Tier 3
Fixed Effect	Yes	Yes	Yes	Yes	Yes

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Note: Selected coefficients (with standard errors clustered at the individual level) and average treatment effects (with bootstrapped standard errors) are reported. The $TAATT^1$ is with respect to the probability of receiving a service in an average month after referral. The $TAATT^2$ is with respect to average monthly expenditures after referral, conditional on receiving a service. The TAATT is with respect to the unconditional average monthly expenditures after referral. For DSS, N = 265 for Durham, N = 45 for Wake. For DJJ, N = 130 for Durham, N = 258 for Wake. 'Tier 1' - N=204 for Durham, N=170 for Wake. 'Tier 2' - N=105 for Durham, N=101 for Wake. Tier 3 - N=87 for Durham, N=34 for Wake.

Appendix B – Identification Details

Trends in service use and expenditures are noisy, making the strong counterfactual assumption required for time-period specific treatment effects difficult to justify. Instead, we turn to an estimand with a more reasonable counterfactual assumption. We are interested in the average difference in the average monthly cost of care for youth receiving TCC and the average monthly cost of care for treated youth if they had not received TCC. We call this the Time-Averaged Average Treatment Effect on the Treated (TAATT), written as:

$$TAATT = E(\bar{Y}^1_{t\geq 0} - \bar{Y}^0_{t\geq 0} \mid D = 1) \tag{B.1}$$

We can rewrite the average cost of care as the product of the conditional probability of receiving a service and the cost of services conditional on receiving a service:

$$\bar{Y}_{t\geq 0} = E(Y_t|t \geq 0) = P(Y_t > 0|t \geq 0) * E(Y_t|Y_t > 0, t \geq 0) \tag{B.2}$$

Using this decomposition, we can rewrite the TAATT for the two-part model as:

$$\begin{aligned} TAATT = \; & P(Y^1_t > 0|t \geq 0, D = 1) * E(Y^1_t|Y^1_t > 0, t \geq 0, D = 1) \\ & - P(Y^0_t > 0|t \geq 0, D = 1) * E(Y^0_t|Y^0_t > 0, t \geq 0, D = 1) \end{aligned} \tag{B.3}$$

We can also decompose equation 3 into two separate TAATTs:

$$TAATT^{\mathbf{1}} = \; P(Y^1_t > 0|t \geq 0, D = 1) - \; P(Y^0_t > 0|t \geq 0, D = 1) \tag{B.4}$$

$$TAATT^{\mathbf{2}} = \; E(Y^1_t|Y^1_t > 0, t \geq 0, D = 1) - \; E(Y^0_t|Y^0_t > 0, t \geq 0, D = 1) \tag{B.5}$$

To identify the $TAATT$ in equation B.3, we must identify the $TAATT^1$ and $TAATT^2$. The second terms in equations B.4 and B.5 (i.e., the second line of equation B.3) are unobserved; identification assumptions will define these unobservables in terms of observed outcomes. Identification rests on making two assumptions of the same form, which depend on how we model the conditional means of outcomes. Consider the following conditional mean function, where Y_{it} is the outcome (either receiving a service or expenditures), H() is a nonlinear link function, P_t is an indicator equal to 1 if in the post period ($t \geq 0$), D_i is an indicator equal to 1 if in the treatment group, c_i is an individual-level fixed effect, and ϵ_{it} is an error term with mean zero:

$$E(Y_{it}|D_i, P_t, c_i) = H(P_t\beta_1 + D_i\beta_2 + P_tD_i\beta_3 + c_i + \epsilon_{it}) \tag{B.6}$$

Since H() is nonlinear, the traditional difference-in-differences counterfactual assumption is too restrictive, namely because between-group differences in the average outcome cannot be differenced out, thus requiring that there are no between-group differences in the outcome. To see this, consider the usual counterfactual assumption that $E(Y^0|P = 1, D = 1) - E(Y^0|P = 0, D = 1) = \; E(Y^0|P = 1, D = 0) - E(Y^0|P = 0, D = 0)$. Plugging in for the conditional mean function, this equates to $H(\beta_1 + \; \beta_2) - H(\beta_2) = H(\beta_1) - H(0)$. For this to be true, then $\beta_2 = 0$, implying no differences in the outcome by treatment group. See Lechner (2011) for a more complete treatment.

