EVALUATING PROCESS IMPROVEMENT EFFECTS ON WAIT-TIME IN SUBSTANCE ABUSE TREATMENT PROGRAMS VIA NONLINEAR QUANTILE REGRESSION

By

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CERTIFICATE OF APPROVAL

This is to certify that the Master's thesis of

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ABSTRACT

Objectives: Evaluate the effects of process improvement methods on wait-time across each study period (baseline, intervention, sustain) for patients entering substance abuse treatment programs participating in the NIATx 200 study through the use of quantile and least squares regression. Determine whether more intensive process improvement methods result in greater reductions in wait-time for patients entering substance abuse treatment programs participating in the NIATx 200 study.

Methods: Data derived from the 201 organizations in five states participating in NIATx 200. Process improvement methods involve interest circle calls, coaching, learning sessions and a combination of all three. The primary analysis is the development of a nonlinear quantile regression model for process improvement method evaluation. Secondary analysis consists of the development of a nonlinear least squares regression model.

Results: Among all groups, the coaching intervention (-56.8%) resulted in the greatest overall predicted reduction in wait-time for the duration of the study in the 50% quantile. The interest circle calls (-33.21%) and learning sessions (-14.29%) groups had the greatest wait-time reductions among all groups in the 90% quantile between the intervention and sustain periods of the study.

Conclusions: High cost/complexity process improvement methods do not necessarily result in greater reductions in wait-time for substance abuse treatment centers. Aside from an unusual baseline period, the combination intervention was generally the least effective at reducing wait-time. By contrast, the interest circle calls and learning sessions interventions were effective at reducing wait-time during the intervention and sustain periods. The coaching intervention consistently resulted in wait-time increases during the intervention period, but resulted in significant wait-time reduction during the baseline and sustain periods.

1 Introduction

NIATx 200 is a cluster-randomized, 17-month long clinical trial developed in partnership between the National Institute on Drug Abuse (NIDA) and the Network for the Improvement of Addiction Treatment (NIATx) (Quanbeck, et al., 2011). Based upon prior NIATx research (Capoccia, et al., 2007; McCarty, et al., 2009; Ford, et al., 2007), NIATx 200 focuses on the application of four process improvement interventions that are intended to improve waiting time, rates of admissions to treatment, and continuation in treatment for participating substance abuse treatment programs. The overall objective for NIATx 200 is to identify which process improvement methods work better/worse in achieving those goals.

The primary objective of this thesis will be to evaluate the effects of process improvement methods on wait-time for patients entering substance abuse treatment programs participating in the NIATx 200 study. In this evaluation, particular focus will be placed on the impact of the process improvement methods involved in the NIATx 200 study on wait-time through various study periods and the complexity of the process improvement methods. The general hypothesis, based on earlier results from NIATx based studies, is that more intensive process improvement methods result in greater reductions in wait-time for patients entering substance abuse treatment programs.

In order to evaluate the efficacy of the process improvement methods being considered in the NIATx 200 study, a conventional least squares and quantile regression methods were utilized to evaluate how each process improvement method (treatment) effects changes in both portions (quantiles) of patient wait-time distribution and also

mean patient wait-time. This modeling effort began with nonparametric methods involving cubic B-spline and density plots of wait-time distribution across time and NIATx 200 study periods. Ultimately, a nonlinear quantile regression model and nonlinear least squares model were developed such that wait-time trend estimates and predicted changes in wait-time could be evaluated relative to the process improvement methods employed in the NIATx 200 study.

2 Background

2.1 NIATx

The Network for the Improvement of Addiction Treatment (NIATx) is a national initiative that was established to provide its members with services intended to help them initiate and sustain process improvement approaches, specifically concerning access to and retention in addiction treatment (Capoccia, et al., 2007; McCarty, et al., 2009; Ford, et al., 2007). The principles of the program are derived from process improvement research: understand and involve the customer, fix key problems, pick a powerful change leader, get ideas from the outside, and use rapid cycle testing (Hoffman, et al., 2012). NIATx was jointly developed by the Robert Wood Johnson Foundation (RWJF) and the Center for Substance Abuse Treatment (CSAT) of the Substance Abuse and Mental Health Services Administration (SAMSHA). Agencies participating in NIATx were selected through a grant submission and award process with 25 agencies being funded for NIATx participation for 18 months through RWJF (10 in an initial cohort and 15 in a second round of awards) and 13 agencies funded for 36

months through CSAT. The grant submission and site selection process are outlined in McCarty, et al. (2007) and Hoffman, et al. (2011).

The central aims of NIATx were to (1) reduce waiting time between the first request for service and the first treatment session, (2) reduce the number of patients who do not keep an appointment, (3) increase the number of people admitted to treatment, and (4) increase continuation from the first through the fourth treatment session (Capoccia, et al., 2007). In order to achieve these objectives, process improvement efforts in the NIATx sites involved agency walkthrough procedures to identify key problem areas. Following the walkthrough process, change teams utilized rapid cycle change initiatives to evaluate the efficacy of changes made to the admission processes. Wait-time results from this study were based on a conventional least squares mixed effects regression analysis and estimated rates of change in wait-times of 30 days or less (Hoffman, et al., 2011). These results indicated that the purported theory that faster entry into treatment programs following assessment increases treatment program completion was valid. Since the process improvement methods were uniformly applied, however, it was not possible to determine which process improvement methods resulted in the observed improvements (Hoffman, et al., 2011).

Subsequent analysis via quantile regression of the initial NIATx study data (Choi, et al., 2012) demonstrated that relying upon conventional least squares regression analysis can miss important behaviors in other portions of the response variable distribution. In fact, because one of the key aspects of the process improvement methods utilized in the earlier NIATx study is to reduce variation through treatment

intervention, it was no surprise that high quantiles of wait-time behaved differently from changes in mean values (Choi, et al., 2012). In this earlier NIATx study, Choi, et al. (2012) found that improvements in high-quantile cases were detected regardless of significant changes at the mean level.

2.2 NIATx 200

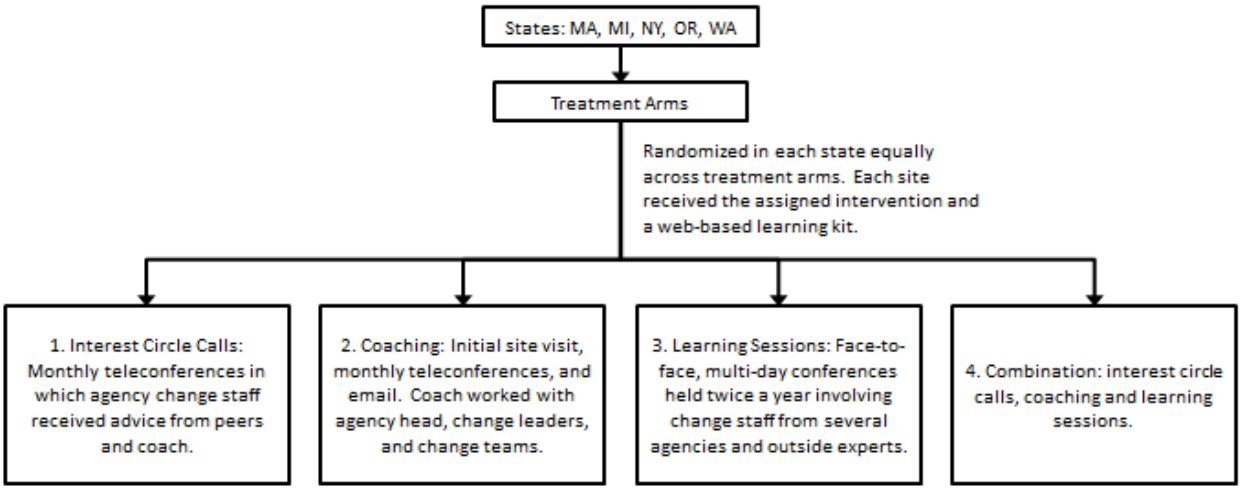
Building on the earlier NIATx study results, NIATx 200 was a cluster-randomized study conducted through the Center for Health Enhancement System Studies (CHESS) at the University of Wisconsin - Madison, the Center for Substance Abuse Research and Policy at Oregon Health & Science University, and the Health Economics Research Group and the University of Miami (Quanbeck, et al., 2011). Similar to the initial inception of NIATx, the intent of NIATx 200 was to apply process improvement techniques at the organization and service delivery level of community-based addiction treatment centers. Unlike NIATx, the primary focus of the NIATx 200 study (Quanbeck, et al., 2011) was to assess which of the four process improvement methods would produce the greatest improvement in waiting time, rates of admissions to treatment, and continuation in treatment. In this case, waiting time was defined as the number of days from first contact to treatment. Secondary study objectives focused on the effects of treatment interventions on treatment completion rates, adoption and sustainability of recommended practices, and employee turnover. Associated cost analysis was not initially included in the scope of study objectives. Participating clinics were randomized with equal allocation at the state level into one of four treatment groups: (1) interest circle calls, (2) coaching, (3) learning sessions, and (4) a combination of 1-3.

Randomization was based on clinic size and management score where the management score was based on a pre-randomization interview with clinic leaders.

Across all treatment groups, the 17-month period following the baseline period was divided into three intervention periods, each with specific aims. The first 5-month period focused on wait-time improvements, the second 6-month period focused on retention of patients in the treatment program and the third 6 month program focused on increasing the number of new patients. For the scope of this thesis, we limited the focus to the intervention period focusing on improvements in wait-time; the following intervention descriptions are based on the study protocol (Quanbeck, et al., 2011) and cost analysis carried out by Gustafson, et al. (2013). Interest circle calls were monthly teleconferences during which change team members from the programs involved discuss issues and progress and have an opportunity to get advice from experts or one another. At a cost per clinic of $1329 (Gustafson, et al., 2013) these teleconferences are inexpensive, but the quality of such calls can vary by facilitator and, because they are scheduled in advance, competing priorities of the participants can limit involvement. Coaching involves the assignment of a process improvement expert to work directly with program leaders and change teams to help implement and sustain process improvements. In NIATx 200, coaching consisted of one site visit, monthly teleconferences, and email correspondence. Coaching gives a program process improvement assistance that is customized to their needs and the ability to access an expert on demand. Coaching, however, is more expensive ($2878 per clinic [Gustafson, et al., 2013]) than interest circle calls and the match between the coach and program

may not always be a good one. Learning sessions, which occurred twice a year in this case, were in-person multi-day conferences that bring together program change teams to learn and gather support from outside experts and one another. Despite these benefits, learning sessions are very expensive at $4495 per clinic (Gustafson, et al., 2013) and require a substantial time investment for the participants. The combination intervention involved all three forms of process improvement and was, of course, the most intensive and expensive option at a cost of $7930 per clinic.

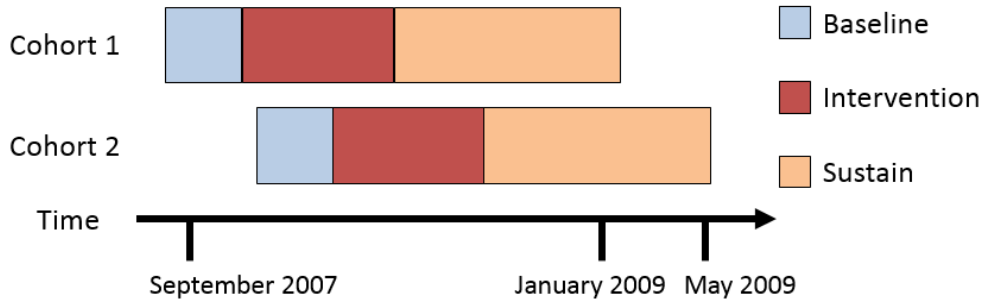
Figure 1: Design of the NIATx 200 cluster-randomized trial.



