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# Conducting Survival Analysis in SAS® using Medicare Claims as a Real-world data source

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## ABSTRACT

Applications of Survival analysis as a statistical technique extend to longitudinal studies, and other studies in health research. The SAS/STAT® package contains multiple procedures for performing and running survival analysis. The most well-known of these are PROC LIFETEST and PROC PHREG. As a data source, Medicare claims are often used in Real-world evidence studies and observational research. In this paper, survival analysis and the SAS® procedures for performing it will be explored, and survival analyses will be conducted using Medicare claims data sets to assess patient's prognosis amongst Medicare beneficiaries.

## INTRODUCTION

Survival analysis is a technique used in clinical and longitudinal studies which concentrates on the time or duration until a specific event occurs. The specific event might be the fatality of a patient, or the readmission of a patient into a healthcare facility for further treatment. In survival analysis, patients are monitored and followed up until they experience the event of interest. However, not every patient will experience the event of interest. Taking account of the patients who don't experience the event of interest is known as censoring. One of the first steps in survival analysis is the estimation of the Survival function. There are several types of survival functions, as well as survival distributions. The survival functions can be estimated using survival curves, which you can produce using one or more of the survival analysis procedures. To perform survival analysis, there are non-parametric and parametric methods. The method used to conduct a survival analysis depends on the SAS/STAT procedure you use.

## SURVIVAL ANALYSIS CONCEPTS

In survival analysis, one of the main tasks is to compute a distribution of survival times for a defined population. Survival times are referred to as failure times, and event times are called uncensored survival times. Procedurally, to compute the distribution of survival times, you estimate the distribution, using one of several survival functions.

The survival distribution function, SDF, also known as the survivor function, describes the lifetimes of the population of interest. The SDF is represented in the equation below by S(t)

$$S(t) = Pr(T > t)$$

The survival distribution function is the probability that an experimental unit from the population will have a lifetime that exceeds *t*, that is, $Pr(T > t)$. Where T is the lifetime of a randomly selected experimental unit.

Other types of survival functions are the cumulative distribution function, CDF, the probability density function, PDF, and The Hazard function. The equation for the CDF is provided below.

$$F(t) = 1 - S(t)$$

The CDF, which is F(t) is defined as 1 – S(t) and is the probability that a lifetime does not exceed t. The PDF, f(t), is defined as the derivative of CDF, or F(t).

The hazard function is another survival function used by SAS/STAT procedures. It is defined as the ratio of the PDF to SDF, that is, f(t) / S(t).

## CENSORING

In survival analysis, patients are followed up in a study from the point they experience a specific event, such as being admitted to a hospital, being diagnosed with a specific medical condition, or being discharged from a hospital. However, not every patient in the study will be able to be tracked or monitored. For example, some patients might leave or drop out of the study. Other patients might move and not provide up to date contact information. For these patients, the exact survival time can't be calculated, because this data can't be collected. These individuals are considered censored.

Censored patients have no actual time to event data. For study participants who are censored, the time to event data has to be estimated. There are different methods for doing this. The methods include right-censoring, left-censoring, and interval censoring. Regardless of the method, censored observations cannot be ignored and must be taken into account when performing survival analysis.

The various types of censoring are illustrated in Figure 1 below.

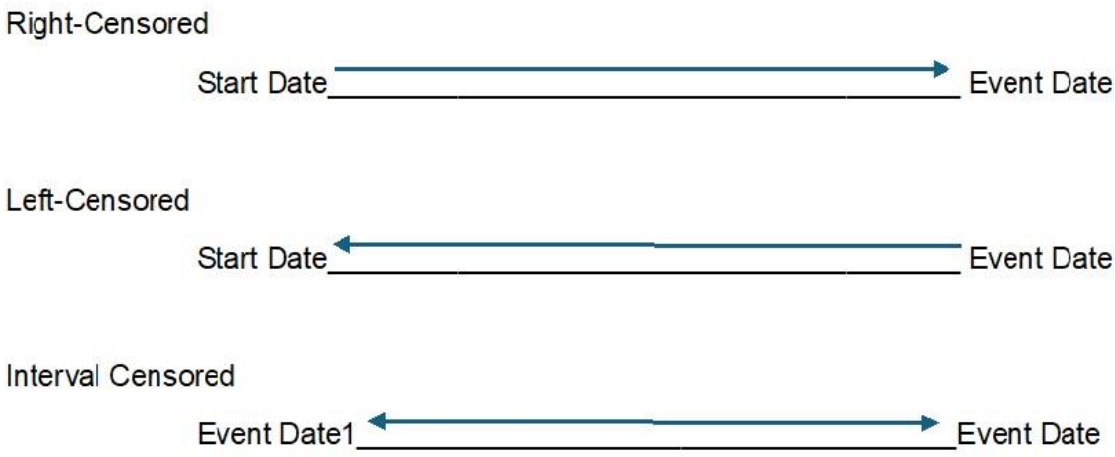



**Figure 1. Different types of censoring diagram**

The above continuum illustrates and compares the different kinds of censoring. Right-censoring is when the event is unobserved for some individuals because the event date is greater than the event date for individuals with observed events. Left-censoring is when the event date is known to be less than or before the event date. Interval-censoring is where an event falls outside of an interval between 2 dates.

## SAS PROCEDURES FOR SURVIVAL ANALYSIS

The primary procedures for conducting survival analysis in SAS/STAT are the LIFETEST procedure and the PHREG procedure, known as PROC LIFETEST and PROC PHREG, respectively. There are also other survival analysis procedures in other SAS modules.

The SAS/STAT module includes 8 different procedures for performing survival analysis, according to version 15.3 of SAS/STAT. The survival analysis procedures are listed and characterized by different attributes.

Besides PROC LIFETEST and PROC PHREG, the survival analysis procedures include variations of these PROCs for interval-censored data, procedures which use parametric estimates on any type of censored data, procedures which use quantile regression, and restricted mean survival time, as well as procedures using the Cox Proportional Hazards model for survey sample data. The SAS/STAT survival analysis procedures are listed in Figure 2.

| SAS Procedure | Type of Model | Type of Censoring |
|---|---|---|
| **LIFETEST** | **Non-parametric** | **Right-Censored** |
| **PHREG** | **Semi-Parametric** | **Right-Censored** |
| **ICLIFETEST** | **Non-parametric** | **Interval-Censored** |
| **ICPHREG** | **Parametric** | **Interval-Censored** |
| **LIFEREG** | **Parametric** | **Left-Censored, Right-Censored, or Interval-Censored** |
| **QUANTLIFE** | **Parametric** | **Right-Censored** |
| **RMSTREG** | **Parametric** | **Right-Censored** |
| **SURVEYPHREG** | **Semi-Parametric** | **Right-Censored** |

**Figure 2. Survival Analysis procedures in SAS/STAT**

For each survival analysis procedure listed, the table displays the type of model and type of censoring encompassed. Most of the procedures have a parametric form for the underlying model or function, with the exception of the LIFETEST and ICLIFETEST procedures.

Most of the procedures work with only right-censored data, or data with unobserved failure times. The ICLIFETEST and ICPHREG procedures are versions of LIFETEST and PHREG procedures specifically for interval-censored data. The LIFEREG procedure can be applied to any type of censored data; left, right, or interval.

## THE LIFETEST PROCEDURE

With PROC LIFETEST, you perform a non-parametric survival analysis. This means that the procedure doesn't produce estimates of population parameters. PROC LIFETEST uses two different methods to perform survival analysis; the product-limit method, and the life-table method. The product-limit method is known as the Kaplan-Meier method, and the life-table method as the actuarial method, respectively. The life-table estimate is a grouped-data analog of the Kaplan-Meier estimate.

Besides these two methods, PROC LIFETEST can also compute the Breslow estimate, or the Fleming-Harrington estimate. We won't dive into these methods in this paper, as they're outside its scope.

The basic syntax of the LIFETEST Procedure is provided below.

```
Proc Lifetest <Options>;
    Time Variable / Option>;
    Strata Variable </ Options>;
    Test Variable;
Run;
```

Besides the PROC LIFETEST statement, the primary statements in PROC LIFETEST are the TIME statement and the STRATA statement. The TEST statement is where you include any covariates. Whereas the STRATA statement is for specifying stratification variables. PROC LIFETEST uses right-censoring as the censoring method.

## THE PHREG PROCEDURE

The PHREG procedure conducts a survival analysis using the Cox Proportional Hazards Model. PHREG stands for Proportional Hazards Regression.

