ALTERNATIVE STATISTICAL MODELS THAT ACCOUNT FOR CLUSTERING IN DENTAL IMPLANT FAILURE DATA

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ABSTRACT

Longitudinal data analysis is a major component of public health care assessment. It is important to know how treatments compare over time, how diseases occurr and recurr, and how environmental or other exposures influence to a disease processes over time. Investigations of such topics involve the statistical analysis of time-to-event data in various areas of health care.

Long term dental assessment of dental restorations have typically employed statistical analyses that assume independence of the restorations within the patient. Dental data naturally occur in the form of clusters. The patient is a cluster of correlated dental units (teeth) to be evaluated. Statistical analysis of the dental units without acknowledgement of within-cluster correlation can underestimate standard errors, which can erroneously inflate the significance level of between-cluster predictors in a model.

The purpose of this thesis is to 1) review the statistical literature on the analysis of dental implant data, 2) create a suitable longitudinal data file of dental implant failure, 3) describe the data management and statistical methods used, 4) compare alternative statistical models to analyze clustered survival data, and 5) show how these models can be used to identify some patient-level and implant site-level predictors of implant failure. We consider logistic regression, discrete survival, generalized estimating equations and the Cox model with and without frailty, and examine the associations between implant failure and patient race, implant type, and oral location of implant. Models that ignore the clustering consistently overestimate the significance of patient race.

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CHAPTER 1

Introduction

Root form or endosseous dental implants were introduced to the dental community by Dr. Per Ingmar Branemark, an orthopedic surgeon, in 1969 (Branemark. P.I., 1969, and 1983). Dr. Branemark (Branemark. P.I., 1981, 1983, 1984) has been a major contributor to the literature on scientific studies of root form dental implants as well as their current clinical application. Clinically, dental implants have provided patients with the ability to wear prostheses with considerable comfort, function, and esthetic advantages. However, the prosthetic advantages depend on the survival of the actual implant fixtures.

A dental implant is a surgically placed element that can support a prosthetic replacement of an edentulous region. The word "edentulous" refers to a "patient who is without teeth" or "region of the mouth that is without teeth". Implants are also a useful, and often necessary, means of retaining extraoral prostheses for patients who have facial defects due to surgery for tumor removal, trauma, or congenitally missing tissues. These implants do not replace teeth, but serve to retain an often large prosthesis or a prosthesis that possibly will lie on a tissue bed that is either mobile or not conducive to holding a prosthesis by conventional means (e.g. retention via either mechanical or adhesive modes). Dental implants can be of various materials (e.g. titanium, ceramic, glass, or other metals), forms (e.g. root form, staple, blade), and coatings and surfaces (e.g. hydroxyappatite, titanium, serrated, or acid etched).

This thesis will focus on only the endosseous root form dental implants that are involved with intraoral treatment. Implants of this type are placed under several circumstances. In

scenario (1), patients require the replacement of only one tooth (single-tooth replacement). Typically these are patients who have an anterior (front tooth region) missing and do not want the teeth adjacent to the edentulous space to be altered, defaced, or used as abutments for a bridge or partial denture as replacement for this missing tooth. Also, patients can have single posterior (back tooth region) implant placed. In scenario (2) patients are partially edentulous in either arch (maxilla (upper arch) or mandible (lower arch)). These patients can have two or more implants, depending on the edentulous span and the treatment plan of the prosthodontist and surgeon. Sometimes a single implant that is linked to a natural tooth in a bridge is placed to decrease the number of implants required, due to either the finances of the patient and/or the compromised and questionable health status of the natural tooth. The bridge usually has a precision attachment to allow for the provision of loss of the tooth without total destruction of all bridge units, allowing placement of an implant in the region where the tooth is lost. The inequitable force distribution in this restorative design has been implicated as a cause of the ultimate failure of the restoration. The implant is anklosed (the implant is fused to the bone) whereas the tooth is joined to the bone by a periodontal ligament. The implant will not move under function, but a natural tooth would. This situation does not occur very frequently. In scenario (3) patients are totally edentulous in either arch (maxilla or mandible).

In the first scenario, the restoration is in the form of a crown that is cement or screw retained. In the second scenario the form of the restoration is usually a fixed bridge or independent units and may or may not be removable. In the third scenario, a fixed screw-retained bar secures a denture that can be removed by the patient. Another option for some patients is a "hybrid prosthesis", which is a metal substructure with an acrylic super-structure that is screw-retained. This prosthesis is only removed by the prosthodontist for annual

evaluations, cleanings and maintenance. Scenarios two and three present opportunities for multiple implants and multiple implant failures per patient. All three scenarios present the opportunity for multiple failures and subsequent replacement of the failed implants.

Statistical analysis of implant failure times can be based on survival analysis, or time-toevent analysis, which incorporates placement dates and evaluations over time, and a censoring
indicator to denote whether an implant has in fact failed by the end of follow-up. Standard
survival methods assume that observations are independent. However, dental implant data are
often clustered. Each individual has potentially 32 teeth to be evaluated. Spatial clustering can
also occur, such as teeth within a quadrant or other region in the mouth. For example anterior or
posterior teeth or teeth that are alike contralaterally in the same arch may be more similar to each
other than to teeth in other regions. In this thesis we focus on within person clustering and
investigate some aspects of spatial characteristics with respect to implant survival.

Another characteristic in survival data is that of variable time at risk. Dental implants may be placed in a patient at different times, or a patient may have several implants placed at one time. It is clinically practical to place several implants at one time. Also, implants may be replaced after failing. The survival analysis of dental implant failure presents the complexities of varying time at risk, repeated failures, and clustered observations.

This thesis involves the secondary analysis of an existing dataset from the dissertation of Robert Weyant, D.M.D., Dr. P.H. (1991), which includes placement dates and follow-up for dental implants over almost 7 years, for 1,246 patients in five participating sites. These data were obtained from the Department of Veterans Affairs' Dental Implant Registry, which was created in 1987. In his initial investigation of these data, Weyant described a "quasi-experimental study design" whose purpose was to evaluate the association of patient and treatment facility

characteristics on dental implant performance and to estimate the survival probabilities of various dental implants. He uses a correlated binomial model to determine the degree of intraclass (within-patient) correlation and to adjust the binomial probability of several dependent variables (surgical complications, implant health status, and implant failures). In his survival analysis of dental implant data, Weyant used the Kaplan-Meier (1959) or life-table methods, ignoring the dependency of the implants within each patient. In his dissertation, Dr. Weyant acknowledges the need to account for intra-patient correlation and suggests but does not implement two procedures to address this issue statistically, bootstrapping and ordinary least squares (linear) regression,.

Statistical analysis of clustered data should take into account the dependence of the units within the cluster. The purpose of this thesis is to 1) review the statistical literature on the analysis of dental implant data, 2) create a suitable longitudinal data file of dental implant failure, 3) describe the data management and statistical analysis methods used on the Weyant data, 4) compare alternative statistical models to analyze clustered survival data, and 5) Show how these models can be used to identify some patient-level and implant site-level predictors of implant failure.

CHAPTER 2

Review of the Literature

Statistical Approaches Taken in the Dental Literature on Implant Failure

The majority of articles discussing the survival analysis of dental implants utilize statistical methods that ignore the correlation structure or innate clustering of such dental data. Such analyses treat multiple dental implants within each patient as independent units. The implicit assumption is that the failure of each implant does not depend on either the status of any other implant unit within the same patient or patient characteristics shared by all implants within a patient. This assumption is not justified clinically. Often the failure of an implant in one region of the mouth may coincide with bone loss around the failing implant. Implants near the failing implant may also fail due to this bone loss and subsequent lack of bone. Local or disperse periodontal problems, infection, patient habits, treatments or medications, and other anatomic or systemic problems are patient-specific factors that can contribute to implant failure. Positional and systemic variables potentially influence the failure of all implants placed in each patient. These effects contribute to within-patient correlation.

Some of the more recent articles on the analysis of implant survival have acknowledged the issue of intracluster dependence, and have used statistical techniques to account for this. We now review some statistical methods used to analyze dental implant failure data.

Kaplan-Meier Estimator

The Kaplan-Meier, or Product-Limit, estimator is typically presented as an overall measure of implant survival (Kaplan-Meier 1959). The majority of studies reporting this type of analysis implicitly assume that implants are independent of each other (Wheeler, 1996; Buser et. al., 1997; Brocard et. al., 2000). The Kaplan-Meier estimator is a step function that jumps at the event times and can accommodate more than one failure at each event time. The survival estimator at a given time t_k is the product of conditional probabilities of survival at the previous event times. The conditional probability of survival beyond t_k is given by $\left[1-d_k/n_k\right]$ where k is the time interval of interest, d_k denotes the number of implant failures at t_k and t_k is the total number of implants at risk for failure just prior to t_k (e.g. not yet failed and still under observation). No assumption is made about the functional form of the survival function. The variance estimator does not account for the clustering of implants within patients.

Logistic Regression

Logistic regression is used frequently to describe biological relationships between predictor variables and dichotomous or binary outcome variables (Hosmer and Lemeshow (1989)). The logistic distribution is a flexible and convenient function from a mathematical perspective, and provides a suitable model for many biological mechanisms. Logistic regression is a generalized linear model with the logit link function (McCullough and Nelder), where logit $p = \log[(p)/(1-p)]$ and p is the probability of an event in a fixed interval of time.

In logistic regression, the likelihood function is constructed under the assumption that each observation is independent. For the logistic model, $E(y_{ij}) = \pi_{ij} = (1 + e - X'_{ij}T\beta)^{-1}$ where X_{ij} is the column vector of covariates x_{ij} , i indexes the cluster (patient) and j indexes the

observations within the cluster. Parameters in a logistic model are estimated by maximizing the binomial likelihood. The log likelihood equations are differentiated with respect to the parameters, and the resulting score equations, $X^TAV^{-1}(y-\pi)=0$, are set equal to zero to obtain maximum likelihood estimates of the parameters. Because these likelihood equations are not linear in the parameters, iterative methods are required for their solution using generalized weighted least squares (McCullough and Nelder). The score equation for the logistic regression model is modified as follows to define generalized estimating equations:

One problem in using a simple logistic model for time-to-event outcomes is that every patient is assumed to be at risk for the entire time interval. This assumption may not be valid for studies with long follow-up or other situations where patients have variable time at risk.

In several studies (Albrektsson et. al., 1996; Jemt et. al., 1996; Lazzara et. al., 1996; Rosenquist and Grenthe, 1996; Hising et. al., 2001) oral implant survival data are analyzed using survival as a binary outcome over a fixed interval of time. This approach often overestimates survival because long-term failures are mixed with the early success of recently placed implants (Eckert and Wollan, 1998).

The Discrete Proportional Odds and Discrete Proportional Hazards Model

The discrete-time proportional odds model (Cox, 1972) is an extension of logistic regression that accounts for time at risk. In this model, the conditional probability of an event (e.g. implant failure) during time interval m, (m=1,...,M), is p_m , and $\log p_m(x) = \alpha_m + x^t \beta$. The α_m parameters represent time-interval specific intercepts for a patient with a reference vector of regression variables (x=0), the log-odds of failure in interval m conditional on not failing prior to m. The $x^t \beta$ is the linear predictor, which is interpreted as the logarithm of the relative risk of failure at time t_m for an individual with covariates $x \neq 0$ relative to an individual with x=0.

Under this model, the odds ratio of an event at time m for two individuals with covariates x_1 and x_2 respectively, does not depend on the time interval m, which is the *proportional-odds* assumption:

$$p_m(x_1)[1-p_m(x_2)]/[1-p_m(x_1)p_m(x_2)] = \exp\{(x_1-x_2)^t \beta\}$$
 (1) (Breslow, Nelson, 1992)

The odds ratio approximates the hazard ratio (relative risk) when the probability of an event in the time interval is small.

Prentice and Gloeckler (1978) showed that the discrete-time analog of the continuous time proportional hazards model is:

$$\log(-\log(1 - p_m(x))) = \alpha_m + x^t \beta \tag{2}$$

Here $\log[-\log(1-p)]$ is the complementary $\log\log$ (c-log-log) transform. The conditional probability of an event occurring in each time interval is assumed to be binomial with the denominator equal to the number at risk at time m. If two time intervals are of interest, the conditional probability of survival over the two periods is $c - \log(p) = [1 - p_1(x)][1 - p_2(x)] = \exp[-(e_1^{\alpha} + e_2^{\alpha})e^{x'\beta}]$ which is linear in x. When p is small, there is not a substantial difference numerically between the discrete proportional odds and discrete proportional hazards models. However, the interpretations of the parameter estimates are different. The β_m represent log hazard ratios in the discrete proportional hazards model.

For both models, patients contribute $1 - p_m(x)$ to the likelihood function for each interval m in which they have not yet failed. Patients experiencing a failure contribute $p_m(x)$. Computationally, a separate record for each time interval for each patient is created; this data setup also accommodates time-dependent predictors. In longitudinal data, time-dependent predictors can be key to understanding a history and mechanism of a potential disease process.

These variables change in value over the time period of study and can include history of previous failures as predictors. The proportional odds (or hazard) assumption can be tested by including interactions of time and x in the model.

Robust Variance Estimation

Four assumptions are made with a logistic regression model: (1) the link function is specified correctly, (2) the error structure is specified correctly, and (3) the form of the linear predictor $(x^t \beta)$ is correct, and (4) the observations are independent. The score equations (or likelihood equations) are:

$$U(\beta_k) = \frac{\partial l}{\partial \beta_k} = \sum_i \sum_k x_{ik} (y_i - \pi_i) = 0 \quad (3) \text{ (Carlin, J.B., et.al., 1999)}$$

Here k indexes the β parameters and i indexes the patients. A vector form of the score equations is presented as:

$$U(\beta) = X^{T}(y - \pi) = 0 (4)$$
 (Carlin, J.B., et.al.,1999)

where \mathbf{y} and π are vectors of the data and parameters respectively and \mathbf{X} is a design matrix with the number of rows equal to the length of the \mathbf{y} vector (\mathbf{n}) , and the number of columns equal to the number of estimated parameters. The corresponding information matrix is:

$$COV(\hat{\beta}^{ML}) = (X^t \hat{A} X)^{-1}$$
 (5) (Carlin, J.B., et.al.,1999)

where $\hat{A} = \operatorname{diag}(\hat{\pi}_i(1 - \hat{\pi}_i))$, a diagonal matrix of the binomial variances calculated at the values of π as the solution to the maximum likelihood (ML) equations. This is the model-based variance.

When responses are potentially correlated, consistent estimates of $\hat{\beta}$ can be obtained using ML as long as the first-order specification is correct (this means that the model for the mean of y is correct). Consistency means that point estimates become close to the true population values as

the sample size increases. However, the standard errors of between-cluster predictors generally will tend to be underestimated, because the covariance matrix will be estimated based on the assumption that the observations are independent. Some of the methods proposed to account for this dependence are the Jack-knife and Bootstrap, which involve resampling with replacement (for the Bootstrap) and without replacement (for the Jack-knife) (J.B. Carlin et. al., 1999). Another general approach is to use the information-sandwich variance estimator variance proposed by Huber and White (1967). This approach incorporates a ""robust" variance estimator is consistent even when the covariance structure is not correctly specified. The robust estimator is:

$$COV_{\mathbf{R}}(\hat{\beta}^{ML}) = (X^T \hat{A} X)^{-1} \sum_{i=1}^{n} \{ X^T (y_i - \pi_i) (y_i - \pi_i)^T X_j (X^T \hat{A} X)^{-1} \}$$
 (6)

The robust estimator is often called the sandwich estimator because the "bread" is the $COV_{\mathbb{R}}(\hat{\beta})^{ML}$ and the empirical estimator of the variance is the filling.

This empirical correction can be summed over independent observations (i=1,...,n) or over clusters (i=1,...,C). The "poor man's GEE" approach is to fit a logistic regression model ignoring the clustering and use a robust variance estimator calculated at the cluster level.

Marginal Models

(Generalized Estimating Equations) GEE

GEE is an extension of generalized linear models that relaxes the independence assumption. In this quasi-likelihood approach, parameters are estimated by solving the quasi-score equations:

$$U^{q}(\beta) = D^{T}V^{-1}(y - \pi) = 0$$
 (7)

where D is an $(n \times k)$ matrix of the derivatives of the expectation of the response variable with respect to β . The covariance matrix, V = Cov(y), may not correspond to a likelihood

In **GEE**, the variance matrix in the score equation is a block diagonal with n submatrices, V_i where:

$$V_i = A_i^{1/2} R(\alpha) A_i^{1/2}$$
 (8)

and $R(\alpha)$ is the "working" correlation matrix. This $R(\alpha)$ may contain unknown parameters α that specify the correlation structure. Provided that the model for the mean is correctly specified, the standard error estimates obtained using **GEE** are consistent, even if $R(\alpha)$ is misspecified. However, the efficiency of estimating (β) increases when the correlation structure is more accurately specified.

The commonly specified working correlation structures include: (1) exchangeable; where the observations are equally correlated within a cluster, (2) autoregressive; where the correlation between two observations decreases exponentially over time, (3) stationary; where the correlation between observations depends on how far apart they are in time but not on the specific time points, or (4) unstructured, where the α_{st} allows for arbitrary correlation between observations at times s and t.

The **GEE** model can be fit using either a "model-based" or a "robust" variance estimator. The "robust" information-sandwich matrix in GEE is:

$$COV_{R}(\hat{\beta}^{GEE}) = (D^{T}V^{-1}D)^{-1} \sum_{i=1}^{n} \{D^{T}V_{i}^{-1}(y_{i} - \hat{\pi}_{i})(y_{i} - \hat{\pi}_{i})^{T}V_{i}^{-1}D_{i}(D^{T}V^{-1}D)^{-1}\}$$
(9)

Although GEE for longitudinal data with time-dependent and time-independent predictors was proposed in 1986, these methods have only recently appeared in the dental literature. For example, Lambert PM et. al. (2000), use (GEE) to analyze the survival of dental implants. Morris et. al. (2000) evaluated implant survival in patients with type 2 diabetes over a period of 36 months and report that diabetic patients had more failures than non-diabetic patients. They compare models assuming independence vs. those considering correlation.

Ochi (2000) elaborates on the evaluation of clustered dental implant data. The authors explain that the implants are highly clustered in several hierarchical levels (i.e. implants within cases, implants within patients and implants within hospitals). The statistical methods used for this study involved a logistic regression analysis of the effects of predictors on survival to given The authors used GEE as implemented in **SUDAAN** (Research Triangle Institute, Research Triangle Park, NC.) where the patient was the primary cluster. The primary clusters in some analyses were the participating institutions. Exchangeable and independent working correlations were assumed and statistical results were compared with the logistic regression analyses. Jacknifing was attempted and required very long computational times especially with large data sets. Kaplan-Meier survival analysis was done, and the authors state that the Cox regression plots and analyses were not routinely performed because of uncertainty of assessing survival status using a scheduled uncovering surgery date. In their paper, logistic regression was used to model the probability of failure by a specific timepoint. Despite reported difficulties with availability of software to handle the analysis of clustered data, this group acknowledges the need to account for this clustering statistically.

Survival Models

Cox Model

The Cox Proportional Hazards model is a semiparametric approach to survival analysis where failures are assessed in continuous time (Cox, 1972, 1975). In the Cox proportional hazards model the hazard of an event at time t in a patient with covariates x is:

$$h(t) = h_0(t)e^{x\beta} \tag{10}$$

where, $h_0(t)$ is the baseline hazard and the covariates multiply the baseline hazard. The baseline hazard is not parameterized and the hazard shape over time is not specified. The partial likelihood function (Cox, 1975) is:

$$\prod_{i=1}^{I} \frac{\exp(x\beta)}{\sum_{l \in R(t_i)} \exp(x\beta)}$$
 (11)

The value $R(t_i)$ represents a risk set at t_i , and includes those patients who have not yet failed and are under observation just before time t_i , the failure time for the i^{th} failure. The covariates of the patient who experienced the failure at t_i appear in the x term in the numerator. The parameter β is estimated by maximizing the partial likelihood function. The reference cumulative incidence function is:

$$H_0(t) = \int_0^t h_0(s) ds$$
 (12)

The Breslow estimator of this function, which accommodates covariates, is:

$$\hat{H}_{0}(t) = \sum_{t_{i} \le t} \frac{d_{i}}{\sum_{l \in R(t_{i})} \exp\left(x_{l}^{t} \beta\right)}$$

$$\tag{13}$$

The t_j term indicates times that patients have failed, d_i indicates the number of cases at the i^{th} failure time $(d_i \ge 1)$ (Breslow, 1974). When $\hat{\beta} = 0$ the denominator sum equals the total number at risk at t_i in equation (13).

The simplest version of this model assumes that the relative risk of an event for two groups of individuals with different covariate values is constant across the time interval studied. This is the "proportional hazards" assumption. However, the underlying incidence rate for the two groups is permitted to be different in a structured manner. The hazard of an event at thime t

for a person with predictors x_i compared to a person with predictors x_j , under the Cox proportional hazards model is:

$$h_0 e^{x_i \beta} / h_0 e^{x_j \beta} \tag{14}$$

If the covariates x_i and x_j are constant over time, then the above ratio is constant. In fact the baseline hazard cancels out of the calculation. The $e^{(x\beta)}=e^{(x_i\beta_1+x_2\beta_2+...+x_j\beta_j)}$ part of the Cox model represents the hazard relative to a patient with x=0, and $x\beta$ is the log-relative hazard. A parametric form is assumed for the covariates involved with the model but not for the baseline hazard.

The *ordering* of the failure times is the essential information used in the Cox model, not the actual failure time values. The Cox likelihood is a partial likelihood because the estimate of β obtained by maximizing this partial likelihood produces an asymptotic normal distribution with a mean equal to β and a variance-covariance matrix equal to the matrix of second derivatives of the partial likelihood with respect to β (Kalbfleisch and Prentice, 1980).

Tied Failure Times

The Cox model assumes that failure times are distinct, although ties do occur in practice. One way of dealing with tied failure times in the Cox model is by a marginal or continuous-time calculation. We do not know the exact ordering of the failures and can consider the possibility that implant a failed slightly before b. As implants are considered to fail in various orders the risk set will change to exclude the implants that failed. Since we are unsure of the order of implant failures, the marginal calculation uses both probabilities in the calculation $(P_{ab} + P_{ba})$. The term continuous-time arises because there is no assumption that the implants failed at the exact same time.

Another method of calculating the probability of tied failures is the partial, conditional logistic or discrete-time calculation (Peto, R., 1972). There is an assumption that the implants failed at the same time and the computation becomes a multinomial calculation where all the possibilities of implant failures is considered.

Another method of calculating the probability of tied failures is the Breslow (Breslow, 1974) approximation which is a less computationally intensive method. The calculation is an approximation of the exact marginal probability of tied failures. The risk set is not adjusted for prior failures. This approximation is adequate when failures are a small fraction of the risk set.

Another approximation that handles tied failures is the Efron approximation (Efron, B 1977), which adjusts the risk sets using probability weights and averages the risk sets. This approach is more accurate than the Breslow approximation, although computation time is higher.

Stratified Cox Model

A stratified Cox model allows a separate baseline hazard for each group. The proportionality assumption between groups is dropped. However the estimates β are constrained to be the same. The stratified model is:

$$h_x(t) = h_{0S} e^{(x\beta)}$$
 where S denotes the stratum. (15)

The multiplicative effect covariate x is $e^{(x\beta)}$ in each stratum.

Manz M (2000) utilized a stratified analysis that indicated different bone loss patterns where the stata analyzed were, arch (maxillary vs. mandibular), jaw region (anterior vs. posterior), bone quality surface type (texture status), implant design (endosseous vs. other), smoking status (smoker vs. non-smoker), and postoperative antibiotic treatment (treatment vs. no-treatment). Manz (2000) points out the importance of controlling for confounding and accounting for correlation of data over time within patient.

Marginal Model

The marginal model, introduced by Lee et al. (1992), assumes proportional hazards for each implant given the patient's covariates. The model is:

$$h_{ii}(t|X_{ii}) = h_0(t)e^{(X_{ij}\beta)}, i = 1,...,n \quad j = 1,...,J_i$$
 (16)

The estimation of β is approached with an independence working model for the data. This assumes that the observations within a patient are independent and the estimation is based on partial likelihood. According to Lee et. al. (1992) the estimator for β is consistent if the marginal model is specified correctly. The variance-covariance matrix of the estimator, β , is not valid when obtained from the corresponding information matrix.

The robust or "sandwich" estimator adjusts the covariance matrix for correlations between implants within patients. Based on the independence working model, the estimate of the variance correction matrix utilizes the following definitions:

 T_{ij} is the time of evaluation of implant j within patient i, δ_{ij} is the failure indicator, and X_{ij} is a covariate vector for the jth implant in the ith patient. $Y_{ij}(t)$ is an indicator that implant j in patient i is at risk at time t. The survival functions are:

$$S_0(t) = \sum_{i=1}^n \sum_{j=1}^{J_i} [Y_{ij}(t)X_{ijk} \exp(\beta t X_{ij})], \text{ and } S_{1k}(t) = \sum_{j=1}^n \sum_{j=1}^{J_i} [Y_{ij}(t)X_{ijk} \exp(\beta t X_{ij})], k = 1,..., p$$
 (17)

where k is the number of covariates. The adjusted estimator of the variance of β presents is:

$$V = \hat{V}C\hat{V} \tag{18}$$

The β estimator follows a large sample p-variate normal distribution with a mean of β and variance estimate obtained from V. A Wald test can be employed locally and globally. This model provides no estimate of the correlation between observations within a person.

Lin and Wei (1993) also consider the situation where the baseline hazard rate is different for each group and a common β represents covariate effects. They use the independence working model with a sandwich estimator for the variance.

Spiekerman and Lin (1998) evaluated the survival of teeth that are in different positions (anterior vs. posterior) relative to each other. Their analyses indicate that teeth in similar positions contralaterally tend to have similar survival distributions. The authors extend the concept of Lee, Wei, and Amato (1992) and Wei, Lin, and Weissfeld (1989) using the "quasi-likelihood" estimating equations with an independence working assumption and relate this to a stratified Cox model for univariate failure data (Kalbfleisch and Prentice (1980) where the strata (anterior vs. posterior regions of the mouth) are correlated and there is clustering of failure times within each stratum.

Frailty Models

Vaupel et. al. (1979) first presented the term "frailty" for the analysis of univariate data. Clayton (1979) considered frailty for the analysis of multivariate survival data. The frailty model is often described as a "random effects" model for time-to-event data. However, this model can be further categorized into two types, *shared* (random-effects) and *unshared* (overdispersion and heterogeneity).

Shared Frailty

The hazard calculated by averaging over the surviving population is termed the population hazard, which can differ from that displayed by individuals. If the study population encompasses significant heterogeneity, the population hazard can decrease with time as the risk set becomes more dense with patients who are less frail and less likely to experience the event. This phenomenon is known as the "frailty effect". In the present study each patient would have a frailty that would be shared by all the implants that he or she had placed. In the framework of

the Cox model, a frailty is a latent random effect that multiplies the hazard. For the *j*th implant in the *i*th patient, the frailty model is:

$$h_{ij}(t) = h_0(t)\alpha_i \exp(x_{ij}\beta)$$
 (19) Cleves, M.A., Gould, W.W. and

Gutierrez, R.G. 2004, Revised Edition.

For $v_i = \log \alpha_i$, this model can be rewritten as $h_{ij}(t) = h_0(t) \exp(x_{ij} \beta t v_i)$, where the log frailties, v_i are analogous to random effects in standard linear models. The estimated variance of the frailty parameters is compared to a 50:50 mixture of $\chi^2(0)$ and $\chi^2(1)$ distributions.

Andersen and Commenges (1995) derived a score test to assess association between groups of patients, after adjustment for covariate effects in a Cox proportional hazards model. This test may also be utilized for the assessment of overdispersion in (stratified and unstratified) Cox proportional hazards models.

The hazard rate for the frailty model can be written as:

$$h_{ij}(t) = h_0(t) \exp((\theta)w_i + \beta_i X_{ij}), i = 1 \text{ to } n \text{ and } j = 1 \text{ to } J_i$$
 (20)

where $h_0(t)$ is the baseline hazard for the jth implant in the ith patient, X_{ij} is the covariate vector, $\boldsymbol{\beta}$ is the regression coefficient vector, \boldsymbol{w}_i represents the frailties, and $\boldsymbol{\theta}$ is the variance of the frailty. When $\boldsymbol{\theta}$ equals zero, this model becomes the proportional hazards model.

Likelihood Derivation

Therneau and Gramsch (2002) describe the estimation of θ as a maximum profile log-likelihood. The value for θ is fixed as β and r_i are estimated by maximizing the likelihood as follows:

$$L(\theta) = L_c(\beta, r_i) + \sum_{i=1}^{N} \left[\frac{1}{\theta} \left\{ r_i - \exp(r_i) \right\} + \left(\frac{1}{\theta} + d_i \right) \left\{ 1 - \ln\left(\frac{1}{\theta} + d_i\right) \right\} - \frac{\ln \theta}{\theta} + \ln \Gamma\left(\frac{1}{\theta} + d_i\right) - \ln \Gamma\left(\frac{1}{\theta}\right) \right]$$
(21)

(Survival Analysis and Epidemiological Tables, STATA Manual release 8, 2003)

Where $L_c(\beta, r_i)$ is the traditional Cox partial likelihood, the r_i represent the coefficients of indicator variables for the patients and d_i indicates the number of implant failures for patient i, which ranges from 1 to J_i . In this calculation each observation for the ith patient has a log-relative hazard represented by:

$$x_{ii}\beta + r_i \tag{22}$$

The estimates of θ , β and r_i are those that maximize $L(\theta)$.

A variance-covariance matrix of $(\hat{\beta}, \hat{r}_i)$ is obtained from the inverse of the negative Hessian Matrix of $L(\hat{\theta})$. The variance-covariance matrix of $\hat{\beta}$ can be found as a submatrix of the variance-covariance matrix of $(\hat{\beta}, \hat{r}_i)$. Any inference based on the estimation of β is conditional on the estimation of θ .

Recent Articles of Analysis of Dental Implant Survival

Herrmann I et. al., (1999) discuss the risk of failure of implants in each patient after any one failure in the same patient. If one implant fails, will the risk of subsequent failures increase? The hypothesis evaluated was whether dependency exists among implants in the same patient/jaw. This article identified a dependency among implants that existed prior to functional loading, i.e. the risk for failure among remaining implants in the same patient/jaw increased after the first failure. The authors state that study design and statistical analysis are important when comparing success rates from various investigations, since dependency among implants in the same patient/jaw may influence success rates. Chuang et. al. (2001) compare three statistical

models for survival estimation. The first model involved randomly selecting one implant per patient. The second statistical model evaluated utilized all implants, assuming independence among implants from the same subject and the third model used all implants, assuming dependence among implants from the same subject (The GEE approach was employed). These authors of this study state that the point estimates for five-year survival were similar for all three approaches. The differences in the standard error estimates were small as well. However, the authors state also that the assumption of independent observations produces statistically invalid results. A few articles address the interdependency of implants with respect to survival analysis (Mau (1993) and Haas et. al. (1996)). These authors state that independence of implants cannot be assumed in patients with multiple implants (especially when multiple implants exist in one arch) and that the total number of implants should not be used to obtain statistical results for survival analysis. The statistical method of handling dependent observations is discussed further by Haas et. al. (1996), Ivanoff et. al. (1999), Lekholm et. al. (1999), and Herman et. al. (1999). These authors recommend the random selection of one implant per patient, where the sample procedure is repeated several times, to guarantee representative results. This method is inefficient with respect to estimation because not all observations are used at the same time during sampling.

To our knowledge, no articles address the concept of frailty in the analysis of survival of dental implants. This will be the focus of this thesis.

CHAPTER 3

Methods

Creation of an Analytical Dataset

The data that were provided to me by Dr. Weyant included survival information with almost 7 years of follow-up (maximum follow-up time=2,520 days). However, these data were not in longitudinal follow-up form, and considerable data management was required to create a suitable analytic dataset for this thesis. We describe the creation of an analytic data file, data cleaning and formatting for analysis. This process is summarized in Figure 1.

Data Forms and Corresponding Files

Clinicians involved with the study were required to fill out six data forms (**Form A, Form B1, Form C, Form D, Form U, and Form X**) during their clinical evaluations of study patients.