Addiction treatment centers in five states (Massachusetts, Michigan, New York, Oregon, Washington) were recruited by state authorities for the study. Treatment centers in these five states formed two cohorts due to a staggered study implementation timeline. Centers from Michigan, New York, and Washington make up Cohort 1, while centers from Massachusetts and Oregon make up Cohort 2. Recruitment in Cohort 1 took place between March and August of 2007, with a baseline

data collection period occurring between September 2007 and November 2007 and wait-time intervention occurring between December 2007 and April 2008. The corresponding study timeline for Cohort 2 was shifted four months later. After recruitment, a baseline period of three months occurred where treatment center staff were instructed on collecting data and their assigned process improvement intervention. Then a six month intervention period was followed by a nine month sustainability period where the wait-time intervention was removed.

Figure 2: NIATx 200 cohort study timelines.



Gustafson, et al. (2013) published results for the NIATx 200 study and utilized a mixed-effect model for fitting wait-time improvement, including fixed effects for state and group. Random effects at the organization level were included to account for correlation among clinics in the same organization and random effects at the clinic level were included to account for correlation between repeated observations from the same clinic over time. In this model, Gustafson, et al. (2013) utilized monthly averages of wait-time, which both served as the unit of analysis and also gave equal weight to all clinics, regardless of size. After the wait-time intervention period, both the coaching and combination groups had statistically significant reductions in wait-time (-4.9 days, $p = 0.013$ and -6.2 days, $p = 0.002$, respectively). Learning sessions had a modest wait-

time reduction and interest circle calls resulted in an increase in wait-time, but neither were statistically significant at the 0.05 level. When the groups were compared, however, a statistically significant difference was only found between the interest circle calls group and the combination group. Sensitivity analysis was also used in order to evaluate the effect of giving equal weight to the clinics in the model by weighting each clinic based on patient counts in an alternative model. This alternative model did not change the rank order of wait-time reduction effect among the treatment groups (Gustafson, et al., 2013).

2.3 Quantile Motivation

Least squares regression is a useful and pervasive tool in modern statistics, but it only informs the user about a portion of the distribution of the response variable. Mosteller and Tukey (1977) noted that other portions of the response variable distribution could be explored, but that it is not commonly done and, thus, we rarely arrive at a complete picture of the relationships between variables. Conventional least squares regression also will not meet the need if certain percentiles or quantiles of a response variable distribution require estimation. Furthermore, if heterogeneity in the data cannot be mostly explained by changes in the mean, then it is necessary to pursue an alternative method in order to derive inferential conclusions (Choi, et al., 2012).

Quantile regression is a method for estimating functional relations between variables for all portions of a probability distribution (Koenker and Bassett, 1978). Least squares regression can be used to estimate conditional quantiles, but this method requires an assumption of normally distributed residuals. Least squares regression also

assumes that covariates do not affect the scale or distributional shape of the conditional response. Quantile regression, by contrast, makes neither of these assumptions and, thus, has a distinct advantage over least squares regression in modeling data with heterogeneous conditional distributions. Lastly, compared to least squares regression, quantile regression estimates are more robust in the presence of outliers in the response variable (Koenker, 2005).

2.4 Quantile Estimation

Consider a real-valued random variable Y with cumulative distribution function F_Y. The τth quantile of Y, y_τ , can be written as

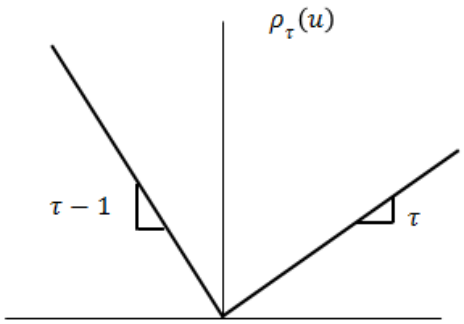
$$F_Y(y_\tau) = P(Y \leq y_\tau) = \int_{-\infty}^{y_\tau} f(u)du = \tau$$

where $\tau \, \epsilon \, (0,1)$. The boundaries on τ are not included in order to preserve uniqueness and F_Y will be a strictly monotonic increasing function if τ is unique. The foundation of quantile estimation for a univariate sample $\{y_1, y_2, \dots, y_n\}$ is the piecewise linear loss function (Figure 3),

$$\rho_\tau(u) = u(\tau - I(u < 0))$$

for some $\tau \in (0,1)$.

Figure 3: Quantile estimator function $\rho_\tau(u)$



We minimize the expected loss of $Y - \hat{y}$ with respect to $\hat{y}$:

$$\min_{\hat{y}} E\big(\rho_\tau(Y-\hat{y})\big) = \min_{\hat{y}}(\tau-1)\int_{-\infty}^{\hat{y}}(y-\hat{y})dF(y) + \tau\int_{\hat{y}}^{\infty}(y-\hat{y})dF(y)$$

and then set the derivative with respect to $\hat{y}$ equal to 0:

$$0 = (1-\tau)\int_{-\infty}^{\hat{y}} dF(y) - \tau\int_{\hat{y}}^{\infty} dF(y) = F(\hat{y}) - \tau$$

Thus we have found that any element of $\{x: F(y) = \tau\}$ minimizes expected loss since $F(y)$ is monotone. When the solution is unique, $\hat{y} = F^{-1}(\tau)$ and the solution will be an interval of τth quantiles otherwise. In this case, the smallest element must be chosen in order to ensure that the empirical quantile function be left-continuous.

In the case of an empirical distribution, we can estimate the τth sample quantile to be

$$\min_{\xi\in\mathbb{R}} \sum_{i=1}^{n} \rho_\tau(y_i - \xi)$$

Rather than relying upon ranking observations, this quantile estimator can then be transformed into a linear program by adding $2n$ artificial variables $\{u_i, v_j: 1, \dots, n\}$ to

represent the positive and negative parts of the vector of residuals. Then we have a new minimization problem:

$$\min_{(\xi,u,v)\in\mathbb{R}\times\mathbb{R}_+^{2n}}\{\tau 1_n^T u + (1-\tau)1_n^T v | 1_n\xi + u - v = y\}$$

which can be solved either by the simplex method (Koenker and D'Orey, 1987) or interior point method (Portnoy and Koenker, 1997).

If we now consider Y as a response variable and random variable $\boldsymbol{X}$ as a p-dimensional predictor, which we may begin to think of as representing an independent variable having some effect on Y, then a conditional quantile of Y can be similarly written as

$$F_Y(y_\tau(\boldsymbol{x})|\boldsymbol{X}=\boldsymbol{x}) = P(Y \le y_\tau(x)|\boldsymbol{X}=\boldsymbol{x}) = \tau$$

Thus the quantile function $Q_\tau(\tau|\boldsymbol{X}=\boldsymbol{x})$ is the smallest y where the quantile property is fulfilled if F_Y is not strictly monotonic. This can alternatively written as:

$$Q_Y(\tau|\boldsymbol{X}=\boldsymbol{x}) = inf\{y: F_y(y|\boldsymbol{x}) \ge \tau\}$$

We can then observe that this is the inverse of the CDF of Y if F_Y is strictly increasing, i.e.,

$$F_Y(y_\tau(x)|\boldsymbol{X}=\boldsymbol{x}) = \tau \quad \Leftrightarrow \quad Q_Y(\tau|\boldsymbol{X}=\boldsymbol{x}) = y_\tau(\boldsymbol{x})$$

and that this function describes $\tau \times 100\%$ quantiles of Y depending on covariates $\boldsymbol{x}$ and quantile parameter $\tau\ \epsilon\ (0,1)$.

2.5 Quantile Regression

Quantile regression is a method for modeling the conditional quantile function of a continuous variable Y depending on a set of p-dimensional covariates $\boldsymbol{X}$. Similar to conventional least squares modeling, we will denote Y as our response variable and $\boldsymbol{X}$

as our independent variable(s). In a conventional least squares linear regression model we have $Y = \boldsymbol{X}^T\beta + \varepsilon$ and $E(\varepsilon) = 0$. Similarly, the linear quantile regression model can be written as $y_i = \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau + \varepsilon_{\tau i}$ where y_i represents the sample $\{y_1, y_2, \dots, y_n\}$, $\boldsymbol{x}_i = (1, x_{i1}, \dots, x_{ip})^T$ represents the covariate vector for observation i and $\boldsymbol{\beta}_\tau = (\beta_{\tau 0}, \beta_{\tau 1}, \dots, \beta_{\tau p})^T$ represents the quantile-specific linear effects (Buchinsky, 1998). Note that the first element of $\boldsymbol{x}$ is one and corresponds to the model intercept. Lastly, the quantile parameter $\tau \in (0,1)$ is fixed in advance of model fit. Unlike least squares linear regression, no firm assumptions are made with regards to the distribution of error terms $\varepsilon_{\tau i}$ aside from independence and the quantile restriction $Q_\tau(\varepsilon_{\tau i}|\boldsymbol{x}_i) = 0$ (Buchinsky, 1998). Based on the quantile restriction, the linear quantile regression model as defined above describes the quantile function $Q_{Y_i}(\tau|\boldsymbol{x}_i)$ of the response variable Y_i conditional on covariate vector $\boldsymbol{x}_i$ at a given quantile parameter $\tau \in (0,1)$. To prove this relationship we first write the CDF of Y_i in terms of the CDF of $\varepsilon_{\tau i}$:

$$F_{Y_i}(y_\tau|\boldsymbol{x}_i) = P(Y_i \le y_\tau|\boldsymbol{x}_i) = P(\boldsymbol{x}_i^T\boldsymbol{\beta}_\tau + \varepsilon_{\tau i} \le y_\tau|\boldsymbol{x}_i)$$

$$= P(\varepsilon_{\tau i} \le y_\tau - \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau|\boldsymbol{x}_i) = F_{\varepsilon_{\tau i}}(y_\tau - \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau|\boldsymbol{x}_i)$$

Since the $\tau \times 100\%$ quantiles of Y depending on covariates $\boldsymbol{x}$ and quantile parameter $\tau \in (0,1)$ is $F_{Y_i}(y_\tau|\boldsymbol{x}_i) = \tau$, we can now show that the linear quantile regression function is derived as follows:

$$F_{Y_i}(y_\tau|\boldsymbol{x}_i) = \tau$$

$$F_{\varepsilon_{\tau i}}(y_\tau - \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau|\boldsymbol{x}_i) = \tau$$

$$y_\tau - \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau = F_{\varepsilon_{\tau i}}^{-1}(\tau)$$

$$y_\tau = \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau + F_{\varepsilon_{\tau i}}^{-1}(\tau)$$

Due to the quantile restriction $F_{\varepsilon_{\tau i}}^{-1}(\tau) = 0$ and we have:

$$Q_{Y_i}(\tau|\boldsymbol{x}_i) = \boldsymbol{x}_i^T \boldsymbol{\beta}_\tau$$

which is a function that describes the linear relationship between covariates $\boldsymbol{x}$ and the quantile function of Y based on parameters $\boldsymbol{\beta}_\tau$ and fixed $\tau \in (0,1)$.