PROC PHREG is a semiparametric procedure which models survival time using the Hazard function. It's defined as a semiparametric procedure because it assumes a parametric form for the effects of explanatory variables, but it permits an unspecified form for the underlying survival function.

Other distinct features of PROC PHREG are the use of time-dependent explanatory variables, variable selection methods, and methods for handling ties in failure times. PROC PHREG allows the inclusion of time-dependent explanatory variables as covariates. The procedure uses four different variable selection methods; Forward, Backward, Stepwise and Best subset. It also provides four methods for dealing with ties in failure times.

The basic syntax of the PHREG Procedure is provided below.

```
Proc Phreg Options;
    Class Variable / Options;
    Model Response*Censor(List) = Effects / Options;
    Strata Variable (List) / Option;
Run;
```

Similar to PROC LIFETEST, PROC PHREG involves specifying the censor or status variable and the response variable, in this case, survival time. The MODEL statement is used to specify these variables along with the covariates in a regression-like equation, where the covariates are the effects. PROC PHREG also uses right-censoring as the censoring method, the same as PROC LIFETEST.

## THE DATA SOURCE – MEDICARE CLAIMS

For this project, the primary data source is a Medicare claims data set containing healthcare utilization data for Medicare beneficiaries.

The file is an Inpatient Medicare claims data set, specific to an inpatient facility. This claims file contains claims for inpatient hospital visits. The claims file is a header file filetype, which contains summary information about each claim. The file has one record per claim, and multiple records per beneficiary since some beneficiaries have more than one claim.

There approximately a dozen variables on the file, including diagnosis code, procedure code, admission and discharge dates, claim payment amounts, and other administrative variables.

In Figure 3 below, is a snapshot of the Inpatient Medicare claims data set.

| Obs | BENE_ID | CLM_ID | ADMSN_DT | DSCHRGDT | DRG | ICD_DIAG1 | ICD_PRCDRCD1 | ADMTG_DGNS_CD | NPI | PMT_AMT | DED_AMT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 00013D2EFD8E45D1 | 196661176988405 | 20100312 | 20100313 | 217 | 7802 | | 4580 | 3139083564 | 4000.00 | 1100.00 |
| 2 | 00016F715862898F | 196261176983265 | 20100626 | 20100701 | 983 | 3559 | | 5849 | 6108100173 | 16000.00 | 1100.00 |
| 3 | 0007F12A492FD25D | 196551177025145 | 20100522 | 20100612 | 950 | V5789 | | V5789 | 1907446990 | 14000.00 | . |
| 4 | 0007F12A492FD25D | 196821177025734 | 20100602 | 20100606 | 205 | 49121 | | 49392 | 5838958809 | 9000.00 | 1100.00 |
| 5 | 0007F12A492FD25D | 196831176966961 | 20100616 | 20100619 | 456 | 7356 | 0073 | 99641 | 4959466403 | 29000.00 | 1100.00 |
| 6 | 0013E139F1F37264 | 196141176989106 | 20100830 | 20100907 | 238 | 4280 | | 8738 | 3771255921 | 3000.00 | 1100.00 |
| 7 | 00196F07C2489342 | 196751177019091 | 20100318 | 20100324 | 178 | 41519 | | 41519 | 3149964648 | 7000.00 | 1100.00 |
| 8 | 00196F07C2489342 | 196991177014269 | 20100114 | 20100119 | 229 | 42731 | 4516 | 7802 | 7087360414 | 8000.00 | 1100.00 |
| 9 | 001EA2F4DB30F105 | 196131176973560 | 20100316 | 20100319 | 508 | 99541 | 0082 | 99677 | 7872369581 | 0.00 | 1100.00 |
| 10 | 002354398A00234E | 196731176991192 | 20100820 | 20100831 | 282 | 45341 | 8848 | 45341 | 8198589276 | 10000.00 | 1100.00 |
| 11 | 00271F7DF9C2B88A | 196711177025513 | 20100113 | 20100114 | 854 | 0389 | 8345 | 78060 | 7774053843 | 28000.00 | 1100.00 |
| 12 | 0028A82FE0CA0802 | 196241177011101 | 20100514 | 20100617 | 880 | 29633 | | 30390 | 4199341016 | 9000.00 | 1100.00 |
| 13 | 00292D3DDD23CE44 | 196121176990349 | 20100710 | 20100715 | 683 | 5849 | 4516 | 40391 | 4903645489 | 8000.00 | . |
| 14 | 00292D3DBB23CE44 | 196721177025054 | 20100703 | 20100712 | 251 | 7802 | | 7802 | 1499149511 | 3000.00 | 1100.00 |
| 15 | 002B62031F086ABA | 196871176990954 | 20100125 | 20100129 | 466 | 71536 | 8152 | 71536 | 4037882287 | 12000.00 | 1100.00 |
| 16 | 003AE4429AC2BDE7 | 196121177011276 | 20100222 | 20100302 | 245 | 41401 | 3722 | 4111 | 7115813911 | 10000.00 | 1100.00 |
| 17 | 003AF4429AC2BDE7 | 196891176990986 | 20100121 | 20100127 | 188 | 486 | | 99591 | 7115813911 | 7000.00 | 1100.00 |
| 18 | 0045838358BCA530 | 196691176959586 | 20100608 | 20100612 | 500 | 1985 | 8154 | 71535 | 2950647400 | 12000.00 | 1100.00 |
| 19 | 0049CB2A111F2225 | 196081176975386 | 20100129 | 20100208 | 664 | 5849 | 3995 | 78097 | 6962810697 | 6000.00 | 1100.00 |
| 20 | 004D364955271F56 | 196111176994552 | 20100708 | 20100710 | 285 | 42731 | | 42731 | 7319323665 | 7000.00 | 1100.00 |
| 21 | 00531E60E969C69E | 196141177016557 | 20100211 | 20100218 | 167 | 7381 | 8107 | 7242 | 3780108997 | 26000.00 | 1100.00 |
| 22 | 00534E60E969C69E | 196621176976944 | 20100202 | 20100204 | 475 | 71536 | 8154 | 71535 | 1949223467 | 12000.00 | 1100.00 |
| 23 | 00565644D5332C24 | 196481176979455 | 20100602 | 20100613 | 025 | 1919 | 8891 | 78097 | 2628405021 | 4000.00 | 1100.00 |
| 24 | 005715FA817344A7 | 196181177011825 | 20100121 | 20100123 | 485 | 71536 | 8154 | 71536 | 2413038049 | 13000.00 | 1100.00 |
| 25 | 00641FD6499D535C | 196381177017239 | 20101212 | 20101213 | 867 | 0389 | | 7802 | 6452216373 | 10000.00 | 1100.00 |

**Figure 3. Medicare Inpatient claims data set**

Listed below are the primary variables we're interested in for this project, along with their definitions.

**BENE_ID** is the Medicare Beneficiary Identifier, which identifies the patient or beneficiary.

**ADMSN_DT** is Admission date. The date the patient was admitted to the hospital.

**DRG** is Diagnosis Related Grouper. It's a diagnosis code which can be used to select patients who received treatment for a specific medical condition.

**ICD_DIAG1** is an ICD9 diagnosis code. ICD9 codes are similar to DRG codes, except they're more granular, providing more detail about a condition.

## OTHER MEDICARE DATA FILES

Besides the main claims file, the membership file and the diagnosis code file contain useful variables for our analysis. These files can be used as lookup tables to extract additional useful data for Medicare beneficiaries.

The membership file contains beneficiary-level information on Medicare beneficiaries and is known as the Medicare Beneficiary Summary File (MBSF). The MBSF contains demographic variables which can be used as group or subgroup variables in the analysis, and other variables which are essential in survival analysis. The MBSF contains one record per Medicare beneficiary.

The Diagnosis Code file is a reference lookup table for ICD9 Diagnosis Codes. The data set provides descriptions for diagnosis codes. The table is used to focus on specific medical diagnoses in the analysis, such as congestive heart failure, kidney disease and diabetes. This SAS data set contains only two variables; Code and description.