Flowchart of Data Management:

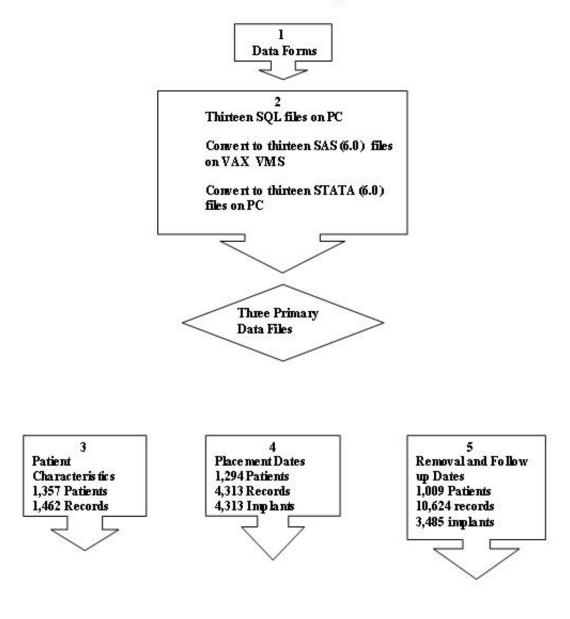


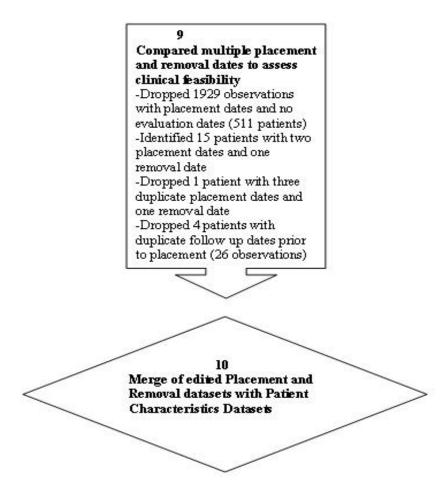
Figure 1 Flowchart of Data Management



7 Placement Dates -Only Relevant Variables -Identified records with duplicate and/or discrepant dates (75 multiple records with duplicate or different dates)

Removal Dates -Only Relevant Variables - Identified 22 duplicate removal dates (7 patients and 10 implants) -Dropped 21 records (5 patients) with dates preceding study time or birthdate of patient -Identified 79 records with multiple removal dates involving 40 patients and 68 implants -Identified 26 records involving 4 patients with follow up dates prior to placement dates

Figure 1 continued



This merge resulted in dropping 653 records that were not associated with follow up times or identifiers from the datasets that were in the merged **Placement Dates** and **Removal Dates** dataset. There was maintenance of 781 patients, 8,129 observations and 103 failures at this point.

- -26 records involving 4 patients with follow up time after failure were dropped.
- -117 records were dropped via manual edition due to date and record discrepancies revealed after the STSET procedure in STATA.

11 The **Analytic Dataset** had 777 patients, 7,986 records, 2,305 implants and 103 failures

Figure 1 continued

These six forms are shown in **Appendix A**. The information from these forms was entered into thirteen separate SQL files on a Personal Computer. The data were available on a VAX VMS system in the form of SAS (version 6.0) files. The data were transferred from SAS (version 6.0) to STATA (version 6.0) system files, utilizing STAT Transfer (version 5.0). The files in both systems were compared for data transfer errors. This process is summarized in the first two steps of Figure 1.

A data dictionary was not available, and the coding of some variables in the datasets did not agree with the forms. These variables were not considered further. Also, there were no variables to represent natural dentition, although it was mentioned in Dr. Weyant's thesis. I do not have the same core data that were used in Dr. Weyant's dissertation, because his data are reported to span a three year time period and the present data span 6.9 years and include a larger number of patients. The relevant information for the present analysis was obtained by merging the three datasets corresponding to Forms A, B, and C.

Three Primary Data Files

The primary data required for a survival analysis include a unique patient identifier, an implant identifier, a starting time (placement date of an implant) and follow-up time(s) (evaluation date(s) of implants), and a variable to indicate censorship or failure. The component datasets are described in **Appendix B**, and the number of patients, records, and implants in each data set is summarized in steps 3-5 of Figure 1. The number of implants placed per patient for each dataset is shown in Figure 2, which shows that many patients have more than one implant placed.

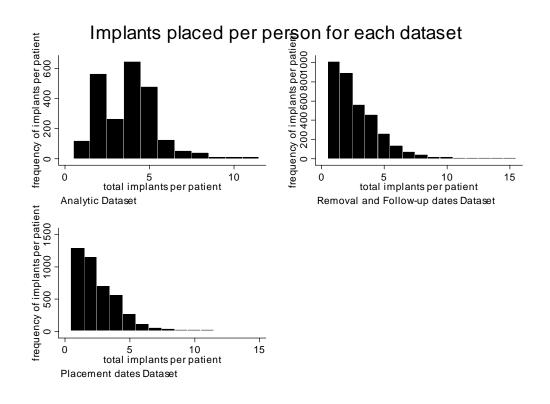


Figure 2 Implants placed in the Component Datasets

Patient Characteristics Dataset

The **Patient Characteristics** dataset contains basic patient characteristics such as each patient's unique identifier, birth date, race, and gender. **Patient Characteristics** contains no data on implants. There are more records (1,462) than patients (1,357) in the **Patient Characteristics** dataset, indicating duplicate records (**Figure 1, Step 3**). These were ultimately deleted.

Placement Dates Datasets

The **Placement Dates** dataset contains the unique patient identifier and the placement date of each implant. Other variables in this dataset include description of implants (i.e. brand, coating, length, width, etc.), bone width and height, gingival attachment measurements, and a description of opposing occlusion. There are 1,294 reported patients and 4,313 reported implants (**Figure 1**, **Step 4**). The greater number of implants than patients reflects the multiple placements of

implants per patient as well as duplicate records per implant and multiple placements per implant-site. Indicators for records with duplicate placement dates and different placement dates were created. Records for missing placement dates were dropped.

The **Placement Dates** dataset required substantial editing. The key variables for patient identifier, implant placement date, and site of placement had to be converted from string to numeric. In STATA version 7 the "destring" command was used. Because the **site** variable was differently named than in the other datasets, a common variable name was coded. The patient identifier and placement date variables were retyped to numeric form and renamed.

Multiple placement dates at an implant site

The next step was to evaluate the multiple placement dates at some implant sites for the same patient. There appeared to be 75 records with multiple placements per implant. In the one case where a placement date was duplicated, the duplicate record was dropped. One implant had three different placement dates and the remaining implants had two different placement dates

Removal and Follow up Dates Dataset

The **Removal and Follow up Dates** dataset contains the unique patient identifier, the dates of follow-up visits and possibly removal of each implant, and other descriptive variables (**Figure 1**, **Step 5**). This dataset included 1009 patients, 10,624 records, and 3,485 implants. Each patient could have multiple follow-up visits for each implant. This dataset also contains duplicate records and implants with multiple removal dates. Indicators for duplicate and different placement dates were created.

The Primary issues to address with the Removal and Follow up Dates dataset:

- (1) How many implant removal dates existed?
- (2) Were there multiple removal dates per implant?
- (3) If multiple removals existed, were these replacement dates or typographical errors?

(4) Were there implant removal dates before evaluation dates?

Indeed, some implant removal dates were found to precede some first evaluation dates. Implants without placement dates were dropped from the dataset. A variable, **ctr1**, was created to count the multiple removal dates. Another variable, **dup**, was created to count the duplicates among the multiple removal dates. A censoring variable, **rem**, was created with a dichotomous coding of 0 or 1, where 1 indicated failure and evidence of an implant removal date, and 0 otherwise. In the **Removal and Follow up Dates** dataset, a new variable, **followup**, was created for follow-up times for those implants that were either censored or failed. This was the time variable used for statistical analysis. The following STATA code was used:

g followup=nevldate, replace followup=nimrdate if rem=1. These commands identified 43 records as containing an evaluation date and an implant removal date that differed and therefore, indexed those implants as failures. The data were sorted by patient identifier, site and followup. Date values preceding the study time or possibly the birth date of the patient were deleted; 21 observations and 5 patients were dropped from the dataset. This did not affect removal dates, of which there were 158 in this dataset.

The Number of Implant Removal Dates

An evaluation of implant removal revealed a total of 3,434 implants that were ever evaluated and not removed, and 124 implants that were "ever" removed, giving a total of 3558 implants with at least one evaluation or follow-up date. There were 1009 patients in this file.

Multiple Removal Dates

There were 10,624 records for these 1009 patients, including 22 records in which there are duplicate removal dates on the same implant. This involved 7 patients and 10 implants. There are 79 records with multiple removal dates that are different. This involved 40 patients and 68 implants.

The multiple different removal dates were compared with the placement dates to assess:

(1) the potential for multiple corresponding placement dates (2) the clinical feasibility of the placement, removal and evaluation dates and (3) the potential for analysis of repeated failures per implant site in the resulting dataset.

The **Placement Dates** and **Removal and Follow up Dates** datasets were first subsetted into separate files that included only the relevant variables (patient identifier, implant site, placement date, removal date and evaluation dates) and the corresponding indicators of problematic records that were created in **Steps 6** and **7** of **Figure 1**. The abbreviated files were then merged and evaluated for date and record discrepancies (**Figure 1**, **Step 8**). Duplicate observations were removed and the ordering of multiple placements and removals were assessed for clinical feasibility. This cleaned dataset was remerged with the two separate source datasets.

The Process of Evaluation

The **Placement Dates** and **Removal and Follow up Dates** datasets were merged by employing the "joinby" command in STATA (**Step 9 of Figure 1**). The "master" dataset was the abbreviated **Placement Dates** dataset, which had 4,297 records, and the "using" dataset was the abbreviated **Removal and Follow up Dates** dataset, which had 10,308 records. STATA's joinby procedure enables one to track the source of the records in the combined dataset and discern discrepancies in merging with a **_merge** variable. A tabulation of the **_merge** variable showed that 1,929 records were only in the "master" (**Placement Dates**) dataset and did not merge with the "using" (**Removal and Follow up Dates**) dataset, giving 8,379 records in the combined dataset. These 1,929 dropped records (511 patients) have only placement dates and no evaluation dates or implant removal dates. The total number of unique patient identifiers in the combined dataset is now 781.

A new variable, **place**, represents the implant placement date for each implant. A variable named **failure** was created to denote censoring or failure of each implant at any specific follow-up time. There were 15 verified patients who had two separate implant placement dates and only one removal date. The decision was made to choose the first, or earliest, implant placement date for the analysis. This decision was based on the clinical feasibility of the timing of the placement dates. There was one case that had three duplicate placement dates and only one removal date. We decided to manually edit the data for circumstances involving:

- (1) Multiple placement dates and no removal dates,
- (2) Multiple placement dates and one removal date
- (3) Multiple placement dates and multiple removal dates,
- (4) One unique placement date and multiple removal dates, and
- (5) Duplicate placement dates and/or duplicate removal dates.

The **followup** variable was evaluated and the records were sorted to have the last possible evaluation date listed with the **failure** variable changed to a 0 or 1 to denote censoring or removal, respectively. Duplicate follow-up, placement and removal times were deleted. There were four patients who had evaluation dates or follow up visits prior to the date of placement. If this occurred on the first visit, perhaps as an evaluation before placement of an implant, this could be somewhat reasonable. However, there are several visits (26) for evaluations of implants with no placement records; there were no removals for such observations. These records were removed from the analytic file.

There were situations where an implant was removed and follow up times were present after removal, for the same implant. One question that clinicians may pose is; "Why was a site evaluated several times after removal"? This may have been an oversight on the part of anyone

evaluating the patient, he or she may have been evaluating other sites, or a subsequent placement date could be missing. However, in evaluating sites we are assuming that there is an implant to evaluate. If an implant is not present, implant failure cannot be assessed. These observations were left until the demographic variables in the **Patient Characteristics** dataset were merged with this dataset and then dropped.

Creating the Analytic Dataset

The analytic dataset was formed by using the **joinby** command with the merged abbreviated dataset and the three original datasets separately in order to collect all the variables (**Figure 1**, **Step 10**). In merging the subsetted datasets, it became apparent that there were site indicators that differed in both datasets and had to be renamed in one. Careful inspection of all the variables with respect to type is required with all data merging, procedures and especially so here. Merging can be unsuccessful if variables are typed or named differently in the component datasets.

The Patient Characteristics dataset was merged with the combined cleaned dataset (Placement Dates/ Removal and Follow up Dates). After merging there were 95 records that did not have follow-up times corresponding with the Removal and Follow up Dates dataset and did not have placement date information in the Placement Dates dataset. There were more observations in the Patient Characteristics dataset than in the combined dataset. This could be attributed to unmatching patient identifiers. A total of 653 records were lost in the merge because of matching problems. Records in which there were no demographic data were kept because survival data exist; at this point there were 781 patients, 8,129 records and 103 records with failures. The STSET procedure sets the data for survival analysis in STATA with the appropriate unique identifier and time variables. This procedure also identifies date and record errors pertinent to survival analysis. Twenty-six records involving 4 patients were identified with

follow up times occurring after a failure. These observations were dropped with manual editing. After manually editing for date and record discrepancies that were revealed in the STSET procedure in STATA, a total of 777 patients, 7,986 records, 2,305 implants and 103 failures were maintained in the final analytic dataset (**Step 11, Figure 1**)

Statistical Models

We will illustrate the following models using implant-level predictors (type and location) and patient-level predictors (race/ethnicity).

- 1. Logistic regression of first implant per patient with first year follow-up
- 2. Logistic regression of multiple implants per patient with first year follow-up
- 3. Logistic regression of multiple implants per patient first year followup using Generalized Estimating Equations (GEE)
- 4.Discrete Proportional Odds of first implant per patient with multiple time intervals
- 5. Discrete Proportional Hazards of first implant per patient with multiple time intervals
- 6. Discrete Proportional Odds of multiple implants per patient with multiple time intervals
- 7. Discrete Proportional Odds of multiple implants per patient with multiple time intervals using (GEE)
- 8. Discrete Proportional Hazards of multiple implants per patient with multiple time intervals using (GEE)
- 9. Continuous-time Cox Model of single implant per patient over time
- 10. Continuous-time Cox Model of multiple implants per patient over time
- 11. Continuous-time Shared Frailty Model of multiple implants per patient over time

Table 1 describes the statistical models evaluated for the various data situations involved which corresponds with the preceding list.

Table 1 Statistical Models Evaluated

1	Logistic regression	$\log it(p_i) = \beta_0 + \beta_1(loc2)_i + \beta_2(loc3)_i + \beta_3(loc4)_i +$ $\beta_4(type2)_i + \beta_5(type2)_i$	Single site per person and single time interval
2,3	Logistic regression, Generalized Estimating Equations (GEE)	$\log it(p_{ijt}) = \beta_0 + \alpha_t + \beta_1 (loc2)_{ij} + \beta_2 (loc3)_{ij} + \beta_3 (loc4)_{ij} + \beta_4 (race2)_i + \beta_5 (type2)_j$	Multiple sites per person and single time interval
4,5	Logistic regression with Discrete proportional odds and hazards	$\begin{split} \log it(p_{it}) &= \beta_0 + \alpha_t + \beta_1(loc2) + \beta_2(loc3) + \beta_3(loc4) + \\ & \beta_4(race2) + \beta_5(type2) \\ \\ c - \log - \log(p_{it}) &= \beta_0 + \alpha_t + \beta_1(loc2) + \beta_2(loc3) + \beta_3(loc4) + \\ & \beta_4(race2) + \\ & \beta_5(type2) \end{split}$	Single site per person with multiple time intervals
6,7,	Discrete Proportional Odds and hazards and (GEE) model	$\begin{aligned} \log it(p_{ijt}) &= \beta_0 + \alpha_t + \beta_1 (loc 2)_{jt} + \beta_2 (loc 3)_{jt} + \beta_3 (loc 4)_{jt} + \\ & \beta_4 (race 2)_i + \beta_5 (type 2)_{jt} \\ c - \log - \log(p_{ijt}) &= \beta_0 + \alpha_t + \beta_1 (loc 2)_{jt} + \beta_2 (loc 3)_{jt} + \\ & \beta_3 (loc 4)_{jt} + \\ & \beta_4 (race 2)_i + \\ & \beta_5 (type 2)_{jt} \end{aligned}$	Multiple sites per person and multiple time intervals
9	Continuous- time Survival (Cox model)	$h(t;x_i) = h_0(t)e^{(\beta_1(loc2)_{ij} + \beta_2(loc3)_{ij} + \beta_3(loc4)_{ij} + \beta_4(race2)_i + \beta_5(type2)_{ij})}$	Single site per person and continuous time
10	Continuous- time Survival (Cox model)	$\lambda(t; x_{ij}) = \lambda_0(t)e^{(\beta_1(loc2)_{ij} + \beta_2(loc3)_{ij} + \beta_3(loc4)_{ij} + \beta_4(race2)_j + \beta_5(type2)_{ij})}$	Multiple sites per person and continuous time
11	Shared Frailty Model	$\lambda(t; x_{ij}) = \lambda_0(t)e^{(\beta_1(\log 2)_{ij} + \beta_2(\log 3)_{ij} + \beta_3(\log 4)_{ij} + \beta_4(race 2)_{j} + \beta_5(type 2)_{ij})}$	Multiple sites per person and continuous time

Coding of predictor variables

The models discussed in this thesis incorporate both between and within patient variables (oral location, implant type and race of patient). We also considered differences between model-based and robust variance estimates.

The variable for oral location was created by the site variable and is categorized as follows: Iloc_1=mandibular anterior, Iloc_2=maxillary anterior, Iloc_3=mandibular posterior, and Iloc_4=maxillary posterior. Therefore, the mandibular anterior region was considered the baseline value.

The variables of implant type and race were categorized as well. Implant type started out with 7 unique values. Due to the small numbers in all but type 19 and 4, the variable was collapsed to two categories. Type 19 was the baseline or (Itype_1) and all other types were grouped into Itype_2. The same was done for race where the baseline race was white (Irace_1) and non-white was Irace_2.

CHAPTER 4

Descriptive Analysis

Patient Demographic Characteristics

Patient demographic characteristics are summarized in Table 2. The high percentage of males reflects a typical Veterans Administration population. Both gender and race/ethnicity were missing for 36 patients (278 records) and ethnicity was unknown for 9 patients. The mean age of the patient population is 62 years, with a minimum and maximum of 25 and 82 years, respectively. A variable was created to assess the possibility of multiple recordings of gender and race/ethnicity across visits. There was one such patient, who had records specifying Hispanic and White, and this patient was counted as Hispanic. The majority of these patients were white (80.8%).

Table 2 Patient Demographic Characteristics

(n=777)

C	Characteristic	Frequency	Percent
Gender	Male	710	95.8
	Female	20	2.7
	Unknown/	47	3.5
	Missing		
Race/	White	628	80.8
Ethnicity	Black	77	9.9
	Asian	1	0.1
	Native Am.	2	0.3
	Hispanic	22	2.8
	Other	2	0.3
	Missing	45	5.8
Those not	recording any		
ethnic val	ue (i.e. only		
0's)			
Total numb	per of Patients	777	100.0

Implant Characteristics

As can be seen in this Table 3, 36.3% of the patients have two implants and 20.7% have four implants. A single implant is the third most frequent situation, occurring in 14.9% of patients. In this dataset, 85.1% of patients have multiple implants.

Table 3 Distribution of Number of Implants: Overall and By Patient Frequencies and Percents

Number	Implants		Patients	
Of Implants	(k=23	05)	(n=777)
	Freq	Percent	Freq	Percent
1	116	5.03	116	14.9
2	564	24.47	282	36.3
3	261	11.32	87	11.2
4	644	27.94	161	20.7
5	475	20.61	95	12.2
6	126	5.47	21	2.7
7	49	2.13	7	0.9
8	40	1.87	5	0.6
9	9	0.39	1	0.1
10	10	0.43	1	0.1
11	11	0.48	1	0.1

Although seven implant types are reported in this dataset, only one, Type 19, was used for the vast majority (725) of patients (Table 4). A total of 45 (5.8%) of patients received implants of Type 4, and very few patients received the other implant types. The six patients who received more than one type of implant are listed more than once in column 2 of Table 3. A total of 94% of the implants were of Type 19 and 4% were of Type 4. Sixty-four patients experienced at least one implant failure. A total of 103 failures were observed out of the 2,305 implants placed. The "Within" Percent value indicates that the patients who have received implant Type 19 received this implant type 99.5% of the time, while patients who received Type 4 received this type 85.6% of the time.

Table 4 Numbers of Patients, Implants by Type of Implant and Implant Failures

Type of Implant	Number of Patients	Number of implants	Number of failures	Failure rate	Number of patients with failures	Within Percent
2	5	13	0	0.00	0	100.0
4	45	95	6	0.06	3	85.6
5	1	4	0	0.00	0	100.0
6	2	6	4	0.70	1	60.0
10	1	2	0	0.00	0	33.3
18	4	16	0	0.00	0	94.1
19	725	2169	93	0.04	60	99.5
Total	783*	2305	103	0.04	64	98.4
*Note: S	ix (6) patients	s had more th	an one type	of implant	t	

Figure 3 displays the frequency of implants placed per patient in the analytic dataset. As shown, there are many opportunities to evaluate multiple failures per patient with most patients having more than one implant.

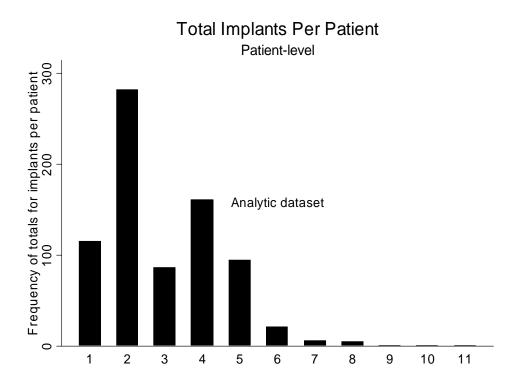


Figure 3 Total Implants per Patient in the Analytic Dataset

Figure 4 displays the frequency of implants placed by site per patient. The two histograms separate the frequencies by dental arch ((maxillary-upper jaw) vs. (mandibular-lower jaw)). For both arches the higher frequencies occur in the canine regions, where the bone density may be greater.

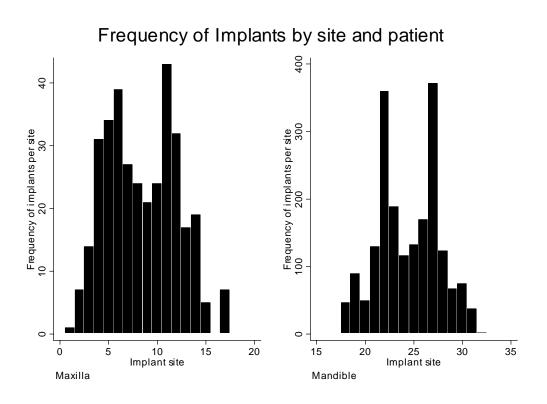


Figure 4 Frequency of Implants placed by site and patient

Table 5 shows the frequencies of first, second and subsequent visits. One patient had 25 visits.

Table 5 Distribution of follow-up visits

Number of Visits	Frequency of Visits	Percent of Visits
1	777	100.0
2	548	70.5
3	394	50.7
4	279	35.9
5	196	25.2
6	146	18.8
7	105	13.5
8	80	10.3
9	63	8.1
10	44	5.7
11	37	4.8
12	25	3.2
13	19	2.5
14	12	1.5
15	11	1.4
16	8	1.0
17	8	1.0
18	5	0.6
19	5	0.6
20	5	0.6
21	4	0.5
22	4	0.5
23	4	0.5
24	1	0.1
25	1	0.1
Total	2,781	357.9

It should be noted that this table presents the frequencies and percents at the patient-level where each patient could be included in several visit categories. A patient who had seventeen visits also was included in the count for one through sixteen visits. Therefore, although there are 777 patients in the study, each patient may be counted more than once for each visit that they participated in. This follows for the "percent" values. The visit frequencies and percents are evaluated at each visit.

CHAPTER 5

Modeling Results

Table 6 summarizes Logistic regression analysis of the first implant per patient with one year of follow-up (Model 1). There is a nonsignificant elevation of the odds ratios for the maxillary anterior and posterior regions relative to the mandibular anterior region. Implant types other than type 19 have a nonsignificantly decreased odds of failure. Non-whites have nonsignificantly increased odds of failure relative to whites. The model-based and robust standard errors were virtually identical.

Table 6 Model 1 Results: Logistic regression of first implant with one year follow-up

Number of observations: 872

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Odds	Standard error		Standard error	
	Ratio				
Oral Location					
Mandibular	1.0				
anterior					
Maxillary	1.52	1.21	0.60	1.20	0.60
anterior					
Mandibular	0.64	0.34	0.40	0.33	0.40
posterior					
Maxillary	2.20	1.50	0.26	1.50	0.25
posterior					
Type					
Type 19	1.0	-		-	
Others	0.71	0.55	0.66	0.55	0.66
Race					
White	1.0	-		-	
Others	1.88	1.00	0.24	1.01	0.24

Table 7 summarizes the Logistic regression analysis of multiple implants per patient with one year of follow-up (Model 2). There is a nonsignificant increase in the odds of failure for the maxillary anterior and mandibular posterior regions relative to the mandibular anterior region. The maxillary posterior region had a significantly elevated odds of implant failure based on a model-based standard error (p=0.04), but this odds ratio of 2.86 is not statistically significantly elevated when a robust standard error was used. The robust standard error accounts for the multiple implants per patient.

Table 7 Model 2 Results: Logistic regression of multiple implants with one year follow up Number of observations: 2610

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Odds	Standard error		Standard error	
	Ratio				
Oral Location					
Mandibular anterior	1.0	-		-	
Maxillary anterior	2.15	0.99	0.10	1.13	0.15
Mandibular posterior	1.12	0.37	0.74	0.37	0.73
Maxillary posterior	2.86	1.43	0.04	1.89	0.11
Type					
Type 19	1.0	-			
Others	0.85	0.46	0.77	0.64	0.84
Race					
White	1.0	-			
Others	1.97	0.67	0.05	0.95	0.16

Table 8 summarizes the a GEE (Logistic regression) analysis of multiple implants per patient over the first year of follow-up (Model 3) and an assumed exchangeable correlation structure. The highest odds of failure is observed for the maxillary anterior and posterior regions. The odds ratio was somewhat elevated for the mandibular posterior region. However, no region was statistically significant.

Non-whites have a significantly elevated odds of failure based on the model-based standard error (p=0.04), but this odds ratio of 2.18 is not statistically significant when a robust standard error was used.

Table 8 Model 3 Results: GEE (Logistic Regression), Multiple Implants, First year followup

Number of observations: 2610

Predictor	Estimated Odds Ratio	Model-based Standard error	P-value	Robust Standard error	P-value
Oral Location					
Mandibular anterior	1.0	-		-	
Maxillary anterior	1.83	0.99	0.26	1.08	0.31
Mandibular posterior	1.26	0.41	0.48	0.34	0.40
Maxillary posterior	2.62	1.43	0.08	1.69	0.14
Туре					
Type 19	1.0	-			
Others	0.80	0.51	0.72	0.64	0.78
Race					
White	1.0	-			
Others	2.18	0.84	0.04	1.06	0.11

Table 9 summarizes the discrete proportional odds model analysis for the first implant per patient with multiple time intervals of follow-up (Model 4). We see a significantly decreased odds of failure in year 2 relative to year 1, with a nonsignificant decrease in the odds of implant failure in subsequent years until year 8. In year 8, four implants failed among the 16 patients still at risk.

The maxillary anterior and posterior regions had elevated odds ratios (p=0.001 and 0.07 respectively) relative to the mandibular anterior region. The odds of failure for the two mandibular regions were similar. The model-based and robust standard errors are virtually identical.

Table 9 Model 4 Results for Discrete Proportional Odds. First implant per patient with multiple time intervals

Number of Observations: 3651

Predictor	Estimated Odds	Model-based Standard error	P-value	Robust Standard error	P-value
	Ratio				
Year					
Year 1	1.0	-		-	
Year 2	0.37	0.17	0.03	0.17	0.03
Year 3	0.57	0.28	0.26	0.28	0.25
Year 4	0.20	0.20	0.11	0.20	0.11
Year 5	0.37	0.38	0.33	0.38	0.33
Year 6	0.82	0.85	0.85	0.85	0.85
Year 7	-	-	-	-	-
Year 8	12.7	14.4	0.02	13.7	0.02
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	5.1	2.46	0.001	2.51	0.001
anterior					
Mandibular	0.95	0.41	0.90	0.40	0.90
posterior					
Maxillary	2.6	1.41	0.07	1.40	0.07
posterior					
Type					
Type 19	1.0	-		-	
Others	1.4	0.78	0.60	0.71	0.55
Race					
White	1.0	-		-	
Others	1.3	0.58	0.60	0.60	0.61

Table 10 summarizes the discrete proportional hazards model analysis for the first implant per patient with multiple time intervals for follow-up using the Clog-log function (Model 5). Numerically, these estimates are very similar to the comparable discrete proportional odds model shown in Table 9 (Model 4). However, these parameter estimates are hazard ratios rather than odds ratios.

Table 10 Model 5 Results for Discrete Proportional Hazards using the Cloglog function First implant per patient with multiple time intervals

Number of Observations: 3651

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Hazard	Standard error		Standard error	
	Ratio				
Year					
Year 1	1.0	-		-	
Year 2	0.37	0.17	0.03	0.18	0.04
Year 3	0.57	0.28	0.26	0.28	0.26
Year 4	0.19	0.20	0.11	0.20	0.11
Year 5	0.37	0.38	0.33	0.38	0.33
Year 6	0.87	0.85	0.85	0.86	0.86
Year 7	-	-	-	-	-
Year 8	11.89	12.46	0.02	11.91	0.01
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	4.98	2.38	0.001	2.44	0.001
anterior					
Mandibular	0.96	0.41	0.92	0.40	0.92
posterior					
Maxillary	2.62	1.40	0.07	1.40	0.07
posterior					
Type					
Type 19	1.0	-		-	
Others	1.38	0.78	0.58	0.71	0.54
Race					
White	1.0	-		-	
Others	1.27	0.57	0.60	0.59	0.61

Table 11 summarizes the discrete proportional odds model analysis for multiple implants per patient with multiple time intervals of follow-up (Model 6). The robust standard errors are consistently larger than the corresponding model-based values. In several instances (year 2, year 4, mandibular posterior, and non-white race) the parameter estimates change from significant to nonsignificant when the robust standard errors are used.

Table 11 Model 6 Results for Discrete Proportional odds

Multiple implants per patient over time

Number of observations: 11,217

Predictor	Estimated Odds Ratio	Model-based Standard error	P-value	Robust Standard error	P-value
Year					
Year 1	1.0	-			
Year 2	0.55	0.14	0.02	0.21	0.12
Year 3	0.42	0.15	0.02	0.17	0.03
Year 4	0.33	0.17	0.03	0.23	0.09
Year 5	0.59	0.31	0.32	0.48	0.52
Year 6	0.94	0.57	0.93	0.73	0.95
Year 7	0.72	0.73	0.75	0.75	0.75
Year 8	27.73	17.13	0.000	29.74	0.002
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	4.70	1.42	0.000	1.89	0.000
anterior					
Mandibular posterior	1.40	0.35	0.20	0.35	0.17
Maxillary	3.39	1.13	0.000	1.35	0.002
posterior	3.37	1.13	0.000	1.33	0.002
Type					
Type 19	1.0	-		-	
Others	1.42	0.52	0.33	0.64	0.42
Race					
White	1.0	-		-	
Others	1.79	0.45	0.02	0.72	0.15

Table 12 summarizes the discrete proportional odds model for multiple implants per patient with multiple time intervals for follow-up using a GEE analysis (Model 7) and an assumed exchangeable correlation structure. After the first year the odds ratios appear to be less than one until year six. The odds ratios for the maxillary anterior and posterior regions are significantly elevated relative to the mandibular anterior region when the model-based or robust standard errors are employed. The type of implant does not appear to be significant in this model. Non-white race appears to be significantly associated with increased failure using the model-based standard error but not the robust standard error.

Table 12 Model 7 Results for Discrete Proportional odds Multiple implants per patient over time with GEE analysis

Number of observations: 11,217

Predictor	Estimated Odds	Model-based Standard	P-value	Robust Standard	P-value
	Ratio	Error		error	
Year					
Year 1	1.0	-		-	
Year 2	0.70	0.16	0.12	0.22	0.25
Year 3	0.63	0.19	0.13	0.19	0.12
Year 4	0.55	0.22	0.15	0.23	0.16
Year 5	0.81	0.37	0.64	0.42	0.69
Year 6	1.36	0.69	0.54	0.76	0.58
Year 7	1.20	0.95	0.81	0.73	0.75
Year 8	28.67	17.4	0.000	29.89	0.001
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	4.06	1.35	0.000	1.41	0.000
anterior					
Mandibular	1.38	0.34	0.19	0.28	0.11
posterior					
Maxillary	3.08	1.12	0.002	1.17	0.003
posterior					
Type					
Type 19	1.0	-		-	
Others	1.35	0.57	0.48	0.63	0.53
Race					
White	1.0	-		_	
Others	1.93	0.56	0.02	0.78	0.10

Table 13 summarizes the a discrete proportional hazards model for multiple implants per patient with multiple time intervals of follow-up with the Clog-log link using GEE (Model 8) and an assumed exchangeable correlation structure. The estimates are similar numerically to those in the comparable discrete proportional odds analysis using GEE in Table 12.

Table 13 Model 8 Results for Discrete Proportional hazards using C-log-log and GEE analysis

Number of observations: 11,217

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Hazards	Standard		Standard	
	Ratio	Error		error	
Year					
Year 1	1.0	-		-	
Year 2	0.70	0.16	0.13	0.22	0.26
Year 3	0.63	0.19	0.13	0.19	0.12
Year 4	0.55	0.23	0.15	0.23	0.16
Year 5	0.81	0.37	0.64	0.42	0.68
Year 6	1.36	0.68	0.54	0.75	0.58
Year 7	1.20	0.93	0.82	0.72	0.76
Year 8	24.07	12.74	0.000	21.38	0.000
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	4.03	1.32	0.000	1.39	0.000
anterior					
Mandibular	1.40	0.34	0.17	0.28	0.10
posterior					
Maxillary	3.08	1.11	0.002	1.16	0.003
posterior					
Type					
Type 19	1.0	-		-	
Others	1.43	0.58	0.38	0.63	0.42
Race					
White	1.0	-		-	
Others	1.87	0.54	0.03	0.75	0.12

Table 14 summarizes the continuous-time proportional Cox model analysis for the first implant per patient over time (Model 9). The hazard ratios are significantly elevated for the maxillary anterior region and nonsignificantly elevated for the maxillary posterior region, both relative to the mandibular anterior region. The model-based and robust standard errors are virtually identical.