Returning to the least squares linear regression model $Y = \boldsymbol{X}^T\beta + \varepsilon$ where $E(\varepsilon) = 0$, we may also write this such that β represents the marginal change in the mean of Y due to a marginal change in x: $E(Y|\boldsymbol{X} = \boldsymbol{x}) = \boldsymbol{x}^T\beta$. As we have shown, this relationship is similarly extended to the linear model for the τth conditional quantile function $Q_{Y_i}(\tau|\boldsymbol{x}_i) = \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau$ such that $\boldsymbol{\beta}_\tau$ is the marginal change in the τth quantile due to a marginal change in $\boldsymbol{x}$. In the least squares case, $E(Y) = \mu_Y = \min_a E\{(Y-a)^2\}$ and the sample mean solves $\min_a \sum_{i=1}^n (y_i - a)^2$. If we then consider the conditional mean of Y given x to be $E(y|x) = \boldsymbol{x}^T\beta$, then β can be estimated by solving $\min_\beta \sum_{i=1}^n (y_i - x_i^T\beta)^2$. Again, this estimation method is extended to the linear quantile regression model since the τth sample quantile, $\hat{\alpha}_\tau$, solves $\min_\alpha \sum_{i=1}^n \rho_\tau(y_i - \alpha)$ and in the conditional quantile function $Q_{Y_i}(\tau|\boldsymbol{x}_i) = \boldsymbol{x}_i^T\boldsymbol{\beta}_\tau$ the estimator of β_τ is

$$\hat{\beta}_\tau = \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^n \rho_\tau(y_i - x_i^T\beta)$$

Since this estimation is a generalization of the sample quantile to a linear regression context, this method has commonly been referred to as least absolute deviations (LAD) (Koenker & Bassett, 1978; Buchinsky, 1998). This estimation method too can be transformed into linear programming optimization problem:

$$\min_{(\beta,u,v)\in\mathbb{R}^p\times\mathbb{R}_+^{2n}}\{\tau 1_n^T u + (1-\tau)1_n^T v | X\beta + u - v = y\}$$

where X represents the n by p regression design matrix. Just as with the quantile estimator, this optimization problem can be solved either by the simplex method (Koenker and D'Orey, 1987) or interior point method (Portnoy and Koenkey, 1997). In the nonlinear case, the asymptotic behavior of the nonlinear quantile regression estimator closely parallels that of the nonlinear least squares estimator (Koenker, 2005). For the nonlinear quantile regression model we are trying to solve $\min_{\theta\in\mathbb{R}^p}\sum_{i=1}^n \rho_\tau(g_i(\theta))$ where the functions g_i are continuously differentiable in θ. Parameter estimates in the nonlinear case can be solved via an interior point method suggested by Koenker and Park (1996).

In the case of independent and identically distributed (IID) errors for univariate sample $\{y_1, y_2, \dots, y_n\}$, asymptotic normality can be extended from the conventional linear regression model to the quantile regression process. Consider the linear model $y_i = X_i\beta + \varepsilon_i$ with IID errors ε_i with common distribution F (i.e. $\varepsilon_i \sim F$). Suppose that F has density f such that $f\left(F^{-1}(\tau_i)\right) > 0$ for $i = 1, \dots, m$ and $n^{-1}\sum x_i x_i^T \equiv Q_n$ converges to a positive definite matrix Q_0. Koenker and Bassett (1978) then showed that the joint asymptotic distribution of the mp-variate quantile regression estimators $\hat{\zeta}_n = (\hat{\beta}_n(\tau_1)^T, \dots, \hat{\beta}_n(\tau_m)^T)^T$ takes the form

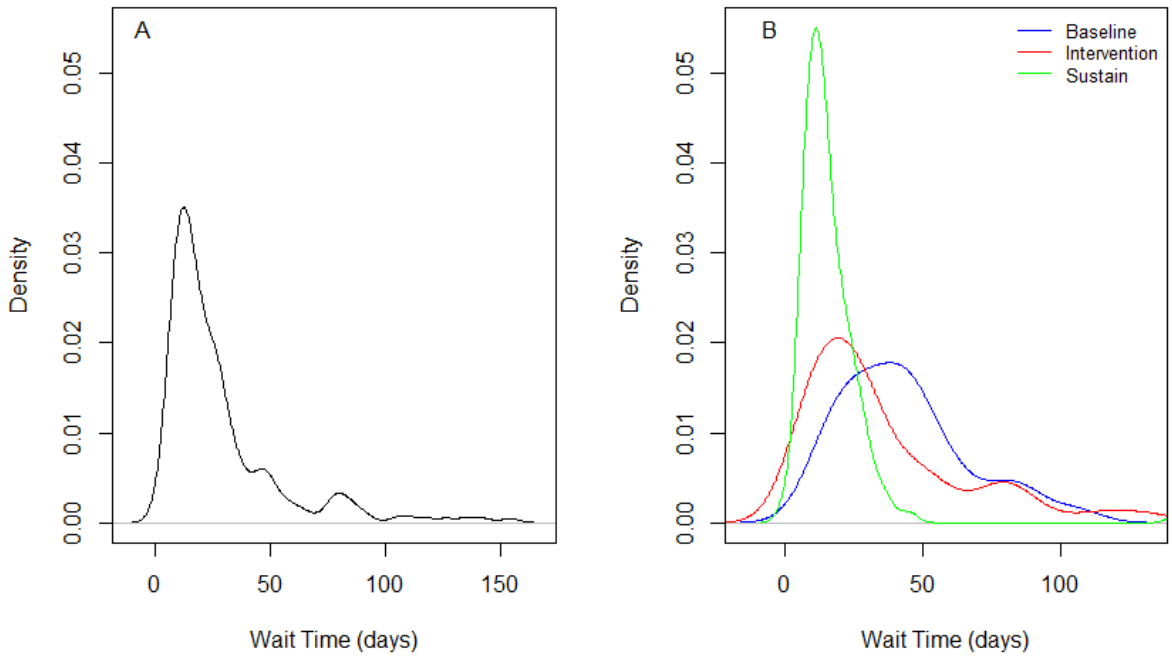
$$\sqrt{n}\left(\hat{\zeta}_n - \zeta\right) = \left[\sqrt{n}\left\{\hat{\beta}_n\left(\tau_j\right) - \beta\left(\tau_j\right)\right\}\right]_{j=1}^m \xrightarrow{F} N(0, \Omega \otimes Q_0^{-1})$$

where $\Omega = \omega^2 = \tau(1-\tau)/f^2(F^{-1}(\tau))$. Recall that $F^{-1}(\tau)$ refers to the quantile function $Q_{Y_i}(\tau|\boldsymbol{x}_i)$ of the distribution F. Asymptotic normality of quantile regression estimators then enables the use of the Wald test for hypothesis testing.

2.6 Quantile Regression Applications

In recent years, quantile regression has become a popular alternative to conventional least squares regression and has been applied in a number of different areas. Applications range from environment and ecological sciences (Cade, et al., 2008; Pandey and Nguyen, 1999); medicine and biology, with particular importance in the development of reference and growth charts (Wei, et al., 2006; Koenker and Geling, 2001); economics (Buchinsky, 1994; Matano and Naticchioni, 2012); and social and educational sciences (Hao and Naiman, 2007; Arulampalam, et al., 2011). Additional examples are available in Koenker (2005). Regardless of the area of application, quantile regression is a useful tool when the response has distributional features such as asymmetry, heavy tails or outliers, or whenever the response's distributional shape depends on covariates (Koenker, 2005).

Figure 4: Distribution of first treatment session wait-time in organization "MA-06". (A) Density plot for wait-time across all study time periods ($n = 224$) . (B) Density plot by study time periods: baseline ($n = 30$), intervention ($n = 80$), sustain ($n = 114$).



Given the importance of reducing patient-level wait-time and patient-level wait-time variance for improving admission rates to treatment and continuation in treatment (Hoffman, et al., 2011), quantile regression methods are a logical choice for modeling the treatment effects of NIATx 200 on wait-time. Figure 4 shows wait-time density across all study time periods in NIATx 200 (Figure 4a) and wait-time density for each individual study time period in NIATx 200 (Figure 4b) for a single organization, "MA-06". As Choi, et al. (2012) noted, the variation in the densities of wait-time across time that can be seen in Figure 4 indicate that there is more than one slope that describes the overall distribution of wait-times. In the presence of such heterogeneity in the response variable distribution, least squares regression may be inadequate for characterizing

changes in mean response of the response variable (Cade, et al., 1999). By contrast, quantile regression extends the examination of treatment effects beyond the mean response via least squares regression and into the lower and upper quantiles, which is something that was shown to be relevant in an earlier NIATx study (Choi, et al., 2012). In the applied setting, the superiority of the interior point method (Koenker, 2005) in application to linear or nonlinear fixed effects models allows for inferential conclusions to be drawn about group-wide treatment effects in these lower and upper quantiles.

3 Methods

3.1 Sample

The source data from which a sample was drawn for this analysis is data from the NIATx200 study from outpatient treatment agencies from both cohorts. Because the analysis objectives of this study deal with treatment effects on wait-time only, then the data timeframe was restricted to study time periods concerning wait-time improvements for each cohort: September 2007 to January 2009 for cohort 1 and January 2008 to May 2009 for cohort 2. Due to data quality issues with the underlying data, inclusion/exclusion criteria were utilized. Overall, the NIATx 200 study involved 201 individual sites though some sites were eventually lost to follow-up due to closures or time/scheduling problems. Individual records within the data set represent individual patients requesting enrollment for treatment in the participating treatment centers during the timeframes for each respective cohort. As such, record level inclusion/exclusion criteria will be applied first and then organization level criteria.

At the record level, treatment request and first treatment dates were required to be populated. Additionally, logical criteria such as the treatment request date occurring during the study period for the corresponding cohort and chronologically sequential treatment sessions were also required at the record level. At the organization level, organizations without any data during the study period corresponding to their cohort were removed. Organizations without at least one data point recorded during each of the first eleven months of the intervention and sustainability periods were also removed so as to establish a minimum data threshold for contributing organizations.

Table 1: Attrition diagram for inclusion/exclusion criteria at organization level. Timeframe indicates the study time period relevant to wait-time intervention for each cohort.

	Interest Circle Calls	Coaching	Learning Sessions	Combination	Total
NIATx 200 Source Data	49	50	54	48	201
- Lack of data	3	8	11	6	28
- Insufficient data	11	17	15	12	55
Included in sample	35	25	28	30	118

The source data consisted of 72338 patient records (53969 for cohort 1 and 18369 for cohort 2) for patients who received a first treatment session during the wait-time relevant timeframe for each cohort following their initial request for treatment. No patient records were removed due to logical issues concerning the temporal sequence of treatment sessions. Following the application of record level inclusion/exclusion criteria, 28 organizations were removed due to a lack of data during the study timeframe corresponding to wait-time. A further 55 organizations were

removed from the sample because they did not have at least one data point recorded during each of the first 11 months of the study period. The resulting sample consisted of 118 organizations and 63475 patient records (47894 for cohort 1 and 15581 for cohort 2) who received a first substance abuse treatment session following their initial request for treatment.

3.2 Statistical Analysis

Initial exploratory analysis was conducted via univariate analysis and density plots of wait-time across the study timeline and individual study time periods. Univariate analysis and density plots were first conducted at the site level, then various combinations of treatment group and state before proceeding to the grouping of data based only on treatment group in order to evaluate the potential influence of the quantile regression approach and data clustering within states and organizations.

Based upon the initial exploratory analysis and cubic B-spline plots, the following parameterization with y representing patient wait-time and t representing the time of initial request for treatment was developed for a nonlinear quantile regression model fit:

$$Q_\tau(y|t) = \begin{cases} \alpha_1(\tau) + \beta_1(\tau)t & for\ 0 \le t < b_1 \\ \alpha_2(\tau) + \beta_2(\tau)t & for\ b_1 < t < b_2 \\ \alpha_3(\tau) + \beta_2(\tau)t & for\ b_2 < t \end{cases}$$

where $\alpha_2(\tau) = \alpha_1(\tau) + \beta_1(\tau)b_1 - \beta_2(\tau)b_1$ and $\alpha_3(\tau) = \alpha_2(\tau) + \beta_2(\tau)b_2 - \beta_3(\tau)b_2$. The time points which define the end/start of study time periods are denoted by b_1 and b_2. The end of the NIATx 200 baseline period occurs at 90 days and the start of the intervention period begins at 91 days and, thus, $b_1 = \frac{90+91}{2} = 90.5$ days. The end of the

NIATx 200 intervention period occurs at 243 days and the start of the sustain period begins at 244 days and so $b_2 = \frac{243+244}{2} = 243.5$ days. Initial values for the nonlinear quantile regression optimization problem (Koenker, 2005) are based upon the following linear least squares regression model:

$$y = \beta_0 + \beta_1 t + \beta_2 t \cdot I(t > b_1) + \beta_3 t \cdot I(t > b_2)$$

where $I(t > b_1)$ and $I(t > b_2)$ represent indicator functions relating to changes in wait-time due to the intervention and sustain study time periods, respectively.