In Figure 4 below is a screenshot of the MBSF (left) with the Diagnosis Code File (right)

| Obs | BENE_ID | BENE_DOB | DEATH_DT | RACE | SEX | CNTY_CD | STATE_CD | BENE_HI_CVRAGE_TOT_MONS |
|---|---|---|---|---|---|---|---|---|
| 1 | 00013D2EFD8E45D1 | 19230501 | . | 1 | 1 | 950 | 26 | 12 |
| 2 | 00016F745862898F | 19430101 | . | 1 | 1 | 230 | 39 | 12 |
| 3 | 0001FDD721E223DC | 19360901 | . | 1 | 2 | 280 | 39 | 12 |
| 4 | 00021CA6FFC3E670 | 19410601 | . | 5 | 1 | 290 | 06 | 12 |
| 5 | 00024B3D2352D2D0 | 19360801 | . | 1 | 1 | 590 | 52 | 9 |
| 6 | 0002DAE1C81CC70D | 19431001 | . | 2 | 1 | 400 | 33 | 12 |
| 7 | 0002F28CE057345B | 19220701 | . | 1 | 1 | 270 | 39 | 12 |
| 8 | 000308435E3E5B76 | 19350901 | . | 1 | 1 | 680 | 24 | 12 |
| 9 | 000345A39D4157C9 | 19760901 | . | 1 | 2 | 810 | 23 | 12 |
| 10 | 00036A21B65BC206 | 19381001 | . | 2 | 2 | 570 | 01 | 12 |
| 11 | 000489E7EAAD463F | 19340201 | . | 1 | 2 | 140 | 15 | 12 |
| 12 | 00048EF1F4791C68 | 19290601 | . | 1 | 1 | 230 | 44 | 12 |
| 13 | 0004F0ABD505251D | 19360701 | . | 1 | 2 | 030 | 41 | 12 |
| 14 | 0005270524 3EA128 | 19340501 | . | 1 | 1 | 982 | 14 | 12 |
| 15 | 00070B63745BE497 | 19360301 | . | 1 | 2 | 270 | 13 | 12 |
| 16 | 0007E57CC13CE880 | 19340101 | 20101201 | 1 | 1 | 140 | 06 | 12 |
| 17 | 0007F12A492FD25D | 19190901 | . | 2 | 2 | 400 | 34 | 12 |
| 18 | 000A005BA0BED3EA | 19191001 | . | 2 | 2 | 160 | 50 | 12 |
| 19 | 000B4662348C35B4 | 19420701 | . | 1 | 2 | 170 | 46 | 12 |
| 20 | 000B97BA2314E971 | 19380401 | . | 1 | 1 | 020 | 22 | 12 |
| 21 | 000C7486B11E7030 | 19320801 | . | 2 | 1 | 350 | 25 | 12 |
| 22 | 000D6D88463D8A76 | 19420801 | . | 5 | 1 | 000 | 32 | 0 |

| Obs | Code | Description |
|---|---|---|
| 1 | 001.0 | CHOLERA DUE TO VIBRIO CHOLERAE |
| 2 | 001 | CHOLERA |
| 3 | 001.1 | CHOLERA DUE TO VIBRIO CHOLERAE EL TOR |
| 4 | 001.9 | UNSPECIFIED CHOLERA |
| 5 | 002.0 | TYPHOID FEVER |
| 6 | 002 | TYPHOID AND PARATYPHOID FEVERS |
| 7 | 002.1 | PARATYPHOID FEVER A |
| 8 | 002.2 | PARATYPHOID FEVER B |
| 9 | 002.3 | PARATYPHOID FEVER C |
| 10 | 002.9 | UNSPECIFIED PARATYPHOID FEVER |
| 11 | 003.0 | SALMONELLA GASTROENTERITIS |
| 12 | 003 | OTHER SALMONELLA INFECTIONS |
| 13 | 003.1 | SALMONELLA SEPTICEMIA |
| 14 | 003.2 | LOCALIZED SALMONELLA INFECTIONS |
| 15 | 003.20 | UNSPECIFIED LOCALIZED SALMONELLA INFECTION |
| 16 | 003.21 | SALMONELLA MENINGITIS |
| 17 | 003.22 | SALMONELLA PNEUMONIA |
| 18 | 003.23 | SALMONELLA ARTHRITIS |
| 19 | 003.24 | SALMONELLA OSTEOMYELITIS |
| 20 | 003.29 | OTHER LOCALIZED SALMONELLA INFECTIONS |
| 21 | 003.8 | OTHER SPECIFIED SALMONELLA INFECTIONS |
| 22 | 003.9 | UNSPECIFIED SALMONELLA INFECTION |
| 23 | 004.0 | SHIGELLA DYSENTERIAE |
| 24 | 004 | SHIGELLOSIS |
| 25 | 004.1 | SHIGELLA FLEXNERI |

**Figure 4. Medicare Beneficiary Summary File and Diagnosis Code File**

The two variables in the diagnosis code file are Code and Description, where Code is a list of ICD9 diagnosis codes and description is the text description of the code. The key variables from the MBSF are defined below.

**BENE_DOB** – Beneficiary or Patient's Date of Birth.

**DEATH_DT -** Death date of the Medicare Beneficiary. Defines the event of interest allowing us To compute the survival times for uncensored observations.

**RACE**- Race of the Beneficiary. Demographic variable defining racial category.

**SEX**- Gender of the Beneficiary. Demographic variable defining Gender.

Other key variables include date of birth, state of residence, number of months of part A coverage, number of months of part B coverage, and flag variables for specific chronic diseases.

## DATA MANAGEMENT TASKS PRIOR TO THE ANALYSIS

Prior to running a survival analysis, we need to perform data manipulation in order to create an analysis data set.

We're going to focus on specific medical diagnoses in our analysis, so we need to access the diagnosis code descriptions in our diagnosis code lookup table to subset inpatient claims to specific medical conditions. We also need to retrieve demographic and other variables from our beneficiary summary file to use these variables as group or subgroup variables in the analysis.

We have our three files as SAS data sets; Inpatient claims file, diagnosis code file, and the beneficiary summary file. The first step is to merge or join the Inpatient claims data set with the diagnosis code reference table to obtain the diagnosis code description. The subsequent task is to merge the resulting data set with the beneficiary summary file to obtain demographic and other variables.

```
            /* Add DX Description - Join IP Claims File with DX Code Lookup Table */
Data ip2010claim;
                    Length DXCD1-DXCD10 $6;

    Set SURVMEDI.ip2010claim;

    Array ICDDX{10}$ ICD_DGNS_CD1-ICD_DGNS_CD10;
    Array DXCode{10}$ DXCD1-DXCD10;

    Do I = 1 to 10;
        DXCode{i} = Substr(ICDDX{I}, 1, 3)||'.'||Substr(ICDDX{I}, 4, 2);
    End;

    Drop ICD_DGNS_CD1-ICD_DGNS_CD10;
Run;

Proc Sql;
    Create Table IPClaim_v2 as
    Select A.*, B.Description
    From ip2010claim as A Left Join SurvMedi.ICD9DX as B
    On A.DXCD1=B.Code;
Quit;

Proc Freq Data=IPClaim_v2 Order=FREQ;
    Tables Description / List Missing;
Run;
                    /* Join New IP Claim File with Membership File */
Data mbsf_ab_2010;
    Set SurvMedi.mbsf_ab_2010(Rename=(Race=RaceGrp));

                    /* Create Race and Gender variables with formatted values */
    Race = Put(RaceGrp, $RaceCat.);
    Gender = Put(Sex, $Gender.);

    If Death_Dt^=. Then
        DeathStatus='Y';
    Else
        DeathStatus='N';

    Drop RaceGrp Sex;
Run;

Proc Sort Data = mbsf_ab_2010 Nodupkey;
    By Bene_ID;
Run;

Proc Sql;
    Create Table Claim_MBSF as
    Select A.*, B.Race, B.Gender, B.State_Cd, B.Cnty_Cd, B.Death_Dt, B.DeathStatus,
        B.Bene_Dob
    From IPClaim_v2 as A, mbsf_ab_2010 as B
    Where A.Bene_ID=B.Bene_ID;
Quit;
```

**Figure 5. SAS Code to perform data manipulation tasks**

The SAS code used to perform both of these tasks is displayed in Figure 5 above. The SAS logs from running the full program is located in the appendix.

As shown in the code, I used a PROC SQL join to combine the inpatient claims file with the diagnosis code file. In a later step, PROC SORT with the NODUPKEY option is used to delete multiple beneficiary records from the beneficiary summary file (MBSF). Then PROC SQL was used again to merge the claims file with the beneficiary summary SAS data set.

One of the advantages of using the PROC SQL Join is it sorts data implicitly thus avoiding the need to sort explicitly with PROC SORT. Although its used here to delete duplicates, PROC SORT can be costly and resource-intensive in terms of performance, depending on the size of the data.

Now that all of our variables are in a single SAS data set, we need to subset the claims file to claims for specific medical conditions using ICD9 diagnosis codes. This step is often one of the first steps a lead study programmer performs in an observational research study.