Table 14 Model 9 Results for Continuous-time Cox Model Single implant per patient over time

Number of observations: 2,483

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Hazard	Standard error		Standard error	
	Ratio				
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	4.04	1.92	0.003	1.92	0.003
anterior					
Mandibular	0.88	0.37	0.76	0.36	0.75
posterior					
Maxillary	2.05	1.09	0.18	1.09	0.18
posterior					
Type					
Type 19	1.0	-		-	
Others	1.58	0.92	0.43	0.80	0.36
Race					
White	1.0	-		-	
Others	1.31	0.59	0.55	0.60	0.55

Table 15 summarizes the continuous-time proportional Cox model analysis for the multiple implants per patient over time. The hazard ratios for the maxillary regions are significantly elevated when either the model-based or robust standard errors are used. The odds ratio of 1.80 associated with non-white race is significant using the model-based standard error and not significant using the robust standard error estimator.

Table 15 Model 10 Results for Continuous-time Cox Model Multiple implants per patient over time

Number of observations: 7,633

Predictor	Estimated	Model-based	P-value	Robust	P-value
	Hazard	Standard error		Standard error	
	Ratio				
Oral Location					
Mandibular	1.0	-		-	
anterior					
Maxillary	3.85	1.14	0.000	1.55	0.001
anterior					
Mandibular	1.29	0.32	0.30	0.31	0.28
posterior					
Maxillary	2.64	0.87	0.003	1.03	0.01
posterior					
Type					
Type 19	1.0	-		-	
Others	1.54	0.56	0.23	0.67	0.32
Race					
White	1.0	-		-	
Others	1.80	0.45	0.02	0.70	0.13

Table 16 summarizes the continuous-time shared frailty model for multiple implants per patient over time. The maxillary arch in both regions shows significantly elevated hazard ratios relative to the mandibular anterior region. The non-white race level presents a highly elevated hazard ratio, which is significant (p=0.002). The frailty estimate for this model is highly significant (Chibar=0.000) which means that there is significant unobserved patient-level frailty.

Table 16 Model 11 Results: Continuous time shared frailty model for multiple implants per patient over time

Number of observations: 7,633

Number of groups: 732

Predictor	Estimated Hazard Ratio	Standard error	P-value
Oral Location			
Mandibular	1.0		
anterior			
Maxillary	5.76	4.23	0.02
anterior			
Mandibular	1.51	0.54	0.24
posterior			
Maxillary	5.82	4.59	0.03
posterior			
Type			
Type 19	1.0	-	
Others	1.16	1.12	0.88
Race			
White	1.0	-	
Others	17.74	16.09	0.002

Likelihood-ratio test of $\theta = 0$: $\chi^2(0.1) = 225.1$ and p=0.000

The year-specific numbers of implant failures, implants, and proportion of failures are summarized in Table 17 by Intraoral region and in Table 18 by Type of Implant. The year- and race- specific distributions are shown in Table 19.

Table 17 Implant Failure rates by Intraoral Region and Year

Intraoral	Year	Year	Year	Year	Year	Year	Year	Year	Total
location	1	2	3	4	5	6	7	8	failures
Mandibular									
Anterior region									
r	28	5	6	1	3	2	1	2	48
n	1,339	974	623	415	264	143	54	11	
p	0.021	0.0051	0.010	0.0024	0.011	0.014	0.019	0.18	
Maxillary									
Anterior region									
r	6	8	1	1	0	0	0	0	16
n	178	109	61	23	9	0	0	0	
p	0.004	0.07	0.020	0.043	0.00	0.00	0.00	0.00	
Mandibular									
Posterior region									
r	15	9	3	0	1	0	0	2	27
n	628	424	74	122	63	33	15	4	
p	0.024	0.021	0.041	0.00	0.016	0.00	0.00	0.50	
Maxillary									
Posterior region									
r	5	1	3	2	0	1	0	0	12
n	160	123	74	26	9	5	0	0	
р	0.031	0.0081	0.041	0.077	0.00	0.20	0.00	0.00	
Total failures									
r	54	23	10	4	4	3	1	4	103
n	2,305	1630	982	586	345	181	69	15	
p	0.023	0.014	0.010	0.0068	0.012	0.017	0.014	0.27	

r=number of implant failures, n=number of implants p=proportion of failures=number of failures/n

Table 18 Implant Failure Rates by Type and Year

Implant	Year	Year	Year	Year	Year	Year	Year	Year	Total
Type	1	2	3	4	5	6	7	8	failures
Type 19									
r	50	23	10	4	4	1	1	0	93
n	2,169	154	928	547	314	154	55	7	
р	0.023	0.15	0.011	0.0073	0.013	0.013	0.018	0.00	
Other than									
Type 19									
r	4	0	0	0	0	2	0	4	10
n	136	89	53	39	31	27	14	8	
р	0.029	0.00	0.00	0.00	0.00	0.074	0.00	0.50	
Total failures									
r	54	23	10	4	4	3	1	4	103
n	2,305	1,630	982	586	345	181	69	15	
р	0.023	0.014	0.010	0.0068	0.012	0.017	0.014	0.27	

r=number of implant failures, n=number of implants p=proportion of failures=number of failures/n

Table 19 Implant Failure Rates by Race and Year

Race	Year	Year	Year	Year	Year	Year	Year	Year	Total
	1	2	3	4	5	6	7	8	failures
White									
r	42	15	8	4	4	3	1	4	81
n	1,891	1,332	811	489	291	148	48	12	
р	0.022	0.011	0.010	0.0082	0.014	0.020	0.021	0.33	
Non-									
White									
r	12	8	1	0	0	0	0	0	21
n	283	201	98	67	40	25	19	3	
р	0.042	0.040	0.010	0.00	0.00	0.00	0.00	0.00	
Total									
failures									
r	54	23	9	4	4	3	1	4	* 102
n	2,174	1,533	909	556	331	173	67	15	
р	0.025	0.015	0.01	0.0072	0.012	0.017	0.015	0.27	

r=number of implant failures, n=number of implants p=proportion of failures=number of failures/n

^{*}Note: The discrepancy in one failure was due to the Hispanic ethnicity variable being labeled as white and non-white.

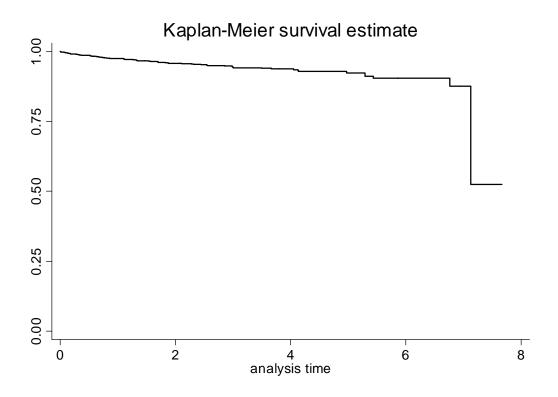


Figure 5 Kaplan-Meier Estimate

Figure 5 displays the Kaplan-Meier estimate of implant survival. The survival estimates slowly but steadily decrease over the first four to six years. The extreme drop occurs at year 7, when the risk set is very small. This estimate does not account for clustering of the data.

CHAPTER 6

Discussion

Longitudinal data can be analyzed by various methods. As demonstrated in this thesis, each method requires distinct formatting and therefore knowledge of the data. The Weyant data came in several independent datasets that required thorough evaluation and cleaning prior to linking. Our analysis occurred years after data collection. Ideally, planning of the study would consider the data analysis prior to data collection, so that data collection could be managed more efficiently. These data include many variables that would have been interesting to analyze with respect to implant failure. However, a variety of data discrepancies precluded such analyses. Typically age would be included as a basic univariate descriptive of the population being studied. However, there are 5,999 missing values for age out of 7,986. Other variables, such as descriptives of implants or the surrounding periodontium, were also often missing. However, the basic variables required for survival analysis exist, and the strengths of the analysis include a large number of patients with long follow-up time. The statistical assumption of random censorship was made throughout, i.e, that the probability of loss to follow-up is unrelated to the probability of failure. This assumption may be suspect if sicker patients may not return for follow-up visits.

The logistic regression analyses have the limitation of only allowing a view of survival probability over the entire study period as a single time interval. There is an assumption that patients are at risk over the entire study period. This may not be true for all patients and variable time at risk is not addressed. **Models 1** and **2** indicate that the failure risk is not significantly influenced by any of the variables in the model. However, the discrete analyses, **Models 4, 5, 6,**

7, and 8, permit a view of failure risk over time. The decreased odds ratio during the third through fifth years may be an indicator for the osseointegration process within the first two years of placement. If the implant does not fail within the first two years, the expectation of survival thereafter may be higher. The higher odds ratios in the last year are to be considered with caution because of the low number of patients remaining at that time. The plateau of failures during the three-five year period can be likened to a "frailty effect" where the implants (or clusters of implants) with higher frailty will not be in the risk set after the first two years. However, the more robust or stable implants still will be at risk after the first two years. The shared frailty analysis is computationally intensive because this is an iterative process involving several iterations per cluster. Each of the 777 patients is a cluster with a frailty value that is shared by all implants within a cluster. A STATA statistician suggested the robust variance option and clustering on the patient as an alternative to the shared frailty procedure. This option is much less computer-intensive. The shared frailty model (Model 11) displayed a significant frailty effect. Also hazard ratios for the maxillary anterior regions and non-white race were significantly elevated. This was consistent with the analysis for Model 10 (the continuous-time Cox model for multiple implants per patient). This frailty model (which is comparable to a random-effects model) indicates that there is an unobserved patient-level effect that influences the hazard ratio.

An interesting finding with all models is that an implant placed in the maxillary arch is at greater risk of failure than an implant placed in the mandible. This is witnessed clinically. Some attributing factors involved may include the difference in bone integrity and vascularity between the arches. The proximity of the maxillary sinuses in the posterior regions can present more infection, which is a potential influence on implant failure.

Implants placed in patients of non-white race appear to be at greater risk of failure than those placed in white patients. However, when the robust variance is used, the significance of the difference between the race levels disappears. It is important to address the difference between patient-level and implant-level variables with respect to the different results obtained in our models. Race is a patient-level variable. The robust variance calculated at the patient-level accounts for the repeated observations per patient. The model-based variance assuming independence presumes an inappropriately larger number of independent observations, and generally underestimates the variance of the cluster-level predictors. However, with an implant-level variable (i.e. intraoral location), variances can be over or underestimated when the clustering is ignored. In this study, variances of such variables were generally underestimated when clustering was ignored.

It is clear that the correlation structure of dental implant data must be considered with a time to failure analysis. Each patient represents a cluster of implants which are correlated with respect to failure. Our analyses show that although predictor variables are significant influences on the risk to failure when clustering is ignored, introduction of the cluster-level robust variance often deflates this significance. When we utilize the robust variance analysis at the observation (implant) level in the logistic regression model, the model-based binomial variance structure is relaxed. However, the robust variance at the cluster level relaxes the model-based variance structure and calculates each cluster's independent contribution to the variance.

The need to adjust for correlation between observations becomes apparent in most dental data. Most studies of implant failure and certainly implant companies have employed Kaplan-Meir and Cox models without regarding the correlation between observations. Only more recent

dental implant studies have executed GEE or robust variance analyses. The need for adjusting for correlated observations has been acknowledged in earlier studies (within the recent decade).

Some issues of interest to address in future studies of time-to-failure of dental implant would include an assessment of repeated failures. This could not be addressed with this data due to confusion with respect to placement and follow up dates per implant, as discussed in Chapter 3. Also, the influence of natural teeth approximating implants and their risk of failure is a clinical topic not yet evaluated. Clinical issues involving smoking, medication use, the patient's current prosthetic or restorative status and periodontal status could be investigated in other studies employing some of the methods described in this thesis. Another statistical issue to investigate would be the risk of failure of implants that approximate a site of an implant that has failed. This can be done with these data but requires considerably more time for programming with respect to evaluating each implant site conceptually and determining whether or not an implant was adjacent to it and if so, whether the implant failed. Other possible approaches not considered here are spatial analysis and Bayesian techniques.

Researchers in clinical dentistry need to be informed of the unique clustering of observations involved with this health specialty. Planning for dental studies requires acknowledgement of such clustering and subsequent planning for proper data collection, formatting and analysis.

APPENDIX A DATAFORMS

FORM A Patient History Implant Rationale	va dental in	iplant registry		
PATIENT SSN	Provider ID	Station No.		
1. Patient date of BIRTH ? M M D D Y Y	9. What is the date of this EX	M M D D Y Y		
2. Patient ethnic identification? (check all that apply) White Asian Hispanic Black Native Am Other 3. Patient Gender Male Female 4. How will this case be paid for? (check all that apply) Patient Insurance Research Teaching Medicaid No fee OTHER 5. What was the primary source of demand for implants in this case? (Check all that apply) Patient initially requested implants Dentist initially suggested implants	Discrete Cancer Check all that apply			
OPatient was referred by dentist OPatient was referred by physician OUnknown OTHER	What medications is the p (check all that apply)	atient currently taking		
6. What factors motivated the use of implants in this case? (check all that apply) Max Mand (indicate to which arch this applies) Previous prosthetic failure Inadequate alveolus Post maxillofacial trauma Post maxillofacial pathology Gagging Anatomic anomaly Previous implants Single tooth replacement Poor denture retention Patient dissatisfaction Provider preference/Tx of choice	Analgesics NSAID Analgesics Anticoagulants Anticonvulsants Antidepressant Antihypertensive Antihypertensive Antimicrobial Antineoplastic Antimeoplastic Antipsychotic Bronchodilators 12. What is the patient's ASA ASA CODES 1= normal healthy patient 2= mild to moderate systemic d 3= severe but not incapacitating	lisease		
7. What PROSTHESES is the patient currently wearing? (check all that apply) Max Mand O CD No Max Dentures		tivity and is a constant threat to life		
RPD No Mand Dentures FPD 8. Does patient have Oral Habits ? (check all that apply) Bruxism/clenching Tengue theory	○ Class I ○ Class II ○ Class III			
 Tongue thrust Foreign objects (e.g. pipe) Mouth breather OTHER NONE 	complete	redentulous? In that ANY remaining natural teether BACK of this form)		

EXISTING DENTITION Place an X over the number of all MISSING NATURAL TEETH	-	1			UA	1.5			UL
all MISSING NATURAL TEFTH	1 2	3 4	5	6 7	8 9 1	0 11	12 13	14 15	16
(large spans of missing teeth can be indicated	22 21	20. 20	20	7 AC					
with two Xs connected by a line)	32 31 LF	30 29	28 2	7 26 2	LA .	23 22	21 20		LL
The following is an assessment of the Ca Please answer each question by marking (KEY: UR=upper right, UA=upper please indicate NONE if condition	ALL sexta anterior, U	ints that I L=upper	left, LF	charact	eristic ind	icated.			
Please mark for each sextant where there is ANY occura	ance of the foll	lowing:	NON	E UR	UA	UL	LL	LA	LR
Periodontal bleeding on gentl	le probing						*		
Supragingival calculus				000	8	000	000	8	000
Subgingival calculus			. ŏ	ŏ	ŏ	ŏ	ŏ	ŏ	ŏ
Periodontal pockets between				ŏ	ŏ	ŏ	ŏ	ŏ	Õ
Periodontal pockets greater th	han > 5 mm	n	· ŏ	ŏ	ŏ	ŏ	ŏ	ŏ	00
Unfilled coronal caries			. 0	0	0	0	0		0
Unfilled root caries			· ŏ	ŏ	00	ŏ	ŏ	00	Ö
+1 Tooth mobility			. 0	0	.0	0	0	0	0
+2 Tooth mobility			. 0	8	000	ŏ	000	ŏ	00
+3 Tooth mobility			- 0	0	0	Ō	0	0	0
Received scaling/root planing Will be scaled/root planed be				00	00	00	00	0	0
		1							
	n registry and	i	_						
Comments (note: comments will not be stored in cannot be retreived in reports.):	n registry and	1							
Comments (note: comments will not be stored in	n registry and								
Comments (note: comments will not be stored in	n registry and								
Comments (note: comments will not be stored in	n registry and								
Comments (note: comments will not be stored in	n registry and								
Comments (note: comments will not be stored in	n registry and								
Comments (note: comments will not be stored in annot be retreived in reports.):	n registry and								

FORM B1 Cylinder Implant Surgery	VA DENTAL IMPLANT REGISTRY
PATIENT SSN	Provider Station No.
USE A SEPARATE SHEET	FOR EACH ARCH
1. This form is for implants in which arch? Maxilla Mandible 2. TOTAL number of implants in this ARCH? 3. Date of implant placement? MMDDYY 4. Location of implant surgery? Dental operatory Dental Office surgical suite Hospital OR OTHER 5. Patient's status for implant surgery Outpatient Inpatient OTHER 6. What anesthesia was used for implant surgery (mark all that apply) General Local (block) IV. Sedation Decade (infiltration) Nitrous Oxide OTHER 7. How long did implant surgery take (incision to close)? Less than 1/2 hr. 1 to 2 hrs 1/2 to 1 hr more than 2 hrs 8. Please rate the complexity of the surgery? Highly complex Complex Routine 9. If management of case is complex, is it due to:(check all that apply) Patient health complications Implant surgery requirements Prosthetic requirements Prosthetic requirements OTHER	10. Which medications were given in association with the implant surgery? (check all that apply and note duration) Antibiotics/Antiseptics: duration (days) Penicillin Amoxicillin Erythromycin Erythromycin Ocephalosporin Oboxycycline Clindamycin Clindamycin OTHER NONE Analgesics/Sedative: ASA Acetaminophen Narcotic ASA+Narcotic ASA+Narcotic Acetaminophen+Narcotic NSAID Barbiturate Diazepam Other Steroid: NONE 11. Will the uncovering procedure be done by another dentist? No Yes No Yes
Comments:	

Manufacturer Codes	2. Implan	Material Co	des		3. Ir	nplant C	oating (Codes	
1 Branemark 10 OTC 2 Calcitek 11 Osteo 3 Collagen 12 Park Do 4 Core Vent 13 Stryker 5 Denar 14 Synthes 6 IMZ 15 Titanod 7 ITI 16 Ultimati 8 Miter 17 Zimmer 9 Oratronic 18 OTHER	ont 6 ((staple) 8 7	Fitanium - all Vitallium - su Vitreous carb	ium - commercially pure ium - alloy ium - surgical grade ous carbon ninum oxide or crystal nic less steel lum 1 NONE 2 Hydroxylapatite 3 Titanium plasma spra 4 Ceramic plasma spra 5 Carbon 6 Titanium /HA 7 Titanium macropore lum 8 OTHER			ay			
4 Stage Codes (cylinder/blad 1 One stage 2 Two stage (submer 3 Not applicable			5. Implant Morphology Codes 1 Basket 4 OTHER 2 Bullet 5 Not Applicable 3 Screw						
The questions below apply to nore than 8 implants are used ubperiosteal implants. Refer	I in this arch - use additiona to each cylinder by reference	d sheets. Pleate to the number	ase use th	e other s	pecified	forms fo	r - blade	es, staple	s, and
IMPLANT'S	ITE NUMBER	\	l m						
1. Implai	nt Manufacturer Code				1 10-50				0
2. Implai	nt Material Code			100	incell (in		- 0	200	10
3. Implai	nt Coating Code				Sign (7 500		
4. Stage	Code			100	A SOUND IS		P. Kal		1 11 11 13
5. Impla	nt Morphology Code						12 10		18
6. Implan	t height (mm)(top to botton	n)		П			П	П	
7. Implan	width/diameter (mm)			П		П	\Box	П	
8. Height	of available bone (mm)				100		-	H	inner i
SECURORAGES TOWN IN	of available bone (mm)		\mathbb{H}	H		H		H	
	ed Gingiva (bucc/ling width in		H	H		H		H	8
	mark bone classification (1-4		Н		Н			H	8
12. SURGICAL DETAILS For each implant note any occurrence of the following during the implant surgery (mark all that apply)	Implant altered (describe be Alveoler ridge perforation Jaw Fracture	n		0000000000000		000000000000000000000000000000000000000		000000000000	000000000000000000000000000000000000000

PATIENT SSN		Provider Station No.
Comp	plete one FORM C f	or EACH PROSTHESIS
1.This form is for a prosthesis in which are Maxilla Mandible 2. Is the prosthesis: Anterior Posterior 3. Date implants UNCOVERED? Not applicable Unknown 4. Date TEMPORARY PROSTHESIS in Not applicable Unknown 5. Date FINAL PROSTHESIS inserted for the same of the	O Full Arch M M D D Y Y mserted ? M M D D Y Y entist who surgically	10. What type of prosthesis was placed in this arch? Partial Arch: Single tooth (free standing) Single tooth (rests on adjacent teeth) Implant abutment for RPD Implant abutment rigidly fixed to natural teeth Implant abutment with nonrigid attachment to nat. to Totally implant borne FPD OTHER Complete Arch: Overdenture without bar Fixed detachable prosthesis Cast metal bar with overdenture Fixed bridge OTHER 11. Was implant position/alignment acceptable for planned prosthesis? Yes No 12. Was surgical guide/stent used at time of surgery? Yes No 13. The occlusal surface(s) of the prosthesis was constructed (check all that apply) Porcelain Resin OTHER
What type of dentition opposes this pro- (check all that apply)	sthesis?	15. How is abutment attached to implant? (check all that app
Natural dentition only RPD Complete denture OTHER	C Edentulous FPD Implants	Screw Cement Friction OTHER 16. How is substructure attached to abutment? (check all that a Company Cement)
9. Are there implants in the opposing arch	7	○ Friction ○ No Substructure ○ OTHER
O Yes O No		17. If substructure is used, how is prosthesis retained ?
		Not applicable Screw Magnet Clips (all kinds) Cement Rubber O-ring Resilient liner OTHER

IMPLANT DATA at each abutment: Use standard 1-32 tooth numbering to identify each implant. Be sure implant numbers are consistant with FORM B								
IMPLANT SITE NUMBER —	27	0/2						
IMPLANT HEALTH STATUS								
1. PERIODONTAL (Associated with implant) Bleeding on probing Gingival recession >3 mm Probing depth > 3mm Dehiscence Hyperplasia (peri-implant) Mobility	0000	00000	000000	00000	000000	000000	000000	000000
Peri-implant inflamation								
Width of keratinized mucosa (mm): Mandible <u>buccal</u> :								
Mandible: lingual : Maxilla: buccal:	Ц							
2. RADIOGRAPHIC	Ш	Ш	Ш		Ш		Ш	
Bone not well adapted to implant	0000000	000000000	000000000	000000000	000000000	00000000	000000000	000000000
3. IMPLANT HEALTH CATEGORY (Loma Linda) 1= no clinical pathology at implant site 2= minor clinical path, no intervention, prognosis good 3= clinical path, surgical intervention needed, prognosis good 4= clinical path, intervention need, prognosis poor 5= NOT treatable, prognosis poor, implant still in place 6= Implant removed (note date below)	8							
DATE OF IMPLANT REMOVAL (IF APPLICABLE) D Y		H	H	目	H	Ħ		
4. FUNCTIONALITY Implant functioning well Implant less than optimal but serviceable Implant SUBMERGED (sleeper) Implant TO BE REMOVED OTHER	000		00000] 00000] 00000] 00000	00000	
5. PATIENT COMPLAINTS (implant related) Pain associated with implant Pain elsewhere due to implant Loss of sensation near implant Esthetics due to implant Mastication problems due to implant Speech problems due to implant OTHER	000000) 00000000	0000000) 0000000	0000000) 000000) 0000000	0000000
6. Check here if a COMPROMISED IMPLANT INTERVENTION WAS USED (e.g. bone graft, bone substitute, guided tissue regeneration)	0	0	0	0	0	0	0	PORM C/D 692

PATIENT	Provider Station No.
Use a separate form for EACH 1	PROSTHESIS
. This form is for the prosthesis in which arch?	10. What was the patient's level of satisfaction with the
○ Maxilla ○ Mandible	prosthesis at this appointment?
2. Date of this appointment ?	Very Satisfied Satisfied Unsatisfied Unsatisfied Unsatisfied
O O M M D D Y Y	11. If patient was dissatisfied, why ?(check all that apply)
3. The dentist completing this form provided which service(s) ? (check all that apply)	O Not applicable (patient satisfied) O Pain with prosthesis
○ Implant surgery ○ OTHER ○ Prosthodontics	Speech/phonetics difficulties Esthetics Mastication
4. Is this appointment? Routine recall (scheduled by dentist) Emergency appointment OTHER	Retention problems Stability problems Poor cleaning access No improvement over previous prosthesis
5. Who initiated this appointment ? (check all that apply)	OTHER
O Implant surgeon O Patient (or family)	12.How was patient satisfaction determined:
Other dentist Other dentist OTHER	Clinical impression of dentist Patient volunteered information Dentist asked patient directly
6. Has the patient's medical status changed significantly since	OTHER
last visit ?	13. What is your evaluation of this prosthesis?
○ Yes ○ No ○ First visit with patient	(check all that apply)
7. Does patient have any new oral habits which affect this case?	Prosthesis function is acceptable Prosthesis esthetics is acceptable
O Bruxism/clenching O Mouth breathing	O Prosulesis estiletics is acceptable
O Tongue thrust O OTHER	O Prosthesis requires remake/major revison
○ Foreign objects ○ NONE	 ☐ Implant attachment breakage ☐ Prosthesis fracture
9. What is your accessment of the nationts and hugiens ?	Restorative material freacture
8. What is your assessment of the patients oral hygiene?	O Loose screw
Excellent (no debris, plaque, or calculus detectable) Good (no debris, minor isolated areeas of plaque/calculus)	Occlusal difficulties
Fair (most teeth affected by small amounts of plaque/calculus)	Stability difficulties Retention difficulties
O Poor (widespread oral debris, plaque/calculus affecting most teeth)	Esthetics unacceptable
	OOTHER
0 NA i i del ei this amaistmant	O Prothesis NOT EVALUATED
 What services were provided at this appointment? (check all that apply) 	OTHER.
O Examination O Radiographs	. PATIENT COMPLAINTS (impliest related)
O Prophylaxis	14. Do you believe the implant(s) were at least in part
O Denture adjustment	responsible for any prosthesis difficulties?
Occlusal adjustment Prosthesis tightened OTHER	○ Yes ○ No ○ Not applicab
0 0 0 0 0 0	Si seleta de seleta de 12 83HTO

IMPLANT DATA at each abutment: Use standard 1-32 tooth numbering to identify each implant. Be sure implant numbers are consistant with FORM B								
IMPLANT SITE NUMBER —	19 :							TABITAS
IMPLANT HEALTH STATUS								
1. PERIODONTAL (Associated with implant) Bleeding on probing	00000	00000	000000	000000	0000000	000000	0000000	000000
Width of keratinized mucosa (mm): Mandible buccal: Mandible: lingual: Maxilla: buccal:				900				C Imple
2. RADIOGRAPHIC Bone not well adapted to implant	0000000		000000000		000000000		000000000	
3. IMPLANT HEALTH CATEGORY (Loma Linda) 1= no clinical pathology at implant site 2= minor clinical path, no intervention, prognosis good 3= clinical path, surgical intervention needed, prognosis good 4= clinical path, intervention need, prognosis poor 5= NOT treatable, prognosis poor, implant still in place 6= Implant removed (note date below) DATE OF IMPLANT REMOVAL (IF APPLICABLE)								7. D zzs qui O hi O To O Nou no
4. FUNCTIONALITY Implant functioning well Implant less than optimal but serviceable. Implant SUBMERGED (sleeper) Implant TO BE REMOVED OTHER	0000		00000		00000	00000	00000	00000
5. PATIENT COMPLAINTS (implant related) Pain associated with implant Pain elsewhere due to implant Loss of sensation near implant Esthetics due to implant Mastication problems due to implant Speech problems due to implant OTHER	000000	0000000	0000000) 0000000) 0000000) 0000000) 0000000	000000
Check here if a COMPROMISED IMPLANT INTERVENTION WAS USED (e.g. bone graft, bone substitute, guided tissue regeneration)	0	0	0	0	0	0	O	FORM C/D 6/9

FORM U Implant Uncovering		VA [ENT	al im	PLAN	T RE	GIST	RY			
PATIENT SSN		Provid ID	er			Stati	2010000				
Please Complete one FORM U for EACH ARCH											
1.This form is for a prosthesis in which arch? O Maxilla Mandible		3. Da	ate impla	ants UNC	OVERE D	D ?					
IMPLANT DATA: AT UNCOVERING											
Place the tooth number for EACH cyclinder in the space provided. Use standard 1-32 tooth numbering to identify each implant											
IMPLANT SITE NUMBER ——											
IMPLANT HEALTH STATUS 1. RADIOGRAPHIC											
Bone not well adapted to implant)0000000	00000000	000000000	000000000	000000000	00000000	0000000000	000000000			
2. IMPLANT MOBILITY YESNO	8	00	8	8	8	8	8	8			
Width of keratinized mucosa (mm): Mandible <u>buccal</u> : Mandible: <u>lingual</u> : Maxilla: buccal:											
3. IMPLANT UNCOVERED BY: Biopsy Punch Crestal Incision Already Exposed at this Appointment OTHER	Ŏ.		0000	0	0000	0000	0000	0000			
Check here if IMPLANT WAS REMOVED at THIS APPOINTMENT	0	0	0	0	0	0	0	0			
5. Implant NOT UNCOVERED (Sleeper)	0	0	0	0	0	0	0	.0			
Comments:				9				6	/92		

FORM X	Patient nactivation	va dental i	MPLANT REGISTRY	
PATIENT SSN		Provider ID	Station No.	
2. Date of this report ?]		
1.5	MMDDYY			
	ve will be flagged in the r to follow-up reason unknown	egistry for the following	eason:	
O All implant O Eligibility i				
O No implant O Status of ir O All implant	nplants unknown			
Implant site number of REMOVED implants DATE of IMPLANT REMOVAL (if known) mm/dd/yy		77777		
Comments				•
•			*	
		*		
3 3 3				6/5

APPENDIX B CODEBOOK LISTING AND VARIABLES OF DATASET

Description of Premerged Datasets

Form A Dataset: (See Table 1)

There are 1,462 records in this dataset.

There are 1,357 unique identifiers (representing patients) indicating duplicate records.

Variable names:

ssn Social Security Number (scrambled)

xdate Date of initial examination

provid Provider

station Location of treatment

bdate Birthdate

Ethnicity:

ethw White

ethb Black

etha Asian

ethnam Native American

ethhis Hispanic

ethoth Other

sex Sex

Diagnostic variables affiliated with the FormA dataset:

These are dichotomous variables that can not be validated (as one can see from a comparison of the hard copy form and the order of the suffix numbers attached to the prefix dia_). Much information can be obtained from such variables if (1) more descript names were provided and/or (2) a data dictionary or labeling was provided with the dataset(s). Because validation of these variables is impossible, these variables were not included in the final dataset.

diag1-diag68

sedhyp Sedative/Hypnotic medications used by the patient

othmed Other medications used by the patient

mednone No medications noted asarate ASA rating (1-5): 1=normal healthy patient

2=mild to moderate systemic disease

3=severe but not incapacitating systemic disease

4=severe disease that limits activity and is a constant threat to life

5=moribund

edenttot Is the patient completely edentulous? (yes/no).

oralhyg Oral Hygiene:

A-Excellent

B-Good

C-Fair

D-Poor

The following variables were presented initially in string format and were converted to numeric form so that they may be used for analysis.

newssn Numeric Social security numbers

nxdate Numeric initial examination date

nbdate Numeric birthdate

gender Numeric Sex

There are no variables in the dataset with names that would correspond with information on existing teeth, periodontal status, prosthesis type that the patient is currently wearing, jaw relation, primary source of demand for implants, or how the patient paid for the treatment. However, these variables are listed on the questionnaire for the Form A dataset. It was also stated, via personal communication with Robert Weyant, that the order of the dataset variables were to follow the order of the questions in the questionnaire. As mentioned above, this ordering was not followed.

Placement Dataset: (See figure 1)

This is the dataset that incorporates the placement dates for the implants.

There are 4,313 observations or records.

There are 1,294 unique identifiers.

There appears to be 1294 patients (all patients would be expected to have at least one visit) with the first placement date, 46 patients who have ever had a second visit or placement date, and only one person who has ever experienced a third placement date for an implant in the same implant site.