A nonlinear least squares model was fit for comparison against the nonlinear quantile regression models. The least squares model had a parameterization similar to the quantile regression model:

$$y = \begin{cases} \alpha_1 + \beta_1 t & for\ 0 \leq t < b_1 \\ \alpha_2 + \beta_2 t & for\ b_1 < t < b_2 \\ \alpha_3 + \beta_2 t & for\ b_2 < t \end{cases}$$

where $\alpha_2 = \alpha_1 + \beta_1 b_1 - \beta_2 b_1$ and $\alpha_3 = \alpha_2 + \beta_2 b_2 - \beta_3 b_2$. The time points b_1 and b_2 were defined the same way as with the quantile regression models. The starting values for the nonlinear least squares optimization problem were also defined by the same linear regression model used for defining the starting values for the nonlinear quantile regression models.

Attempts were made to address the hierarchical structure of the NIATx 200 data in the modeling effort through the initial development of a nonlinear mixed effects model. In this mixed effects model, treatment groups were handled as fixed effects and organizations as a random effect. These efforts, however, were not successful due to a lack of convergence for the parameter estimates, which was likely due to very few

organization level covariates being present in the data. Given the problems encountered with a developing a nonlinear least squares mixed effects model, efforts to produce a nonlinear quantile regression mixed effects model were similarly abandoned.

Sample data processing was conducted using Statistical Analysis Software, version 9.3 (SAS Institute Inc., 2013). All statistical analysis was conducted in R, version 2.15.2 (R Core Team, 2013).

4 Results

Exploratory quantile regression model fits of each treatment arm via nonparametric cubic B-splines with 5 degrees of freedom are presented in Appendix section 8.1. These plots provided the basis for nonlinear model parameterization and subsequent model fits of 10%, 50% and 90% quantiles in addition to conditional mean plots resulting from a least squares model, which are shown in Figures 5 through 8. Indications of variations in the behavior of wait-time at different areas of the distribution which were suggested in earlier density plots are reinforced with the cubic B-spline and parametric nonlinear plots. In particular, both cubic B-spline and parametric nonlinear plots corresponding to the regression quantiles for learning sessions and coaching treatment groups demonstrate this behavior. Furthermore, it can be seen in most plots that the 90% and 10% regression quantiles are not parallel to the conditional mean line within each study period, which suggests that variability in patient wait-time is not constant in the data. The overall similarity between the nonparametric cubic B-spline plots (Appendix section 8.1) and parametric nonlinear plots (Figures 5-8)

suggest that the chosen parameterization is appropriate for modeling wait-time quantiles and conditional mean response.

Figure 5: Nonlinear quantile and least squares regression model fits (10%, 50% and 90% quantiles) for the interest circle calls treatment group. Vertical reference lines indicate the baseline, intervention and sustain study periods.

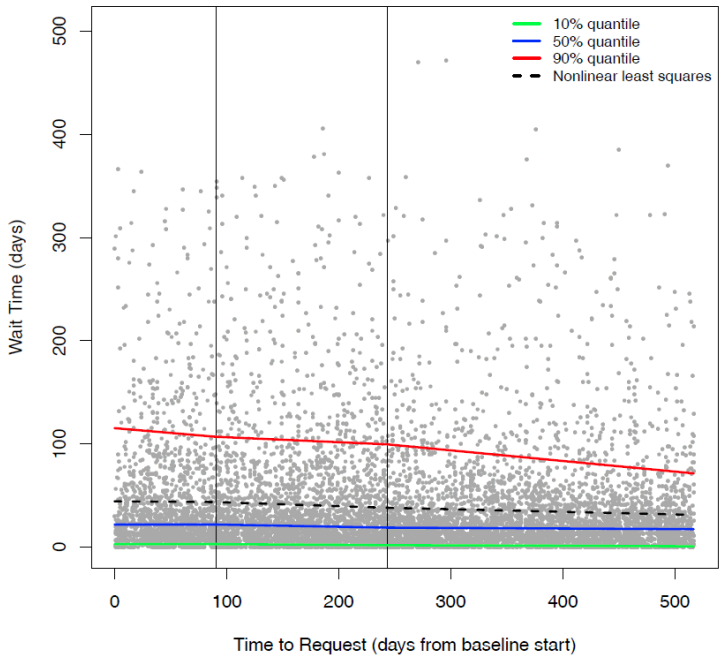


Figure 6: Nonlinear quantile and least squares regression model fits (10%, 50% and 90% quantiles) for the coaching treatment group. Vertical reference lines indicate the baseline, intervention and sustain study periods.

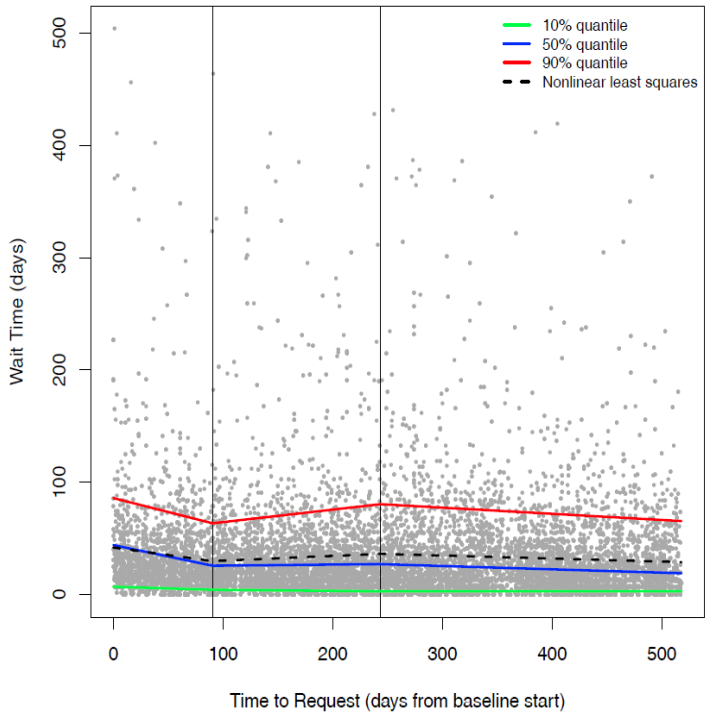


Figure 7: Nonlinear quantile and least squares regression model fits (10%, 50% and 90% quantiles) for the learning sessions treatment group. Vertical reference lines indicate the baseline, intervention and sustain study periods.

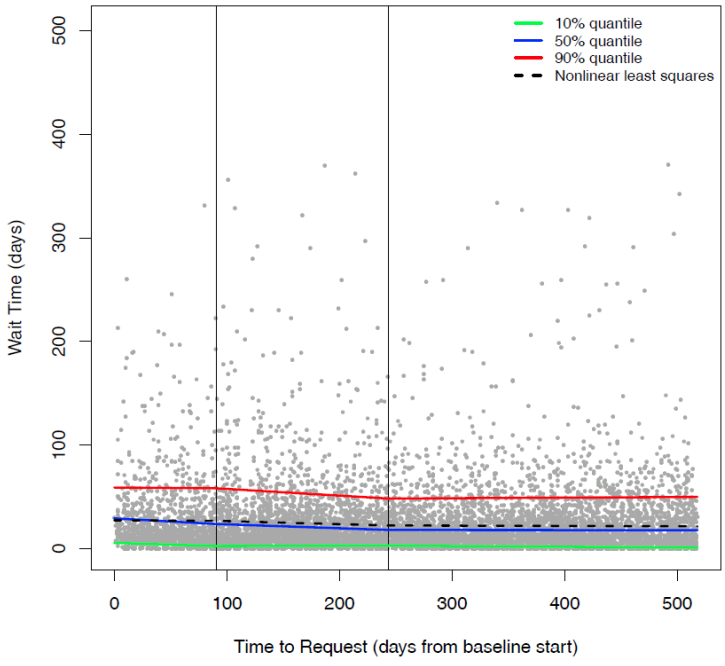
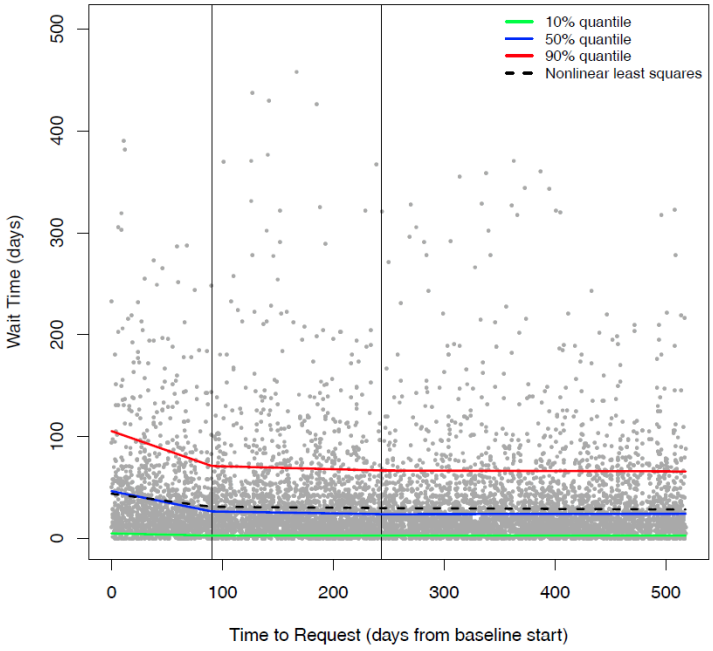


Figure 8: Nonlinear quantile and least squares regression model fits (10%, 50% and 90% quantiles) for the combination treatment group. Vertical reference lines indicate the baseline, intervention and sustain study periods.



Model parameter estimates for both nonlinear least squares and quantile regression models are presented in Table 2. Regression quantiles for the coaching, learning session and the combination treatment groups were compared against the interest circle calls group and these results are also shown in Table 2. All model results are deemed to be statistically significant for $p < 0.05$.

Results for the baseline period in the 10% and 50% regression quantiles indicate that all treatment groups were statistically significant with a negative slope estimate, with the exception of interest circle calls. At the 10% regression quantile in the baseline period, the coaching ($t = -2.504$, $p = 0.012$), learning sessions ($t = -2.817$, $p = 0.005$) and combination ($t = -2.193$, $p = 0.028$) groups all had significantly greater reductions in wait-time than the learning sessions group. Similarly, at the 50% regression quantile in the baseline period, the coaching ($t = -9.547$, $p < 0.001$), learning sessions ($t = -2.629$, $p =$

0.009) and combination ($t = -8.570$, $p < 0.001$) were all found to have significantly greater reductions in wait-time than the learning sessions group. At the 90% quantile in the baseline period, only the coaching ($t = -4.098$, $p < 0.001$) and combination ($t = -3.964$, $p < 0.001$) groups were found to have significant reductions in wait-time and none of the other treatment group effects were found to be significantly different from interest circle calls. Within the least squares model, the conditional mean of wait-time in the baseline period was found to have a significant reduction in the coaching ($t = -5.930$, $p < 0.001$) and combination ($t = -6.704$, $p < 0.001$) groups.