Typically, an epidemiologist creates the specifications in a study protocol. They usually create a code list; a file containing the set of diagnosis, procedure, or drug codes to focus on for the study, contained in an excel spreadsheet. The programmer then imports the file into SAS, and subsets the real-world data sets they're using based on the medical codes.

For our analysis, we're interested in focusing on 3 specific medical conditions in our analysis; Congestive Heart Failure (CHF), Diabetes, and Chronic Kidney Disease (CKD). Using the diagnosis code description, we've located the relevant diagnosis codes for our 3 conditions of interest.

```
Data Claim_MBSF_v2;
        Length Condition $20;
    Set Claim_MBSF;

    Array DXCode {10} $ DXCD1-DXCD10;

    Do I=1 to 10;

        If Substr(DXCode{i}, 1, 3)='250' or DXCode{i}='253.5'
                    Then Condition='Diabetes';

        Else If Substr(DXCode{i}, 1, 3)='428'
                    Then Condition='CHF';

        Else If Substr(DXCode{i}, 1, 3) In ('580', '581', '582', '583', '584',
                                            '585', '586', '587', '588', '589',
                                            '590', '591', '592', '593')
                    Then Condition='CKD';
    End;

    Keep Bene_ID Clm_ID From_Dt Thru_Dt Admsn_Dt DschrgDt Race Gender Bene_Dob
        State_Cd Cnty_Cd Death_Dt DeathStatus Description Condition DXCD1-DXCD10;

    If Condition In ('Diabetes', 'CHF', 'CKD');
Run;
```

**Figure 6. Subsetting using a Diagnosis code list.**

The code displayed in Figure 6 above shows this process. A new variable, condition, is created to flag claim records for each of the conditions, given the set of diagnosis codes. Each condition spans a range of diagnosis codes.

In claims files, there usually is a primary diagnosis code variable, with many secondary diagnosis codes, as many as 12. To include conditions in primary as well as secondary diagnoses an array is created to hold the 10 diagnosis code variables. An iterative do-loop is then used to cycle through each diagnosis as an element of the array.

Inside the loop, all the codes within a given range of codes are selected, by extracting only the first 3 characters of the code using the SUBSTR function. At the bottom of the step, a subsetting IF statement is used to limit the claims to conditions of interest based on the Condition variable. In a step not shown, the claims were further subsetted to Chronic Kidney Disease.

## COMPUTING SURVIVAL TIME AND CENSORING

The next step in the project is to compute survival time and also to derive a binary variable to indicate censoring and other variables to use as stratification variables or covariates in the analysis.

To compute survival time, we use Death date and Admission date. Death date is our event date, with death being the event of interest. Admission date is our start date or index date. Where death date is missing, we estimate it using the last day of the current of following calendar year.

In Figure 7 below, is the DATA STEP code which computes three variables; Age, Survival time, and Censor. Age is computed from Beneficiary Date of Birth and either Admission Date or Death Date. If Death date is missing, then Admission date is used.

```
Data KidDis;
        Set Claim_MBSF_KidDis;

                *Use Death Date or Discharge Date to Compute Age;
                *Compute Survival Time Based on Death Date and Admission Date;
                *Create CENSOR flag variable for Censored patients;

                *Compute Survival time based on Death Date and Admission date;
        SurvTime=Death_Dt-Admsn_Dt;

        If DeathStatus='Y' Then Do; *Recorded Death Dates;
                Age=Floor((Death_Dt-Bene_Dob)/365.25);
                Censor=0;
        End;
                /* Death Date Missing;              */
                /* Patients lossed to followup */
        Else Do;
                Age=Floor((DschrgDt-Bene_Dob)/365.25);
                Censor=1;
        End;

        If _N_<=10 Then Put ADMSN_DT= DSCHRGDT= DEATH_DT= BENE_DOB= AGE=
                                SURVTIME= CENSOR=;
Run;
```

**Figure 7. DATA STEP with IF-THEN-ELSE Conditional Logic**

The variable CENSOR is created as a binary variable and assigned values of 0 and 1.
For beneficiaries missing a date of death, values of 1 are assigned to censored observations, which didn't experience the event of interest.

For beneficiaries which have an actual date of death, values of 0 are assigned to uncensored observations which experienced the event of interest. Age is calculated from date of birth, and date of death. If death date is missing, then admission date is used as a proxy.

## EXPLORATORY DATA ANALYSIS

Before actually running the survival analysis, we conducted exploratory data analysis to detect trends in the data and to view how survival time is distributed within specific categories of demographic variables.

Now that all the variables are in a single SAS data set, we're ready to produce descriptive statistics on survival time and our demographic group/subgroup variables. BASE SAS and ODS GRAPHICS contain many useful procedures and constructs for performing preliminary data analysis.

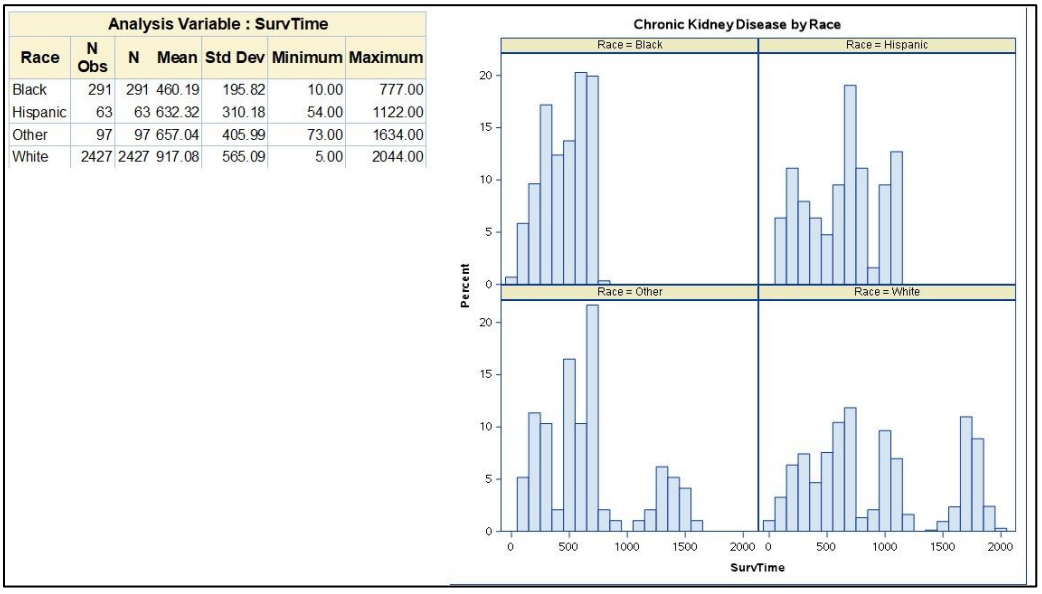
To that end, PROC MEANS was used to produce descriptive statistics for numeric variables. We also generated graphics and visualizations using PROC SGPLOT and PROC SGPANEL from the ODS GRAPHICS toolset. The SAS code to produce the descriptive statistics and graphics is presented below. Notice that only the code for chronic kidney disease (CKD) is displayed

```
Proc Means Data=KidDis N Mean Std Min Max;
     Var SurvTime;
     Class Race;
     Title'Chronic Kidney Disease by Race';
Run;

Proc SGPanel Data=KidDis;
     Panelby Race;
     Histogram SurvTime;
     Title'Chronic Kidney Disease by Race';
Run;
```

In PROC MEANS, we specify race as our CLASS statement variable, since we're interested in analyzing survival time based on race.

For the task of visualizations, PROC SGPANEL was a better choice than PROC SGPLOT, because it generates multiple graphs based on the values of a categorical variable, which allows you to do a side-by-side visual comparison of the distributions. To analyze the distribution of survival time we choose a histogram as our chart type. The SAS output is presented below in Figure 8.



Analysis Variable : SurvTime

| Race | N Obs | N | Mean | Std Dev | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Black | 291 | 291 | 460.19 | 195.82 | 10.00 | 777.00 |
| Hispanic | 63 | 63 | 632.32 | 310.18 | 54.00 | 1122.00 |
| Other | 97 | 97 | 657.04 | 405.99 | 73.00 | 1634.00 |
| White | 2427 | 2427 | 917.08 | 565.09 | 5.00 | 2044.00 |



**Figure 8. PROC MEANS and PROC SGPANEL Output**

Reviewing the PROC MEANS output, we notice the small set of observations in the frequency counts for blacks (291), Hispanic (63) and other races (97) as compared to the large set for whites (2427) for Medicare beneficiaries diagnosed with chronic kidney disease.