The range of implants placed per person is from 1-14 implants. All patients have at least one (1) implant placed

Variable names:

ssn - Social Security (string format)

isdate - Placement date

imparch - Arch (Maxilla or Mandible)

imp1-Implant site locator (1-32)

imp2 – Implant manufacturing code

imp3 – Implant material code

imp4 – Implant Coating code

imp5 – Stage code

imp6 – Implant Morphology code

imp7 – Implant Height (mm)(top to bottom)

imp8 - Implant Width/diameter (mm)

imp9 – Height of available bone (mm)

imp10 – Width of available bone (mm)

avboneht – Average bone height (mm)

avbonewi – Average bone width (mm)

attginwi - Attached gingival width

bonclass – Bone classification (I assume Branemark Classification)

Surgical Details:

surocc1 - Implant altered

surocc2 – Alveolar ridge perforation

surocc3 – Jaw Fracture

surocc4 – Neurological damage

surocc5 – Inferior Mandibular Border Perforation

surocc6 – Sinus Lift

surocc7 – Perforated Sinus/Nasal Cavity

surocc8 – Equipment complications

surocc9 – Unable to seat implant

surocc10 – Implant not well adapted to site

surocc11 - Ridge augmentation used

surocc12 – Periodontal tissue damage

surocc13 – Patient experienced pain

surocc14 – Excessive bleeding

surocc15 – Guided tissue regeneration (Membrane e.g. Gore Tex)

surocc16 - Other

newssn – Numeric Social Security Number

nisdate – Numeric placement date

newid – Numeric id used which incorporates the site with an individual social security number.

Removal Dataset: (See figure 1)

This is the dataset that incorporates the removal and evaluation or follow-up dates for the implants.

There are 10,624 observations in the dataset.

There are 1009 unique values in the dataset.

Newid is a variable which indicates the number of patient-sites in the dataset which equals 3485 in this dataset.

The variable sitetot2 indicates the total number of implants per individual. A summary of sitetot2 presents that the mean implants per patient was 2-3 per patient and that there is the possibility of having 15 implants ever placed.

The visit2 variable indicates the number of visits the patients had. It appears that the range of visits was from 1-25. There are 1009 patients with at least one visit and one patient who ever had 25 visits. There is a mean of 3 visits per individual.

Variable names:

Ssn - Social Security number (string format)

Site – Implant site indicator (1-32)

Evaldate – Evaluation date (string format)

Mobil - Mobility

Periminf – Peri-implant inflammation

Imphcat – Implant Health Category

Imprdate – Implant removal date

Impfunc - Functionality

Impltopt – Implant less than optimal but serviceable

Impnonsp – Can't be verified (Could refer to whether or not the implant is submerged)

imp2brmv – Implant to be removed

funother - Can not be verified

painlswr – Can not be verified(Could refer to pain associated with implant or elsewhere)

esthetic – Esthetics due to implant

mastprob – Mastication problems due to implant

speechpr – Speech problems due to implant

cmplnoth – Implant related complaints-other

compimpi – If compromised implant intervention was used (bone graft, bone substitute, guided tissue regeneration)

newssn – Numeric Social Security

nevldate - Numeric evaluation date

nimrdate – Numeric implant removal date

newid - Numeric id used which incorporates the site with an individual social security number.

Imph – A variable created to be an index for the 6^{th} level of implant health category which indicated removal of an implant.

Rem – A variable used to index removal of an implant and used in the creation of other variables Post – A variable used as an index for times after removal of an implant

Ps – A variable used as an index to remove implant removal dates after an implant was removed

Analytical Dataset

Commands for created variables

A variable "freq" was created to count the first records for each patient and each site. The xttab command for the overall frequency and percent calculations accounts for all records and this includes all follow-up records. This inflates the value for implants.

- . by id site:gen freq=followup[1]
- . by id site:replace freq=1 if followup==freq (2305 real changes made) replace freq=0 if freq~=1 (5681 real changes made)
- . tabulate freq

freq	-	Percent	
0 1	5681 2305	71.14	71.14 100.00
		100.00	

It appears that there are 2305 total implants in 777 patients.

An xttab procedure on the records representing the first placement date produces the following:

- . iis id
- . tis followup
- . xttab imptype if freq==1

	Over	all	Bet	ween		Withir	1
imptype	Fre	eq. Percei	nt	Freq.	Perce	nt	Percent
+							
2	13	0.56	5	0.64	. [100.00	
4	95	4.12	45	5.79	9	85.59	
5	4	0.17	1	0.13	1	00.00	
6	6	0.26	2	0.26	(50.00	
10	2	0.09	1	0.13	}	33.33	
18	16	0.69	4	0.5	1	94.12	
19	2169	94.10	7	25 9	3.31	99	0.45
+							
Total	2305	5 100.00)	783	100.77	7	98.44
		$(n = 7)^{n}$	77)				

Here the "Between frequency" and "percent" have not changed. However, the "Overall Frequency" and "Percent" changed because the records of followup were not counted.

Codebook for Analytical Dataset:

. codebook

surocc9 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5683 / 7986 tabulation: Freq. Value 2277 0 26 1 surocc10 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5701 / 7986 tabulation: Freq. Value 2222 0 63 1 surocc11 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5733 / 7986 tabulation: Freq. Value 2242 0 11 1 surocc12 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5793 / 7986 tabulation: Freq. Value 2164 0 29 1

surocc13 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5837 / 7986 tabulation: Freq. Value 2134 0 15 1 surocc14 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 5934 / 7986 tabulation: Freq. Value 1996 0 56 1 surocc15 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 6391 / 7986 tabulation: Freq. Value 1556 0 39 1 surocc16 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 7729 / 7986 tabulation: Freq. Value 256 0 1 1

_merge ----- (unlabeled) type: numeric (byte) range: [2,3] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 278 2 7708 3 age1 ----- (unlabeled) type: numeric (float) range: [.40273973,82.331505] units: 1.000e-08 unique values: 306 coded missing: 5999 / 7986 mean: 62.6349 std. dev: 10.4379 percentiles: 10% 25% 50% 75% 90% 45.3589 58.8411 65.8192 69.1671 72.6219 newid2 ----- group(id site) type: numeric (float) range: [1,2305] units: 1 unique values: 2305 coded missing: 0 / 7986 mean: 1130.18 std. dev: 648.061 25% 50% percentiles: 10% 75% 90% 199 600 1098 1659 2007 y ------ (unlabeled) type: numeric (float) range: [1,1] units: 1 unique values: 1 coded missing: 7961 / 7986 tabulation: Freq. Value

25 1

id -----id type: numeric (double) units: 1 range: [1,1492] range: [1,1492] units: 1 unique values: 777 coded missing: 0 / 7986 mean: 753.539 std. dev: 406.257 50% percentiles: 10% 25% 90% 461 738 1071 129 1296 nisdate -----isdate type: numeric daily date (double) range: [7748,12386] units: 1 or equivalently: [19mar1981,29nov1993] units: days unique values: 638 coded missing: 0 / 7986 mean: 10689.4 = 07apr1989 (+ 9 hours)std. dev: 710.906 10% percentiles: 25% 50% 75% 90% 9799 10267 10713 11170 11562 30oct1986 10feb1988 01may1989 01aug1990 28aug1991 place ----- (unlabeled) type: numeric daily date (float) range: [7748,12386] units: 1 or equivalently: [19mar1981,29nov1993] units: days unique values: 638 coded missing: 0 / 7986

mean: 10689.3 = 07apr1989 (+ 8 hours) std. dev: 710.893

percentiles: 10% 25% 50% 75% 90% 9799 10267 10713 11170 11562 30oct1986 10feb1988 01may1989 01aug1990 28aug1991

nevldate ----- evaldate type: numeric daily date (double) range: [7906,12745] units: 1 or equivalently: [24aug1981,23nov1994] units: days unique values: 1462 coded missing: 0 / 7986 11375 = 22feb1991 (+ 1 hour) mean: std. dev: 768.548 50% percentiles: 10% 25% 75% 90% 10307 10898 11442.5 11995 12331 21mar1988 02nov1989 30apr1991 03nov1992 05oct1993 followup ----- (unlabeled) type: numeric daily date (float) range: [7906,12745] units: 1 or equivalently: [24aug1981,23nov1994] units: days unique values: 1465 coded missing: 0 / 7986 mean: 11374.6 = 21feb1991 (+ 16 hours) std. dev: 768.485 50% percentiles: 10% 25% 75% 90% 10307 10898 11442 11994 12331 21mar1988 02nov1989 30apr1991 02nov1992 05oct1993 nimrdate -----imprdate type: numeric daily date (double) range: [9735,12589] units: 1 or equivalently: [27aug1986,20jun1994] units: days unique values: 75 coded missing: 7872 / 7986 mean: 11068.7 = 21apr1990 (+ 17 hours)std. dev: 748.244 percentiles: 10% 25% 50% 75% 90% 10074 10455 10942.5 11648 12087

01aug1987 16aug1988 16dec1989 22nov1991 03feb1993

site ----- site type: numeric (double) units: 1 range: [1,32] unique values: 31 coded missing: 0 / 7986 mean: 22.8123 std. dev: 5.72435 percentiles: 10% 25% 50% 75% 90% 14 22 23 27 28 failure ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7883 0 103 1 rownames ----- (unlabeled) type: string (str5) unique values: 7984 coded missing: 2 / 7986 examples: "240" "4342" "6116" "82" evaldate ----- (unlabeled) type: string (str11) unique values: 1462 coded missing: 2 / 7986 examples: "07-APR-1993" "13-APR-1993" "18-SEP-1986" "24-MAY-1988"

```
mobil ----- (unlabeled)
        type: numeric (float)
    range: [0,1] units: 1
unique values: 2 coded missing: 2 / 7986
     tabulation: Freq. Value
           7885 0
            99 1
periminf ----- (unlabeled)
        type: string (str1)
    unique values: 4 coded missing: 3562 / 7986
     tabulation: Freq. Value
           3426 "0"
            801 "1"
            126 "2"
            71 "3"
imphcat ----- (unlabeled)
        type: numeric (float)
    range: [1,6] units: 1
unique values: 6 coded missing: 186 / 7986
     tabulation: Freq. Value
           6556 1
            771 2
            213 3
            35 4
            91 5
            134 6
imprdate ----- (unlabeled)
        type: string (str11)
    unique values: 75 coded missing: 7872 / 7986
      examples: ""
           11 11
           ** **
```

impfunc ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 3663 0 4321 1 impltopt ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2/7986tabulation: Freq. Value 7812 0 172 1 impnonsp ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7912 0 72 1 imp2brmv ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2/7986tabulation: Freq. Value 7926 0 58 1

funother ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2/7986tabulation: Freq. Value 7934 0 50 1 painlswr ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7960 0 24 1 esthetic ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7970 0 14 1 mastprob ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7932 0 52 1

speechpr ----- (unlabeled) type: numeric (float) units: 1 range: [0,1] range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7979 0 5 1 cmplnoth ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7867 0 117 1 compimpi ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 2 / 7986 tabulation: Freq. Value 7964 0 20 1 newid ----- group(newssn) type: numeric (float) range: [1.22,1005.19] units: .01 unique values: 2305 coded missing: 2 / 7986 mean: 496.084 std. dev: 282.62 percentiles: 10% 25% 50% 75% 90% 77.08 274.27 485.73 724.245 877.23

isdate ----- (unlabeled) type: string (str11) unique values: 638 coded missing: 0 / 7986

> examples: "06-OCT-1988" "12-OCT-1989" "19-MAR-1981" "25-JUL-1991"

imparch ----- (unlabeled)

type: string (str1)

unique values: 2 coded missing: 0 / 7986

tabulation: Freq. Value 7155 "N" 831 "X"

imp1 ----- (unlabeled)

type: numeric (float)

range: [1,32] units: 1 unique values: 31 coded missing: 0 / 7986

mean: 22.8123 std. dev: 5.72435

25% 50% percentiles: 10% 75% 90%

14 22 23 27 28

imptype ----- Implant Type type: numeric (float) range: [2,19] units: 1 unique values: 7 coded missing: 0 / 7986 tabulation: Freq. Value 30 2 466 4 16 5 46 6 2 10 28 18 7398 19 matcode ----- Material Code type: numeric (float) range: [1,19] units: 1 unique values: 14 coded missing: 0 / 7986 mean: 6.05672 std. dev: 5.16541 percentiles: 10% 25% 50% 75% 1 1 4 12 12 90% coatcode ----- Coating Code type: numeric (float) range: [1,9] units: 1 unique values: 6 coded missing: 0 / 7986 tabulation: Freq. Value 3643 1 4222 2 71 3 13 6 20 7 17 9

stagecode ----- Stage Code type: numeric (float) range: [0,25] units: 1 unique values: 8 coded missing: 0/7986tabulation: Freq. Value 484 0 1349 1 3134 2 2617 3 376 4 17 8 5 13 4 25 morphcode ----- Morphology Code type: numeric (float) range: [0,24] units: .01 unique values: 15 coded missing: 0 / 7986 units: .01 mean: 1.09504 std. dev: 1.30029 percentiles: 10% 25% 50% 75% 90% 0 0 1 2 2 implantheight ----- Implant Height (mm) type: numeric (float) range: [0,37] units: .1 unique values: 23 units: .1 coded missing: 0 / 7986 mean: 1.03418 std. dev: 2.62501

percentiles: 10%

0

0

3

75%

90%

25% 50%

2

0

implantwidth ----- Implant Width/Diameter (mm) type: numeric (float) units: .01 range: [0,45] unique values: 28 coded missing: 35 / 7986 mean: 3.55757 std. dev: 6.05446 25% 50% 75% 90% percentiles: 10% 0 0 8 13 0 availboneheight ------ Height of Available Bone (mm) type: numeric (float) range: [0,40] unique values: 23 units: .01 coded missing: 262 / 7986 units: .01 mean: 1.18031 std. dev: 2.8932 percentiles: 10% 50% 75% 90% 25% 0 0 0 3.125 3.75 availbonewidth ------ Width of Available Bone (mm) type: numeric (float) range: [0,35] units: .01 unique values: 35 coded missing: 1 / 7986 mean: 4.0065 std. dev: 7.35246 25% 50% 75% 90% percentiles: 10% 0 0 0 3.8 17 avboneht ----- (unlabeled) type: numeric (float) range: [0,30] units: .1 coded missing: 8 / 7986 units: .1 unique values: 29 mean: 2.10834 std. dev: 4.20306 25% 50% 75% 90% percentiles: 10% 4 7

0 0 0

avbonewi ----- (unlabeled) type: numeric (float) range: [0,15] units: .1 unique values: 17 coded missing: 29 / 7986 mean: 1.17906 std. dev: 2.32455 percentiles: 10% 25% 50% 75% 0 0 1 5 90% attginwi ----- (unlabeled) type: numeric (float) units: .1 range: [0,25] unique values: 12 coded missing: 7 / 7986 mean: .477503 std. dev: 1.15463 percentiles: 10% 25% 50% 75% 0 0 0 2 90% bonclass ----- (unlabeled) type: numeric (float) range: [0,4] units: 1 range: [0,4] units: 1 unique values: 5 coded missing: 7 / 7986 tabulation: Freq. Value 7716 0 30 1 163 2 52 3

18 4

surocc1 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7904 0 82 1 surocc2 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7887 0 99 1 surocc3 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7932 0 54 1 surocc4 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7915 0 71 1

surocc5 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0/7986tabulation: Freq. Value 7970 0 16 1 surocc6 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7845 0 141 1 surocc7 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 484 / 7986 tabulation: Freq. Value 7137 0 365 1 surocc8 ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 3072 / 7986 tabulation: Freq. Value 4574 0 340 1

provid ----- (unlabeled) type: string (str4) unique values: 52 coded missing: 278 / 7986 examples: "2301" "2301" "2301" "2307" warning: variable has leading blanks station ----- (unlabeled) type: numeric (float) range: [.,.] units: . unique values: 0 coded missing: 7986 / 7986 tabulation: Freq. Value ethw ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 coded missing: 278 / 7986 tabulation: Freq. Value 1037 0 6671 1 ethb ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 278 / 7986 tabulation: Freq. Value 6884 0 824 1

etha ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 278 / 7986 tabulation: Freq. Value 7702 0 6 1 ethnam ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 278 / 7986 tabulation: Freq. Value 7691 0 17 1 ethhis ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 coded missing: 278 / 7986 tabulation: Freq. Value 7599 0 109 1 ethoth ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 278 / 7986 tabulation: Freq. Value 7700 0 8 1

```
sex ----- (unlabeled)
        type: string (str1)
    unique values: 4 coded missing: 278 / 7986
     tabulation: Freq. Value
            63 "0"
            137 "F"
            7501 "M"
             7 "X"
asarate ----- (unlabeled)
        type: numeric (float)
    range: [1,4] units: 1
unique values: 4 coded missing: 7581 / 7986
     tabulation: Freq. Value
            16 1
            268 2
            116 3
             5 4
edenttot ----- (unlabeled)
        type: numeric (float)
    range: [1,2] units: 1
unique values: 2 coded missing: 7579 / 7986
     tabulation: Freq. Value
            319 1
             88 2
```

nxdate ----- numeric xdate type: numeric daily date (float) range: [-17583,12610] units: 1 or equivalently: [11nov1911,11jul1994] units: days unique values: 634 coded missing: 278 / 7986 mean: 10631.1 = 08 feb 1989 (+ 3 hours)std. dev: 1180.38 50% 75% 90% percentiles: 10% 25% 9799 10275 10685 11140 11521 30oct1986 18feb1988 03apr1989 02jul1990 18jul1991 nbdate ----- numeric bdate type: numeric daily date (float) range: [-18323,11846] units: 1 or equivalently: [01nov1909,07jun1992] units: days unique values: 288 coded missing: 5999 / 7986 mean: -11443.5 = 02 sep 1928 (+ -13 hours)std. dev: 3871.09 50% 75% percentiles: 10% 25% 90% -14914 -13887 -12473 -9801 -4903 03mar1919 24dec1921 07nov1925 02mar1933 30jul1946 gender ----- numeric sex type: numeric (long) label: gender range: [1,6] units: 1 unique values: 4 coded missing: 278 / 7986 units: 1 tabulation: Freq. Numeric Label 1 0 63 3 F 137 7501 4 M

7 6 X

rem ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7872 0 114 1 index ----- (unlabeled) type: numeric (float) range: [2,2] units: 1 unique values: 1 coded missing: 7985 / 7986 tabulation: Freq. Value 1 2 ind ----- (unlabeled) type: numeric (float) range: [1,2] units: 1 unique values: 2 coded missing: 7802 / 7986 tabulation: Freq. Value 183 1 1 2 ctr ----- (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 coded missing: 0/7986tabulation: Freq. Value 7872 0 114 1

ctr1 ----- (unlabeled) type: numeric (float) range: [1,3] units: 1 unique values: 3 coded missing: 7880 / 7986 tabulation: Freq. Value 97 1 7 2 2 3 dupimp ----- (unlabeled) type: numeric (float) range: [1,1] units: 1 unique values: 1 coded missing: 7982 / 7986 tabulation: Freq. Value 4 1 y2 ----- (unlabeled) type: numeric (float) range: [.,.] units: .
unique values: 0 coded missing: 7986 / 7986 tabulation: Freq. Value visit ----- (unlabeled) type: numeric (float) range: [1,25] units: 1 unique values: 25 coded missing: 0 / 7986 mean: 3.73616 std. dev: 3.36536 percentiles: 10% 25% 50% 75% 1 1 3 5 8 90%

vistot ----- (unlabeled)

type: numeric (float)

range: [1,25] units: 1 unique values: 19 coded missing: 0 / 7986

mean: 6.47245 std. dev: 4.87356

percentiles: 10% 25% 50% 75% 2 3 5 9 13 90%

sittot ----- (unlabeled)

type: numeric (float)

range: [1,25] units: 1

unique values: 25 coded missing: 0 / 7986

mean: 3.73616 std. dev: 3.36536

percentiles: 10% 25% 50% 75% 1 1 3 5 8 90%

sit ----- (unlabeled)

type: numeric (float)

range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986

tabulation: Freq. Value

5681 0 2305 1

sitetot ----- (unlabeled)

type: numeric (float)

units: 1 range: [1,11]

unique values: 11 coded missing: 0 / 7986

mean: 2.40947 std. dev: 1.41142

percentiles: 10% 25% 50% 75% 1 1 2 3 4 90%

sittotal ----- (unlabeled)

type: numeric (float)

range: [1,11] units: 1

unique values: 11 coded missing: 0 / 7986

mean: 2.40947 std. dev: 1.41142

percentiles: 10% 25% 50% 75% 1 1 2 3 4 90%

sittotal2 ----- (unlabeled)

type: numeric (float)

range: [1,11] units: 1

unique values: 11 coded missing: 0 / 7986

mean: 3.82795 std. dev: 1.58522

percentiles: 10% 25% 50% 75% 2 2 4 5 5 90%

_st ----- (unlabeled) type: numeric (byte) range: [1,1] units: 1 unique values: 1 coded missing: 0 / 7986 tabulation: Freq. Value 7986 1 _d ----- (unlabeled) type: numeric (byte) range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986 tabulation: Freq. Value 7883 0 103 1 _origin ----- (unlabeled) type: numeric (int) range: [7748,12386] units: 1 unique values: 637 coded missing: 0 / 7986 mean: 10689.3 std. dev: 710.895 percentiles: 10% 25% 50% 75% 90% 9799 10267 10713 11170 11562 _t ----- (unlabeled) type: numeric (double) range: [.00273785,7.6687201] units: 1.000e-10 unique values: 1327 coded missing: 0 / 7986 mean: 1.87636 std. dev: 1.43829 percentiles: 10% 25% 50% 75% 90% .503765 .799452 1.41684 2.64476 4.01095

_t0 ----- (unlabeled) type: numeric (double) range: [0,7.2443532] units: 1.000e-10 unique values: 1074 coded missing: 0 / 7986

> mean: 1.25179 std. dev: 1.38378

25% 50% 75% 90% percentiles: 10% 0 0 .859685 1.86174 3.32923

freq ----- The counter for all first records by id and site type: numeric (float)

> range: [0,1] units: 1

range: [0,1] units: 1 unique values: 2 coded missing: 0 / 7986

tabulation: Freq. Value 5681 0 2305 1

AVBHPlus1 ----- Availboneheight+1 for log scale type: numeric (float)

range: [1,41] units: .01 unique values: 23 coded missing: 262 / 7986

mean: 2.18031 std. dev: 2.8932

percentiles: 10% 25% 50% 75% 90% 1 1 1 4.125 4.75

AVBWPlus1 ------ Availbonewidth+1 for log scale

type: numeric (float)

range: [1,36] units: .01

unique values: 35 coded missing: 1 / 7986

mean: 5.0065 std. dev: 7.35246

10% 25% 1 1 1 25% 50% 75% 90% percentiles: 10%

4.8 18

implhtPlus1 ----- implantheight+1 for log scale

type: numeric (float)

units: .1 range: [1,38]

unique values: 23 coded missing: 0 / 7986

mean: 2.03418 std. dev: 2.62501

percentiles: 10% 25% 50% 1 1 1 3 4 90% 75%

implwdthPlus1 ----- implantwidth+1 for log scale

type: numeric (float)

range: [1,46] units: .01

unique values: 28 coded missing: 35 / 7986

mean: 4.55757 std. dev: 6.05446

percentiles: 10% 50% 75% 90% 25%

1 1 1 9 14

APPENDIX C ANNOTATIONS FOR FIGURES AND TABLES

Annotations for Figure 1:

Patient Characteristics dataset (otherwise presented as the forma.dta dataset).

desc

Contains data from C:\DATA\forma.dta

obs: 1,462

There are 1,462 records in this dataset which is contains information at the patient level. Each patient entering the study to receive implant(s) is expected to be in this dataset. Therefore, there should be one record per patient. The fact that there are 1,357 patients and 1,462 records indicates that there are multiple records that were ultimately removed from the final analytic dataset.

Placement Dates dataset (otherwise presented as the surgsite.dta dataset)

There are 1,294 patients with 4,313 records and it is and assumed that there is one placement date per implant.

. desc

Contains data from C:\DATA\surgsite.dta

obs: 4,313

A variable freqs1 was temporarily generated to evaluate the number of multiple placement dates (in this dataset the placement date was called nisdate) and hence multiple records that are initially in this dataset.

. gen freqs1=1 if newssn[_n]==newssn[_n+1] & imp1[_n]==imp1[_n+1] & nisdate[_n]~= nisdate[_n+1]

(4234 missing values generated)

Since there are 4,313 records and from this STATA command, there appears to be a total of (4,313-4,234=79) 79 records with multiple placement dates that are different.

```
. replace freqs=1 if newssn[_n]==newssn[_n+1] & imp1[_n]==imp1[_n+1] & nisdate[_n]==nisdate[_n+1] (2 real changes made)
```

The two changes made reflect the number of multiple records that have the same placement date. Therefore, there are 81 total multiple records that ultimately were removed from the final analytic dataset.

Removal Dates dataset (otherwise presented as the evalx.dta dataset)

. desc

Contains data from C:\DATA\evalx.dta obs: 10.624

This is the original dataset with removal dates. Note that this dataset also has multiple removal dates (in this dataset nevldate was the variable name for evaluation dates) that must be accounted for.

Sorted by: newssn site nevldate nimrdate

A temporary variable, frequerg, was created to evaluate the number of implants placed in all patients.

- . by newssn site:gen freqsurg=nevldate[1]
- . by newssn site:replace freqsurg=1 if nevldate==freqsurg (3485 real changes made)

This variable is accounting for only one placement of and implant. That is to say that if an implant were removed more than once (i.e. multiple removal), it should be verified that it is placed more than once. If there is only one placement date, then subsequent removal dates were removed. The first evaluation date was used for the purpose of establishing "one" implant placement, since there is the possibility of any implant having multiple evaluation dates and hence multiple records. Otherwise the number of implants will be evaluated wrongly as the number of records.

. replace freqsurg=0 if freqsurg~=1 (7139 real changes made)

. tabulate freqsurg

freqsurg	•	Percent	
0	7139 3485	67.20 32.80	67.20 100.00
Total	10624	100.00	

There are 3485 implants in 1009 patients, not accounting for multiple records for implant removal.

- . iis newssn
- . tis nevldate
- . xttab freqsurg

	Overall		Betw	een	Within		
freqsurg	Freq.	Percent	Freq.	Percent	Percent		
0	7139	67.20	648	64.22	75.13		
		32.80			32.80		
	- 						
Total	10624	100.00	1657	164.22	49.36		
(n = 1009)							

The xttab presents the number of first records (3,485 overall) and the remainder (7,139) or those records which are follow-up evaluation dates. The between frequencies and percents reflect the number of implants at the patient level. Therefore, there are 1009 patients with implants placed. There are 648 patients that have ever had freqsurg=0 or with follow-up records.

Analysis dataset (otherwise presented as the final9.dta dataset)

. desc

Contains data from C:\Stata\final9.dta obs: 7,986

The variable freq was temporarily created to indicate all first records by patient id and site of implant. The tabulation command shows that there are 2,305 total implants. The number of patients with implants is 777 and there are 7,986 total records. This dataset does not contain duplicate records or multiple placement or removal dates. There are 5,681 follow-up records represented in this dataset.

. tabulate freq

The counter for all first records by			
id and site	Freq.	Percent	
0	5681		71.14
1	2305	28.86	100.00
Total	 7986	100.00	

Percentile results from surgsite "placement" dataset for fig 1.

Contains data from C:\DATA\surgsite.dta . summarize sitetot1,detail

sitetot1

	Percentiles	s Smallest		
1%	1	1		
5%	1	1		
109	6 1	1	Obs	4313
259	6 1	1	Sum of Wg	gt. 4313
50%	6 2		Mean	2.664503
		Largest S	Std. Dev.	1.809679
75%	6 4	13		
90%	6 5	14	Variance	3.274939
95%	6	14	Skewness	1.78664
99%	6 10	14	Kurtosis	7.843539

. desc

Contains data from C:\DATA\evalx.dta

Percentile results from evalx "removal" dataset for figure 1.

. summarize sitetot2,detail

sitetot2

	Perce	ntiles	Smalles	st	
]	1%	1	1		
4	5%	1	1		
1	0%	1	1	Obs	10624
2	5%	1	1	Sum of Wg	gt. 10624
5	0%	2		Mean	2.817771
		L	argest	Std. Dev.	1.820817
7	5%	4	14		
9	0%	5	14	Variance	3.315373
9	5%	6	15	Skewness	1.28899
9	9%	8	15	Kurtosis	5.160435

Contains data from C:\Stata\final9.dta

Percentile results from final9 "analysis" dataset for figure 1.

. summarize sittotal2,detail

sittotal2

	Percenti	les	Smalles	t	
1	%	1	1		
5	%	2	1		
10)%	2	1	Obs	7986
25	5%	2	1	Sum of Wg	gt. 7986
5()%	4		Mean	3.827949
	<i>3</i> 7 0	L	argest	Std. Dev.	1.585217
75	5%	5	11		
9()%	5	11	Variance	2.512912
95	5%	6	11	Skewness	.6826816
99	9%	9	11	Kurtosis	4.263949

Annotations for Table 2:

A univariate evaluation of race or ethnicity looking at the between values primarily.

- . sort id site place followup iis newid2
- . iis id
- . tis followup
- . xttab ethw

ethw	_	Percent	Percent	Within Percent
0	1037	13.45 86.55		100.00 100.00
Total	7708	100.00 (n = 74)	100.00	100.00

. xttab e	thb					
	Overal	1	Betwe	een	Within	
ethb	Freq.	Percent	Freq.	Percent	Percent	
	+					
0	6884	89.31	664	89.61	100.00	
1 أ	824	10.69	77	10.39	100.00	
Total	7708	100.00	741	100.00	100.00	
10001	,,,,,	(n = 7)		100.00	100.00	
$(\mathbf{n} - 7.11)$						

. xttab etha

	1	all Percent 	•	Percent	Within Percent
0 1	7702 6	99.92	740 1	99.87 0.13	100.00 100.00
		100.00 (n = 74	741		100.00

. xttab ethnam

	Overall		Between		Within	
ethnam	Freq.	Percent	Freq.	Percent	Percent	
+						
0	7691	99.78	739	99.73	100.00	
1	17	0.22	2	0.27	100.00	
+						
Total	7708	100.00	741	100.00	100.00	
(n = 741)						

. xttab ethhis

	Overall Freq. Percent		Free	•	
0 1	7599 109	98.59	719 22	97.03 2.97	100.00 100.00
	•		741	100.00	100.00

. xttab ethoth

·	Freq. 1	all Percent 	•	Percent	Within Percent
0 1	7700	99.90 0.10	739 2	99.73 0.27	100.00 100.00
	'		741	100.00	100.00

. xttab gender

		Ove	rall	Bet	tween	Within			
	gender	Frec	q. Percent	Fr	eq. Percei	nt Percent			
-			0.02						
	0	63	0.82	10	1.35	100.00			
	F	137	1.78	20	2.70	100.00			
	M	7501	97.31	710	95.82	100.00			
	X	7	0.09	1	0.13	100.00			
-	'		100.00			100.00			
	Total	7/08	100.00	741	100.00	100.00			
	(n = 741)								

^{*}This generates a minority variable to determine potentially multiple recordings of ethnicity.

[.] gen minor=0 if ethw==1

⁽¹³¹⁵ missing values generated)

[.] replace minor=1 if ethb+etha+ethnam+ethhis+ethoth>0 (1242 real changes made)

1475. | 344 | 1476. | 344 | 1477. | 344 | 1478. | 344 |

. codebook minor minor (unlabeled) type: numeric (float) range: [0,1] units: 1 unique values: 2 missing .: 75/7986 tabulation: Freq. Value 6669 0 1242 1 75 . . *There are 75 records involved with a missing minor variable. . list id if minor==. | id | 1218. | 241 | 1219. | 241 | 1220. | 241 | 1221. | 241 | 1222. | 245 | |----| 1223. | 245 | 1224. | 245 | 1225. | 245 | 1346. | 299 | 1347. | 299 | |----| 1348. | 299 | 1349. | 299 | 1471. | 344 | 1472. | 344 | 1473. | 344 | |----| 1474. | 344 |

```
1479. | 344 |
1480. | 344 |
1481. | 344 |
1482. | 344 |
1483. | 344 |
   |----|
1484. | 344 |
1966. | 455 |
1967. | 455 |
1968. | 455 |
1969. | 455 |
   |----|
1970. | 455 |
1971. | 455
3280. | 654 |
3281. | 654 |
3282. | 654 |
   |----|
3283. | 654 |
3284. | 654 |
3285. | 654 |
3286. | 654 |
3287. | 654 |
   |----|
3288. | 654 |
3289. | 654 |
3290. | 654 |
3291. | 654 |
3292. | 654 |
   |----|
3293. | 654 |
3294. | 654
3295. | 654 |
3296. | 654 |
```

3297. | 654 | |-----| 3298. | 654 | 3299. | 654 | 3300. | 654 | 3301. | 654 | 3302. | 654 |

```
|----|
3303. | 654 |
3304. | 654 |
3305. | 654 |
3306. | 654 |
3307. | 654 |
   |----|
6045. | 1089
6236. | 1157 |
6237. | 1157
6238. | 1157 |
6239. | 1157 |
   |----|
6240. | 1157 |
6241. | 1157
6242. | 1157 |
6243. | 1157
6244. | 1157 |
   |-----
6245. | 1157
7916. | 1466
7917. | 1466
7918. | 1466
7919. | 1466 |
    +----+
```

. * this involves nine patients.