Compared to the baseline period, the results for the intervention period were much more mixed. Despite a significant wait-time reduction in the 10% regression quantile ($t = -2.418$, $p = 0.016$), the coaching group experienced a wait-time increase in the 50% ($t = 2.089$, $p = 0.037$) and 90% ($t = 5.350$, $p < 0.001$) regression quantiles. Relative to interest circle calls, the coaching group also had significantly increased wait-time in the 50% ($t = 3.641$, $p < 0.001$) and 90% ($t = 2.791$, $p = 0.005$) regression quantiles. In addition, the coaching treatment group experienced a significant increase in the conditional mean of wait-time during the intervention period ($t = 4.762$, $p < 0.001$). In contrast, wait-time reductions were found in some regression quantiles in the interest circle calls and learning sessions groups. At the 10% regression quantile (-2.654, $p = 0.008$), 50% regression quantile (-2.983, $p = 0.003$) and conditional mean ($t = -3.309$, $p = 0.001$) in the intervention period, the interest circle calls group was found to have significant reductions in wait-time. Meanwhile, at the 50% regression quantile ($t = -11.156$, $p < 0.001$), 90% regression quantile ($t = -4.352$, $p < 0.001$) and conditional

mean ($t = -4.605$, $p < 0.001$) in the intervention period, the learning sessions groups was found to have significant reductions in wait-time. Quantile and least squares model response during the intervention period may reflect the potentially beneficial and disruptive effect of process improvement.

During the sustain period, the interest circle calls groups had significant reductions in wait-time in the 10% regression quantile ($t = -3.951$, $p < 0.001$), 90% regression quantile ($t = -5.504$, $p < 0.001$), and conditional mean ($t = -3.936$). Given this reduction during the sustain period for the interest circle calls group, only the coaching group had a significant reduction in wait-time relative to the interest circle calls group in the 50% regression quantile ($t = -4.309$, $p < 0.001$). All other treatment groups either had non-significant wait-time response during this period or had relative increases in wait-time when compared to interest circle calls: 10% regression quantile for coaching ($t = 2.078$, $p = 0.038$), 90% regression quantile for coaching group ($t = 2.140$, $p = 0.032$), 90% regression quantile for learning sessions group ($t = 5.512$, $p < 0.001$), 90% regression quantile for combination group ($t = 4.591$, $p < 0.001$). Despite the trend of increasing wait-time during the intervention period for most models for the coaching group, the coaching group had significant reductions in wait-time in the 50% regression quantile ($t = -8.348$, $p < 0.001$), 90% regression quantile ($t = -4.369$, $p < 0.001$) and conditional mean ($t = -5.197$, $p < 0.001$). It is important to recall that during the sustain period, the intervention for a specific group is removed and it is then possible to observe the post-intervention effects on wait-time.

Table 2: Nonlinear quantile and nonlinear least squares regression model estimates for treatment groups across study time periods. Between group comparisons are made with interest circle calls as the referent. Shaded cells indicate statistical significance at the 0.05 level.

		Baseline						Intervention						Sustain					
10% Quantile	N	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value
Interest Circle Calls	15645	0.000	0.009	-0.017	0.017	0.000	1.000	-0.007	0.002	-0.011	-0.002	-2.654	0.008	-0.004	0.001	-0.006	-0.002	-3.951	< 0.001
Coaching	14129	-0.030	0.008	-0.047	-0.014	-3.618	< 0.001	-0.009	0.004	-0.016	-0.002	-2.418	0.016	0.000	0.002	-0.003	0.003	0.000	1.000
Learning Sessions	17134	-0.034	0.008	-0.050	-0.018	-4.091	< 0.001	0.003	0.003	-0.003	0.009	0.879	0.379	-0.007	0.002	-0.011	-0.003	-3.665	< 0.001
Combination	16567	-0.024	0.007	-0.037	-0.011	-3.655	< 0.001	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.002	-0.004	0.004	0.000	1.000
Coaching vs Interest Circle Calls		-0.030	0.012	-0.054	-0.007	-2.504	0.012	-0.002	0.004	-0.011	0.007	-0.464	0.643	0.004	0.002	0.000	0.008	2.078	0.038
Learning Sessions vs Interest Circle Calls		-0.034	0.012	-0.058	-0.010	-2.817	0.005	0.009	0.004	0.002	0.017	2.364	0.018	-0.003	0.002	-0.008	0.001	-1.484	0.138
Combination vs Interest Circle Calls		-0.024	0.011	-0.045	-0.003	-2.193	0.028	0.007	0.002	0.002	0.011	2.641	0.008	0.004	0.002	0.000	0.008	1.828	0.068
50% Quantile	N	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value
Interest Circle Calls	15645	0.000	0.018	-0.036	0.036	0.000	1.000	-0.020	0.007	-0.033	-0.007	-2.983	0.003	-0.005	0.004	-0.014	0.003	-1.260	0.208
Coaching	14129	-0.203	0.011	-0.224	-0.181	-18.465	< 0.001	0.009	0.004	0.001	0.018	2.089	0.037	-0.030	0.004	-0.037	-0.023	-8.348	< 0.001
Learning Sessions	17134	-0.060	0.014	-0.086	-0.033	-4.388	< 0.001	-0.038	0.003	-0.044	-0.031	-11.156	< 0.001	-0.001	0.002	-0.006	0.004	-0.325	0.745
Combination	16567	-0.220	0.018	-0.255	-0.184	-12.146	< 0.001	-0.017	0.006	-0.029	-0.005	-2.806	0.005	0.001	0.003	-0.005	0.008	0.335	0.738
Coaching vs Interest Circle Calls		-0.203	0.021	-0.245	-0.161	-9.547	< 0.001	0.029	0.008	0.013	0.045	3.641	< 0.001	-0.024	0.006	-0.035	-0.013	-4.309	< 0.001
Learning Sessions vs Interest Circle Calls		-0.060	0.023	-0.104	-0.015	-2.629	0.009	-0.018	0.007	-0.033	-0.004	-2.436	0.015	0.005	0.005	-0.005	0.014	0.941	0.347
Combination vs Interest Circle Calls		-0.220	0.026	-0.270	-0.170	-8.570	< 0.001	0.002	0.009	-0.015	0.020	0.260	0.795	0.007	0.005	-0.004	0.017	1.201	0.230
90% Quantile	N	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value
Interest Circle Calls	15645	-0.092	0.155	-0.396	0.211	-0.598	0.550	-0.048	0.053	-0.152	0.056	-0.904	0.366	-0.103	0.019	-0.139	-0.066	-5.504	< 0.001
Coaching	14129	-0.248	0.061	-0.367	-0.129	-4.098	< 0.001	0.111	0.021	0.070	0.152	5.350	< 0.001	-0.055	0.013	-0.079	-0.030	-4.369	< 0.001
Learning Sessions	17134	-0.008	0.058	-0.122	0.107	-0.135	0.893	-0.065	0.015	-0.094	-0.036	-4.352	< 0.001	0.006	0.006	-0.006	0.018	0.908	0.364
Combination	16567	-0.378	0.095	-0.565	-0.191	-3.964	< 0.001	-0.028	0.027	-0.081	0.024	-1.057	0.291	-0.003	0.011	-0.025	0.018	-0.319	0.749
Coaching vs Interest Circle Calls		-0.156	0.166	-0.481	0.170	-0.937	0.349	0.159	0.057	0.047	0.271	2.791	0.005	0.048	0.022	0.004	0.092	2.140	0.032
Learning Sessions vs Interest Circle Calls		0.085	0.165	-0.240	0.409	0.511	0.609	-0.017	0.055	-0.125	0.091	-0.304	0.761	0.108	0.020	0.070	0.147	5.512	< 0.001
Combination vs Interest Circle Calls		-0.286	0.182	-0.642	0.071	-1.572	0.116	0.019	0.060	-0.097	0.136	0.327	0.744	0.099	0.022	0.057	0.142	4.591	< 0.001
Nonlinear Least Squares	N	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value	Estimate	SE	95% CI LB	95% CI UB	t-value	P-value
Interest Circle Calls	15645	-0.008	0.029	-0.066	0.049	-0.288	0.773	-0.036	0.011	-0.058	-0.015	-3.309	0.001	-0.025	0.006	-0.037	-0.012	-3.936	< 0.001
Coaching	14129	-0.134	0.023	-0.178	-0.089	-5.930	< 0.001	0.042	0.009	0.025	0.060	4.762	< 0.001	-0.027	0.005	-0.037	-0.017	-5.197	< 0.001
Learning Sessions	17134	-0.006	0.018	-0.041	0.029	-0.335	0.737	-0.029	0.006	-0.041	-0.017	-4.605	< 0.001	-0.003	0.003	-0.010	0.004	-0.850	0.395
Combination	16567	-0.142	0.021	-0.183	-0.100	-6.704	< 0.001	-0.008	0.008	-0.024	0.008	-0.997	0.319	-0.005	0.005	-0.014	0.004	-1.066	0.286

Predicted values and changes in wait-time based on quantile and least squares regression models are presented in Table 3. These predicted values are largely reflective of the significant increasing or decreasing wait-time slope estimates for the study time periods previously mentioned. Based on the least squares model, all treatment groups had reductions in wait-time with the combination and coaching groups having the largest reductions in predicted mean wait-time. The largest predicted wait-time reduction across the entire study timeline in the 90% regression quantile was in the interest circle calls and combination groups. By the end of the study, 90% of patients in the interest circle calls group were predicted to wait 71.4 days or less; a reduction of 38.1% from the predicted wait-time at the start of the study (115.4 days or less). Within the combination group, 90% of patients were predicted to wait 66 days or less at the end of the study; a reduction of 37.5% from the predicted wait-time at the start of the study (105.5 days or less).

Table 3: Changes in wait-time through study periods as predicted by nonlinear quantile and least squares regression models.

	Baseline			Intervention			Sustain			Baseline to Sustain	Intervention to Sustain
10% Quantile	Start	End	% Change	Start	End	% Change	Start	End	% Change	% Change	% Change
Interest Circle Calls	3.0	3.0	0.0%	3.0	2.0	-33.5%	2.0	0.9	-53.8%	-69.4%	-69.33%
Coaching	7.1	4.3	-38.6%	4.3	3.0	-30.4%	3.0	3.0	0.0%	-57.5%	-30.46%
Learning Sessions	5.7	2.7	-53.1%	2.7	3.1	15.1%	3.1	1.1	-63.6%	-80.5%	-58.08%
Combination	5.2	3.0	-41.7%	3.0	3.0	0.0%	3.0	3.0	0.0%	-41.9%	0.00%
50% Quantile	Start	End	% Change	Start	End	% Change	Start	End	% Change	% Change	% Change
Interest Circle Calls	22.0	22.0	0.0%	22.0	19.0	-13.6%	19.0	17.5	-7.9%	-20.5%	-20.45%
Coaching	44.1	25.9	-41.4%	25.8	27.2	5.5%	27.2	19.1	-29.8%	-56.8%	-26.00%
Learning Sessions	29.4	24.0	-18.3%	24.0	18.2	-23.9%	18.2	18.0	-1.2%	-38.8%	-24.90%
Combination	46.6	26.8	-42.5%	26.7	24.1	-9.9%	24.1	24.4	1.3%	-47.7%	-8.74%
90% Quantile	Start	End	% Change	Start	End	% Change	Start	End	% Change	% Change	% Change
Interest Circle Calls	115.4	107.0	-7.2%	107.0	99.7	-6.8%	99.6	71.4	-28.3%	-38.1%	-33.21%
Coaching	86.0	63.6	-26.0%	63.6	80.5	26.6%	80.5	65.5	-18.6%	-23.8%	3.06%
Learning Sessions	59.1	58.4	-1.2%	58.4	48.6	-16.9%	48.5	50.1	3.1%	-15.4%	-14.29%
Combination	105.5	71.5	-32.3%	71.3	66.9	-6.1%	66.9	66.0	-1.4%	-37.5%	-7.44%
Nonlinear Least Squares	Start	End	% Change	Start	End	% Change	Start	End	% Change	% Change	% Change
Interest Circle Calls	44.5	43.8	-1.7%	43.8	38.2	-12.6%	38.2	31.4	-17.8%	-29.5%	-28.24%
Coaching	42.0	29.9	-28.7%	29.9	36.3	21.5%	36.3	29.0	-20.3%	-31.0%	-3.09%
Learning Sessions	27.6	27.0	-2.0%	27.0	22.6	-16.4%	22.6	21.8	-3.6%	-21.0%	-19.40%
Combination	44.1	31.3	-29.0%	31.3	30.0	-4.0%	30.0	28.6	-4.6%	-35.1%	-8.37%

An interesting result is the predicted increase in wait-time in the coaching group during the intervention period. At the end of this period, 90% of patients in the coaching group were predicted to wait 80.5 days or less; an increase of 26.6% from the predicted wait-time at the start of the intervention period (63.6 days or less). Within the intervention period, the coaching group also had a similar predicted wait-time increase in mean wait-time (21.5%) and a small increase in wait-time in the 50% regression quantile (5.5%). The combination group had large reductions in predicted wait-time in all regression quantiles and conditional mean during the baseline period, but either modest predicted wait-time reductions or increases in all other study periods. Despite wait-time trend changes during individual study periods, all intervention groups experienced substantial wait-time reductions in all quantiles and the conditional mean.