Taking a look at the other statistics, we notice the different ranges and distributions of survival time for each racial group, based on minimum, maximum and mean survival time values. The minimum and maximum survival time provide us with the distribution starting and ending point, which shows substantial differences in the range of survival times between the race categories

Specifically, blacks have the lowest mean (average) survival time, and the narrowest distribution out of the four race categories. Conversely, whites have the highest average survival time and the widest distribution. The other two groups, Hispanics and other races, fall between the distribution for black and whites, respectively.

The output of PROC SGPANEL allows the visualization of survival time distributions by race.
For blacks, the distribution of survival times is skewed to the left, with the highest percentage of beneficiaries having medium range survival times. For the other race categories, the distribution of survival time is more evenly distributed amongst the range.

Hispanics have a distribution closer to normal, although still skewed to the left. Whites and other races have multiple-peak distributions, with other races having a left-skewed distribution, and whites having an approximately normal distribution. For Hispanics, the highest percentage of beneficiaries have a mid-level survival time, same as for blacks and other races. For white, the highest percentages have a survival time below the middle of the range, with high percentages at mid-level and high-level survival times also.

Based on the results of our investigatory data analysis, there is sufficient evidence that the distribution of survival times for beneficiaries is dependent on race, and at this juncture proceed with the survival analysis.

## PRODUCT-LIMIT ESTIMATES WITH PROC LIFETEST

The first step in executing the survival analysis is to run PROC LIFETEST to generate product-limit estimates of the survival distribution function. As stated earlier, product-limit estimates are Kaplan-Meier estimates of the probability of survival.

For this example, we're interested in computing survival probabilities for Medicare beneficiaries diagnosed with chronic kidney disease (CKD). Based on our exploratory data analysis, we want to see how survival distributions vary by categories of race, and perform statistical significance tests on them.

AGE is included as a covariate in our model to explore the impact which patient age has on the survival functions. The SAS code for this first example is provided below.

```
Proc LifeTest Data=KidDis Plots=(s, ls, lls) Maxtime=600;
    Time SurvTime*Censor(1);
    Strata Race;
    Test Age;
Run;
```

The primary variables are specified in the TIME statement; SURVTIME for survival time and CENSOR. One of the initial procedures in survival analysis is to generate survival curves for groups of interest. The survival curves are produced using the PLOTS=(s, ls, lls) option on the PROC LIFETEST statement.

The STRATA statement is used to specify RACE as the stratification variable, and AGE is included as a covariate on the TEST statement. PROC LIFETEST will produce separate survival curves for each category of the RACE.

PROC LIFETEST generates 3 graphs in the SAS output, survival time against survival probability, Survival Time against the Negative Log of Survival Probability, and The Log of Survival Time and the Log of the Negative Log of Survival Probability. Survival time is measured in days until the event is experienced. In Figure 9 are a set of three graphs containing survival curves which plot survival time against survival probabilities for Medicare beneficiaries by race.

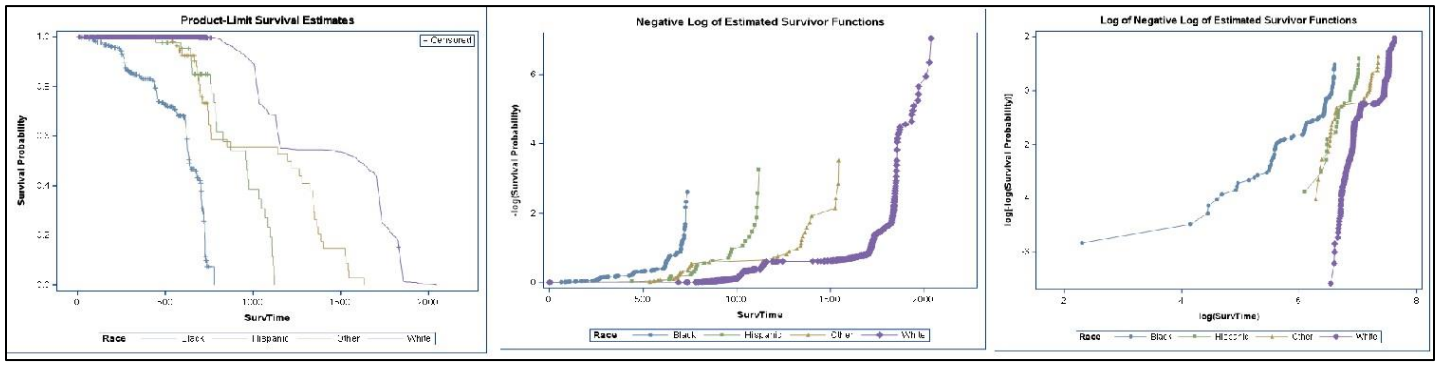



**Figure 9. PROC LIFETEST OUTPUT – Survival Curves for Race Strata**

In general, the survival functions show a decreasing probability of survival as survival time increases, regardless of racial group. However, the survival curves for blacks show the sharpest decrease in survival probability, with an angle closest to 90 degrees.

For Hispanics, the curves also show a sharp decrease, but with a higher probability of survival for longer durations.

For both other races and whites, the curves flatten out at a given probability level for a range of survival time before decreasing again. Both these groups have a higher probability of survival for longer durations than blacks and Hispanics.

Along with the survival curves, PROC LIFETEST produces a separate table with product-limit estimates for each value of the STRATA variable. The estimates are the probability of survival for computed survival times. Listed below is an excerpt from the product-limit table for black Medicare beneficiaries.

| Product-Limit Survival Estimates | | | | | | |
|---|---|---|---|---|---|---|
| SurvTime | | Survival | Failure | Survival Standard Error | Number Failed | Number Left |
| 0.00 | | 1.0000 | 0 | 0 | 0 | 291 |
| 10.00 | | 0.9966 | 0.00344 | 0.00343 | 1 | 290 |
| 19.00 | * | . | . | . | 1 | 289 |
| 61.00 | * | . | . | . | 1 | 288 |
| 63.00 | | 0.9931 | 0.00690 | 0.00486 | 2 | 287 |
| 66.00 | * | . | . | . | 2 | 286 |
| 85.00 | | 0.9896 | 0.0104 | 0.00596 | 3 | 285 |
| 86.00 | | 0.9862 | 0.0138 | 0.00687 | 4 | 284 |
| 91.00 | * | . | . | . | 4 | 283 |
| 95.00 | * | . | . | . | 4 | 282 |
| 99.00 | | 0.9827 | 0.0173 | 0.00769 | 5 | 281 |
| 100.00 | * | . | . | . | 5 | 280 |

PROC LIFETEST produces a series of additional tables containing results from other statistical tests and analytics. Not every table produced in PROC LIFETEST output is presented here due to reasons of practicality.

The procedure produces a summary table containing frequencies for each category of the strata variable, which experienced the event ('Failed'), and which did not experience the event ('Censored'). This table is presented below.

**Summary of the Number of Censored and Uncensored Values**

| Stratum | Race | Total | Failed | Censored | Percent Censored |
|---|---|---|---|---|---|
| 1 | Black | 291 | 134 | 157 | 53.95 |
| 2 | Hispanic | 63 | 28 | 35 | 55.56 |
| 3 | Other | 97 | 37 | 60 | 61.86 |
| 4 | White | 2427 | 1153 | 1274 | 52.49 |
| Total | | 2878 | 1352 | 1526 | 53.02 |

The summary data reveals that blacks were the group with the highest percentage of censored observations, followed by Hispanics, other races, and whites, respectively.

Of primary interest is the set of statistical tests PROC LIFETEST performs to determine the relationship between the stratification variable (race) and survival time. PROC LIFETEST conducts multiple tests to determine if there's a statistically significant difference in the survival functions based on this variable.

It initially computes a set of rank statistics, for each stratification level race category using two different methodologies; Log-Rank and Wilcoxon.

It conducts a set of three different significance tests; The Log-Rank, Wilcoxon, and Likelihood Ratio (LR) tests, to test for homogeneity over strata. It computes Chi-square test statistics and p-values for the three tests. Tables containing rank statistics and test of homogeneity are presented in Figure 10 below.