. list eth* if id=241

ethw ethb etha ethnam ethhis ethoth 1218. | 0 0 0 0 0 0 | 0 0 1219. | 0 0 0 0 | 1220. | 0 0 0 0 0 0 | 1221. | 0 0 0 0 |

. list eth* if id=245

ethw ethb etha ethnam ethhis ethoth 1222. | 0 0 0 0 0 0 | 0 0 1223. 0 0 0 | 0 1224. 0 0 0 0 0 0 | 0 1225. 0 0 0 0 0 |

+-----

list	eth*	if	id	l = 299
115ι	cm.	ш	IU	ーームフラ

	+ ethw		ethb		ethna		thhis	ethoth
- 1346 1347			0 0		0 0	0	0 0	
1348 1349			0	0	0	0	0 0	

. list eth* if id==344

+							+
(ethw				m eth		
- 1471	. 0	0	0	0	0	0	
	. 0	0	0	0	0	0	
	. 0	0	0	0	0	0	
	. 0	0	0	0	0	0	
1475	. 0	0	0	0	0	0	
-							
1476	. 0	0	0	0	0	0	
1477	. 0	0	0	0	0	0	
1478	. 0	0	0	0	0	0	
1479	. 0	0	0	0	0	0	
1480	. 0	0	0	0	0	0	
-							
1481	. 0	0	0	0	0	0	
1482	. 0	0	0	0	0	0	
1483	. 0	0	0	0	0	0	
1484	. 0	0	0	0	0	0	
+							+

. list eth* if id==455

	+							+ his ethoth	
	eun								
100			_					'	
	6.		0	U	U	U	0		
196	7.	0	0	0	0	0	0		
196	8.	0	0	0	0	0	0		
196	9.	0	0	0	0	0	0		
197	0.	0	0	0	0	0	0		
197	1.	0	0	0	0	0	0		

+----+

. list eth* if id==654

	+							+
	et	hw	ethb	etha	ethnam	е		ethoth
328	n N 1	0	0	0	0	0	0	'
328		0	0	0	0	0	0	
328		0	0	0	0	0	0	
328		0	0	0	0	0	0	
328		0	0	0	0	0	0	
	· · · · 							
328		0	0	0	0	0	0	'
328		0	0	0	0	0	0	
328		0	0	0	0	0	0	
328			0	0	0	0	0	
328		0	0	0	0	0	0	
329	0.	0	0	0	0	0	0	
329	1.	0	0	0	0	0	0	
329	2.	0	0	0	0	0	0	
329	3.	0	0	0	0	0	0	
329		0	0	0	0	0	0	
329		0	0	0	0	0	0	
329		0	0	0	0	0	0	
329		0	0	0	0	0	0	
329		0	0	0	0	0	0	
329		0	0	0	0	0	0	1
330	 በ	0	0	0	0	0	0	
330		0	0	0	0	0	0	
330		0	0	0	0	0	0	
330		0	0	0	0	0	0	
330		0	0	0	0	0	0	
550	ı 						·	
330	5.	0	0	0	0	0	0	ı
330	6.	0	0	0	0	0	0	
330		0	0	0	0	0	0	
	+							+

. list eth* if id==1089

. list eth* if id==1157

```
ethw ethb etha ethnam ethhis ethoth
6236. | 0
             0
                 0
                       0
                             0
                                   0 |
                       0
                             0
                 0
6237.
        0
                                   0 |
6238. |
                       0
                             0
        0
             0
                 0
                                   0 |
6239.
        0
             0
                 0
                       0
                             0
                                   0 |
                       0
                             0
6240. | 0
             0
                 0
                                   0 |
6241. | 0
                 0
                       0
                             0
                                   0 |
6242. |
        0
             0
                 0
                       0
                             0
                                   0 |
                       0
                             0
6243.
        0
             0
                 0
                                   0 |
6244.|
        0
             0
                 0
                       0
                             0
                                   0 |
                 0
                       0
                             0
6245. | 0
                                   0 |
```

. list eth* if id==1466

	++							
	ethw		ethb	ıb etha ethi		am ethhis		ethoth
791			_	_		0	0	
791	17.	0	0	0	0	0	0	
791	18.	0	0	0	0	0	0	
791	19.	0	0	0	0	0	0	
	+							+

. *All ethnicity values reveal 0's and do not report a missing value and do not report any ethnicity.

. count if ethhis==1 & ethw==1

- . *There are two records having multiple recordings of ethw and ethhis.
- . list id if ethhis==1 & ethw==1

```
+----+
| id |
|----|
953. | 183 |
954. | 183 |
+----+
```

. list eth* if id=183

gender numeric sex

type: numeric (long) label: gender

range: [1,6] units: 1

unique values: 4 missing :: 278/7986

- . count if gender==3 & gender==4 0
- . *There are no patients listed in both categories of gender.
- . codebook sitetot

Annotations for Table 3 and Table 4:

A variable "freq" was created to count the first records for each patient and each site. The xttab command for the overall frequency and percent calculations accounts for all records and this includes all follow-up records. This inflates the value for implants.

- . by id site:gen freq=followup[1]
- . by id site:replace freq=1 if followup==freq
- (2305 real changes made)
- . replace freq=0 if freq~=1

(5681 real changes made)

. tabulate freq

freq	•	Percent	
0 1	5681 2305	71.14 28.86	71.14 100.00
		100.00	

It appears that there are 2305 total implants in 777 patients.

An xttab procedure on the records representing the first placement date produces the following:

- . iis id
- . tis followup
- . xttab imptype if freq==1

Overall			Between			Withir	1	
imptype	Fre	q. Percen	ıt	Freq.	Percei	nt	Percent	
+-								
2	13	0.56	5	0.64	. 1	00.00		
4	95	4.12	45	5.79	9	85.59		
5	4	0.17	1	0.13	1	00.00		
6	6	0.26	2	0.26	ϵ	60.00		
10	2	0.09	1	0.13		33.33		
18	16	0.69	4	0.5	1	94.12		
19	2169	94.10	72	25 9	3.31	99	0.45	
+-								
Total	2305	100.00		783	100.77		98.44	
(n=777)								

Here the "Between frequency" and "percent" have not changed. However, the "Overall Frequency" and "Percent" changed because the records of followup were not counted.

. by imptype:xttab failure if freq==1

--> imptype = 2

	Overall		Betw	een	Within	
failure	Freq	. Percent	Fre	eq. Percent	Percent	
+						
0	13	100.00	5	100.00	100.00	
+						
Total	13	100.00	5	100.00	100.00	
		(n = 5)	5)			

 $\overline{\text{imptype}} = 4$

	Overall		Between		Within		
failure	Freq	. Percent	Fı	req. Perce	nt Percent		
+-							
0	93	97.89	45	100.00	97.89		
1	2	2.11	1	2.22	50.00		
+-							
Total	95	100.00	4	6 102.22	96.85		
(n=45)							

 $\overline{\text{imptype}} = 5$

	Overall	Between	Within	
failure	Freq. Percent	Freq. Percent	Percent	
+-				
0	4 100.00	1 100.00	100.00	
+-				
Total	4 100.00	1 100.00	100.00	
·	(n = 1)	1)		

•				_
1m	ntv	ne	_	h
im	νιγ	ν	_	v

	Overall	Between	Within
failure	Freq. Percent	Freq. Percent	Percent
+-			
0	6 100.00	2 100.00	100.00
+-			
Total	6 100.00	2 100.00	100.00
	(n=2)	2)	

imptype = 10

·	Freq. Percer	Between nt Freq. Percent	
0	2 100.00	1 100.00	
		1 100.00	

imptype = 18

	Overall		Betw	een '	Within
failure	Freq. 1	Percent	Fre	q. Percent	Percent
+					
0	16 10	0.00	4	100.00	100.00
+					
Total	16 1	00.00	4	100.00	100.00
		(n = 4))		

imptype = 19

	Overa	ıll	Betwe	een	Within
failure	Freq.	Percent	Free	q. Percen	t Percent
					98.84
				3.86	
Total	2169			5 102.7	6 96.70
		(n = 72)	25)		

This was the xttab procedure using only the first records, (i.e. freq=1) subset of patients. The "Between Frequencies" are reported in the table as the "Number of Failures" by type. The "Overall Frequencies" are reported in the table as the "Number of Patients With Failures".

Annotations for Figure 4

- . iis newid2
- . tis followup
- . xttab sittotal2

	Overa	ıll	Betw	een	Within
sittotal2	Freq.	Percent	Fr	eq. Perce	nt Percent
+					
1	288	3.61	116	5.03	100.00
2	1815	22.73	564	24.47	100.00
3	779	9.75	261	11.32	100.00
4	2720	34.06	644	27.94	100.00
5	1654	20.71	475	20.61	100.00
6	346	4.33	126	5.47	100.00
7	125	1.57	49	2.13	100.00
8	149	1.87	40	1.74	100.00
9	89	1.11	9	0.39	100.00
10	10	0.13	10	0.43	100.00
11	11	0.14	11	0.48	100.00
Total	7986			05 100.	00 100.00
		(n = 23)	05)		

- . iis id
- . tis site
- . xttab sittotal2

	Overa	.11	Betw	reen	Within
sittotal2	Freq.	Percent	Fre	eq. Percer	nt Percent
1	288	3.61	116	14.93	100.00
2	1815	22.73	282	36.29	100.00
3	779	9.75	87	11.20	100.00
4	2720	34.06	161	20.72	100.00
5	1654	20.71	95	12.23	100.00
6	346	4.33	21	2.70	100.00
7	125	1.57	7	0.90	100.00
8	149	1.87	5	0.64	100.00
9	89	1.11	1	0.13	100.00
10	10	0.13	1	0.13	100.00
11	11	0.14	1	0.13	100.00
Total	7986			7 100.00	100.00
(n=777)					

The between freq/percent using id as an iis variable is appropriate for assessing the number of "patients" with implants of the site total indexed. That is to say that there are 116 patients with one implant and there are 95 patients with 5 implants. However, the overall frequency and percent assess the follow-up times or visits for each implant and is not useful information to present. When iis is newid2, the between frequency and percent are a true assessment of the number of implants for patients at the various site total levels.

Annotations for Table 5

- . iis id
- . tis followup
- . xttab visit

	Ove	erall	Bet	tween	Within
visit	Freq.	Percent	Freq.	Percent	Percent
1	2305	28.86	777	100.00	28.86
2	1544	19.33	548	70.53	21.07
3	1102	13.80	394	50.71	16.87
4	777	9.73	279	35.91	13.73
5	563	7.05	196	25.23	11.82
6	430	5.38	146	18.79	10.47
7	316	3.96	105	13.51	9.27
8	244	3.06	80	10.30	8.52
9	181	2.27	63	8.11	7.54
10	133	1.67	44	5.66	6.98
11	109	1.36	37	4.76	6.48
12	69	0.86	25	3.22	5.96
13	51	0.64	19	2.45	5.43
14	31	0.39	12	1.54	5.00
15	30	0.38	11	1.42	4.95
16	19	0.24	8	1.03	4.17
17	19	0.24	8	1.03	4.17
18	10	0.13	5	0.64	3.47
19	10	0.13	5	0.64	3.47
20	10	0.13	5	0.64	3.47
21	9	0.11	4	0.51	3.60
22	9	0.11	4	0.51	3.60
23	9	0.11	4	0.51	3.60
24	3	0.04	1	0.13	3.16
25	3	0.04	1	0.13	3.16
Total	7986	100.00	2781 (n = 777)	357.92	18.52

. *This attempts to evalutate visits per patient. It appears that naturally there is at least one visit and therefore this would lend well to being the highest value. Also the greater the visit frequency the less patients involved. The minimum value is one and the maximum is 25.

The overall freq/percent reveal values for those who have had visits and therefore is cumulative. This could be presented as "There are 146 patients who have ever had six (6) visits." There are patients who are in this category that have also been in the category of those who have had seven (7) implants. Therefore, the same patients who have been counted for the six (6) visits are also in the seven visit category.

APPENDIX D ANNOTATIONS AND PROGRAMS FOR ANALYSIS

```
Program for Analyses producing Tables for Models 1 through 11 and Tables 6-19
use "C:\unzipped\final9folder\final9.dta", clear
sort newid2 site place followup
*The final9 data set that has been stset for continuous time survival
analysis.
desc
*note the number of observations being 7,986
codebook race race2 type loc
*The race variable was created with the following value labels:
*1-white, 2-black, 3-asian, 4-native american, 5-hispanic, 6-other.
*I need to account for the missing values.
*There are 353 missing values that are maintained
*The race variable was then changed to collapse the cells to the following
value labels for the variable race2:
*1-white, 2-black+asian+native american+hispanic, 3-other, missing.
*In my analysis for discrete survival and continuous survival I found that
the number of failures for each category was sparse and therefore further
collapsed the cells and created a race3 variable.
/*gen race3=1 if race2==1 & race2~=.
codebook race2 race3
replace race3=2 if race2==2 race2==3 & race2~=.*/
codebook race2 race3
*This will present the value labels for race3 as 1-white and 2-other and
missing.
*Now I will also collapse the cells for the loc (location variable) into four
instead of 6 cells.
/*gen loc2=1 if loc==5 & loc~=.
codebook loc loc2
replace loc2=2 if loc==2 & loc~=.
codebook loc loc2
replace loc2=3 if loc==4|loc==6 & loc~=.
codebook loc loc2
replace loc2=4 if loc==1|loc==3 & loc~=.
codebook loc loc2*/
tab failure loc
*Clearly the higher failure frequencies occur in the loc==5 and 2 regions
which influenced the value labels in the loc2 variable which designates the 1
and 2 values as these to regions.
*The value labels for loc2 are as follows:
*1-mandibular anterior region, 2-maxillary anterior region, 3-mandibular
```

posterior region, 4-maxillary posterior region.

```
/*save "C:\unzipped\final9Folder\final9.dta", replace*/
sort failure
tab failure loc2
by failure:xttab loc2
by failure:xttab type2
by failure:xttab race3
sort id site place followup
*Here in the loc2 variable the failures do not increase but the frequency is
higher in the four cells which may present an analysis with less of an issue
regarding "perfect predictors" due to sparse failure counts.
*Now I will attempt to analyze the data using the six models discussed in my
thesis.
*(A) Single site per person and single time interval
*I need to limit my evaluation to the first year in the study and that means
that [first year of follow up-place (placement date of implant)] needs to be
indicated.
*I also must assure that the censoring variable is maintained.
sort id site place followup
/*by id:gen year=1 if followup-place<=365.25
replace year=2 if followup-place<=2*365+0.25 & year~=1
replace year=3 if followup-place<=3*365+0.25 & year~=2
replace year=4 if followup-place<=4*365+0.25 & year~=3
replace year=5 if followup-place<=5*365+0.25 & year~=4
replace year=6 if followup-place<=6*365+0.25 & year~=5
replace year=7 if followup-place<=7*365+0.25 & year~=6
replace year=8 if followup-place<=8*365+0.25 & year~=7
codebook year*/
codebook year
*Now I will attempt a logistic regression for a single site per person and
single time. I will also incorporate in the code a variable called firstimp
to indicate the first record and only include this implant for evaluation.
*The code used to generate such a variable follows.
/*firstimp=0
by id:gen firstimp=1 if site==site[1]*/
codebook firstimp
*firstimp indicates implant first records at an implant level
list newid2 id site place followup firstimp failure in 1/72
*(A) Single site per person and single time interval (first year of study).
count if firstimp==1 & year==1
xi:logistic failure i.loc i.type i.race if firstimp==1 & year==1
*I will use the other variables that were created to evaluate this model.
xi:logistic failure i.loc2 i.type i.race3 if firstimp==1 & year==1
testparm _Iloc*
*Type is still an issue.
codebook type
/*gen type2=1 if type=1 and type~=.
gen type2=1 if type==1 and type~=.
gen type2=1 if type==1 & type~=.
codebook type type2
replace type2=2 if type==2 type==3 & type~=.
codebook type type2
save "C:\STATA\final9.dta", replace*/
xi:logistic failure i.loc2 i.type2 i.race3 if firstimp==1 & year==1
```

```
*The type variable no longer is presented as being problematic.
testparm _Iloc*
*I will now incorporate the robust variance into the analysis.
xi:logistic failure i.loc2 i.type2 i.race3 if firstimp==1 & year==1, robust
cluster(id)
testparm _Iloc*
*(B) The next model evaluates the situation for Multiple sites per person and
a single time interval.
count if year==1
xi:logistic failure i.loc2 i.type2 i.race3 if year==1
testparm _Iloc*
*This does not incorporate the robust variance
xi:logistic failure i.loc2 i.type2 i.race3 if year==1,robust cluster(id)
testparm Iloc*
*Now using the xt command structure in Stata to evaluate GEE
set matsize 80
xi:xtgee failure i.loc2 i.type2 i.race3 if year==1, family(bin) link(logit)
corr(exc) i(id) eform
testparm _Iloc*
*I will now analyze the data using the robust variance analysis.
xi:xtgee failure i.loc2 i.type2 i.race3 if year==1, family(bin) link(logit)
corr(exc) i(id) eform
testparm _Iloc*
*These are the population averaged models. The second model incorporating
the robust variance procedure.
*The next situation to evaluate is the single site per person with multiple
time intervals. In this situation I must reorganize the data to accommodate
one record per person per time interval. I will use the stsplit command in
Stata where time intervals will be established and the observation level will
change according to this. I do not want to change this dataset and will use
another dataset that has been established for this analysis (final9b.dta).
use "C:\unzipped\final9Folder\final9b.dta", clear
desc
sort id site place followup
*This data was modified using the stsplit command to create a categorical
variable called annualt which separates the data into yearly time intervals
and allows for discrete survival analysis. Also the analysis requires that
other variables be created: (A) one to index each patient (B) a binary
dependent variable to indicate censorship within the time intervals, and (C)
a variable to summarize the pattern of duration dependence.
*The data in it's current form has more observations than the final9.dta.
Also, the race loc and type variables need to be collapsed as well.
          race race2 type loc
codebook
/*Code for generating race3, loc2 and type2 variables
gen race3=1 if race2==1 & race2~=.
          race2 race3
codebook
replace race3=2 if race2==2 | race2==3 & race2~=.
codebook
          race2 race3
save "C:\unzipped\final9Folder\final9b.dta", replace
gen type2=1 if type==1 & type~=.
codebook type type2
replace type2=2 if type==2 type==3 & type~=.
codebook type type2
```

```
save "C:\unzipped\final9Folder\final9b.dta", replace
gen loc2=1 if loc==5 & loc~=.
codebook loc loc2
replace loc2=2 if loc==2 & loc~=.
codebook loc loc2
replace loc2=3 if loc==4|loc==6 & loc~=.
codebook loc loc2
replace loc2=4 if loc==1 loc==3 & loc~=.
codebook loc loc2*/
codebook annualt
*I need to create another censorship indicator
codebook _d
/*gen dfail= d*/
codebook dfail
*I will also need to code a variable to indicate the first record in this
dataset "firstimp" and only include this implant for evaluation.
*The code used to generate such a variable follows.
/*gen firstimp=0
by id:gen firstimp=1 if site==site[1]*/
list id site place followup annualt firstimp in 1/72
*firstimp indicates implant first records at an implant level.
tabulate failure annualt
*(C)Discrete Proportional Odds model.
*This is the situation of the single site per patient with multiple time
intervals.
count if firstimp==1
xi:logit dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1
logit, or
testparm _Iloc*
testparm _Iannualt*
xi:logit dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1, robust
cluster(id)
logit, or
testparm _Iloc*
testparm _Iannualt*
*Now to evaluate the Discrete proportional hazards using the cloglog function
xi:cloglog dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1
matrix b=e(b)
matrix v=e(V)
ereturn post b v
ereturn display, eform(exp_b)
testparm _Iloc*
testparm _Iannualt*
xi:cloglog dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1,robust
cluster(id)
matrix b=e(b)
matrix v=e(V)
ereturn post b v
ereturn display, eform(exp_b)
testparm Iloc*
testparm Iannualt*
*Next I will evaluate the situation of multiple sites per patient and
multiple time intervals. This will be a Discrete Proportional Odds model.
```

```
*(D) Multiple sites per person and multiple time intervals
*Discrete Proportional Odds.
xi:logit dfail i.annualt i.loc2 i.type2 i.race3
logit, or
testparm _Iloc*
testparm _Iannualt*
*Next I will incorporate the robust variance
xi:logit dfail i.annualt i.loc2 i.type2 i.race3, robust cluster(id)
logit, or
testparm _Iloc*
testparm _Iannualt*
*Now we will analyze the data using GEE for the Discrete Proportional Odds
and Cloglog Models.
set matsize 110
xi:xtgee dfail i.annualt i.loc2 i.type2 i.race3, family(bin) link(logit)
corr(exc) i(id) eform
testparm _Iloc*
testparm _Iannualt*
xi:xtgee dfail i.annualt i.loc2 i.type2 i.race3, family(bin) link(logit)
corr(exc) i(id) eform robust
testparm _Iloc*
testparm _Iannualt*
*Now for the Cloglog evaluation of GEE
xi:xtcloglog dfail i.annualt i.loc2 i.type2 i.race3, pa i(id)
testparm _Iloc*
testparm _Iannualt*
matrix b=e(b)
matrix v=e(V)
ereturn post b v
ereturn display, eform(exp_b)
xi:xtcloglog dfail i.annualt i.loc2 i.type2 i.race3, pa robust i(id)
testparm _Iloc*
testparm _Iannualt*
matrix b=e(b)
matrix v=e(V)
ereturn post b v
ereturn display, eform(exp_b)
*The next situation to evaluate involves the single site per patient with
continuous time. This would involve the Cox model and I will now evaluate
this on the final9.dta dataset.
/*save "C:\unzipped\final9Folder\final9b.dta", replace
clear*/
use "C:\unzipped\final9Folder\final9.dta", clear
*(E)Single site per patient and continuous time Cox Proportional Hazards
Model
count if firstimp==1
xi: stcox i.loc2 i.type2 i.race3 if firstimp==1
testparm _Iloc*
xi: stcox i.loc2 i.type2 i.race3 if firstimp==1, robust cluster(id)
testparm Iloc*
*The next situation to evaluate involves multiple sites per patient with
continuous time. This also would involve the Cox model.
```

*(F) Multiple sites per patient and continuous time Cox Proportional Hazards Model

xi: stcox i.loc2 i.type2 i.race3

testparm _Iloc*

xi: stcox i.loc2 i.type2 i.race3 , robust cluster(id)

testparm _Iloc*

xi: stcox i.loc2 i.type2 i.race3 , shared(id)

end of log

Log file from Analysis Program:

log: C:\DATA\aug1b2004.smcl

log type: smcl

. do c:\stata\aug1ed2004.txt

. use "C:\unzipped\final9folder\final9.dta", clear

. sort newid2 site place followup

. *The final9 data set that has been stset for continuous time survival analysis.

. desc

Contains data from C:\unzipped\final9folder\final9.dta

obs: 7,986 vars: 121

size: 4,016,958 (68.1% of memory free)

variable name	_	display format	variable label
implwdthPlus1	float	%9.0g	implantwidth+1 for log scale
nxdate	float	%d	numeric xdate
nbdate	float	%d	numeric bdate
surocc9	float	%9.0g	Unable to Seat Implant
surocc10	float	%9.0g	Implant Not Well Adapted to
Site			
surocc11	float	%9.0g	Ridge Augmentation Used
surocc12	float	%9.0g	Periodontal Tissue Damage
surocc13	float	%9.0g	Patient Experienced Pain
surocc14	float	%9.0g	Excessive Bleeding
surocc15	float	%9.0g	Guided Tissue Regeneration
surocc16	float	%9.0g	
_merge	byte	%8.0g	
age1	float	%9.0g	
newid2	float	_	group(id site)
У	float	%9.0g	
id	double	%9.0g	id
nisdate	double	%d	isdate
place	float	%d	
nevldate	double		evaldate
followup	float	%d	
nimrdate	double	%d	imprdate

site failure rownames	double float str5	%9.0g %5s	site
evaldate	str11	%11s	
mobil	float	%9.0g	
periminf	str1	%1s	Peri-implant Inflammation
imphcat	float	%9.0g	Implant Health Category
imprdate	strl1	%11s	
impfunc	float	%9.0g	Implant Functionality
impltopt	float	%9.0g	Implant Less Than Optimal but Functional
impnonsp	float	%9.0g	
imp2brmv	float	%9.0g	
funother	float	%9.0g	
painlswr	float	%9.0g	
esthetic	float	%9.0g	Martinetian Dualilana Dua ta
mastprob	float	%9.0g	Mastication Problems Due to Implant
speechpr	float	%9.0g	Speech Problems Due to Implant
cmplnoth	float	%9.0g	
compimpi	float	%9.0g	If Compromised Implant Intervention Was Used
newid	float	%9.0g	group(newssn)
isdate	str11	%11s	
imparch	str1	%1s	Arch Location
imp1	float	%9.0g	
imptype	float	%9.0g	Implant Type
matcode	float	%9.0g	Material Code
coatcode	float	%9.0g	Coating Code
stagecode	float	%9.0g	Stage Code
morphcode	float	%9.0g	Morphology Code
implantheight	float	%9.0g	Implant Height (mm)
implantwidth	float	%9.0g	<pre>Implant Width/Diameter (mm)</pre>
availboneheight		%9.0g	Height of Available Bone (mm)
availbonewidth	float	%9.0g	Width of Available Bone (mm)
avboneht	float	%9.0g	
avbonewi	float	%9.0g	
attginwi	float	%9.0g	
bonclass	float	%9.0g	Bone Classification
surocc1	float		Implant Altered
surocc2	float	%9.0g	Alveolar Ridge Perforation
surocc3	float	%9.0g	Jaw Fracture
surocc4	float	%9.0g	Neurological Damage
surocc5	float	%9.0g	Inferior Mandibular Border Perforation
surocc6	float	%9.0g	Sinus Lift
surocc7	float	%9.0g	Perforated Sinus/Nasal Cavity
surocc8	float	%9.0g	Equipment Complications
provid	str4	%4s	
station	float	%9.0g	
ethw	float	%9.0g	
ethb	float	%9.0g	
etha	float	%9.0g	
ethnam	float	%9.0g	

```
ethhis
              float %9.0g
ethoth
              float %9.0g
sex
              str1
                     %1s
asarate
              float %9.0q
              float %9.0g
edenttot
gender
              long
                     %8.0g
                                gender
                                        numeric sex
              float %9.0g
rem
ind
              float %9.0g
ctr
              float %9.0g
ctr1
              float %9.0g
dupimp
              float %9.0g
у2
              float %9.0g
visit
              float %9.0g
              float %9.0g
                                          Total number of Visits
vistot
sittot
              float %9.0g
sit
              float %9.0g
sitetot
              float %9.0g
sittotal
              float %9.0g
                                          Total number of sites per
sittotal2
              float %9.0g
                                            patient
              float %9.0g
                                          The counter for all first
freq
                                           records by id and site
              float %9.0g
AVBHPlus1
                                           Availboneheight+1 for log
scale
AVBWPlus1
              float %9.0q
                                          Availbonewidth+1 for log scale
             float %9.0g
implhtPlus1
                                          implantheight+1 for log scale
              float %9.0g
age2
              float %9.0g
agecat
              float %9.0g
arch
                     %8.0g
_st
              byte
              byte
                     %8.0g
_d
_origin
              int
                     %10.0g
              double %10.0g
_t
              double %10.0g
_t0
failind
              float %9.0g
seq
             float %9.0g
firstrec
              float %9.0g
race
race2
              float %9.0q
type
              float %9.0g
              float %9.0g
loc
              float %9.0g
race3
loc2
              float %9.0g
              float %9.0g
type2
              float %9.0g
index
folupind
              float %9.0g
maxfolup
              byte
                     %10.0g
              float %9.0g
maxind
                                          loc2==2
_Iloc2_2
              byte
                     %8.0g
                                          loc2==3
_Iloc2_3
              byte %8.0g
Iloc2 4
              byte
                     %8.0g
                                          loc2==4
year
              float %9.0q
firstimp
              float %9.0g
```

^{. *}note the number of observations being 7,986

[.] codebook race race2 type loc

race (unlabeled) ______ type: numeric (float) range: [1,6] units: 1 unique values: 6 missing .: 353/7986 tabulation: Freq. Value 6669 1 824 2 6 3 17 109 5 8 6 353 . ______ race2 (unlabeled) type: numeric (float) range: [1,3] units: 1 missing .: 353/7986 unique values: 3 tabulation: Freq. Value 6669 1 956 2 8 3 353 type (unlabeled)

type: numeric (float)

range: [1,3] units: 1

unique values: 3 missing .: 0/7986

tabulation: Freq. Value

7398 1 466 2 122 3

```
loc
(unlabeled)
_____
                type: numeric (float)
               range: [1,6]
                                                 units: 1
        unique values: 6
                                             missing .: 0/7986
           tabulation: Freq. Value
                         208 1
                         415 2
                         209 3
                         986 4
                        5238 5
                         930 6
. *The race variable was created with the following value labels:
. *1-white, 2-black, 3-asian, 4-native american, 5-hispanic, 6-other.
. *I need to account for the missing values.
. *There are 353 missing values that are maintained
. *The race variable was then changed to collapse the cells to the following
value labels for the variable race2:
. *1-white, 2-black+asian+native american+hispanic, 3-other, missing.
. *In my analysis for discrete survival and continuous survival I found that
the number of failures for each category was sparse and therefore further
collapsed the cells and created a race3 variable.
. /*gen race3=1 if race2==1 & race2~=.
> codebook race2 race3
> replace race3=2 if race2==2|race2==3 & race2~=.*/
. codebook race2 race3
race2
(unlabeled)
                type: numeric (float)
               range: [1,3]
                                                 units: 1
                                              missing .: 353/7986
        unique values: 3
           tabulation: Freq. Value
                       6669 1
                         956 2
                         8 3
```

353

race3
(unlabeled)

type: numeric (float)

range: [1,2] units: 1

unique values: 2 missing .: 353/7986

tabulation: Freq. Value

6669 1 964 2 353 .

- . *This will present the value labels for race3 as 1-white and 2-other and missing.
- . *Now I will also collapse the cells for the loc (location variable) into four instead of 6 cells.
- . /*gen loc2=1 if loc==5 & loc~=.
- > codebook loc loc2
- > replace loc2=2 if loc==2 & loc~=.
- > codebook loc loc2
- > replace loc2=3 if loc==4|loc==6 & loc~=.
- > codebook loc loc2
- > replace loc2=4 if loc==1 loc==3 & loc~=.
- > codebook loc loc2*/
- . tab failure loc

		1	OC		
failure	1	2	3	4	Total
0 1	200 8	399 16	205 4	975 11	7,883
Total	208	415	209	986	7,986

 failure	loc 5	6	Total
0 1	5,190 48	914 16	7,883
Total	5,238	930	7,986

- . *Clearly the higher failure frequencies occur in the loc==5 and 2 regions which influenced the value labels in the loc2 variable which designates the 1 and 2 values as these to regions.
- . *The value labels for loc2 are as follows:
- . *1-mandibular anterior region, 2-maxillary anterior region, 3-mandibular posterior region, 4-maxillary posterior region.