We follow Lechner (2011) and use a counterfactual assumption based on the latent variable for Y_{it}, Y^*_{it}. Assume that $E(Y_{it}|D_i, P_t, c_i) = H(E(Y^*_{it}|D_i, P_t, c_i))$, implying that:

$$E(Y_{it}^*|D_i, P_t, c_i) = P_t\beta_1 + D_i\beta_2 + P_tD_i\beta_3 + c_i + \epsilon_{it} \qquad \text{(B.7)}$$

We make the following identifying assumption in terms of the latent variable:

$$E(\bar{Y}_{t\geq 0}^{*0} - \bar{Y}_{t<0}^{*0}|\ D = 1) = \ (\bar{Y}_{t\geq 0}^{*0} - \bar{Y}_{t<0}^{*0}|\ D = 0) \qquad \text{(B.8)}$$

This assumption can be rearranged to identify the unobserved outcome $E(Y^0|D = 1, P = 1)$ in terms of observed quantities, thus identifying the TAATT for the outcome Y_{it}. We make the assumption in equation B.8 twice: once when modeling the probability of receiving a service (to identify the $TAATT^1$), and once when modeling expenditures conditional on receiving a service (to identify the $TAATT^2$).

When we model expenditures conditional on receiving a service , we assume an exponential conditional mean function. We can substitute the exponential function in for H() in equation B.8 and rearrange it to get a more intuitive interpretation of the identifying assumption:

$$\frac{E(\bar{Y}_{t\geq 0}^{0}|D = 1)}{E(\bar{Y}_{t<0}^{0}|D = 1)} = \frac{E(\bar{Y}_{t\geq 0}^{0}|D = 0)}{E(\bar{Y}_{t<0}^{0}|D = 0)} \qquad \text{(B.9)}$$

As discussed in the text, the assumption is that, conditional on receiving a service and absent either group receiving treatment, youth from Wake County and Durham County would have equivalent average *proportional* increases in expenditures from the year before referral to the year after referral.

In Figure _, conditional on receiving a service, DJJ-referred youth in Wake County saw an 82.64% increase in average monthly expenditures following referral. For Durham youth, the increase following referral was much smaller. The identifying assumption here is that, in absence of treatment, Durham youth would have experienced an 82.64% increase in average expenditures, represented by the dashed black line at the top of the graph. This assumption does not require parallel pre trends, although similar pre trends may make it more plausible. This assumption stands in contrast to usual counterfactual assumptions, which require identical differences in levels of the outcome.

Appendix C – Comparing Unconditional and Conditional Fixed Effects Logit

Unconditional fixed effects logit suffers from incidental parameters bias. While this bias is less serious when there are many observations per fixed effect, it is important to understand the direction and severity of the bias. We assume that a Conditional Fixed Effects (CFE) Logit is the correct data generating process for determining whether a youth receives a service in a given month. Note that while CFE Logit produces consistent estimates of parameters in the conditional mean function, it cannot be used to calculate predictions in terms of the probability of receiving a service since it does not estimate the fixed effects. This leaves us with either an UFE Logit or a Logit without fixed effects. In Table B.1, we compare estimates from a logit without fixed effects, UFE Logit, and CFE Logit to assess differences in estimates. We restrict the sample to the 'fixed effects' sample (i.e., youth with variation in service use) for all columns.

Columns 1-3 show specifications from the DJJ sample. The CFE coefficient in column 3 is -0.36. Using UFE in column 2 slightly overestimates the coefficient with bias of 2.77%. However, excluding a fixed effect altogether in column 1 results in a larger downward bias of -5.55%. In columns 4-6, the difference in bias is more severe. Using UFE results in an upward bias of 7.27%, while not using a fixed effect underestimates the coefficient by 46.36%. In both cases, UFE overestimates the coefficient, while no fixed effect underestimates it. However, withholding a fixed effect appears to have a much larger impact on the coefficient estimate than incidental parameters bias, implying that addressing unobserved heterogeneity is especially important in this case. We use UFE Logit in our main results, and we caution that coefficient estimates are likely biased upward slightly.