**Rank Statistics**

| Race | Log-Rank | Wilcoxon |
|---|---|---|
| Black | 124.99 | 244409 |
| Hispanic | 20.57 | 21926 |
| Other | 20.56 | 18710 |
| White | -166.12 | -285045 |

**Test of Equality over Strata**

| Test | Chi-Square | DF | Pr > Chi-Square |
|---|---|---|---|
| Log-Rank | 1986.2729 | 3 | <.0001 |
| Wilcoxon | 1558.8424 | 3 | <.0001 |
| -2Log(LR) | 45.5710 | 3 | <.0001 |

**Figure 10. Rank Statistics and Log-Rank, Wilcoxon and LR test results.**

For each of the three significance tests, the chi-square test statistics are sufficiently large to generate corresponding p-values less than .05.

This meets the standard to reject the null hypothesis of no relationship between race and survival time. We have sufficient evidence to indicate a statistically significant difference in the survival curves according to race and to support the alternative hypothesis of a relationship between race and the survival time.

PROC LIFETEST also performs rank tests of the association between survival time and any covariates; variables listed on the TEST statement. In our example, Age was specified as the covariate.

By default, PROC LIFETEST performs two statistical tests; the Wilcoxon Test and the Log-Rank test for the covariates and outputs tables with test results for each, which are displayed in Figure 11.

| Univariate Chi-Squares for the Wilcoxon Test | | | | |
|---|---|---|---|---|
| Variable | Test Statistic | Standard Error | Chi-Square | Pr > Chi-Square |
| Age | 317.0 | 270.6 | 1.3727 | 0.2414 |

| Univariate Chi-Squares for the Log-Rank Test | | | | |
|---|---|---|---|---|
| Variable | Test Statistic | Standard Error | Chi-Square | Pr > Chi-Square |
| Age | 430.9 | 445.5 | 0.9353 | 0.3335 |

**Figure 11. Wilcoxon and Log-Rank Test Results for Age as a Covariate.**

For the Wilcoxon test and the Log-Rank test, the Chi-square values are 1.37 and .93 respectively. These test statistics aren't large enough to produce p-values less than .05. Both the Wilcoxon test and the Log-Rank test provide no evidence of an association between age and survival time of Medicare beneficiaries diagnosed with chronic kidney disease.

## PROC PHREG – PROPORTIONAL HAZARDS MODEL

We repeated the survival analysis of Medicare beneficiaries diagnosed with chronic kidney disease using the PHREG procedure to illustrate our results using a different underlying statistical methodology.

The features of PROC PHREG were discussed in an earlier section of this paper. To quickly review, PROC PHREG uses the Cox Proportional Hazards regression model. The underlying survival function is the hazard function which is unspecified. The procedure uses a parametric form for the covariates and explanatory variables, in contrast to PROC LIFETEST which is non-parametric.

One nice feature of PROC PHREG specification of reference categories for the stratification variables. This means that the statistical estimates which PROC PHREG produces can be interpreted in relation to specific categories of the strata variables.

The PROC PHREG code used for our project is provided below

```
Proc Phreg Data=KidDis   Plots(Overlay)=Survival;
     Class Race(refno='Black') Gender(refno='Female');
     Model SurvTime*Censor(1) = Age Gender|Race;
Run;
```

In the CLASS statement, we specify explanatory variables which are classification variables. In contrast, PROC PHREG has a STRATA statement which is used to list any stratification variables. PROC PHREG makes a distinction between these two types of variables. PROC LIFETEST doesn't appear to have the same distinction, although any classification explanatory variables are listed in the TEST statement.

Another difference between PROC PHREG and PROC LIFETEST is that the volume of output is not as high for PROC PHREG as it is for PROC LIFETEST. PROC LIFETEST produces a higher number of output tables.

The CLASS LEVEL information table which displays information about the CLASS variables is displayed below. PROC PHREG creates dummy variables for categorical variables and the number of dummy variables it creates is dependent on the number of unique values in the categorical variables.

| Class Level Information | | | | |
|---|---|---|---|---|
| Class | Value | Design Variables | | |
| Race | Black | 0 | 0 | 0 |
| | Hispanic | 1 | 0 | 0 |
| | Other | 0 | 1 | 0 |
| | White | 0 | 0 | 1 |
| Gender | Female | 0 | | |
| | Male | 1 | | |

As appearing in the table, for the class variables, Race and Gender, 3 dummy variables are created for Race, and 1 dummy variable is created for Gender respectively.

In Figure 12, I've listed 2 additional output tables. In the first table are test results for testing the model validity as a whole, according to three different methods; Likelihood ratio, Score and Wald. The second table contains test results for individual covariates, effect and explanatory variables whether numeric or classification.

| Testing Global Null Hypothesis: BETA=0 | | | |
|---|---|---|---|
| Test | Chi-Square | DF | Pr > ChiSq |
| Likelihood Ratio | 780.0253 | 8 | <.0001 |
| Score | 2012.6255 | 8 | <.0001 |
| Wald | 558.2375 | 8 | <.0001 |

| Joint Tests | | | |
|---|---|---|---|
| Effect | DF | Wald Chi-Square | Pr > ChiSq |
| Age | 1 | 1.0067 | 0.3157 |
| Gender | 1 | 1.9993 | 0.1574 |
| Race | 3 | 470.2797 | <.0001 |
| Race*Gender | 3 | 6.8372 | 0.0773 |

**Figure 12. PHREG Output – Tests for Strata and Individual Covariates.**

For the test of the model as a whole, regardless of which method you use, the model is statistically significant at the .05 level. That is, the chi-square test statistics are large enough to produce p-values less than .05.

For the individual effect tests, PROC PHREG computes the Wald Chi-Square test statistics. The first two explanatory variables, Age and Gender have low Wald Chi-square test statistics, and corresponding p-values greater than .05. Thus, they're both not statistically significant. The third variable, Race, is statistically significant at the .05 level, having a large Wald Chi-square statistic.

The individual effects table also supplies results for the interaction between Race and Gender as a separate variable, Race*Gender. The interaction term is found to be not statistically significant at the .05 level, with a p-value of .0773. Though, of the three statistically invalid variables, Race*Gender is the closest to statistical significance, based on its p-value.

In the last table of output, PROC PHREG produces the Analysis of Maximum Likelihood Estimates table which contains parameter estimates, standard errors, and Chi-square statistics which test the effect of specific categories of covariates in relation to the reference categories of those same covariates. P-values are provided to determine statistical significance.

In addition to these statistics, the table provides Hazard ratios for each parameter, for which the ratio is calculated. The Hazard ratio is defined as the ratio of Hazard rates in response to an increase in one unit of the covariate or explanatory variable.

In order to properly and directly interpret the Hazard Ratios, the provided Hazard ratio in the table must be plugged into the equation;

$$1\text{-}(\text{HazardRatio})^{10,}$$

The result is the percentage decrease in the hazard rate for an increase in 10 units of the covariate.

The maximum likelihood parameter estimates, and other statistics are provided in Figure 13 below.

| Analysis of Maximum Likelihood Estimates | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | | | DF | Parameter Estimate | Standard Error | Chi-Square | Pr > ChiSq | Hazard Ratio | Label |
| Age | | | 1 | -0.00226 | 0.00225 | 1.0067 | 0.3157 | 0.998 | |
| Gender | Male | | 1 | -0.25305 | 0.17896 | 1.9993 | 0.1574 | . | Gender Male |
| Race | Hispanic | | 1 | -3.52040 | 0.33392 | 111.1458 | <.0001 | . | Race Hispanic |
| Race | Other | | 1 | -4.36483 | 0.33527 | 169.4927 | <.0001 | . | Race Other |
| Race | White | | 1 | -5.30480 | 0.25614 | 428.9400 | <.0001 | . | Race White |
| Race*Gender | Hispanic | Male | 1 | 0.78430 | 0.44257 | 3.1404 | 0.0764 | . | Race Hispanic * Gender Male |
| Race*Gender | Other | Male | 1 | 0.83113 | 0.37513 | 4.9087 | 0.0267 | . | Race Other * Gender Male |
| Race*Gender | White | Male | 1 | 0.29827 | 0.18814 | 2.5134 | 0.1129 | . | Race White * Gender Male |

**Figure 13. PHREG Output – Maximum Likelihood Estimates.**

In the table, Hazard ratios have been calculated for only one of the covariates, AGE.

Using Age as an example, and plugging the Hazard ratio for age into the equation, we get

$$1 - (.998)^{10} = 2\%.$$

Thus, an increase in 10 years of Age results in a 2% reduction in the hazard rate for Medicare beneficiaries with chronic kidney disease.

The other covariates in the model, Race and Gender are categorical variables. Notice that the Maximum likelihood estimates table has rows for only specific values of the categorical variables, excluding the reference values. The estimates are computed for non-reference categories of the covariate.