- . /*save "C:\unzipped\final9Folder\final9.dta", replace*/
- . sort failure
- . tab failure loc2

		lo	oc2		_
failure	1 +	2 	3 	4	Total
0 1	5,190 48	399 16	1,889 27	405 12	7,883
Total	5,238	415	1,916	417	7,986

. by failure:xttab loc2

-> failure = 0

	Overall		Bet	Between		
loc2	Freq.	Percent	Freq.	Percent	Percent	
1	5190	65.84	1317	58.17	100.00	
2	399	5.06	174	7.69	100.00	
3	1889	23.96	616	27.21	100.00	
4	405	5.14	157	6.93	100.00	
Total	7883	100.00	2264 (n = 2264)	100.00	100.00	

-> failure = 1

	Ove	Overall Between		n Within	
loc2	Freq.	Percent	Freq.	Percent	Percent
1	48	46.60	48	46.60	100.00
2	16	15.53	16	15.53	100.00
3	27	26.21	27	26.21	100.00
4	12 +	11.65	12	11.65	100.00
Total	103	100.00	103 (n = 103)	100.00	100.00

. by failure:xttab type2

-> failure = 0

type2	Ove Freq.	rall Percent	Bet Freq.	ween Percent	Within Percent
1 2	7305 578	92.67 7.33	2130 134	94.08 5.92	100.00
Total	7883	100.00	2264 (n = 2264)	100.00	100.00

-> failure = 1

	Overall		Bet	tween	Within	
type2	Freq.	Percent	Freq.	Percent	Percent	
	+					
1	93	90.29	93	90.29	100.00	
2	10	9.71	10	9.71	100.00	
	+					
Total	103	100.00	103	100.00	100.00	
			(n = 103)			

. by failure:xttab race3

-> failure = 0

race3	Ove	rall	Bet	ween	Within
	Freq.	Percent	Freq.	Percent	Percent
1 2	6588	87.48	1859	87.15	100.00
	943	12.52	274	12.85	100.00
Total	7531	100.00	2133 (n = 2133)	100.00	100.00

-> failure = 1

	Ove	erall	Bet	Between		
race3	Freq.	Percent	Freq.	Percent	Percent	
	+					
1	81	79.41	81	79.41	100.00	
2	21	20.59	21	20.59	100.00	
	+					
Total	102	100.00	102	100.00	100.00	
			(n = 102)			

- . sort id site place followup
- . *Here in the loc2 variable the failures do not increase but the frequency is higher in the four cells which may present an analysis with less of an issue regarding "perfect predictors" due to sparse failure counts.
- . *Now I will attempt to analyze the data using the six models discussed in $\ensuremath{\mathsf{my}}$ thesis.
- . \star (A) Single site per person and single time interval
- . *I need to limit my evaluation to the first year in the study and that means that [first year of follow up-place(placement date of implant)] needs to be indicated.
- . *I also must assure that the censoring variable is maintained.

```
. sort id site place followup
. /*by id:gen year=1 if followup-place<=365.25
> replace year=2 if followup-place<=2*365+0.25 & year~=1</pre>
> replace year=3 if followup-place<=3*365+0.25 & year~=2
> replace year=4 if followup-place<=4*365+0.25 & year~=3</pre>
> replace year=5 if followup-place<=5*365+0.25 & year~=4</pre>
> replace year=6 if followup-place<=6*365+0.25 & year~=5</pre>
> replace year=7 if followup-place<=7*365+0.25 & year~=6</pre>
> replace year=8 if followup-place<=8*365+0.25 & year~=7</pre>
> codebook year*/
. codebook year
vear
(unlabeled)
                  type: numeric (float)
                 range: [1,8]
                                                      units: 1
         unique values: 8
                                                 missing .: 0/7986
            tabulation: Freq. Value
                          2738 1
                          2442 2
                          1218 3
                           774
                           457 5
                           231 6
                           110 7
                            16 8
. *Now I will attempt a logistic regression for a single site per person and
single time. I will also incorporate in the code a variable called firstimp
to indicate the first record and only include this implant for evaluation.
. *The code used to generate such a variable follows.
. /*firstimp=0
> by id:gen firstimp=1 if site==site[1]*/
. codebook firstimp
firstimp
(unlabeled)
                  type: numeric (float)
                 range: [0,1]
                                                      units: 1
         unique values: 2
                                                 missing .: 0/7986
            tabulation: Freq. Value
                          5377 0
                          2609 1
```

. *firstimp indicates implant first records at an implant level . list newid2 id site place followup firstimp failure in 1/72

1.	1 0 0 0 0 0	0 0 0 0 0
3. 3 1 25 22jun1993 09jun1994 4. 4 1 26 22jun1993 09jun1994	0 0 0 0 	0 0
4. 4 1 26 22jun1993 09jun1994	0 0 	0
ı yanı yanı yanı yanı yanı yanı yanı yan	0	- !
5 5 1 27 22 iun 1002 00 iun 1004	1	0
J. J I 2/ 22 JUIII 773 07 JUII 1774		
6. 6 9 22 16jan1984 25may1984	1	0
7. 6 9 22 16jan1984 09aug1984	1	0
8. 6 9 22 16jan1984 24sep1984	1	0
9. 6 9 22 16jan1984 15nov1984	1	0
10. 6 9 22 16jan1984 01may1985	1	0
11. 6 9 22 16jan1984 16aug1985	1	0
12. 6 9 22 16jan1984 13dec1985	1	0
13. 6 9 22 16jan1984 02jun1986	1	0
14. 6 9 22 16jan1984 05dec1986	1	0
15. 7 9 27 16jan1984 25may1984	0	0
16. 7 9 27 16jan1984 09aug1984	0	0
17. 7 9 27 16jan1984 24sep1984	0	0
18. 7 9 27 16jan1984 15nov1984	0	o i
19. 7 9 27 16jan1984 01may1985	0	0
20. 7 9 27 16jan1984 16aug1985	0	0
21. 7 9 27 16jan1984 13dec1985	0	 0
22. 7 9 27 16jan1984 02jun1986	0	0
23. 7 9 27 16jan1984 05dec1986	0	0
24. 8 10 22 16may1990 27mar1991	1	0
25. 8 10 22 16may1990 25apr1991	1	0
26. 8 10 22 16may1990 29may1991	 1	 0
27. 8 10 22 16may1990 25sep1991	1	0
28. 8 10 22 16may1990 08mar1992	1	0
29. 8 10 22 16may1990 06apr1992	1	0
30. 9 10 27 16may1990 27mar1991	0	0
31. 9 10 27 16may1990 25apr1991	 0	 0
32. 9 10 27 16may1990 29may1991	0	0
33. 9 10 27 16may1990 25sep1991	0	0
34. 9 10 27 16may1990 08mar1992	0	0
35. 9 10 27 16may1990 06apr1992	0	0
36. 10 14 30 29apr1987 13jan1988	 1	 0
37. 11 16 22 01jul1992 10may1994	1	0
38. 12 16 23 01jul1992 10may1994	0	0
39. 13 16 25 01jul1992 10may1994	0	0
40. 14 16 26 01jul1992 10may1994	0	0

- 1							
41.	15	16	27	01jul1992	10may1994	0	0
42.	16	17	22	12jun1992	10dec1992	1	0
43.	16	17	22	12jun1992	24dec1992	1	0
44.	17	17	24	12jun1992	10dec1992	0	0
45.	17	17	24	12jun1992	24dec1992	0	0
1.		17		1041000	1031002		
46. 47.	18 18	17 17	25 25	12jun1992 12jun1992	10dec1992 24dec1992	0 0	0
48.	19	17	25 27	12 jun1992 12 jun1992	10dec1992	0	0 1
49.	19	17	27	12 jun1992 12 jun1992	24dec1992	0	0 1
50.	20	18	6	10jan1991	29jun1994	1	0 1
50.							I
51.	21	20	23	08feb1990	18jun1990	1	0
52.	21	20	23	08feb1990	18sep1990	1	0
53.	21	20	23	08feb1990	21nov1990	1	0
54.	21	20	23	08feb1990	03may1991	1	0
55.	21	20	23	08feb1990	25oct1991	1	0
56.	21	20	 23	08feb1990	 06apr1992	1	 0
57.	22	20	26	08feb1990	18jun1990	0	0
58.	22	20	26	08feb1990	18sep1990	0	0
59.	22	20	26	08feb1990	21nov1990	0	o i
60.	22	20	26	08feb1990	03may1991	0	0
61.	22	20	 26	08feb1990	 25oct1991	0	 0
62.	22	20	26 26	08feb1990	06apr1992	0	0 1
63.	23	20	28	08feb1990	18 jun1990	0	0 1
64.	23	20	28	08feb1990	18sep1990	0	0 1
65.	23	20	28	08feb1990	21nov1990	0	0 1
66.	23	20	28	08feb1990	03may1991	0	0
67.	23	20	28	08feb1990	25oct1991	0	0
68.	23	20	28	08feb1990	06apr1992	0	0
69.	24	21	21	11aug1987	16feb1988	1	0
70.	24	21	21	11aug1987	20oct1988	1	0
71.		21	 21	11aug1987	 20apr1989	1	 1
72.	25	21	23	11aug1987	16feb1988	0	0
	+						+

^{. *(}A) Single site per person and single time interval (first year of study). count if firstimp==1 & year==1 $\,$ 920

note: _Itype_3 != 0 predicts failure perfectly
 _Itype_3 dropped and 14 obs not used

note: _Irace_3 != 0 predicts failure perfectly

_Irace_3 dropped and 1 obs not used

note: _Irace_4 != 0 predicts failure perfectly

_Irace_4 dropped and 1 obs not used

note: _Irace_5 != 0 predicts failure perfectly

_Irace_5 dropped and 19 obs not used

Logistic regression Number of obs = 837

LR chi2(8)= 9.83 Prob > chi2 = 0.2771 Pseudo R2 = 0.0483

Log likelihood = -96.846324

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

Interval]	·					
_Iloc_2 5.80633	.7782141	.797963	-0.24	0.807	.1043029	
Iloc3 28.45894	2.278973	2.93567	0.64	0.523	.1824986	
_Iloc_4	.2561431	.2311472	-1.51	0.131	.0436864	
1.501825 _Iloc_5	.4581945	.3684603	-0.97	0.332	.0947437	
2.215897 _Iloc_6	.6365915	.6576019	-0.44	0.662	.0840554	
4.821209 _Itype_2	.8837802	.7070266	-0.15	0.877	.1842386	
4.239434 _Irace_2	1.790739	1.043359	1.00	0.317	.5715933	
5.610191 _Irace_6	57.57701	84.56057	2.76	0.006	3.236909	
1024.16						

```
. *I will use the other variables that were created to evaluate this model.
```

. xi:logistic failure i.loc2 i.type i.race3 if firstimp==1 & year==1

_Iloc2_1-4 (naturally coded; _Iloc2_1 omitted) i.loc2 i.type _Itype_1-3 (naturally coded; _Itype_1 omitted) _Irace3_1-2 (naturally coded; _Irace3_1 omitted) i.race3

note: _Itype_3 != 0 predicts failure perfectly _Itype_3 dropped and 14 obs not used

Logistic regression

Number of obs = 858LR chi2(5) = 3.70Prob > chi2 = 0.5938Pseudo R2 = 0.0181

Log likelihood = -100.46537

failure Interval]	Odds Ratio	Std. Err.	Z	P> z	[95% Conf.	
Iloc2_2 7.382939		1.233396	0.55	0.585	.3239135	
_Iloc2_3 1.940505	.6706245	.3635448	-0.74	0.461	.231763	
_Iloc2_4 8.456994	2.209078	1.513042	1.16	0.247	.5770404	
_Itype_2 3.792028	.7968733	.6342417	-0.29	0.775	.1674584	
_Irace3_2 5.242202	1.846023	.983033	1.15	0.250	.6500705	

[.] testparm _Iloc*

- $(1) _{10c2_2} = 0$
- (2) _Iloc2_3 = 0 (3) _Iloc2_4 = 0

chi2(3) = 3.02Prob > chi2 = 0.3892

^{. *}Type is still an issue.

. codebook type

type
(unlabeled)

<u>`</u>______

type: numeric (float)

range: [1,3] units: 1 unique values: 3 missing .: 0/7986

tabulation: Freq. Value 7398 1

466 2122 3

- . /*gen type2=1 if type=1 and type~=.
- > gen type2=1 if type==1 and type~=.
- > gen type2=1 if type==1 & type~=.
- > codebook type type2
- > replace type2=2 if type==2 type==3 & type~=.
- > codebook type type2
- > save "C:\STATA\final9.dta", replace*/
- . xi:logistic failure i.loc2 i.type2 i.race3 if firstimp==1 & year==1
- i.loc2 __Iloc2_1-4 (naturally coded; _Iloc2_1 omitted)
 i.type2 __Itype2_1-2 (naturally coded; _Itype2_1 omitted)
 i.race3 __Irace3_1-2 (naturally coded; _Irace3_1 omitted)

Logistic regression Number of obs = 872

LR chi2(5) = 4.04 Prob > chi2 = 0.5437 Pseudo R2 = 0.0197

Log likelihood = -100.65474

failure	Odds Ratio	Std. Err.	Z	P> z	[95% Conf.	
Interval]						
Iloc2 2	+ 1.515704	1 205282		0.601	.3189646	
7.202555	1.313704	1.205202	0.52	0.001	.3107040	
_Iloc2_3	.636673	.3393099	-0.85	0.397	.224014	
1.809496						
_Iloc2_4	2.164733	1.476601	1.13	0.258	.5685721	
8.241823					1506005	
_Itype2_2 3.282281	.7100469	.5546303	-0.44	0.661	.1536025	
3.202201 Irace3 2	1.875067	.9965234	1.18	0.237	.6616631	
5.313694	1 2.373007	.,,,,,,,,,		0.207		

- . *The type variable no loger is presented as being problematic.
- . testparm _Iloc*
- $(1) _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) \quad _{1loc2_4} = 0$

chi2(3) = 3.16Prob > chi2 = 0.3670

- . *I will now incorporate the robust variance into the analysis.
- . xi:logistic failure i.loc2 i.type2 i.race3 if firstimp==1 & year==1, robust
 cluster(id)

i.loc2	_Iloc2_1-4	(naturally coded;	_Iloc2_1 omitted)
i.type2	_Itype2_1-2	(naturally coded;	_Itype2_1 omitted)
i.race3	_Irace3_1-2	(naturally coded;	_Irace3_1 omitted)

Logistic regression Number of obs = 872 Wald chi2(5) = 3.78 Prob > chi2 = 0.5817 Log pseudo-likelihood = -100.65474 Pseudo R2 = 0.0197

(standard errors adjusted for clustering on

id)

failure Interval]	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf.
_Iloc2_2 7.109377	1.515704	1.195212	0.53	0.598	.323145
_Iloc2_3 1.787319	.636673	.335304	-0.86	0.391	.2267936
_Iloc2_4 8.073504	2.164733	1.453811	1.15	0.250	.5804258
_Itype2_2 3.435961	.7100469	.5712074	-0.43	0.670	.1467323
_Irace3_2 5.414504	1.875067	1.014503	1.16	0.245	.6493439

. testparm _Iloc*

- $(1) _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 3.05Prob > chi2 = 0.3846

```
. \ensuremath{^{\star}}(B) The next model evaluates the situation for Multiple sites per person and
```

> a single time interval.

. count if year==1
2738

. xi:logistic failure i.loc2 i.type2 i.race3 if year==1

i.loc2 __Iloc2_1-4 (naturally coded; _Iloc2_1 omitted)
i.type2 __Itype2_1-2 (naturally coded; _Itype2_1 omitted)
i.race3 __Irace3_1-2 (naturally coded; _Irace3_1 omitted)

Logistic regression Number of obs = 2610

LR chi2(5)= 8.89 Prob > chi2 = 0.1136

Log likelihood = -258.41238 Pseudo R2 = 0.0169

failure Interval]	Odds Ratio	Std. Err.	z	P> z	[95% Conf.	
_Iloc2_2 5.314892	2.147211	.9929313	1.65	0.098	.8674711	
_Iloc2_3 2.143961	1.119069	.3712169	0.34	0.735	.5841129	
_Iloc2_4 7.640077	2.861581	1.433786	2.10	0.036	1.071801	
_Itype2_2 2.436024	.8545112	.4567328	-0.29	0.769	.2997464	
_Irace3_2 3.837196	1.966096	.6707841	1.98	0.048	1.007385	

- $(1) _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 6.30Prob > chi2 = 0.0981

[.] testparm _Iloc*

^{. *}This does not incorporate the robust variance

Logistic regression

Number of obs = 2610 Wald chi2(5) = 5.00 Prob > chi2 = 0.4161 Pseudo R2 = 0.0169

Log pseudo-likelihood = -258.41238

(standard errors adjusted for clustering on id)

failure Interval]		Robust Std. Err.	Z	P> z	[95% Conf.	
Iloc2_2 6.047999		1.134491	1.45	0.148	.7623208	
_Iloc2_3 2.122418	1.119069	.3654506	0.34	0.730	.5900419	
_Iloc2_4 10.41213	2.861581	1.885753	1.60	0.111	.7864529	
_Itype2_2 3.740815	.8545112	.6437418	-0.21	0.835	.1951953	
_Irace3_2 5_057064	1.966096	.9476919	1.40	0.161	.7643828	

- $(1) _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) \quad _{1loc2_4} = 0$

$$chi2(3) = 2.86$$

Prob > chi2 = 0.4131

- . *Now using the xt command structure in Stata to evaluate GEE
- . set matsize 80

[.] testparm _Iloc*

```
. xi:xtgee failure i.loc2 i.type2 i.race3 if year==1, family(bin) link(logit)
corr(exc) i(id) eform
           _Iloc2_1-4
i.loc2
                             (naturally coded; Iloc2 1 omitted)
              _Itype2_1-2
i.type2
                             (naturally coded; Itype2 1 omitted)
                             (naturally coded; _Irace3_1 omitted)
i.race3
              _Irace3_1-2
Iteration 1: tolerance = .10700382
Iteration 2: tolerance = .00799128
Iteration 3: tolerance = .00033571
Iteration 4: tolerance = .00004652
Iteration 5: tolerance = 7.987e-06
Iteration 6: tolerance = 1.144e-06
Iteration 7: tolerance = 1.803e-07
GEE population-averaged model
                                      Number of obs=2610
Group variable: id
                                      Number of groups=557
Link: logit Obs per group: min =1
                                      avg =4.7
Family: binomial
Correlation: exchangeable
                                      max = 74
                                      Wald chi2(5) = 8.21
Scale parameter: 1
                                      Prob > chi2 = 0.1451
______
   failure | Odds Ratio Std. Err. z P>|z| [95% Conf.
Intervall
   _Iloc2_2 | 1.828297 .9883837 1.12 0.264 .6337011
5.274839
   _Iloc2_3 | 1.255482 .4067927 0.70 0.483 .6652885
2.369251
   .895923
7.661029
  _Itype2_2 | .7972603 .5085502 -0.36 0.722
                                              .2283717
2.783287
  _Irace3_2 | 2.177236 .8389304
                               2.02 0.043
                                             1.023108
4.633292
______
. testparm _Iloc*
(1) _{10c2_2} = 0
(2) = 110c2_3 = 0
(3) = 110c2_4 = 0
        chi2(3) = 3.63
```

Prob > chi2 = 0.3040

¹⁴⁸

```
. *I will now analyze the data using the robust variance analysis.
. xi:xtgee failure i.loc2 i.type2 i.race3 if year==1, family(bin) link(logit)
corr(exc) i(id) eform
               _Iloc2_1-4
i.loc2
                               (naturally coded; Iloc2 1 omitted)
              _Itype2_1-2
_Irace3_1-2
i.type2
                               (naturally coded; Itype2 1 omitted)
i.race3
                                (naturally coded; _Irace3_1 omitted)
Iteration 1: tolerance = .10700382
Iteration 2: tolerance = .00799128
Iteration 3: tolerance = .00033571
Iteration 4: tolerance = .00004652
Iteration 5: tolerance = 7.987e-06
Iteration 6: tolerance = 1.144e-06
Iteration 7: tolerance = 1.803e-07
GEE population-averaged model
                                        Number of obs = 2610
Group variable: id
                                        Number of groups = 557
Link: logit
                                        Obs per group: min = 1
Family: binomial
                                                  avg = 4.7
Correlation: exchangeable
                                                  max = 74
                                        Wald chi2(5) = 8.21
                                      Prob > chi2 = 0.1451
Scale parameter:1
______
  failure | Odds Ratio Std. Err. z P>|z| [95% Conf.
Interval]
______
   _Iloc2_2 | 1.828297 .9883837 1.12 0.264 .6337011
5.274839
   _Iloc2_3 | 1.255482 .4067927 0.70 0.483 .6652885
2.369251
   _Iloc2_4 | 2.619865    1.4343    1.76    0.079
                                                .895923
7.661029
  _Itype2_2 | .7972603 .5085502 -0.36
                                        0.722
                                                 .2283717
2.783287
              2.177236 .8389304
  _Irace3_2
                                 2.02 0.043
                                                 1.023108
4.633292
```

. testparm _Iloc*

- $(1) _{1loc2_2} = 0$
- $(2) = 11002_3 = 0$
- $(3) = 110c2_4 = 0$

chi2(3) = 3.63Prob > chi2 = 0.3040

^{. *}These are the population averaged models. The second model incorporating the robust variance procedure.

. *The next situation to evaluate is the single site per person with multiple time intervals. In this situation I must reorganize the data to accomodate one record per person per time interval. I will use the stsplit command in Stata where time intervals will be established and the observation level will change according to this. I do not want to change this dataset and will use another dataset that has been established for this analysis (final9b.dta).

. use "C:\unzipped\final9Folder\final9b.dta", clear

. desc

. clear

Contains data from C:\unzipped\final9Folder\final9b.dta

obs: 11,794 vars: 136

size: 6,038,528 (52.0% of memory free)

variable name		display format	variable label
implwdthPlus1		_	 implantwidth+1 for log scale
nxdate		%d	numeric xdate
nbdate	float		numeric bdate
surocc9	float	_	Unable to Seat Implant
surocc10	float	%9.0g	Implant Not Well Adapted to
Site			
surocc11	float	_	Ridge Augmentation Used
surocc12	float	_	Periodontal Tissue Damage
surocc13	float	_	Patient Experienced Pain
surocc14	float	_	Excessive Bleeding
surocc15	float	_	Guided Tissue Regeneration
surocc16	float	_	
_merge	byte	_	
age1	float	-	
newid2	float	_	group(id site)
У	float	_	
id	double	_	id
nisdate	double	%d	isdate
place	float		
nevldate	double		evaldate
followup	float		
nimrdate	double		imprdate
site	double	_	site
failure	float	%9.0g	
rownames	str5		
evaldate	str11	%11s	
mobil	float	%9.0g	
periminf		%1s	Peri-implant Inflammation
imphcat	float	%9.0g	Implant Health Category

imprdate	str11	%11s	
impfunc	float	%9.0g	Implant Functionality
impltopt	float	%9.0g	Implant Less Than Optimal but
		11.155	Functional
impnonsp	float	%9.0g	1 41100101141
imp2brmv	float	%9.0g	
funother	float	%9.0g	
painlswr	float	%9.0g	
esthetic			
	float	%9.0g	Mantination Deallana Deal
mastprob	float	%9.0g	Mastication Problems Due to Implant
speechpr	float	%9.0g	Speech Problems Due to Implant
cmplnoth	float	%9.0g	
compimpi	float	%9.0g	If Compromised Implant
			Intervention Was Used
newid	float	%9.0g	group(newssn)
isdate	str11	%11s	
imparch	str1	%1s	Arch Location
imp1	float	%9.0g	
imptype	float	%9.0g	Implant Type
matcode	float	%9.0g	Material Code
coatcode	float	%9.0g	Coating Code
stagecode	float	%9.0g	Stage Code
	float	%9.0g %9.0g	Morphology Code
morphcode		_	
implantheight	float	%9.0g	Implant Height (mm)
implantwidth	float	%9.0g	Implant Width/Diameter (mm)
availboneheight		%9.0g	Height of Available Bone (mm)
availbonewidth	float	%9.0g	Width of Available Bone (mm)
avboneht	float	%9.0g	
avbonewi	float	%9.0g	
attginwi	float	%9.0g	
bonclass	float	%9.0g	Bone Classification
surocc1	float	%9.0g	Implant Altered
surocc2	float	%9.0g	Alveolar Ridge Perforation
surocc3	float	%9.0g	Jaw Fracture
surocc4	float	%9.0g	Neurological Damage
surocc5	float	%9.0g	Inferior Mandibular Border
			Perforation
surocc6	float	%9.0g	Sinus Lift
Barocco	IIOac	00.09	Billab Bile
surocc7	float	%9.0g	Perforated Sinus/Nasal Cavity
surocc8	float	%9.0g	Equipment Complications
			Equipment Complications
provid	str4	%4s	
station	float	%9.0g	
ethw	float	%9.0g	
ethb	float	%9.0g	
etha	float	%9.0g	
ethnam	float	%9.0g	
ethhis	float	%9.0g	
ethoth	float	%9.0g	
sex	str1	%1s	
asarate	float	%9.0g	
edenttot	float	%9.0g	
		<u> </u>	

gender	long	%8.0q	gender	numeric sex	
rem	float	%9.0g	5011401	IIdiiici Io Bell	
index	float	%9.0g			
ind	float	%9.0g			
	float	%9.0g			
ctr					
ctrl	float	%9.0g			
dupimp	float	%9.0g			
у2	float	%9.0g			
visit	float	%9.0g			
vistot	float	%9.0g		Total number	of Visits
sittot	float	%9.0g			
sit	float	%9.0g			
sitetot	float	%9.0g			
sittotal	float	%9.0g			
sittotal2	float	%9.0g		Total number patient	of sites per
freq	float	%9.0g		The counter f records by	
AVBHPlus1 scale	float	%9.0g			ght+1 for log
AVBWPlus1	float	%9.0g		Availhonewidt	h+1 for log scale
implhtPlus1	float	%9.0g			+1 for log scale
				Implantmengnt	+1 lor log scale
age2	float	%9.0g			
agecat	float	%9.0g			
arch	float	%9.0g			
failind	byte	%8.0g			
seq	float	%9.0g			
firstrec	float	%9.0g			
race	float	%9.0g			
race2		%9.0g			
type		%9.0g			
loc	float	%9.0g			
_st	byte	%8.0g			
_d	byte	%8.0g			
_origin	int	%10.0g			
_t	double	%10.0g			
_t0	double	%10.0g			
annualt	byte	%9.0g			
race3	float	%9.0g			
type2	float	%9.0g			
loc2	float	%9.0g			
durat1	byte	%8.0g		annualt==	0.0000
durat2	byte	%8.0g		annualt==	1.0000
durat3	byte	%8.0g		annualt==	2.0000
durat4	byte	%8.0g		annualt==	3.0000
durat5	byte	%8.0g		annualt==	4.0000
durat6	byte	%8.0g		annualt==	5.0000
durato durat7		%8.0g %8.0g		annualt==	6.0000
	byte	_		annualt== annualt==	
durat8	byte	%8.0g		ammalt==	7.0000
dfail	float	%9.0g			
_Iannualt_1	byte	%8.0g		annualt==1	
_Iannualt_2	byte	%8.0g		annualt==2	
_Iannualt_3	byte	%8.0g		annualt==3	

```
byte
_Iannualt_4
                    %8.0g
                                        annualt==4
_Iannualt_5
            byte %8.0g
                                        annualt==5
_Iannualt_6
            byte %8.0q
                                        annualt==6
Iannualt 7
            byte
                    %8.0q
                                        annualt==7
Iloc2 2
             byte
                    %8.0q
                                        loc2==2
_Iloc2_3
            byte
                    %8.0g
                                        loc2==3
_Iloc2_4
                                        loc2==4
             byte
                    %8.0g
_Itype2_2
             byte
                   %8.0q
                                        type2==2
                                        race3==2
_Irace3_2
             byte
                    %8.0g
firstimp
            float %9.0g
```

Sorted by: id site place followup

- . *This data was modified using the stsplit command to create a categorical variable called annualt which separates the data into yearly time intervals and allows for dicrete survival analysis. Also the analysis requires that other variables be created: (A) one to index each patient (B) a binary dependent variable to indicate censorship within the time intervals, and (C) a variable to summarize the pattern of duration dependence.
- . *The data in it's current form has more observations than the final9.dta dataset. Also, the race loc and type variables need to be collapsed as well. codebook race race2 type loc

race
(unlabeled)

· ------

type: numeric (float)

range: [1,6] units: 1

unique values: 6 missing .: 577/11794

tabulation: Freq. Value
9800 1
1207 2
9 3

23 4 164 5 14 6

577 .

```
race2
(unlabeled)
             type: numeric (float)
            range: [1,3]
                                         units: 1
      unique values: 3
                                      missing .: 577/11794
         tabulation: Freq. Value
                   9800 1
                    1403 2
                    14 3
                    577 .
type
(unlabeled)
______
             type: numeric (float)
            range: [1,3]
                                        units: 1
      unique values: 3
                                     missing .: 0/11794
         tabulation: Freq. Value
                   10945 1
                    660 2
                    189 3
.-----
loc
(unlabeled)
             type: numeric (float)
            range: [1,6]
                                         units: 1
      unique values: 6
                                     missing .: 0/11794
         tabulation: Freq. Value 326 1
                    617 2
                    328 3
                   1475 4
                    7722 5
                   1326 6
. /*Code for generating race3, loc2 and type2 variables
> gen race3=1 if race2==1 & race2~=.
```

> codebook race2 race3

```
> replace race3=2 if race2==2 race2==3 & race2~=.
> codebook race2 race3
> save "C:\unzipped\final9Folder\final9b.dta", replace
> gen type2=1 if type==1 & type~=.
> codebook type type2
> replace type2=2 if type==2 type==3 & type~=.
> codebook type type2
> save "C:\unzipped\final9Folder\final9b.dta", replace
> gen loc2=1 if loc==5 & loc~=.
> codebook loc loc2
> replace loc2=2 if loc==2 & loc~=.
> codebook loc loc2
> replace loc2=3 if loc==4|loc==6 & loc~=.
> codebook loc loc2
> replace loc2=4 if loc==1|loc==3 & loc~=.
> codebook loc loc2*/
. codebook annualt
annualt
(unlabeled)
______
                type: numeric (byte)
               range: [0,7]
                                                 units: 1
        unique values: 8
                                             missing .: 0/11794
           tabulation: Freq. Value
                       4368 0
                       3424 1
                       1804 2
                       1119 3
                        638 4
                        304 5
                        121 6
                         16 7
```

. *I need to create another censorship indicator

. codebook _d

d (unlabeled)

type: numeric (byte)

range: [0,1] units: 1

unique values: 2 missing .: 0/11794

tabulation: Freq. Value 11691 0

103 1

. /*gen dfail=_d*/

. codebook dfail

dfail

(unlabeled)

type: numeric (float)

range: [0,1] units: 1

unique values: 2 missing .: 0/11794

tabulation: Freq. Value

11691 0 103 1

- . *I will also need to code a variable to indicate the first record in this dataset "firstimp" and only include this implant for evaluation.
- . *The code used to generate such a variable follows.
- . /*gen firstimp=0
- > by id:gen firstimp=1 if site==site[1]*/
- . list id site place followup annualt firstimp in 1/72

_							L
	id	site	place	followup	annualt	firstimp	
1.	1	22	22jun1993	09jun1994	0	1	
2.	1	23	22jun1993	09jun1994	0	0	
3.	1	25	22jun1993	09jun1994	0	0	
4.	1	26	22jun1993	09jun1994	0	0	
5.	1	27	22jun1993	09jun1994	0	0	
6.	 9	22	 16jan1984	 25may1984	0	 1	

7. 8. 9. 10.	9 9 9 9	22 22 22 22	16jan1984 16jan1984 16jan1984 16jan1984	09aug1984 24sep1984 15nov1984 15jan1985	0 0 0 0	1 1 1 1
11. 12. 13. 14.	9 9 9 9 9	22 22 22 22 22	16jan1984 16jan1984 16jan1984 16jan1984 16jan1984	01may1985 16aug1985 13dec1985 15jan1986 02jun1986	1 1 1 2	1 1 1 1 1
16. 17. 18. 19. 20.	9 9 9 9	22 27 27 27 27	16jan1984 16jan1984 16jan1984 16jan1984 16jan1984	05dec1986 25may1984 09aug1984 24sep1984 15nov1984	2 0 0 0 0	1 0 0 0 0
21. 22. 23. 24. 25.	9 9 9 9 9	27 27 27 27 27	16jan1984 16jan1984 16jan1984 16jan1984 16jan1984	15jan1985 01may1985 16aug1985 13dec1985 15jan1986	0 1 1 1	0 0 0 0
26. 27. 28. 29.	9 9 10 10 10	27 27 22 22 22	16jan1984 16jan1984 16may1990 16may1990	02jun1986 05dec1986 27mar1991 25apr1991 16may1991	2 2 0 0 0	0 0 1 1 1
31. 32. 33. 34. 35.	10 10 10 10 10	22 22 22 22 22 27	16may1990 16may1990 16may1990 16may1990 16may1990	29may1991 25sep1991 08mar1992 06apr1992 27mar1991	1 1 1 1 0	1 1 1 1 0
36. 37. 38. 39.	 10 10 10 10	27 27 27 27 27 27	16may1990 16may1990 16may1990 16may1990 16may1990	25apr1991 16may1991 29may1991 25sep1991 08mar1992	0 0 1 1	0 0 0 0 0
41. 42. 43. 44. 45.	 10 14 16 16	27 30 22 22 22 23	16may1990 29apr1987 01jul1992 01jul1992 01jul1992	06apr1992 13jan1988 01ju11993 10may1994 01ju11993	1 0 0 1 0	0 1 1 1 0
46. 47. 48. 49.	 16 16 16 16 16	23 25 25 26 26	01jul1992 01jul1992 01jul1992 01jul1992 01jul1992	10may1994 01ju11993 10may1994 01ju11993 10may1994	1 0 1 0	0 0 0 0 0

51. 52. 53. 54. 55.	16 16 17 17 17	27 27 22 22 24	01jul1992 01jul1992 12jun1992 12jun1992 12jun1992	01jul1993 10may1994 10dec1992 24dec1992 10dec1992	0 1 0 0	0 0 1 1 0
56. 57. 58. 59.	 17 17 17 17 17	24 25 25 27 27	12jun1992 12jun1992 12jun1992 12jun1992 12jun1992	24dec1992 10dec1992 24dec1992 10dec1992 24dec1992	0 0 0 0 0	0 0 0 0 0
61. 62. 63. 64. 65.	18 18 18 18 20	6 6 6 23	10jan1991 10jan1991 10jan1991 10jan1991 08feb1990	10jan1992 09jan1993 09jan1994 29jun1994 18jun1990	0 1 2 3 0	1 1 1 1 1
66. 67. 68. 69.	 20 20 20 20	23 23 23 23 23 23	08feb1990 08feb1990 08feb1990 08feb1990 08feb1990	18sep1990 21nov1990 08feb1991 03may1991 25oct1991	0 0 0 0 1 1	1 1 1 1 1
71. 72.	 20 20 +	23 23	08feb1990 08feb1990	08feb1992 06apr1992	1 2	1 1 1

. *firstimp indicates implant first records at an implant level.