Table B.1 – Comparing Logit Coefficients

	DJJ-Referred Youth			DSS-Referred Youth		
	(1)	(2)	(3)	(4)	(5)	(6)
Received a Service						
Treat*Post	-0.34**	-0.37*	-0.36*	-0.59	-1.18*	-1.10*
	(0.16)	(0.21)	(0.22)	(0.46)	(0.63)	(0.64)
Bias (%)	-5.55%	2.77%		-46.36%	7.27%	
Fixed Effect	None	UFE	CFE	None	UFE	CFE
Observations	8,447	8,447	8,447	5,543	5,543	5,543

** p < 0.10 , ** p < 0.05 , *** p < 0.01*
Note: Coefficients are reported with standard errors clustered at the individual level. Columns 1-3 show results for DJJ-referred youth and columns 4-6 show results for DSS-referred youth. Columns 1 and 4 estimate a logit, columns 2 and 5 estimate an unconditional fixed effects logit (UFE), and columns 4 and 6 estimate a conditional fixed effects logit (CFE). The sample in columns 1 and 4 are limited to the sample used by fixed effects estimators (i.e., must have within-person variation in service use) to single out the impact of using a fixed effect. We assume that the CFE Logit is the correct approach and calculate bias of other approaches relative to their estimates.

Appendix D - The Conditional Fixed Effects Poisson Estimator of the AATT

The UFE Poisson estimator does not suffer from incidental parameters bias. As long as there are sufficient degrees of freedom and observations, UFE Poisson is one way to estimate a FE Poisson model. Computational limitations prevent UFE Poisson from always being desirable, particularly when the number of fixed effects exceeds the number of variables allowed by statistical software or when maximum likelihood estimation becomes increasingly difficult. While the dataset used in the current draft of this paper is small enough to avoid these issues and allows us to use UFE Poisson, future iterations of data may prove to be too computationally demanding for us to use UFE Poisson.

Until recently, there was not an estimator available to calculate marginal effects and predictions using CFE Poisson output. As long as the conditional mean function holds, CFE Poisson produces consistent estimates of the coefficients of the conditional mean function. However, it does not produce estimates of the fixed effects that are required for marginal effects and prediction. Consider the AATT below, where n_1 is the number of youth in Durham County:

$$AATT = \frac{1}{n_1}\sum_{i=1}^{n_1} \tilde{c}_i * \mathrm{e}^{\beta_1+\beta_2}(e^{\beta_3} - 1) \tag{D.1}$$

Even with consistent coefficients, the AATT cannot be estimated without an estimate of the individual fixed effect. Martin (2017) provides a consistent estimator of average marginal effects in multiplicative unobserved effects panel models for nonnegative dependent variables. One example of such a model is the CFE Poisson. Martin (2017) proved that a simple estimate of the fixed effect, combined with parameter estimates from CFE Poisson, can be used to consistently estimate marginal effects and predicted values. We provide a brief explanation of the process. Please see Martin (2017) for a full treatment.

First, we estimate the desired regression using CFE Poisson. Next, we calculate the following estimator of the fixed effect for each youth in Durham County:

$$\hat{\tilde{c}}_i = \frac{\sum_{t=-12}^{11} \bar{y}_{it}}{\sum_{t=-12}^{11} \exp(TCC_i\beta_1 + Post_t\beta_2 + TCC_i * Post_t\beta_3)} \tag{D.2}$$

Next, we plug in the estimate of $\hat{\tilde{c}}_i$ and estimated coefficients into equation D.1. Martin (2017) shows that this is a consistent estimator as n approaches infinity. We tweak this approach to estimate the AATT for the relevant population for a two-part model. The consistency of this estimator is dependent on the number of observations asymptotically increasing, not on the number of time periods increasing.