As coded in PROC PHREG, our reference categories for race and gender are ‘Black’ and ‘Female’, respectively. Thus, for Race, estimates are computed for ‘Hispanic’, ‘Other’, and ‘White’. Likewise for Gender, estimates are computed for ‘Male’. For the interaction of Race and Gender, estimates are computed for the combination of ‘Hispanic’, ‘Other’, ‘White’, and ‘Male.

Examining the test statistics and p-values for the classification variables, we notice that for Race, the effects of ‘Hispanic’, ‘Other’ and ‘White’, in relation to ‘Black’ are statistically significant at the .05 level, with p-values of <.0001.

For Race*Gender, Race=”Other’ and Gender=’Male’ in relation to ‘Black’ and ‘Female’ was statistically significant at the .05 level. The other variables (Age, etc.) and categorical values were not statistically significant at the .05 level.

Notice in Figure 13, that the hazard ratio was only calculated for the Age variable. In many scenarios, hazard ratios will not be computed for particular variables and variable values. However, you can override this outcome, using the HAZARDRATIO statement in PROC PHREG. The HAZARDRATIO statement computes hazard ratios for specific covariates, where they were missing from output.

## CONCLUSION

The SAS/STAT package contains a set of procedures for performing survival analysis. To conduct a proper survival analysis, care must be taken to perform required steps of data manipulation, data cleaning, subsetting by applying a code list, and exploratory data analysis. The choice of a particular construct depends on the need to do a parametric vs. a semi-parametric or non-parametric analysis, as well as the underlying survival function. With this paper, the objective was to illustrate the steps involved in performing a survival analysis for a longitudinal study and show the capabilities of the survival analysis procedures on real-world data sets, specifically Medicare claims.

## REFERENCES

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David Shen, & Jane Lu. 2014 'Survival Analysis Approaches and New Developments using SAS'. Proceedings of the Pharmaceutical SAS Users Group Conference, 2014. Paper PO02. https://www.lexjansen.com/pharmasug/2014/PO/PharmaSUG-2014-PO02.pdf

David Shen, & Jane Lu. 2018 'Application of Survival Analysis in Multiple Events using SAS'. Proceedings of the Pharmaceutical SAS Users Group Conference. Paper PO02. https://www.lexjansen.com/pharmasug/2018/EP/PharmaSUG-2018-EP02.pdf

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## CONTACT INFORMATION

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Jay Iyengar is Director of Data Systems Consultants LLC. He's a SAS consultant, trainer, and SAS Certified Advanced Programmer. He's been an invited speaker at several SAS user group conferences (WIILSU, WCSUG, SESUG) and has presented papers and training seminars at SAS Global Forum, Pharmaceutical SAS Users Group (PharmaSUG), and other regional and local SAS User Group conferences (MWSUG, NESUG, WUSS, MISUG). He was co-leader and organizer of the Chicago SAS Users Group (WCSUG) from 2015-19. He received his bachelor's degree from Syracuse University in Public Policy and Economics, and his master's degree from the American University.

## TRADEMARK CITATION

# APPENDIX I – PROC CONTENTS OUTPUT

| | | | |
|---|---|---|---|
| **Data Set Name** | SURVMEDI.IP2010CLAIM | **Observations** | 13916 |
| **Member Type** | DATA | **Variables** | 36 |
| **Engine** | V9 | **Indexes** | 0 |
| **Created** | 10/28/2013 10:10:52 | **Observation Length** | 232 |
| **Last Modified** | 10/28/2013 10:10:52 | **Deleted Observations** | 0 |
| **Protection** | | **Compressed** | NO |
| **Data Set Type** | | **Sorted** | YES |
| **Label** | | | |
| **Data Representation** | WINDOWS_32 | | |
| **Encoding** | wlatin1 Western (Windows) | | |

| Engine/Host Dependent Information | |
|---|---|
| **Data Set Page Size** | 16384 |
| **Number of Data Set Pages** | 200 |
| **First Data Page** | 1 |
| **Max Obs per Page** | 70 |
| **Obs in First Data Page** | 45 |
| **Number of Data Set Repairs** | 0 |
| **Filename** | /home/iyenj/SAS Papers/Suvivial_Anal_Medicare/ip2010claim.sas7bdat |
| **Release Created** | 9.0301M1 |
| **Host Created** | W32_7PRO |
| **Inode Number** | 2170931617 |
| **Access Permission** | rw-r--r-- |
| **Owner Name** | iyenj |
| **File Size** | 3MB |
| **File Size (bytes)** | 3277824 |

| Alphabetic List of Variables and Attributes | | | | | | |
|---|---|---|---|---|---|---|
| **#** | **Variable** | **Type** | **Len** | **Format** | **Informat** | **Label** |
| **12** | ADMSN_DT | Num | 4 | YYMMDDN8. | YYMMDD8. | Inpatient admission date |
| **13** | ADMTG_DGNS_CD | Char | 5 | $5. | | Claim Admitting Diagnosis Code |
| **9** | AT_NPI | Char | 10 | $10. | | Attending Physician - National Provider Identifier Number |
| **1** | BENE_ID | Char | 16 | $16. | | Beneficiary Code |
| **17** | BLDDEDAM | Num | 8 | 12.2 | | NCH Beneficiary Blood Deductible Liability Amount |
| **2** | CLM_ID | Char | 15 | $15. | | Claim ID |
| **16** | COIN_AMT | Num | 8 | 12.2 | | NCH Beneficiary Part A Coinsurance Liability Amount |
| **15** | DED_AMT | Num | 8 | 12.2 | | NCH Beneficiary Inpatient Deductible Amount |
| **20** | DRG_CD | Char | 3 | $3. | | Claim Diagnosis Related Group Code |
| **19** | DSCHRGDT | Num | 4 | YYMMDDN8. | YYMMDD8. | Inpatient discharged date |
| **4** | FROM_DT | Num | 4 | YYMMDDN8. | YYMMDD8. | Claims start date |
| **31** | ICD9_PRCDR_CD_1 | Char | 5 | $5. | | Claim Procedure Code 1 |
| **32** | ICD9_PRCDR_CD_2 | Char | 5 | $5. | | Claim Procedure Code 2 |

| Alphabetic List of Variables and Attributes | | | | | | |
|---|---|---|---|---|---|---|
| # | Variable | Type | Len | Format | Informat | Label |
| 33 | ICD9_PRCDR_CD_3 | Char | 5 | $5. | | Claim Procedure Code 3 |
| 34 | ICD9_PRCDR_CD_4 | Char | 5 | $5. | | Claim Procedure Code 4 |
| 35 | ICD9_PRCDR_CD_5 | Char | 5 | $5. | | Claim Procedure Code 5 |
| 36 | ICD9_PRCDR_CD_6 | Char | 5 | $5. | | Claim Procedure Code 6 |
| 21 | ICD_DGNS_CD1 | Char | 5 | $5. | | Claim Diagnosis Code 1 |
| 22 | ICD_DGNS_CD2 | Char | 5 | $5. | | Claim Diagnosis Code 2 |
| 23 | ICD_DGNS_CD3 | Char | 5 | $5. | | Claim Diagnosis Code 3 |
| 24 | ICD_DGNS_CD4 | Char | 5 | $5. | | Claim Diagnosis Code 4 |
| 25 | ICD_DGNS_CD5 | Char | 5 | $5. | | Claim Diagnosis Code 5 |
| 26 | ICD_DGNS_CD6 | Char | 5 | $5. | | Claim Diagnosis Code 6 |
| 27 | ICD_DGNS_CD7 | Char | 5 | $5. | | Claim Diagnosis Code 7 |
| 28 | ICD_DGNS_CD8 | Char | 5 | $5. | | Claim Diagnosis Code 8 |
| 29 | ICD_DGNS_CD9 | Char | 5 | $5. | | Claim Diagnosis Code 9 |
| 30 | ICD_DGNS_CD10 | Char | 5 | $5. | | Claim Diagnosis Code 10 |
| 10 | OP_NPI | Char | 10 | $10. | | Operating Physician - National Provider Identifier Number |
| 11 | OT_NPI | Char | 10 | $10. | | Other Physician - - National Provider Identifier Number |
| 14 | PER_DIEM | Num | 8 | 12.2 | | Claim Pass Thru Per Diem Amount |
| 7 | PMT_AMT | Num | 8 | 12.2 | | Claim Payment Amount |
| 6 | PROVIDER | Char | 6 | $6. | | Provider Institution |
| 8 | PRPAYAMT | Num | 8 | 12.2 | | NCH Primary Payer Claim Paid Amount |
| 3 | SEGMENT | Num | 3 | 2. | | Claim Line Segment |
| 5 | THRU_DT | Num | 4 | YYMMDDN8. | YYMMDD8. | Claims end date |
| 18 | UTIL_DAY | Num | 3 | 3. | | Claim Utilization Day Count |