. tabulate failure annualt

6 13		ann	nualt		
failure	0 +		2 	3 	Total
0	2,684	2,419	1,208	770 4	7,883
Total	2,738	2,442	1,218	774	7,986

		ann	ualt		
failure	4	5	6	7	Total
	+				+
0	453	232	105	12	7,883
1	4	3	1	4	103
	, +				+
Total	457	235	106	16	7,986

- . *(C)Discrete Proportional Odds model.
- . *This is the situation of the single site per patient with multiple time intervals.
- . count if firstimp==1
 3896
- . xi:logit dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1

i.annualt	_Iannualt_0-7	<pre>(naturally coded; _Iannualt_0 omitted)</pre>
i.loc2	_Iloc2_1-4	<pre>(naturally coded; _Iloc2_1 omitted)</pre>
i.type2	_Itype2_1-2	<pre>(naturally coded; _Itype2_1 omitted)</pre>
i.race3	_Irace3_1-2	<pre>(naturally coded; _Irace3_1 omitted)</pre>

note: _Iannualt_6 != 0 predicts failure perfectly
 _Iannualt_6 dropped and 43 obs not used

Iteration 0: log likelihood = -206.7099
Iteration 1: log likelihood = -206.1689
Iteration 2: log likelihood = -196.4683
Iteration 3: log likelihood = -194.11401
Iteration 4: log likelihood = -193.99376
Iteration 5: log likelihood = -193.99212
Iteration 6: log likelihood = -193.99212

Logit estimates

Number of obs =3651 LR chi2(11) =25.44 Prob > chi2=0.0079 Pseudo R2 =0.0615

Log likelihood = -193.99212

Interval]					[95% Conf.
·					-1.91435 -
_Iannualt_2 .4109851	5688591	.4999297	-1.14	0.255	-1.548703
_Iannualt_3 .377068	-1.633965	1.026056	-1.59	0.111	-3.644999
_Iannualt_4 1.017401	9991932	1.028893	-0.97	0.331	-3.015787
_Iannualt_5	1925976	1.0361	-0.19	0.853	-2.223315
_Iannualt_7 4.758813	2.543793	1.130133	2.25	0.024	.3287724
Iloc2_2 2.575134	1.624892	.4848263	3.35	0.001	.6746496
_Iloc2_3 .7865871	0523555	.4280398	-0.12	0.903	8912981
Iloc2_4 2.019995	.964416	.5385706	1.79	0.073	0911628
_Itype2_2 1.438761	.3072857	.577294	0.53	0.595	8241898
_Irace3_2 1.136198	.2383802	.4580788	0.52	0.603	6594378
	-4.479754	.3276953	-13.67	0.000	-5.122025 -

. logit, or

note: _Iannualt_6 != 0 predicts failure perfectly
 _Iannualt_6 dropped and 43 obs not used

Logit estimates

Number of obs =3651 LR chi2(11) = 25.44 Prob > chi2=0.0079 Pseudo R2 =0.0615

Log likelihood = -193.99212

dfail Interval]	•	Std. Err.			[95% Conf.	
_Iannualt_1					.1474376	
_Iannualt_2	.566171	.2830457	-1.14	0.255	.2125234	
_Iannualt_3 1.458003	.1951542	.2002392	-1.59	0.111	.0261214	
_Iannualt_4 2.765996	.3681764	.3788142	-0.97	0.331	.0490072	
_Iannualt_5 6.284713	.8248138	.8545892	-0.19	0.853	.1082496	
_Iannualt_7 116.6074	12.72785	14.38417	2.25	0.024	1.389262	
_Iloc2_2 13.13308	5.077869	2.461885	3.35	0.001	1.963345	
_Iloc2_3 2.195889	.9489914	.4062061	-0.12	0.903	.410123	
_Iloc2_4 7.538287	2.623255	1.412808	1.79	0.073	.912869	
_Itype2_2 4.215471	1.359729	.7849637	0.53	0.595	.4385902	
_Irace3_2 3.114903	1.269192	.5813897	0.52	0.603	.517142	

[.] testparm _Iloc*

- $(1) \quad _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 14.90Prob > chi2 = 0.0019

```
. testparm _Iannualt*
 (1) Iannualt 1 = 0
      _{\rm Iannualt_2} = 0
 (2)
 (3)
      _{\rm Iannualt_3} = 0
 (4) _Iannualt_4 = 0
 (5) _Iannualt_5 = 0
 (6) _Iannualt_7 = 0
           chi2(6) =
                         13.93
         Prob > chi2 =
                          0.0305
. xi:logit dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1, robust
cluster(id)
                  _Iannualt_0-7
i.annualt
                                      (naturally coded; _Iannualt_0 omitted)
i.loc2
                  _Iloc2_1-4
                                      (naturally coded; _Iloc2_1 omitted)
i.type2
                  _Itype2_1-2
                                      (naturally coded; _Itype2_1 omitted)
i.race3
                                      (naturally coded; _Irace3_1 omitted)
                  _Irace3_1-2
note: _Iannualt_6 != 0 predicts failure perfectly
     _Iannualt_6 dropped and 43 obs not used
Iteration 0:
               log pseudo-likelihood = -206.7099
Iteration 1:
               log pseudo-likelihood = -206.1689
Iteration 2:
               log pseudo-likelihood = -196.4683
Iteration 3:
               log pseudo-likelihood = -194.11401
Iteration 4:
               log pseudo-likelihood = -193.99376
Iteration 5:
               log pseudo-likelihood = -193.99212
Iteration 6:
               log pseudo-likelihood = -193.99212
```

Logit estimates

Number of obs = 3651 Wald chi2(11) = 41.31 Prob > chi2 = 0.0000 Pseudo R2 = 0.0615

Log pseudo-likelihood = -193.99212

(standard errors adjusted for clustering on id)

		•		3		
 dfail Interval			z		[95% Conf.	
_Iannualt_1 .0745071	-1.004123				-1.933738	-
_Iannualt_2 .4095044	5688591	.4991743	-1.14	0.254	-1.547223	
_Iannualt_3	-1.633965	1.023105	-1.60	0.110	-3.639214	
_Iannualt_4	9991932	1.029963	-0.97	0.332	-3.017884	
_Iannualt_5 1.839082	1925976	1.03659	-0.19	0.853	-2.224277	
_Iannualt_7 4.658652	2.543793	1.07903	2.36	0.018	.4289335	
_Iloc2_2 2.594409	1.624892	.4946605	3.28	0.001	.6553749	
_Iloc2_3 .7647657	0523555	.4169062	-0.13	0.900	8694767	
_Iloc2_4 2.011393	.964416	.5341816	1.81	0.071	0825607	
_Itype2_2 1.325132	.3072857	.519319	0.59	0.554	7105609	
_Irace3_2 1.153432	.2383802	.4668716	0.51	0.610	6766713	
_cons 3.775601	-4.479754	.3592683	-12.47	0.000	-5.183907	-

. logit, or

note: _Iannualt_6 != 0 predicts failure perfectly
 _Iannualt_6 dropped and 43 obs not used

Logit estimates

Number of obs = 3651 Wald chi2(11) = 41.31 Prob > chi2 = 0.0000 Pseudo R2 = 0.0615

Log pseudo-likelihood = -193.99212

(standard errors adjusted for clustering on id)

dfail Interval]		Robust Std. Err.			[95% Conf.
_Iannualt_1	l				.1446066
_Iannualt_2	.566171	.282618	-1.14	0.254	.2128383
_Iannualt_3	.1951542	.1996631	-1.60	0.110	.026273
_Iannualt_4 2.771803	.3681764	.3792082	-0.97	0.332	.0489046
_Iannualt_5 6.290759	.8248138	.8549939	-0.19	0.853	.1081456
_Iannualt_7 105.4938	12.72785	13.73373	2.36	0.018	1.535619
_Iloc2_2 13.38867	5.077869	2.511822	3.28	0.001	1.925864
_Iloc2_3 2.148491	.9489914	.3956404	-0.13	0.900	.4191709
_Iloc2_4 7.473719	2.623255	1.401295	1.81	0.071	.9207555
_Itype2_2 3.762683	1.359729	.7061333	0.59	0.554	.4913685
_Irace3_2 3.169049	1.269192	.5925495	0.51	0.610	.5083062

[.] testparm _Iloc*

chi2(3) = 14.60Prob > chi2 = 0.0022

 $⁽¹⁾ _{10c2_2} = 0$

 $^{(2) \}quad _{1loc2_3} = 0$

 $⁽³⁾ _{10c2_4} = 0$

. testparm _Iannualt* (1) Iannualt 1 = 0(2) _Iannualt_2 = 0 (3) _Iannualt_3 = 0 (4) _Iannualt_4 = 0 (5) _Iannualt_5 = 0 (6) _Iannualt_7 = 0 chi2(6) = 14.93Prob > chi2 = 0.0208. *Now to evaluate the cloglog function . xi:cloglog dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1 i.annualt __Iannualt_0-7 (naturally coded; _Iannualt_0 omitted) i.loc2 _Iloc2_1-4 (naturally coded; _Iloc2_1 omitted) __IIOC2_I-4 (naturally coded; __IIOC2_I omitted) __Itype2_1-2 (naturally coded; __Itype2_1 omitted) __Irace3_1-2 (naturally coded; __Irace3_1 omitted) i.type2 i.race3 note: _Iannualt_6 != 0 predicts failure perfectly _Iannualt_6 dropped and 43 obs not used Iteration 0: log likelihood = -194.13645Iteration 1: log likelihood = -194.01783log likelihood = -194.01629Iteration 2: Iteration 3: log likelihood = -194.01629 Number of obs = 3651Complementary log-log regression Zero outcomes = 3614 Nonzero outcomes = 37 LR chi2(11)=25.39Log likelihood = -194.01629Prob > chi2=0.0080 ______ dfail | Coef. Std. Err. z P>|z| [95% Conf. Interval] ______ _Iannualt_1 | -.9904265 .4617544 -2.14 0.032 -1.895448 -.0854046 .4126126 0.113 -3.62965 .382684 _Iannualt_4 | -.9926252 1.025086 -0.97 0.333 -3.001757 1.016506 _Iannualt_5 | -.189057 1.030384 -0.18 0.854 -2.208573 1.830459 _Iannualt_7 | 2.475689 1.047728 2.36 0.018 .4221803 4.529197 _Iloc2_2 | 1.605121 .4777364 3.36 0.001 .668775 2.541467

.7913505

_Iloc2_4	.9630951	.5338906	1.80	0.071	0833113	
2.009502						
_Itype2_2	.3194099	.5702439	0.56	0.575	7982476	
1.437067	2252700	4506440	0 50	0 (02	CE17070	
_Irace3_2 1.122548	. 2353/98	.4526449	0.52	0.603	6517879	
	-4.493444	.326922	-13 74	0 000	-5.1342	_
3.852689	1.175111	. 320322	13.71	0.000	3.1312	

- . matrix b=e(b)
- . matrix v=e(V)
- . ereturn post b v
- . ereturn display, eform(exp_b)

Interval]		Std. Err.			[95% Conf.	
dfail	.3714182 .5713866 .1972107 .3706025 .8277393 11.88989	.171504 .2834543 .2018596 .3798994 .8528894 12.45737 2.378393 .4077606	-2.14 -1.13 -1.59 -0.97 -0.18 2.36 3.36 -0.10	0.032 0.259 0.113 0.333	.1502509 .216105 .0265255 .0496997 .1098573 1.525283 1.951845 .4160818	
_Itype2_2 4.208336				0.575		
_Irace3_2 3.072672	1.265389	.572772	0.52	0.603	.5211132	

- (1) [dfail]_Iloc2_2 = 0
- (2) [dfail]_Iloc2_3 = 0
- (3) [dfail]_Iloc2_4 = 0

chi2(3) = 14.97Prob > chi2 = 0.0018

[.] testparm _Iloc*

(1) [dfail] Iannualt 1 = 0(2) [dfail] Iannualt 2 = 0(3) [dfail]_Iannualt_3 = 0 (4) [dfail]_Iannualt_4 = 0 (5) [dfail]_Iannualt_5 = 0 (6) [dfail]_Iannualt_7 = 0 chi2(6) = 14.56Prob > chi2 = 0.0240. xi:cloglog dfail i.annualt i.loc2 i.type2 i.race3 if firstimp==1,robust clust > er(id) i.annualt _Iannualt_0-7 (naturally coded; _Iannualt_0 omitted) _Iloc2_1-4 i.loc2 (naturally coded; _Iloc2_1 omitted) (naturally coded; _Itype2_1 omitted) (naturally coded; _Irace3_1 omitted) i.type2 _Itype2_1-2 _Irace3_1-2 i.race3 note: _Iannualt_6 != 0 predicts failure perfectly _Iannualt_6 dropped and 43 obs not used Iteration 0: log pseudo-likelihood = -194.13645 Iteration 1: log pseudo-likelihood = -194.01783 Iteration 2: log pseudo-likelihood = -194.01629 Iteration 3: log pseudo-likelihood = -194.01629 Number of obs = 3651Complementary log-log regression Zero outcomes =3614 Nonzero outcomes = 37 Wald chi2(11) = 42.50Log pseudo-likelihood = -194.01629 Prob > chi2=0.0000(standard errors adjusted for clustering on id) Robust Coef. Std. Err. z P>|z| [95% Conf. dfail Interval] .0584745 _Iannualt_2 | -.5596892 .4964257 -1.13 0.260 -1.532666 .4132874 _Iannualt_3 | -1.623483 1.019574 -1.59 0.111 -3.621812 .3748463 _Iannualt_4 | -.9926252 1.024684 -0.97 0.333 -3.000968 1.015718

. testparm _Iannualt*

1.835679

2.475689	1.001414	2.47	0.013	.5129531	
1.605121	.4904733	3.27	0.001	.643811	
0427614	.4182068	-0.10	0.919	8624317	
.9630951	.5319986	1.81	0.070	079603	
.3194099	.5182746	0.62	0.538	6963897	
.2353798	.4624613	0.51	0.611	6710277	
-4.493444	.3612863	-12.44	0.000	-5.201552	-
	1.605121 0427614 .9630951 .3194099 .2353798	1.605121 .4904733 0427614 .4182068 .9630951 .5319986 .3194099 .5182746 .2353798 .4624613	1.605121 .4904733 3.27 0427614 .4182068 -0.10 .9630951 .5319986 1.81 .3194099 .5182746 0.62 .2353798 .4624613 0.51	1.605121 .4904733 3.27 0.001 0427614 .4182068 -0.10 0.919 .9630951 .5319986 1.81 0.070 .3194099 .5182746 0.62 0.538 .2353798 .4624613 0.51 0.611	1.605121 .4904733 3.27 0.001 .643811 0427614 .4182068 -0.10 0.919 8624317 .9630951 .5319986 1.81 0.070 079603 .3194099 .5182746 0.62 0.538 6963897 .2353798 .4624613 0.51 0.611 6710277

[.] matrix b=e(b)

. ereturn display, eform(exp_b)

Interval]		Std. Err.			[95% Conf.	_
dfail _Iannualt_1 .9432023	.3714182	.1766073	-2.08	0.037	.1462587	
_Iannualt_2 1.511779	.5713866	.283651	-1.13	0.260	.2159592	
_Iannualt_3 1.454768	.1972107	.2010709	-1.59	0.111	.0267342	
_Iannualt_4 2.761344	.3706025	.3797503	-0.97	0.333	.0497389	
_Iannualt_5 6.269392	.8277393	.8550942	-0.18	0.855	.1092853	
_Iannualt_7 84.64146	11.88989	11.90671	2.47	0.013	1.670216	
_Iloc2_2 13.01928	4.978462	2.441803	3.27	0.001	1.903722	
_Iloc2_3 2.174739	.9581399	.4007006	-0.10	0.919	.4221343	
Iloc2_4 7.431987	2.619792	1.393726	1.81	0.070	.9234829	
_Itype2_2 3.800792	1.376315	.7133093	0.62	0.538	.4983814	
_Irace3_2 3.132362	1.265389	.5851935	0.51	0.611	.511183	_

[.] matrix v=e(V)

[.] ereturn post b v

```
(1) [dfail] Iloc2 2 = 0
 (2) [dfail] Iloc2 3 = 0
 (3) [dfail]_Iloc2_4 = 0
       chi2(3) = 14.61
Prob > chi2 = 0.0022
. testparm _Iannualt*
( 1) [dfail]_Iannualt_1 = 0
 ( 2) [dfail]_Iannualt_2 = 0
(3) [dfail]_Iannualt_3 = 0
(4) [dfail]_Iannualt_4 = 0
 ( 5) [dfail]_Iannualt_5 = 0
 (6) [dfail]_Iannualt_7 = 0
         chi2(6) = 15.71
       Prob > chi2 = 0.0154
. *Next I will evaluate the situation of multiple sites per patient and
multiple time intervals. This will be a Discrete Proportional Odds model.
. *(D) Multiple sites per person and multiple time intervals
. *Discrete Proportional Odds.
. xi:logit dfail i.annualt i.loc2 i.type2 i.race3
              _Iannualt_0-7 (naturally coded; _Iannualt_0 omitted)
i.annualt
              _Iloc2_1-4
                                 (naturally coded; _Iloc2_1 omitted)
i.loc2
              _Itype2_1-2
                                (naturally coded; _Itype2_1 omitted)
i.type2
i.race3
               _Irace3_1-2
                                 (naturally coded; _Irace3_1 omitted)
Iteration 0:
             log likelihood = -580.95655
Iteration 1:
             log\ likelihood = -575.74007
Iteration 2:
             log\ likelihood = -555.16986
Iteration 3:
           log\ likelihood = -547.71192
Iteration 4: log likelihood = -546.98009
Iteration 5:
             log\ likelihood = -546.97555
Iteration 6: log likelihood = -546.97555
                                            Number of obs =11217
Logit estimates
                                            LR chi2(12) = 67.96
                                            Prob > chi2] = 0.0000
Log likelihood = -546.97555
                                            Pseudo R2 = 0.0585
     dfail
                Coef. Std. Err. z  P>|z|  [95% Conf.
Interval]
______
.105861
Iannualt 2 | -.870447 .3622894 -2.40 0.016 -1.580521 -
.1603728
```

. testparm _Iloc*

_Iannualt_3 .0838952	-1.104999	.5209809	-2.12	0.034	-2.126103	-
_Iannualt_4 .5014603	5233748	.5228846	-1.00	0.317	-1.54821	
_Iannualt_5 1.125283	0529839	.6011675	-0.09	0.930	-1.23125	
_Iannualt_6 1.670878	3296137	1.020678	-0.32	0.747	-2.330105	
_Iannualt_7 4.533359	3.322425	.6178347	5.38	0.000	2.111491	
_Iloc2_2 2.140351	1.547903	.3022753	5.12	0.000	.9554539	
_Iloc2_3 .8317849	.3409464	.2504324	1.36	0.173	1498922	
_Iloc2_4 1.876737	1.221204	.3344616	3.65	0.000	.5656716	
_Itype2_2 1.071533	.3562401	.3649522	0.98	0.329	3590532	
_Irace3_2 1.07951	.5815332	.2540745	2.29	0.022	.0835563	
_cons 4.451357	-4.830381	.1933834	-24.98	0.000	-5.209406	-

. logit,or

Logit estimates

Log likelihood = -546.97555

Number of obs =11217 LR chi2(12) =67.96 Prob > chi2 = 0.0000 Pseudo R2 =0.0585

dfail Interval]	•				[95% Conf.	
	+ .5495095				.3356798	
	.4187643	.1517139	-2.40	0.016	.2058678	
_Iannualt_3 .9195276	.3312112	.1725547	-2.12	0.034	.1193013	
_Iannualt_4 1.651131	.5925176	.3098183	-1.00	0.317	.2126283	
_Iannualt_5 3.081088	.9483953	.5701444	-0.09	0.930	.2919273	
_Iannualt_6 5.316834	.7192015	.734073	-0.32	0.747	.0972855	
93.07063	27.7275					
_Iloc2_2 8.502425	4.701599	1.421177	5.12	0.000	2.59985	
_Iloc2_3 2.297416	1.406278	.3521775	1.36	0.173	.8608008	

```
_Iloc2_4 | 3.39127 1.13425 3.65 0.000
                                                      1.76063
6.532157
               1.42795 .5211337 0.98
  _Itype2_2
                                            0.329
                                                      .6983372
2.919853
  _Irace3_2 |
             1.788779 .4544831
                                     2.29 0.022
                                                      1.087146
2.943237
              ______
. testparm _Iloc*
(1) _{10c2_2} = 0
(2) _Iloc2_3 = 0
(3) _Iloc2_4 = 0
          chi2(3) = 32.63
        Prob > chi2 = 0.0000
. testparm _Iannualt*
(1) _Iannualt_1 = 0
(2) _Iannualt_2 = 0
(3) _Iannualt_3 = 0
(4) _Iannualt_4 = 0
(5) _Iannualt_5 = 0
( 6) _Iannualt_6 = 0
(7) _Iannualt_7 = 0
          chi2(7) =
                       47.32
        Prob > chi2 =
                     0.0000
. *Next I will incorporate the robust variance
. xi:logit dfail i.annualt i.loc2 i.type2 i.race3, robust cluster(id)
               _Iannualt_0-7 (naturally coded; _Iannualt_0 omitted)
i.annualt
               _Iloc2_1-4
                                   (naturally coded; _Iloc2_1 omitted)
(naturally coded; _Itype2_1 omitted)
i.loc2
                _Itype2_1-2
i.type2
                                   (naturally coded; _Irace3_1 omitted)
i.race3
                _Irace3_1-2
Iteration 0:
             log pseudo-likelihood = -580.95655
Iteration 1:
             log pseudo-likelihood = -575.74007
Iteration 2:
             log pseudo-likelihood = -555.16986
Iteration 3:
             log pseudo-likelihood = -547.71192
Iteration 4:
             log pseudo-likelihood = -546.98009
Iteration 5:
             log pseudo-likelihood = -546.97555
```

log pseudo-likelihood = -546.97555

Iteration 6:

Logit estimates

Number of obs = 11217 Wald chi2(12)=45.93 Prob > chi2 =0.0000 Pseudo R2 =0.0585

Log pseudo-likelihood = -546.97555

(standard errors adjusted for clustering on id)

 dfail Interval					[95% Conf.
_Iannualt_1 .149898					-1.347356
_Iannualt_2 .0656985	870447	.4105935	-2.12	0.034	-1.675195 -
_Iannualt_3 .1847002	-1.104999	.6580218	-1.68	0.093	-2.394698
_Iannualt_4 1.06252	5233748	.8091448	-0.65	0.518	-2.109269
_Iannualt_5 1.464452	0529839	.7742164	-0.07	0.945	-1.57042
_Iannualt_6 1.70134	3296137	1.03622	-0.32	0.750	-2.360568
_Iannualt_7 5.424764	3.322425	1.072642	3.10	0.002	1.220086
_Iloc2_2 2.33691	1.547903	.4025621	3.85	0.000	.7588954
_Iloc2_3 .8257454	.3409464	.247351	1.38	0.168	1438527
_Iloc2_4 2.003347	1.221204	.3990595	3.06	0.002	.4390621
_Itype2_2 1.228765	.3562401	.4451742	0.80	0.424	5162852
_Irace3_2 1.365897	.5815332	.4001928	1.45	0.146	2028302
_cons 4.336254	-4.830381	.2521104	-19.16	0.000	-5.324508 -

. logit, or Logit estimates

Log pseudo-likelihood = -546.97555

Number of obs =11217 Wald chi2(12) = 45.93Prob > chi2 = 0.0000Pseudo R2 = 0.0585

(standard errors adjusted for clustering on id)

dfail Interval]			z		[95% Conf.
_Iannualt_1 1.161716	.5495095				.2599265
_Iannualt_2 .9364131	.4187643	.1719419	-2.12	0.034	.1872716
_Iannualt_3	.3312112	.2179442	-1.68	0.093	.0912002
_Iannualt_4 2.893653	.5925176	.4794325	-0.65	0.518	.1213266
_Iannualt_5 4.325174	.9483953	.7342632	-0.07	0.945	.2079578
_Iannualt_6 5.481289	.7192015	.745251	-0.32	0.750	.0943666
_Iannualt_7 226.9577	27.7275	29.74168	3.10	0.002	3.387478
_Iloc2_2 10.34921	4.701599	1.892686	3.85	0.000	2.135916
2.283582	1.406278			0.168	.8660153
_Iloc2_4 7.413826	3.39127	1.353318	3.06	0.002	1.551252
_Itype2_2 3.417008	1.42795	.6356866	0.80	0.424	.5967332
_Irace3_2 3.919236	1.788779	.7158564	1.45	0.146	.8164168

chi2(3) = 15.42Prob > chi2 = 0.0015

[.] testparm _Iloc*

⁽¹⁾ _Iloc2_2 = 0 (2) _Iloc2_3 = 0 (3) _Iloc2_4 = 0

```
. testparm _Iannualt*
 (1) Iannualt 1 = 0
 (2) _Iannualt_2 = 0
 (3) _Iannualt_3 = 0
 (4) _Iannualt_4 = 0
 (5) _Iannualt_5 = 0
 (6) _Iannualt_6 = 0
 (7) _Iannualt_7 = 0
          chi2(7) = 19.39
        Prob > chi2 = 0.0070
. *Now we will analyze the data using GEE for the Discrete Proportional Odds
an
> d Cloglog Models.
. set matsize 110
. xi:xtgee dfail i.annualt i.loc2 i.type2 i.race3, family(bin) link(logit)
> (exc) i(id) eform
               _Iannualt_0-7
                                  (naturally coded; _Iannualt_0 omitted)
i.annualt
                _Iloc2_1-4
i.loc2
                                  (naturally coded; _Iloc2_1 omitted)
                _Itype2_1-2
i.type2
                                  (naturally coded; _Itype2_1 omitted)
                _Irace3_1-2
i.race3
                                  (naturally coded; _Irace3_1 omitted)
Iteration 1: tolerance = .43971565
Iteration 2: tolerance = .03868157
Iteration 3: tolerance = .01028691
Iteration 4: tolerance = .0022018
Iteration 5: tolerance = .00046132
Iteration 6: tolerance = .00009796
Iteration 7: tolerance = .00002114
Iteration 8: tolerance = 4.619e-06
Iteration 9: tolerance = 1.018e-06
Iteration 10: tolerance = 2.257e-07
GEE population-averaged model
                                            Number of obs = 11217
Group variable: id
                                            Number of groups = 732
Link: logit
                                            Obs per group: min = 1
Family: binomial
                                                       avg = 15.3
Correlation: exchangeable
                                                       max = 106
                                            Wald chi2(12)=64.41
Scale parameter:1
                                            Prob > chi2 = 0.0000
______
      dfail | Odds Ratio Std. Err. z  P>|z|  [95% Conf.
Interval]
 _Iannualt_1 | .700332 .16206 -1.54 0.124
                                                    .4449714
1.102239
_Iannualt_2 | .6281056 .1936827 -1.51 0.132 .3432069
1.149501
```

```
_Iannualt_3 | .5517458 .2289641 -1.43 0.152 .2446282
1.244433
Iannualt 4 | .8111113 .3673954 -0.46
                                        0.644 .3338306
1.970765
_Iannualt_5 | 1.361996 .6852592
                                 0.61
                                        0.539
                                                .5080561
3.651234
_Iannualt_6 | 1.21016 .9466859
                                 0.24
                                        0.807
                                                .2611943
5.60689
_Iannualt_7 | 28.66883
                       17.4287
                                 5.52
                                        0.000
                                                8.708378
94.38058
   _Iloc2_2 | 4.055249 1.348378
                                 4.21
                                        0.000
                                                2.113448
7.781146
   _Iloc2_3 | 1.382045 .3409234 1.31
                                        0.190
                                               .8522114
2.241284
   _Iloc2_4 | 3.077276 1.122668 3.08
                                        0.002 1.505313
6.290805
  _Itype2_2 | 1.346909 .5703833
                                 0.70
                                        0.482
                                               .5873202
3.088883
  _Irace3_2 | 1.930223 .5635115
                                 2.25 0.024
                                               1.089198
3.420647
```

. testparm _Iloc*

```
(1) _{10c2_2} = 0
```

$$chi2(3) = 21.17$$

Prob > $chi2 = 0.0001$

. testparm _Iannualt*

- (1) _Iannualt_1 = 0
- (2) _Iannualt_2 = 0
- (3) _Iannualt_3 = 0
- (4) _Iannualt_4 = 0
- (5) _Iannualt_5 = 0
- (6) _Iannualt_6 = 0
- (7) _Iannualt_7 = 0

chi2(7) = 39.58Prob > chi2 = 0.0000

. xi:xtgee dfail i.annualt i.loc2 i.type2 i.race3, family(bin) link(logit)
corr

```
> (exc) i(id) eform robust
```

 $^{(2) = 110}c2_3 = 0$

 $⁽³⁾ _{10c2_4} = 0$

Iteration 1: tolerance = .43971565
Iteration 2: tolerance = .03868157
Iteration 3: tolerance = .01028691
Iteration 4: tolerance = .0022018
Iteration 5: tolerance = .00046132
Iteration 6: tolerance = .00009796
Iteration 7: tolerance = .00002114
Iteration 8: tolerance = 4.619e-06
Iteration 9: tolerance = 1.018e-06
Iteration 10: tolerance = 2.257e-07

GEE population-averaged model

Group variable: id Link: logit Family: binomial

Correlation: exchangeable

Scale parameter: 1

Number of obs =11217

Number of groups = 732 Obs per group: min = 1

avg = 15.3

max = 106

Wald chi2(12)=42.92Prob > chi2 = 0.0000

(standard errors adjusted for clustering on id)

dfail Interval]	Odds Ratio	Semi-robust Std. Err.			[95% Conf.
_Iannualt_1 1.28342	!				.3821548
_Iannualt_2 1.131137	.6281056	.1885218	-1.55	0.121	.3487788
_Iannualt_3 1.266768	.5517458	.2339718	-1.40	0.161	.240315
_Iannualt_4 2.244713	.8111113	.4212591	-0.40	0.687	.2930894
_Iannualt_5 4.065625	1.361996	.7599633	0.55	0.580	.4562723
_Iannualt_6 3.940328	1.21016	.7288949	0.32	0.751	.3716665
_Iannualt_7 221.2388	28.66883	29.88974	3.22	0.001	3.714998
_Iloc2_2 8.01136	4.055249	1.408705	4.03	0.000	2.052716
_Iloc2_3 2.054473	1.382045	.2795556	1.60	0.110	.929702
_Iloc2_4 6.473853	3.077276	1.167701	2.96	0.003	1.46275
_Itype2_2 3.380193					
_Irace3_2 4.261568	1.930223	.7799835	1.63	0.104	.8742698

```
. testparm _Iloc*
 (1)
      11oc2 2 = 0
 (2)
      11oc2 3 = 0
 (3) _{10c2_4} = 0
           chi2(3) =
                       16.60
        Prob > chi2 =
                         0.0009
. testparm _Iannualt*
 ( 1) _Iannualt_1 = 0
      _{\rm Iannualt_2} = 0
 (2)
 (3) _Iannualt_3 = 0
 (4) _Iannualt_4 = 0
 (5) _Iannualt_5 = 0
 ( 6) _Iannualt_6 = 0
 (7) _Iannualt_7 = 0
           chi2(7) =
                        16.46
        Prob > chi2 =
                         0.0212
. *Now for the Cloglog evaluation of GEE
. xi:xtcloglog dfail i.annualt i.loc2 i.type2 i.race3, pa i(id)
                 _Iannualt_0-7
                                      (naturally coded; _Iannualt_0 omitted)
i.annualt
i.loc2
                  _Iloc2_1-4
                                      (naturally coded; _Iloc2_1 omitted)
                 _Itype2_1-2
                                      (naturally coded; _Itype2_1 omitted)
i.type2
i.race3
                 _Irace3_1-2
                                      (naturally coded; _Irace3_1 omitted)
Iteration 1: tolerance = .43576416
Iteration 2: tolerance = .04073009
Iteration 3: tolerance = .01053104
Iteration 4: tolerance = .0022568
Iteration 5: tolerance = .00047061
Iteration 6: tolerance = .0000994
Iteration 7: tolerance = .00002126
Iteration 8: tolerance = 4.598e-06
Iteration 9: tolerance = 1.002e-06
Iteration 10: tolerance = 2.196e-07
```

GEE population-averaged model

Group variable: id Link: cloglog Family: binomial

Correlation: exchangeable

Scale parameter: 1

Number of obs =11217 Number of groups = 732 Obs per group: min = 1

avg = 15.3 max = 106

Wald chi2(12) =72.47 Prob > chi2=0.0000

dfail Interval]					[95% Conf.	
_Iannualt_1 .1005358					800052	
_Iannualt_2 .1405838	4604452	.306653	-1.50	0.133	-1.061474	
_Iannualt_3 .2202047	5895319	.4131385	-1.43	0.154	-1.399268	
_Iannualt_4 .6726269	2111567	.4509183	-0.47	0.640	-1.09494	
_Iannualt_5 1.283973	.3063307	.4988064	0.61	0.539	6713119	
_Iannualt_6 1.70584	.1820401	.7774632	0.23	0.815	-1.34176	
_Iannualt_7 4.218545	3.181051	.5293436	6.01	0.000	2.143557	
_Iloc2_2 2.037829	1.394244	.3283655	4.25	0.000	.7506597	
_Iloc2_3	.3333388	.2432716	1.37	0.171	1434647	
_Iloc2_4 1.831599	1.124071	.3609903	3.11	0.002	.416543	
_Itype2_2 1.148796	.3553732	.4048151	0.88	0.380	4380498	
	.6282387	.2877997	2.18	0.029	.0641617	
	-4.772188	.2105216	-22.67	0.000	-5.184803 -	

[.] testparm _Iloc*

- $(1) _{10c2_2} = 0$
- $(2) = 11002_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 21.48Prob > chi2 = 0.0001

```
. testparm _Iannualt*
```