5 Discussion

The hypothesis of this thesis was that more intensive process improvement methodologies offered through the NIATx 200 study result in greater reductions in wait-time for patients entering substance abuse treatment programs. In order to evaluate this hypothesis multiple quantile regression models and a least squares model were developed to evaluate changes in wait-time across NIATx 200 study time periods at lower (10%), median (50%) and upper (90%) quantiles in addition to the mean. A nonlinear approach was used in an effort to evaluate wait-time behavior within each study period while still fitting a model across all time periods. One unusual result of these models was numerous significant reductions in wait-time in the baseline period at all regression quantiles and the conditional mean. This unexpected result may indicate a flaw in the definition of the study time periods and/or preliminary initiation of intervention efforts.

Within the intervention period, the interest circle calls and learning sessions groups appeared to perform the best in terms of wait-time reduction in multiple regression quantiles and the conditional mean. The interest circle calls group had significant wait-time reductions in the 10% regression quantile, 50% regression quantile, and conditional mean (Table 2). The interest circle calls group also performed similar to or significantly better than many other treatment groups in all regression quantiles of the intervention period. During the intervention period, only the learning sessions group experienced a significant reduction in wait-time when compared to the interest circle calls group ($t = -2.436$, $p = 0.015$). For the intervention period, in the 50%

regression quantile, 90% regression quantile, and conditional mean, the interest circle calls and learning sessions groups also experienced the greatest reductions in predicted wait-time (Table 3). During the sustain period, however, the learning sessions group had only modest, non-significant reductions in wait-time in most regression quantiles, with the notable exception being the 10% regression quantile, and the conditional mean. In the sustain period, the interest circle calls group continued to experience significant reductions in wait-time in the 10% regression quantile, 90% regression quantile, and conditional mean and these reductions are reflected in the predicted values for that time period (Table 3).

In contrast to the interest circle calls and learning sessions groups, the coaching group had significant increases in wait-time during the intervention period in the 50% regression quantile, 90% regression quantile, and conditional mean (Table 2). The increases in wait-time for the coaching group are reflected in Table 3. These wait-time increases for the coaching group in the intervention period may indicate that, during implementation, coaching is disruptive enough that it is counterproductive to the goals of the process improvement. The situation did improve for the coaching group in the sustain period with significant reductions in wait-time in the 50% regression quantile, 90% regression quantile, and conditional mean. Thus, despite the relatively poor performance of the coaching group during the intervention period, this group was able to achieve wait-time reductions post-intervention. This difference in wait-time trends between the intervention and overall study periods may indicate that the coaching process improvement method has a delayed effect on the organization it is used with.

Most surprising in these results is that the resource-intensive combination group only experienced significant wait-time reductions in the baseline period and in the 50% regression quantile of the intervention period. The combination group did not necessarily perform poorly in terms of wait-time reduction, but there simply was no evidence of much change at all as a result of this intervention. Perhaps this indicates that a battery of process improvement solutions all at once is too much for the organizations to handle.

Overall, if the unexpected results from the baseline study period are ignored (Intervention to Sustain column in Table 3), the interest circle calls and learning sessions groups appeared to have the best performance in terms of wait-time reductions. These two groups experienced significant wait-time reductions in the intervention and sustain period across multiple regression quantiles and the conditional mean. If the entire study timeframe is considered (Baseline to Sustain column in Table 3), however, then the coaching and combination groups appear to perform better or similar to the interest circle calls and learning sessions groups. While the coaching and combination groups generally experienced either significant increases or no reductions in wait-time during the intervention period, they did have wait-time reductions in the baseline and sustain periods (Tables 2-3). Because the coaching intervention resulted in similar wait-time reduction and has significantly lower cost/complexity, the coaching intervention is more cost effective than the combination intervention. The baseline period results are a cause for concern but regardless of whether it is ignored or not, it is clear that higher

cost/complexity process improvement interventions do not necessarily result in greater reductions in wait-time for substance abuse treatment programs in the NIATx 200 study.

These results and conclusions differ somewhat from the earlier NIATx 200 study by Gustafson, et al. (2013), but conclusions drawn from each paper are not necessarily superior to the other because the data and methods used differ. Gustafson, et al. made use of month average outcome metrics, including wait-time, for modeling, while this paper used patient-level data. The use of month averaged outcome metrics, in effect, reduces the data resolution, but also the noise that can be observed in some of the model fits. The noise that we find in patient-level wait-time data may be one of the reasons for lack of convergence in attempted nonlinear quantile regression mixed effects model fits mentioned earlier. The site selection methods also differ between the two analyses. Gustafson, et al. only filtered out organizations which were lost to follow-up (ten organizations) and then removed month averaged data points if the average was based on fewer than five records. In contrast to this thesis (Table 1), Gustafson, et al. utilized data from 45 organizations in the interest circle calls group, 47 in the coaching group, 51 in the learning sessions group, and 48 in the combination group. Thus, there were many more organizations included in the analysis in the Gustafson paper than in this paper. The more stringent site selection method employed in this paper implies high internal validity for conclusions at the sake of external validity. The site selection method used in this paper removed 83 organizations from the initial data sample, which is 41.3% of the participating organizations, but only 12.3% of the patient records were removed as a result. This disparity in the effects on the data sample by the site

selection method appears to indicate that smaller organizations were disproportionately removed from the final data sample. Lastly, Gustafson, et al. only made use of linear mixed effects models for evaluating the changes in monthly mean wait-time during the intervention period and across the entire study period. This linear approach ignores how wait-time change in earlier study periods can influence changes in wait-time in subsequent study periods.

Model development conducted within this paper only considered a fixed effects model. Given the presence of data resulting from a cluster-randomized trial, it is unfortunate that the hierarchical structure of the data could not be evaluated through the use of a nonlinear quantile regression mixed effects model. Mixed effects model fits were attempted, but convergence to a solution was not possible. The lack of organization and patient covariates played a likely role in this result and is a hindrance to accurate statistical model development regardless of method. In this particular data, there may also be the presence of multiple maxima in the response variable distribution, which can also result in the lack of convergence. A method and computational package for producing nonlinear mixed effects quantile regression models is also not readily available. Fortunately, methods for computing quantile regression mixed effects models are being actively developed. Koenker (2005) originally suggested using a distribution-free, penalty method, while Karlsson (2008) explored a likelihood-based, weighted approach. More recently, Kim and Yang (2011) proposed a semiparametric method based on empirical likelihood for random effects models. Based on earlier work with the asymmetric Laplace distribution, Geraci and Bottai

(2013) developed an approach for mixed effects models based on maximization of Laplace likelihood. Lastly, Wang (2012) suggested a Bayesian quantile regression method for nonlinear mixed effects models, which also involved the asymmetric Laplace distribution. A careful review and application of these proposed methods for quantile regression mixed model development would be a logical progression from the results presented in this thesis.

Results in this thesis, particularly those found in Table 2, highlight the power of quantile regression to unearth variation in response variable distribution that conventional least squares regression ignores. Throughout the study periods, significant increases or reductions in wait-time were found in various regression quantiles, but similar significant estimates were not found via least squares regression. The ability of quantile regression to detect such effects reinforces the idea of quantile regression as a high-resolution analysis method that can uncover process improvement effects with remarkable detail.

6 References

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7 Appendix

7.1 Nonparametric B-spline Plots

Figure 9: Nonparametric quantile regression model fit with cubic B-spline and 5 degrees of freedom for the interest circle calls treatment group.

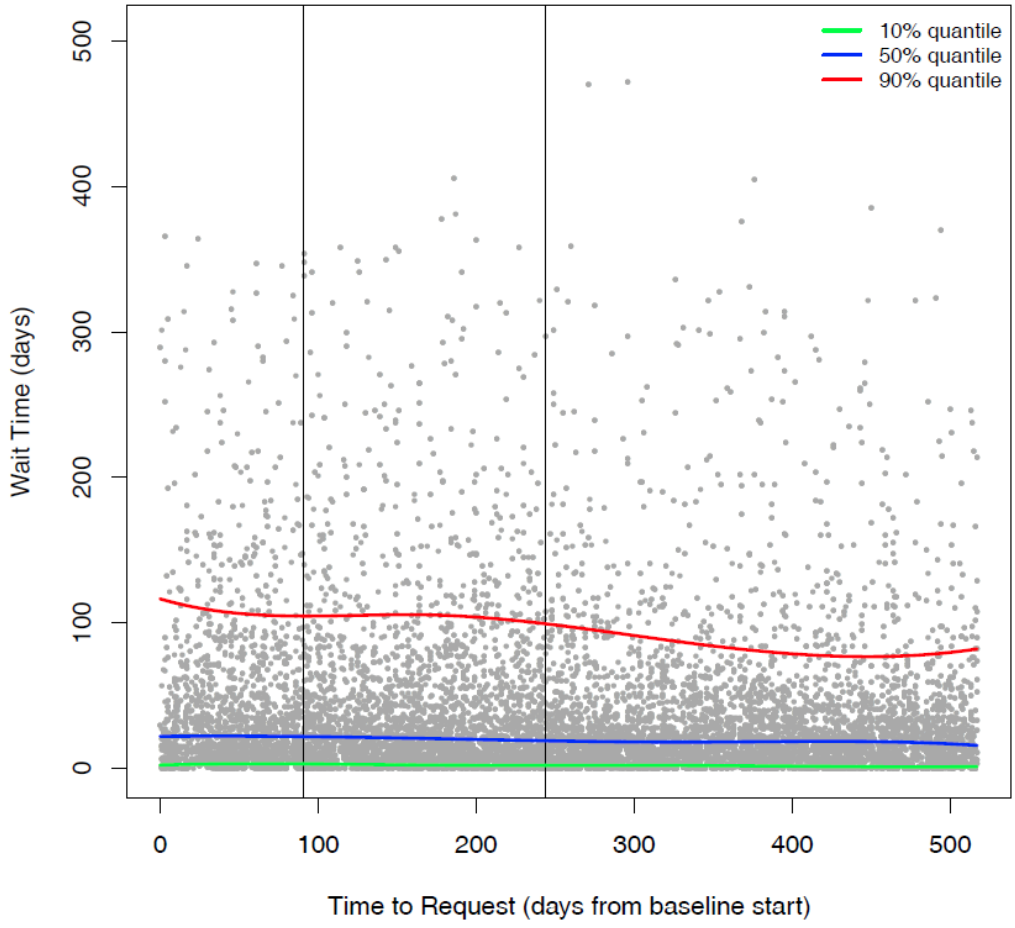


Figure 10: Nonparametric quantile regression model fit with cubic B-spline and 5 degrees of freedom for the coaching treatment group.