- . matrix b=e(b)
- . matrix v=e(V)
- . ereturn post b v
- . ereturn display, eform(exp_b)

 	exp_b	Std. Err.	z	P> z	[95% Conf.
_Iannualt_1 1.105763	.7048586	.1619384	-1.52	0.128	.4493056
_Iannualt_2 1.150945	.6310027	.1934989	-1.50	0.133	.3459455
_Iannualt_3 1.246332	.5545868	.2291212	-1.43	0.154	.2467774
_Iannualt_4 1.959378	.8096472	.3650847	-0.47	0.640	.3345596
_Iannualt_5 3.610959	1.358432	.6775944	0.61	0.539	.5110377
_Iannualt_6 5.506009	1.199662	.9326933	0.23	0.815	.2613853
_Iannualt_7 67.9346				0.000	8.52972
_Iloc2_2 7.67393				0.000	
_Iloc2_3 2.248228				0.171	
_Iloc2_4 6.243862				0.002	
_Itype2_2 3.154393				0.380	
_Irace3_2 3.294702	1.874306	.5394248	2.18	0.029	1.066265

```
. xi:xtcloglog dfail i.annualt i.loc2 i.type2 i.race3, pa robust i(id)
i.annualt __Iannualt_0-7 (naturally coded; _Iannualt_0 omitted)
                 _Iloc2_1-4
i.loc2
                                    (naturally coded; Iloc2 1 omitted)
i.type2
                 _Itype2_1-2
                                   (naturally coded; _Itype2_1 omitted)
                                    (naturally coded; _Irace3_1 omitted)
i.race3
                 _Irace3_1-2
Iteration 1: tolerance = .43576416
Iteration 2: tolerance = .04073009
Iteration 3: tolerance = .01053104
Iteration 4: tolerance = .0022568
Iteration 5: tolerance = .00047061
Iteration 6: tolerance = .0000994
Iteration 7: tolerance = .00002126
Iteration 8: tolerance = 4.598e-06
Iteration 9: tolerance = 1.002e-06
Iteration 10: tolerance = 2.196e-07
```

GEE population-averaged model

Group variable: id Link: cloglog

Family: binomial Correlation: exchangeable

Scale parameter: 1

Number of obs =11217Number of groups =732

Obs per group: min =1 avg = 15.3

max = 106

Wald chi2(12) = 45.89Prob > chi2=0.0000

(standard errors adjusted for clustering on id)

 dfail Interval	Coef.	Semi-robust Std. Err.			[95% Conf.	
_Iannualt_1 .2522689	3497581	.3071623	-1.14	0.255	9517851	
_Iannualt_2	4604452	.2987017	-1.54	0.123	-1.04589	
_Iannualt_3 .240258	5895319	.42337	-1.39	0.164	-1.419322	
_Iannualt_4 .8018536	2111567	.5168515	-0.41	0.683	-1.224167	
_Iannualt_5 1.392649	.3063307	.554254	0.55	0.580	7799872	
_Iannualt_6 1.355324	.1820401	.5986252	0.30	0.761	9912436	
_Iannualt_7 4.921492	3.181051	.8879963	3.58	0.000	1.44061	
_Iloc2_2 2.067766	1.394244	.34364	4.06	0.000	.7207223	
_Iloc2_3 .7249087	.3333388	.1997842	1.67	0.095	058231	
_Iloc2_4 1.861316	1.124071	.3761522	2.99	0.003	.3868262	

```
_Itype2_2 | .3553732 .4426169 0.80 0.422 -.51214
1.222886
  _Irace3_2 | .6282387 .4001439 1.57 0.116 -.1560289
1.412506
  _cons | -4.772188 .2395996 -19.92 0.000 -5.241795 -
4.302581
```

- . testparm _Iloc*
- $(1) _{10c2_2} = 0$
- (2) _Iloc2_3 = 0 (3) _Iloc2_4 = 0

$$chi2(3) = 16.85$$

Prob > $chi2 = 0.0008$

- . testparm _Iannualt*
- (1) _Iannualt_1 = 0
- (2) _Iannualt_2 = 0
- (3) _Iannualt_3 = 0
- (4) _Iannualt_4 = 0
- (5) _Iannualt_5 = 0
- (6) _Iannualt_6 = 0
 (7) _Iannualt_7 = 0

$$chi2(7) = 19.32$$

Prob > $chi2 = 0.0072$

- . matrix b=e(b)
- . matrix v=e(V)
- . ereturn post b v
- . ereturn display, eform(exp_b)

 Interval	1	Std. Err.	z	P> z	[95% Conf.
_Iannualt_1 1.286942		.216506		0.255	.3860513
_Iannualt_2 1.133148	.6310027	.1884816	-1.54	0.123	.3513791
_Iannualt_3 1.271577	.5545868	.2347954	-1.39	0.164	.241878
_Iannualt_4 2.22967	.8096472	.4184674	-0.41	0.683	.2940025
_Iannualt_5 4.025498	1.358432	.7529162	0.55	0.580	.4584119
_Iannualt_6 3.878017	1.199662	.718148	0.30	0.761	.3711149

```
_Iannualt_7 | 24.07204 21.37588 3.58 0.000 4.223272
137.2071
   Iloc2 2 | 4.031927 1.385531 4.06
                                        0.000
                                               2.055918
7.907141
   _Iloc2_3 |
              1.39562 .2788229
                                 1.67
                                        0.095
                                                 .943432
2.064543
   _Iloc2_4 | 3.077356 1.157554
                                 2.99
                                        0.003
                                                 1.472301
6.432194
  _Itype2_2 | 1.426713 .6314873
                                 0.80
                                       0.422
                                                 .5992119
3.396979
  _Irace3_2
            1.874306
                       .7499923 1.57
                                       0.116
                                                 .8555345
4.106234
```

. *The next situation to evaluate involves the single site per patient with continuous time. This would involve the Cox model and I will now evaluate this on the final9.dta dataset.

- . /*save "C:\unzipped\final9Folder\final9b.dta", replace
- > clear*/
- . use "C:\unzipped\final9Folder\final9.dta", clear
- . desc

```
Contains data from C:\unzipped\final9Folder\final9.dta
  obs: 7,986
```

vars: 121

size: 4,016,958 (68.1% of memory free)

- . $^{\star}(\text{E})\text{Single}$ site per patient and continuous time Cox Proportional Hazards Model
- . count if firstimp==1
 2609

```
. xi: stcox i.loc2 i.type2 i.race3 if firstimp==1
```

i.loc2 __Iloc2_1-4 (naturally coded; __Iloc2_1 omitted)
i.type2 __Itype2_1-2 (naturally coded; __Itype2_1 omitted)
i.race3 __Irace3_1-2 (naturally coded; __Irace3_1 omitted)

failure _d: failure

analysis time _t: (followup-origin)/365.25

origin: time place
 id: newid2

Iteration 0: log likelihood = -222.01536
Iteration 1: log likelihood = -219.82572
Iteration 2: log likelihood = -217.08173
Iteration 3: log likelihood = -217.02842
Iteration 4: log likelihood = -217.02835
Refining estimates:

Iteration 0: $\log likelihood = -217.02835$

Cox regression -- Breslow method for ties

No. of subjects = 732No. of failures = 37 Time at risk = 1582.020534 Number of obs=2483

Log likelihood =-217.02835

LR chi2(5) = 9.97Prob > chi2=0.0760

_t Interval]	Haz. Ratio	Std. Err.	Z	P> z	[95% Conf.
_Iloc2_2 10.23098	4.035504	1.915437	2.94	0.003	1.591762
_Iloc2_3 2.019357	.8784375	.3730693	-0.31	0.760	.3821278
_Iloc2_4 5.800642	2.045869	1.087823	1.35	0.178	.7215719
_Itype2_2 4.919389	1.583092	.9157907	0.79	0.427	.5094496
_Irace3_2 3.181332	1.312117	.5929124	0.60	0.548	.5411727

- . testparm _Iloc*
- $(1) _{\text{lloc2}_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 11.66Prob > chi2 = 0.0086

. xi: stcox i.loc2 i.type2 i.race3 if firstimp==1, robust cluster(id) _Iloc2_1-4 (naturally coded; _Iloc2_1 omitted) i.loc2 _Itype2_1-2 (naturally coded; _Itype2_1 omitted)
(naturally coded; _Irace3_1 omitted) i.type2 _Irace3_1-2 i.race3

failure _d: failure

analysis time _t: (followup-origin)/365.25

origin: time place id: newid2

Iteration 0: log pseudo-likelihood = -222.01536 Iteration 1: log pseudo-likelihood = -219.82572 Iteration 2: log pseudo-likelihood = -217.08173 Iteration 3: log pseudo-likelihood = -217.02842 Iteration 4: log pseudo-likelihood = -217.02835 Refining estimates:

Iteration 0: log pseudo-likelihood = -217.02835

Cox regression -- Breslow method for ties

No. of subjects = 732Number of obs = 2483No. of failures = 37

Time at risk = 1582.020534

Wald chi2(5) = 11.81Log pseudo-likelihood = -217.02835 Prob > chi2 = 0.0376

(standard errors adjusted for clustering on id)

_t Interval]	'	Robust Std. Err.	Z	P> z	[95% Conf.
_Iloc2_2 10.26524	4.035504	1.92232	2.93	0.003	1.58645
_Iloc2_3 1.948797	.8784375	.3571286	-0.32	0.750	.3959634
_Iloc2_4 5.785204	2.045869	1.085041	1.35	0.177	.7234974
_Itype2_2 4.269817	1.583092	.8014075	0.91	0.364	.5869528
_Irace3_2 3.215619	1.312117	.600089	0.59	0.553	.5354023

- . testparm _Iloc*
- $(1) _{10c2_2} = 0$
- $(2) = 110c2_3 = 0$
- $(3) _{10c2_4} = 0$

chi2(3) = 11.58Prob > chi2 = 0.0090

- . *The next situation to evaluate involves multiple sites per patient with continuous time. This also would involve the Cox model.
- . *(F) Multiple sites per patient and continuous time Cox Proportional Hazards Model
- . xi: stcox i.loc2 i.type2 i.race3

```
_Iloc2_1-4
i.loc2
                                     (naturally coded; _Iloc2_1 omitted)
                _Itype2_1-2
_Irace3_1-2
i.type2
                                     (naturally coded; _Itype2_1 omitted)
                                     (naturally coded; _Irace3_1 omitted)
i.race3
```

failure _d: failure

analysis time _t: (followup-origin)/365.25

origin: time place id: newid2

Iteration 0: log likelihood = -707.69229 Iteration 1: log likelihood = -697.89642 Iteration 2: log likelihood = -694.96837 Iteration 3: log likelihood = -694.92372 Iteration 4: log likelihood = -694.92369

Refining estimates:

Iteration 0: log likelihood = -694.92369

Cox regression -- Breslow method for ties

No. of subjects = 2174 Number of obs = 7633

No. of failures =102

Time at risk = 4694.20397

LR chi2(5) = 25.54Log likelihood = -694.92369 Prob > chi2 = 0.0001

_t	Haz. Ratio	Std. Err.	Z	P> z	[95% Conf.
<pre>Interval]</pre>					
	+ 3.847636	1.144967	4.53	0.000	2.147318
Iloc2_3 2.099299	1.294654	.3192834	1.05	0.295	.7984228
_Iloc2_4 5.030139	2.635487	.8691616	2.94	0.003	1.380834
_Itype2_2 3.147386	1.542095	.5613253	1.19	0.234	.7555655
_Irace3_2 2.936045	1.796049	.4503715	2.34	0.020	1.098686

[.] testparm _Iloc*

- $(1) _{10c2_2} = 0$
- $(2) _{10c2_3} = 0$
- $(3) = 110c2_4 = 0$

chi2(3) = 24.44Prob > chi2 = 0.0000

. xi: stcox i.loc2 i.type2 i.race3 , robust cluster(id)

i.loc2 __Iloc2_1-4 (naturally coded; _Iloc2_1 omitted)
i.type2 __Itype2_1-2 (naturally coded; _Itype2_1 omitted)
i.race3 __Irace3_1-2 (naturally coded; _Irace3_1 omitted)

failure _d: failure

analysis time _t: (followup-origin)/365.25

origin: time place
 id: newid2

Iteration 0: log pseudo-likelihood = -707.69229
Iteration 1: log pseudo-likelihood = -697.89642
Iteration 2: log pseudo-likelihood = -694.96837
Iteration 3: log pseudo-likelihood = -694.92372
Iteration 4: log pseudo-likelihood = -694.92369

Refining estimates:

Iteration 0: log pseudo-likelihood = -694.92369

Cox regression -- Breslow method for ties

Number of obs =7633No. of subjects = 2174

No. of failures = 102 Time at risk = 4694.20397

Wald chi2(5) = 16.40Log pseudo-likelihood = -694.92369 Prob > chi2 = 0.0058

(standard erro	ors adjusted fo	clustering	on id)
----------------	-----------------	------------	--------

_t Interval]	Haz. Ratio	Robust Std. Err.	z	P> z	[95% Conf.
_Iloc2_2 8.495672	3.847636	1.55498	3.33	0.001	1.74257
_Iloc2_3 2.062592	1.294654	.3076313	1.09	0.277	.812632
_Iloc2_4 5.675859	2.635487	1.031562	2.48	0.013	1.223743
_Itype2_2 3.615484	1.542095	.6704176	1.00	0.319	.6577421
_Irace3_2 3.844902	1.796049	.697502	1.51	0.132	.8389788

- $(1) _{10c2_2} = 0$
- (2) _Iloc2_3 = 0 (3) _Iloc2_4 = 0

chi2(3) = 11.34Prob > chi2 = 0.0100

end of do-file

[.] testparm _Iloc*

Log file for Frailty Model 11 and data in Table 16

```
. xi:stcox i.loc2 i.type2 i.race3, shared(id)
               _Iloc2_1-4 (naturally coded; _Iloc2_1 omitted)
i.loc2
              _Itype2_1-2
i.type2
                                 (naturally coded; _Itype2_1 omitted)
               _Irace3_1-2
                                 (naturally coded; _Irace3_1 omitted)
i.race3
       failure _d: failure
  analysis time _t: (followup-origin)/365.25
           origin: time place
Fitting comparison Cox model:
Estimating frailty variance:
Iteration 0:
            log profile likelihood = -690.08355
Iteration 1:
            log profile likelihood = -685.99749
            log profile likelihood = -685.99734
Iteration 2:
Iteration 3:
            log profile likelihood = -685.99734
Fitting final Cox model:
Iteration 0: log likelihood = -988.28436
Iteration 1: log likelihood = -873.39136
Iteration 2: log likelihood = -742.52786
Iteration 3: log likelihood = -696.17
Iteration 4: log likelihood = -687.09208
Iteration 5: log likelihood = -686.04859
Iteration 6: log likelihood = -685.99776
Iteration 7: log likelihood = -685.99734
Iteration 8: log likelihood = -685.99734
Refining estimates:
Iteration 0: log likelihood = -685.99734
Cox regression -- Breslow method for ties
                                         Number of obs = 7633
Gamma shared frailty
                                          Number of groups = 732
Group variable: id
No. of subjects = 7633
                                          Obs per group: min = 1
No. of failures = 102
                                          avg = 10.4276
Time at risk = 14366.74606
                                          max = 95
                                          Wald chi2(5) = 18.75
                                         Prob > chi2 = 0.0021
Log likelihood = -685.99734
_____
        _{\rm t} | Haz. Ratio Std. Err. z P>|z| [95% Conf.
   _Iloc2_2 | 5.759403 4.227933 2.39 0.017 1.366209
24.27939
   _Iloc2_3 | 1.511322 .5351903 1.17 0.244 .7549687
3.025416
   _Iloc2_4 | 5.823392 4.594466
                                  2.23 0.026
                                                 1.240526
27.33671
             1.158311 1.124599
  _Itype2_2 |
                                   0.15 0.880
                                                  .1727419
7.766989
  _Irace3_2 |
             17.74163 16.08504
                                  3.17 0.002
                                                  3.001038
104.8856
theta 29.63646 6.384354
Likelihood-ratio test of theta=0: chibar2(01) = 225.07 Prob>=chibar2 = 0.000
```

Note: Standard errors of hazard ratios are conditional on theta.

Log file for data in Table 17 Table 18 and Table 19

- . sort failure
- . iis id
- . by failure:xttab loc if year==1

-> failure = 0

	Ove	rall	Bet	ween	Within	
loc	Freq.	Percent	Freq.	Percent	Percent	
1	+ 54	2.01	33	5.66	42.52	
2	166	6.18	54	9.26	69.17	
3	50	1.86	28	4.80	38.76	
4	342	12.74	164	28.13	34.76	
5	1702	63.41	402	68.95	79.02	
6	370	13.79	177	30.36	34.87	
Total	 2684	100.00	858	147.17	58.11	
			(n = 583)			

-> failure = 1

	Ove	rall	Bet	ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	2	3.70	2	5.56	28.57
2	6	11.11	5	13.89	60.00
3	3	5.56	3	8.33	37.50
4	6	11.11	6	16.67	54.55
5	28	51.85	20	55.56	90.32
6	9	16.67	9	25.00	56.25
Total	54	100.00	45 (n = 36)	125.00	69.10

. by failure:xttab loc if year==2

^{-&}gt; failure = 0

	Ove	Overall		ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	89	3.68	34	7.17	38.20
2	122	5.04	37	7.81	46.21
3	82	3.39	27	5.70	38.14
4	329	13.60	142	29.96	33.99
5	1512	62.51	327	68.99	79.04
6	285	11.78	135 	28.48	33.33
Total	2419	100.00	702 (n = 474)	148.10	55.85

-> failure = 1

	Ove	rall	Bet	ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	1	4.35	1	8.33	100.00
2	8	34.78	5	41.67	100.00
4	3	13.04	3	25.00	27.27
5	5	21.74	3	25.00	55.56
6	6	26.09	5	41.67	46.15
Total	23	100.00	17 (n = 12)	141.67	63.49

. by failure:xttab loc if year==3

-> failure = 0

	Overall		Bet	ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	 46	3.81	21	7.34	40.71
2	73	6.04	21	7.34	50.00
3	52	4.30	20	6.99	43.33
4	142	11.75	77	26.92	34.89
5	764	63.25	208	72.73	81.62
6	131	10.84	68	23.78	36.49
Total	1208	100.00	415 (n = 286)	145.10	60.04

	Ove	rall	Bet	ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
+					
1	3	30.00	2	22.22	100.00
2	1	10.00	1	11.11	100.00
5	6	60.00	6	66.67	100.00
Total	10	100.00	9 (n = 9)	100.00	100.00

. by failure:xttab loc if year==4

-> failure = 0

	Ove	Overall Between Wit		Within	
loc	Freq.	Percent	Freq.	Percent	Percent
1	8	1.04	7	3.59	57.14
2	26	3.38	11	5.64	76.47
3	11	1.43	6	3.08	55.00
4	82	10.65	46	23.59	34.75
5	578	75.06	154	78.97	85.88
6	65 	8.44	38	19.49	32.66
Total	770	100.00	262 (n = 195)	134.36	67.32

-> failure = 1

	Ove	rall	Bet	ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	1	25.00	1	33.33	100.00
2	1	25.00	1	33.33	50.00
3	1	25.00	1	33.33	50.00
5	1	25.00	1	33.33	100.00
Total	4	100.00	4	133.33	75.00
			(n = 3)		

. by failure:xttab loc if year==5

	Ove	Overall		ween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
1	2	0.44	2	1.87	50.00
2	12	2.65	5	4.67	100.00
3	7	1.55	3	2.80	87.50
4	41	9.05	29	27.10	29.29
5	353	77.92	89	83.18	84.86
6	38	8.39	21	19.63	30.65
	453	100.00	149 (n = 107)	139.25	66.49

->	failure	= 1				
		Ove	erall	Bet	tween	Within
	loc	Freq.	Percent	Freq.	Percent	Percent
	+					
	4	1	25.00	1	50.00	33.33
	5	3	75.00	2	100.00	75.00
	+					
	Total	4	100.00	3	150.00	61.11
	'			(n = 2)		

. by failure:xttab loc if year==6

-> 1	failure	= 0					
			Ove	rall	Bet	ween	Within
	loc		Freq.	Percent	Freq.	Percent	Percent
	+						
	1		1	0.44	1	1.75	25.00
	3		3	1.32	1	1.75	75.00
	4		26	11.40	16	28.07	38.24
	5		182	79.82	50	87.72	85.45
	6		16	7.02	11	19.30	30.19
	+						
	Total		228	100.00	79	138.60	67.29
					(n = 57)		

->	failure = 1					
		Ove	erall	Bet	ween	Within
	loc	Freq.	Percent	Freq.	Percent	Percent
	1	1	33.33	1	50.00	100.00
	5	2	66.67	1	50.00	100.00
	Total	3	100.00	2	100.00	100.00
				(n = 2)		

. by failure:xttab loc if year==7

	Ove	Overall		Between		
loc	Freq.	Percent	Freq.	Percent	Percent	
4	12	11.01	8	33.33	35.29	
5	90	82.57	21	87.50	86.54	
6	7	6.42	5 	20.83	31.82	
Total	109	100.00	34	141.67	66.43	
			(n = 24)			

-> failure = 1

	Ove	Overall		tween	Within
loc	Freq.	Percent	_	Percent	Percent
5	1	100.00	1	100.00	100.00
Total	1	100.00	$ \begin{array}{c} 1\\ (n = 1) \end{array} $	100.00	100.00

. by failure:xttab loc if year==8

-> failure = 0

	Ove	rall	Between		Within
loc	Freq.	Percent	Freq.	Percent	Percent
4	 1	8.33	1	20.00	33.33
5	9	75.00	4	80.00	90.00
6	2	16.67	1	20.00	100.00
Total	12	100.00	6	120.00	82.22
·			(n = 5)		

-> failure = 1

	Ove	erall	Bet	tween	Within
loc	Freq.	Percent	Freq.	Percent	Percent
	+				
4	1	25.00	1	100.00	25.00
5	2	50.00	1	100.00	50.00
6	1	25.00	1	100.00	25.00
	+				
Total	4	100.00	3	300.00	33.33
			(n = 1)		

. by failure:xttab loc2 if year==1

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	1702	63.41	402	68.95	79.02
2	166	6.18	54	9.26	69.17
3	712	26.53	243	41.68	55.71
4	104	3.87	46	7.89	61.90
Total	2684	100.00	745 (n = 583)	127.79	69.64

-> failure = 1

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	28	51.85	20	55.56	90.32
2	6	11.11	5	13.89	60.00
3	15	27.78	12	33.33	78.95
4	5	9.26	3	8.33	62.50
Total	 54	100.00	40	111.11	81.03
			(n = 36)		

. by failure:xttab loc2 if year==2

-> failure = 0

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	1512	62.51	327	68.99	79.04
2	122	5.04	37	7.81	46.21
3	614	25.38	203	42.83	50.33
4	171	7.07	46	9.70	60.64
Total	2419	100.00	613 (n = 474)	129.32	66.17

	Ove	erall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	5	21.74	3	25.00	55.56
2	8	34.78	5	41.67	100.00
3	9	39.13	5	41.67	69.23
4	1 +	4.35	1	8.33	100.00
Total	23	100.00	(n = 12)	116.67	79.49

. by failure:xttab loc2 if year==3

-> failure = 0

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	764	63.25	208	72.73	81.62
2	73	6.04	21	7.34	50.00
3	273	22.60	104	36.36	53.22
4	98	8.11	30	10.49	64.90
Total	1208	100.00	363 (n = 286)	126.92	70.27

-> failure = 1

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
+					
1	6	60.00	6	66.67	100.00
2	1	10.00	1	11.11	100.00
4	3	30.00	2	22.22	100.00
+					
Total	10	100.00	9	100.00	100.00
			(n = 9)		

. by failure:xttab loc2 if year==4

-> failure = 0

	Ove	erall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	578	75.06	154	78.97	85.88
2	26	3.38	11	5.64	76.47
3	147	19.09	60	30.77	52.31
4	19 +	2.47	11	5.64	67.86
Total	770	100.00	236 (n = 195)	121.03	76.07

	Ove	rall	Between		Within	
loc2	Freq.	Percent	Freq.	Percent	Percent	
	+					
1	1	25.00	1	33.33	100.00	
2	1	25.00	1	33.33	50.00	
4	2	50.00	2	66.67	66.67	
	+					
Total	4	100.00	4	133.33	70.83	

$$(n = 3)$$

. by failure:xttab loc2 if year==5

-> failure = 0

	Ove	erall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1	353	77.92	89	83.18	84.86
2	12	2.65	5	4.67	100.00
3	79	17.44	35	32.71	47.02
4	9 +	1.99	4	3.74	100.00
Total	453	100.00	(n = 107)	124.30	75.92

--

-> failure = 1

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
+					
1	3	75.00	2	100.00	75.00
3	1	25.00	1	50.00	33.33
+					
Total	4	100.00	3	150.00	61.11
·			(n = 2)		

. by failure:xttab loc2 if year==6

	Ove	erall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
+					
1	182	79.82	50	87.72	85.45
3	42	18.42	20	35.09	51.85
4	4	1.75	1	1.75	100.00
Total	228	100.00	 71	124.56	76.19
'			(n = 57)		

-> failure = 1

	Ove	rall	Bet	tween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
					
1	2	66.67	1	50.00	100.00
4	1	33.33	1	50.00	100.00
	+				
Total	3	100.00	2	100.00	100.00
			(n = 2)		

. by failure:xttab loc2 if year==7

-> failure = 0

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
1 3	90 19	82.57 17.43	21 9	87.50 37.50	86.54 52.78
Total	109	100.00	30 (n = 24)	125.00	76.41

-> failure = 1

	Ove	Overall		ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
+					
1	1	100.00	1	100.00	100.00
+	+				
Total	1	100.00	1	100.00	100.00
'			(n = 1)		

. by failure:xttab loc2 if year==8

	Ove	rall	Bet	ween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
+					
1	9	75.00	4	80.00	90.00
3	3	25.00	2	40.00	60.00
+					
Total	12	100.00	6	120.00	80.00
·			(n = 5)		

-> failure = 1

	Ove	erall	Bet	tween	Within
loc2	Freq.	Percent	Freq.	Percent	Percent
	+				
1	2	50.00	1	100.00	50.00
3	2	50.00	1	100.00	50.00
	+				
Total	4	100.00	2	200.00	50.00
			(n = 1)		

. by failure:xttab type2 if year==1

-> failure = 0

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1 2	2428 256	90.46 9.54	533 53	91.42 9.09	99.51 93.77
Total	2684	100.00	586 (n = 583)	100.51	98.99

-> failure = 1

	Ove	erall	Bet	ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1	50	92.59	34	94.44	100.00
2	4	7.41	2	5.56	100.00
Total	54	100.00	36	100.00	100.00
·			(n = 36)		

. by failure:xttab type2 if year==2

	Ove	erall	Bet	tween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1 2	2320 99	95.91 4.09	445 31	93.88 6.54	99.66
Total	2419	100.00	476 (n = 474)	100.42	99.03

-> failure = 1

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
+					
1	23	100.00	12	100.00	100.00
+					
Total	23	100.00	12	100.00	100.00
·			(n = 12)		

. by failure:xttab type2 if year==3

-> failure = 0

	Ove	rall	Bet	ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1 2	1139 69	94.29 5.71	268 22	93.71 7.69	99.13 83.13
Total	1208	100.00	290 (n = 286)	101.40	97.92

-> failure = 1

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
	+				
1	10	100.00	9	100.00	100.00
	+				
Total	10	100.00	9	100.00	100.00
			(n = 9)		

. by failure:xttab type2 if year==4

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
					
1	715	92.86	181	92.82	100.00
2	55	7.14	14	7.18	100.00
	+				
Total	770	100.00	195	100.00	100.00
1	ı		(n = 195)		

-> failure = 1

- 1		Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1	4	100.00	3	100.00	100.00
Total	4	100.00	$ \begin{array}{ccc} 3 \\ (n = 3) \end{array} $	100.00	100.00

. by failure:xttab type2 if year==5

-> failure = 0

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
+					
1	408	90.07	94	87.85	100.00
2	45	9.93	13	12.15	100.00
+					
Total	453	100.00	107	100.00	100.00
			(n = 107)		

-> failure = 1

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1	4	100.00	2	100.00	100.00
Total	4	100.00	2 (n = 2)	100.00	100.00

. by failure:xttab type2 if year==6

	Ove	Overall		tween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
	+				
1	200	87.72	48	84.21	100.00
2	28	12.28	9	15.79	100.00
	+				
Total	228	100.00	57	100.00	100.00
	,		(n = 57)		

-> failure = 1

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1	1	33.33	1	50.00	100.00
2	2	66.67	1	50.00	100.00
Total	3	100.00	2	100.00	100.00
			(n = 2)		

. by failure:xttab type2 if year==7

-> failure = 0

	Ove	Overall I		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
1 2	87 22	79.82 20.18	19 5	79.17 20.83	100.00
Total	109	100.00	24 (n = 24)	100.00	100.00

-> failure = 1

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
	+				
1	1	100.00	1	100.00	100.00
	+				
Total	1	100.00	1	100.00	100.00
			(n = 1)		

. by failure:xttab type2 if year==8

	Ove	Overall		ween	Within
type2	Freq.	Percent	Freq.	Percent	Percent
+					
1	8	66.67	3	60.00	100.00
2	4	33.33	2	40.00	100.00
+					
Total	12	100.00	5	100.00	100.00
'			(n = 5)		

-> failure = 1

type2		rall Percent		ween Percent	Within Percent
+	ricq.				
2	4	100.00	1	100.00	100.00
Total	4	100.00	$ \begin{array}{rcl} 1 \\ (n = 1) \end{array} $	100.00	100.00

. by failure:xttab race3 if year==1 $\,$

-> failure = 0

	Ove	Overall		ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
1	2217	86.74	476	86.55	100.00
2	339	13.26	74	13.45	100.00
Total	2556	100.00	550	100.00	100.00
·			(n = 550)		

-> failure = 1

	Ove	erall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
	+				
1	42	77.78	28	77.78	100.00
2	12	22.22	8	22.22	100.00
	+				
Total	54	100.00	36	100.00	100.00
			(n = 36)		

. by failure:xttab race3 if year==2

	Ove	rall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
1	2061	88.53	393	86.75	100.00
2	267	11.47	60	13.25	100.00
Total	2328	100.00	453	100.00	100.00
			(n = 453)		

-> failure = 1

	Ove	rall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
+					
1	15	65.22	9	75.00	100.00
2	8	34.78	3	25.00	100.00
+					
Total	23	100.00	12	100.00	100.00
			(n = 12)		

. by failure:xttab race3 if year==3

-> failure = 0

	Ove	rall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
1 2	988 137	87.82 12.18	237 29	89.10 10.90	100.00
Total	1125	100.00	266 (n = 266)	100.00	100.00

-> failure = 1

	Ove	erall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
	+				
1	8	88.89	7	87.50	100.00
2	1	11.11	1	12.50	100.00
	+				
Total	9	100.00	8	100.00	100.00
			(n = 8)		

. by failure:xttab race3 if year==4

	Ove	rall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
+					
1	657	89.02	163	88.59	100.00
2	81	10.98	21	11.41	100.00
Total	738	100.00	184	100.00	100.00
·			(n = 184)		

-> failure = 1

race3	Freq.	rall Percent		ween Percent	Within Percent
1		100.00	3	100.00	100.00
Total	4	100.00	3 (n = 3)	100.00	100.00

. by failure:xttab race3 if year==5

->	failure =	0
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	Ove	rall	Bet	ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
+-	204				100.00
1	394	88.94	91	88.35	100.00
2	49	11.06	12	11.65	100.00
Total	443	100.00	103	100.00	100.00
10cai	113	100.00	(n = 103)	100.00	100.00
			(11 = 103)		

-> failure = 1

	Ove	erall	Bet	tween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
1	4	100.00	2	100.00	100.00
Total	4	100.00	(n = 2)	100.00	100.00

. by failure:xttab race3 if year==6

	Ove	erall	Bet	tween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
	+				
1	192	84.96	48	85.71	100.00
2	34	15.04	8	14.29	100.00
	+				
Total	226	100.00	56	100.00	100.00
			(n = 56)		

->	iallure	=	T	

	Ove	Overall		ween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
1	3 3	100.00	2	100.00	100.00
Total	3	100.00	(n = 2)	100.00	100.00

. by failure:xttab race3 if year==7

-> failure = 0

race3	Overall Freg. Percent		Between Freg. Percent		Within Percent
	Freq.		rreq. 		Percent
1	70	67.96	16	72.73	100.00
2	33	32.04	6	27.27	100.00
Total	103	100.00	22	100.00	100.00
·			(n = 22)		

-> failure = 1

	Ove	Overall		Between	
race3	Freq.	Percent	Freq.	Percent	Percent
1	1	100.00	1	100.00	100.00
Total	1	100.00	1 (n = 1)	100.00	100.00

. by failure:xttab race3 if year==8

	Overall		Bet	tween	Within
race3	Freq.	Percent	Freq.	Percent	Percent
	+				
1	9	75.00	4	80.00	100.00
2	3	25.00	1	20.00	100.00
	+ – – – – – – – .				
Total	12	100.00	5	100.00	100.00
			(n = 5)		

	Ove	Overall		Between	
race3	Freq.	Percent	Freq.	Percent	Percent
1	4	100.00	1 1	100.00	100.00
Total	4	100.00	1 (n = 1)	100.00	100.00

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