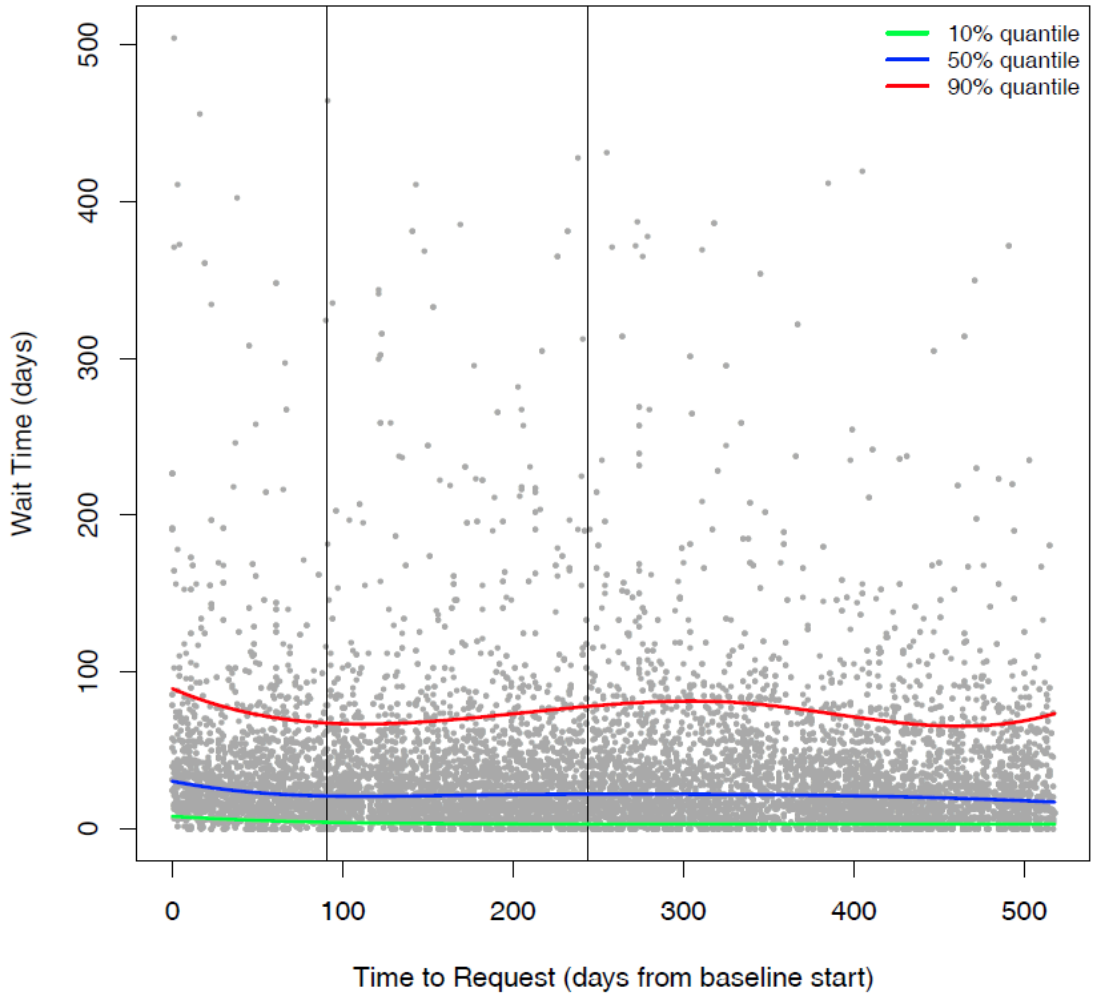


Figure 11: Nonparametric quantile regression model fit with cubic B-spline and 5 degrees of freedom for the learning sessions treatment group.

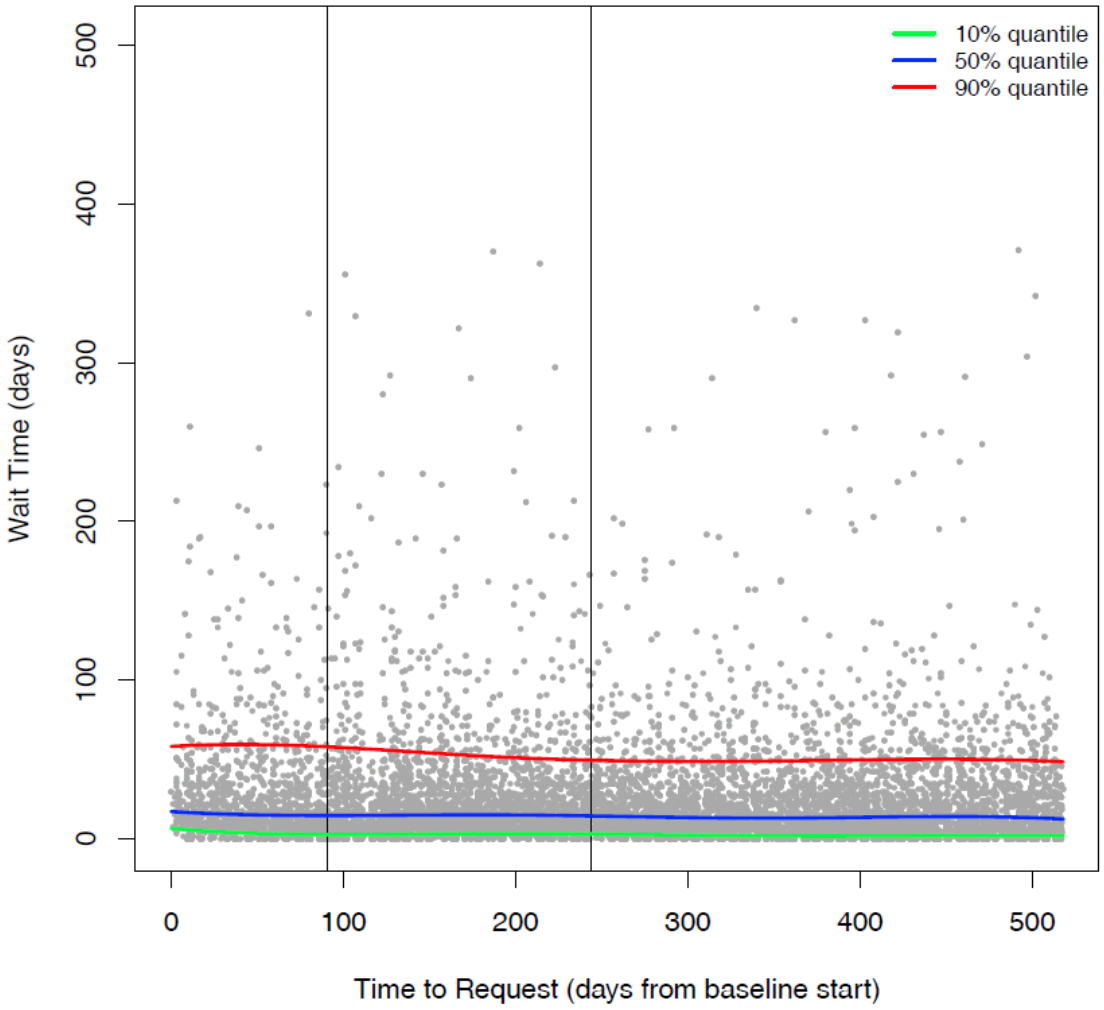
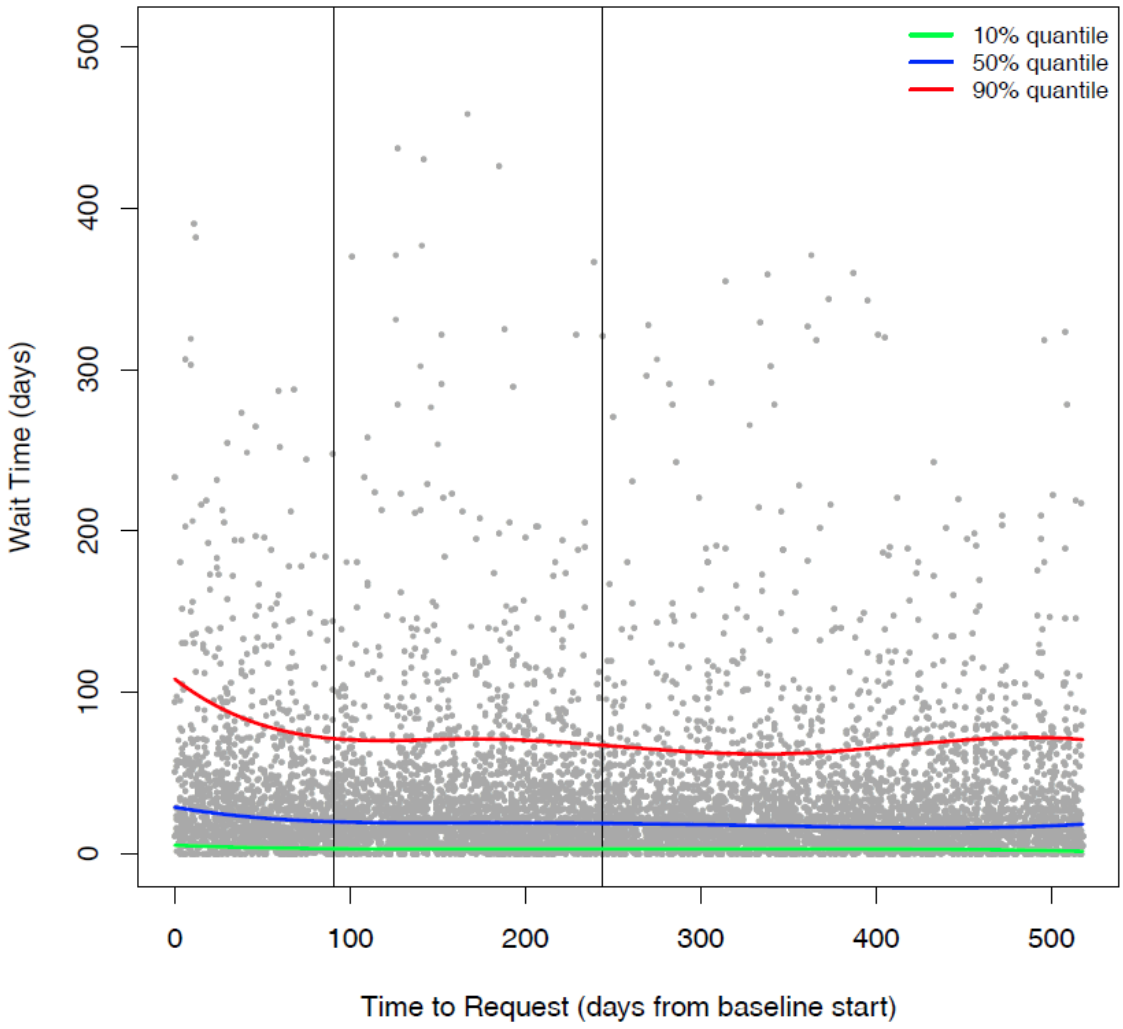


Figure 12: Nonparametric quantile regression model fit with cubic B-spline and 5 degrees of freedom for the combination treatment group.



7.2 Site-level Nonlinear Quantile Regression Slope Estimate Boxplots

Figure 13: Boxplot of site-level slope estimates for the baseline period resulting from nonlinear quantile regression fit of the 10% quantile.

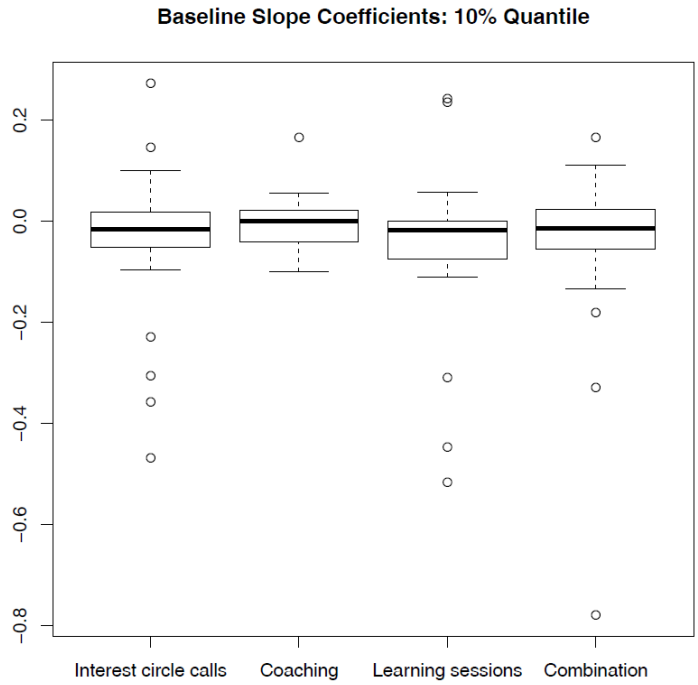


Figure 14: Boxplot of site-level slope estimates for the intervention period resulting from nonlinear quantile regression fit of the 10% quantile.

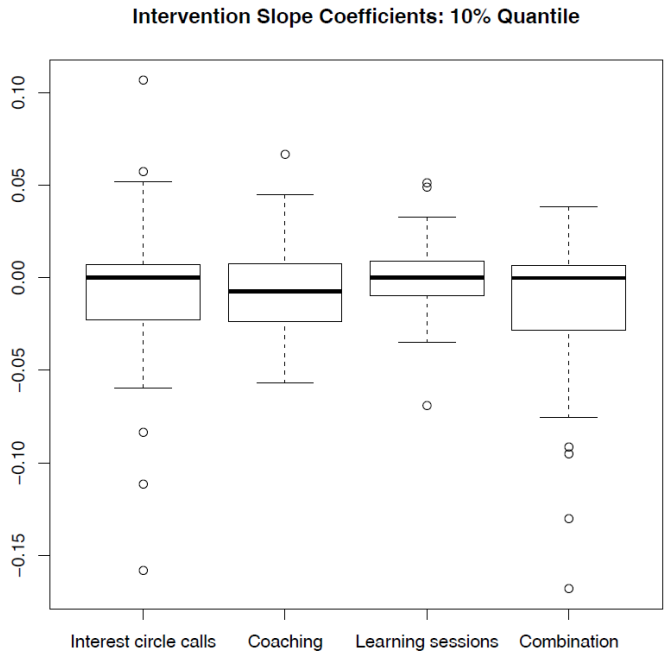


Figure 15: Boxplot of site-level slope estimates for the sustain period resulting from nonlinear quantile regression fit of the 10% quantile.

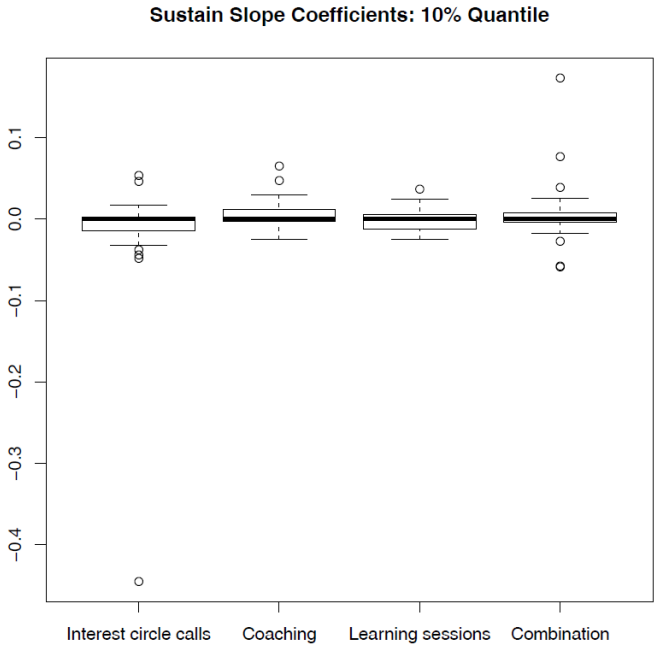


Figure 16: Boxplot of site-level slope estimates for the baseline resulting from nonlinear quantile regression fit of the 50% quantile.

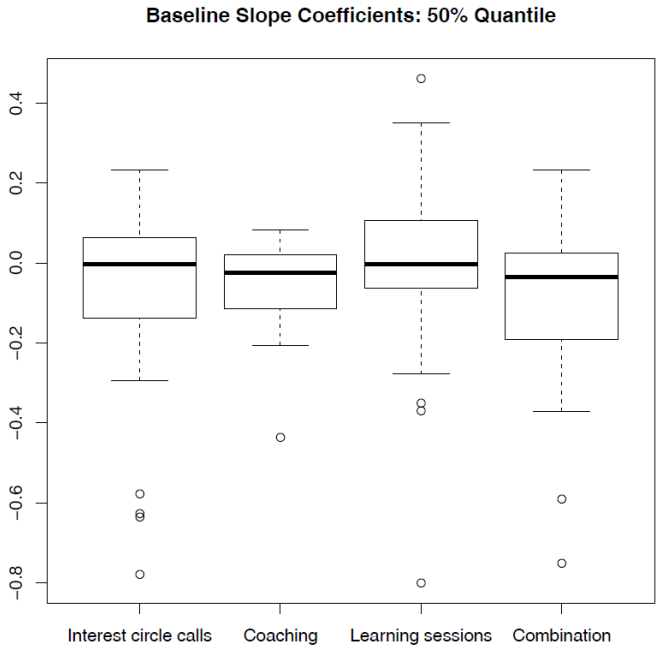


Figure 17: Boxplot of site-level slope estimates for the intervention period resulting from nonlinear quantile regression fit of the 50% quantile.

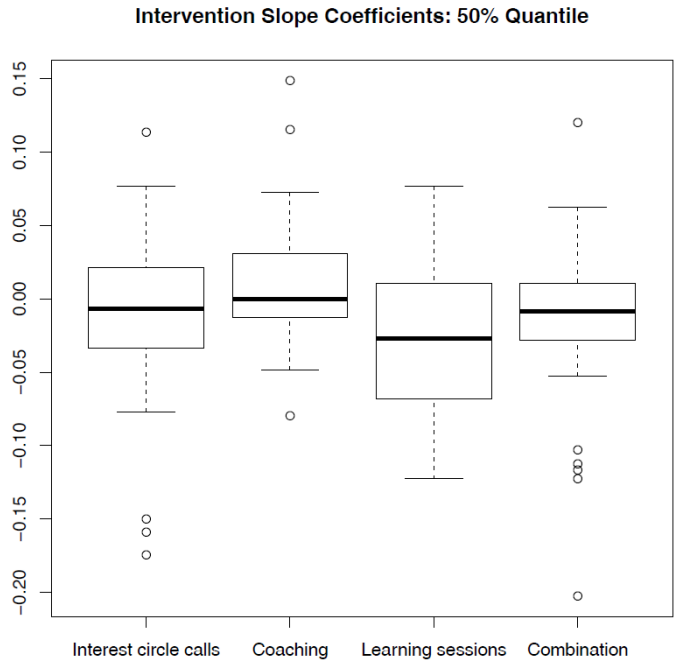


Figure 18: Boxplot of site-level slope estimates for the sustain period resulting from nonlinear quantile regression fit of the 50% quantile.

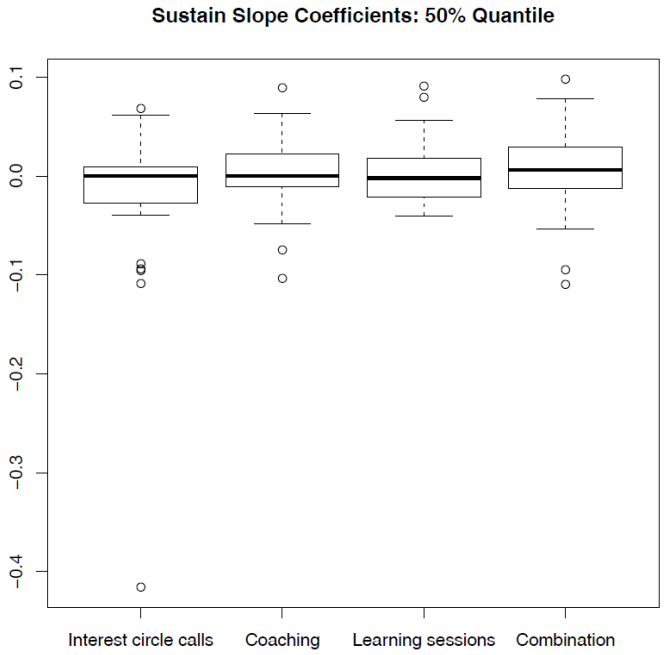


Figure 19: Boxplot of site-level slope estimates for the baseline period resulting from nonlinear quantile regression fit of the 90% quantile.

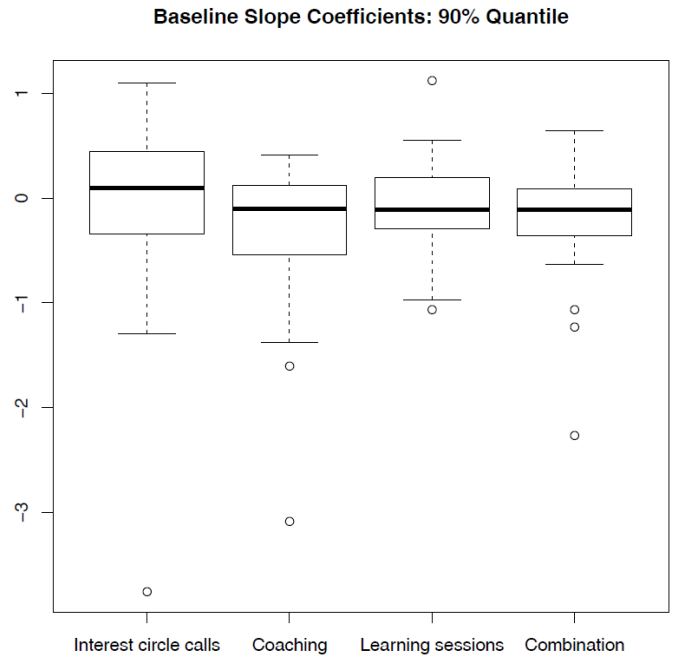


Figure 20: Boxplot of site-level slope estimates for the intervention period resulting from nonlinear quantile regression fit of the 90% quantile.

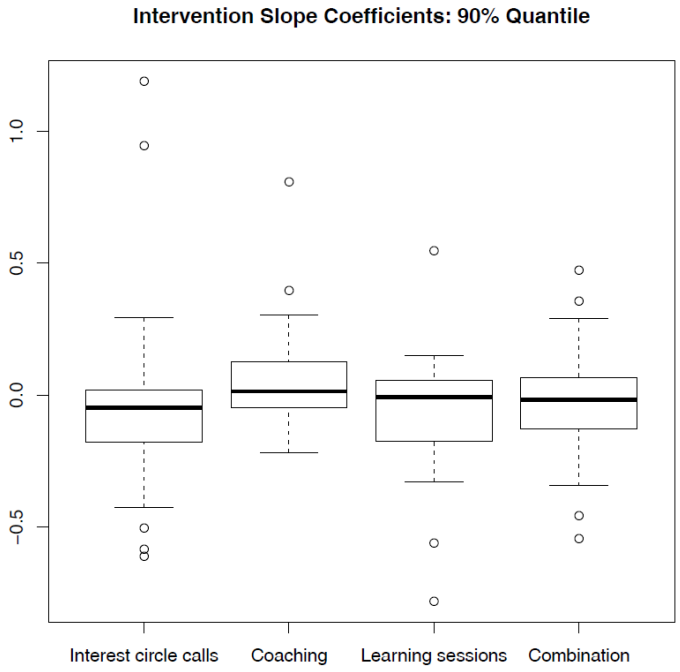


Figure 21: Boxplot of site-level slope estimates for the sustain period resulting from nonlinear quantile regression fit of the 90% quantile.