| Sort Information | |
|---|---|
| Sortedby | BENE_ID CLM_ID |
| Validated | YES |
| Character Set | ANSI |

| | | | |
|---|---|---|---|
| **Data Set Name** | SURVMEDI.MBSF_AB_2010 | **Observations** | 112754 |
| **Member Type** | DATA | **Variables** | 32 |
| **Engine** | V9 | **Indexes** | 0 |
| **Created** | 10/28/2013 10:17:53 | **Observation Length** | 152 |
| **Last Modified** | 10/28/2013 10:17:53 | **Deleted Observations** | 0 |
| **Protection** | | **Compressed** | NO |
| **Data Set Type** | | **Sorted** | NO |
| **Label** | | | |
| **Data Representation** | WINDOWS_32 | | |
| **Encoding** | wlatin1 Western (Windows) | | |

| Engine/Host Dependent Information | |
|---|---|
| **Data Set Page Size** | 12288 |
| **Number of Data Set Pages** | 1410 |
| **First Data Page** | 1 |
| **Max Obs per Page** | 80 |
| **Obs in First Data Page** | 44 |
| **Number of Data Set Repairs** | 0 |
| **Filename** | /home/iyenj/SAS Papers/Suvivial_Anal_Medicare/mbsf_ab_2010.sas7bdat |
| **Release Created** | 9.0301M1 |
| **Host Created** | W32_7PRO |
| **Inode Number** | 2174747054 |
| **Access Permission** | rw-r--r-- |
| **Owner Name** | iyenj |
| **File Size** | 17MB |
| **File Size (bytes)** | 17327104 |

**Alphabetic List of Variables and Attributes**

| # | Variable | Type | Len | Format | Informat | Label |
|---|---|---|---|---|---|---|
| 2 | BENE_DOB | Num | 4 | YYMMDDN8. | YYMMDD8. | Date of birth |
| 9 | BENE_HI_CVRAGE_TOT_MONS | Num | 3 | 2. | | Total number of months of part A coverage for the beneficiary. |
| 11 | BENE_HMO_CVRAGE_TOT_MONS | Num | 3 | 2. | | Total number of months of HMO coverage for the beneficiary. |
| 1 | BENE_ID | Char | 16 | $16. | | Beneficiary Code |
| 10 | BENE_SMI_CVRAGE_TOT_MONS | Num | 3 | 2. | | Total number of months of part B coverage for the beneficiary. |
| 31 | BENRES_CAR | Num | 8 | 10.2 | | Carrier annual beneficiary responsibility amount |
| 25 | BENRES_IP | Num | 8 | 10.2 | | Inpatient annual beneficiary responsibility amount |
| 28 | BENRES_OP | Num | 8 | 10.2 | | Outpatient Institutional annual beneficiary responsibility amount |
| 8 | CNTY_CD | Char | 3 | $3. | | County Code |
| 3 | DEATH_DT | Num | 4 | YYMMDDN8. | YYMMDD8. | Date of death |
| 6 | ESRD_IND | Char | 1 | $1. | | End stage renal disease Indicator |
| 30 | MEDREIMB_CAR | Num | 8 | 10.2 | | Carrier annual Medicare reimbursement amount |
| 24 | MEDREIMB_IP | Num | 8 | 10.2 | | Inpatient annual Medicare reimbursement amount |
| 27 | MEDREIMB_OP | Num | 8 | 10.2 | | Outpatient Institutional annual Medicare reimbursement amount |
| 12 | PLAN_CVRG_MOS_NUM | Char | 2 | $2. | | Total number of months of part D plan coverage for the beneficiary. |
| 32 | PPPYMT_CAR | Num | 8 | 10.2 | | Carrier annual primary payer reimbursement amount |

| Alphabetic List of Variables and Attributes | | | | | | |
|---|---|---|---|---|---|---|
| # | Variable | Type | Len | Format | Informat | Label |
| 26 | PPPYMT_IP | Num | 8 | 10.2 | | Inpatient annual primary payer reimbursement amount |
| 29 | PPPYMT_OP | Num | 8 | 10.2 | | Outpatient Institutional annual primary payer reimbursement amount |
| 5 | RACE | Char | 1 | $1. | | Beneficiary Race Code |
| 4 | SEX | Char | 1 | $1. | | Sex |
| 13 | SP_ALZHDMTA | Num | 3 | 1. | | Chronic Condition: Alzheimer or related disorders or senile |
| 14 | SP_CHF | Num | 3 | 1. | | Chronic Condition: Heart Failure |
| 15 | SP_CHRNKIDN | Num | 3 | 1. | | Chronic Condition: Chronic Kidney Disease |
| 16 | SP_CNCR | Num | 3 | 1. | | Chronic Condition: Cancer |
| 17 | SP_COPD | Num | 3 | 1. | | Chronic Condition: Chronic Obstructive Pulmonary Disease |
| 18 | SP_DEPRESSN | Num | 3 | 1. | | Chronic Condition: Depression |
| 19 | SP_DIABETES | Num | 3 | 1. | | Chronic Condition: Diabetes |
| 20 | SP_ISCHMCHT | Num | 3 | 1. | | Chronic Condition: Ischemic Heart Disease |
| 21 | SP_OSTEOPRS | Num | 3 | 1. | | Chronic Condition: Osteoporosis |
| 22 | SP_RA_OA | Num | 3 | 1. | | Chronic Condition: RA/OA |
| 23 | SP_STRKETIA | Num | 3 | 1. | | Chronic Condition: Stroke/transient Ischemic Attack |
| 7 | STATE_CD | Char | 2 | $2. | | State Code |

## APPENDIX II – SAS LOG

```
1       OPTIONS NONOTES NOSTIMER NOSOURCE NOSYNTAXCHECK;
72
73       Libname SurvMedi '/home/iyenj/SAS Papers/Suvivial_Anal_Medicare';
NOTE: Libref SURVMEDI was successfully assigned as follows:
    Engine:      V9
    Physical Name: /home/iyenj/SAS Papers/Suvivial_Anal_Medicare
74       Libname SurvFmt '/home/iyenj/SAS Papers/Suvivial_Anal_Medicare/FormatLib';
NOTE: Libref SURVFMT was successfully assigned as follows:
    Engine:      V9
    Physical Name: /home/iyenj/SAS Papers/Suvivial_Anal_Medicare/FormatLib
75
76       Proc Format Library=SurvFmt;
77         Value $RaceCat
78                     '0'='Unknown'
79           '1'='White'
80                     '2'='Black'
81                     '3'='Other'
82                     '4'='Asian'
83                     '5'='Hispanic'
84                     '6'='North American Native';
NOTE: Format $RACECAT is already on the library SURVFMT.FORMATS.
NOTE: Format $RACECAT has been written to SURVFMT.FORMATS.
85         Value $Gender
86                      '1'='Male'
87                      '2'='Female';
NOTE: Format $GENDER is already on the library SURVFMT.FORMATS.
NOTE: Format $GENDER has been written to SURVFMT.FORMATS.
87     !
88       Run;

NOTE: PROCEDURE FORMAT used (Total process time):
              real time          0.00 seconds
              user cpu time      0.00 seconds
              system cpu time    0.00 seconds
              memory             296.84k
              OS Memory          31140.00k
              Timestamp          04/07/2025 04:25:28 PM

89
90       Proc Contents Data = SurvMedi.ICD9DX;

NOTE: Data file SURVMEDI.ICD9DX.DATA is in a format that is native to another host, or the file encoding does not
match the session  encoding. Cross Environment Data Access will be used, which might require additional CPU
resources and might reduce  performance.



NOTE: PROCEDURE CONTENTS used (Total process time):
              real time          0.05 seconds
              user cpu time      0.05 seconds
              system cpu time    0.00 seconds
              memory             4151.18k
```

```
      OS Memory       33452.00k
      Timestamp       04/07/2025 04:25:28 PM

91    Proc Contents Data = SurvMedi.ip2010claim;
NOTE: Data file SURVMEDI.IP2010CLAIM.DATA is in a format that is native to another host, or the file encoding does
not match the session encoding. Cross Environment Data Access will be used, which might require additional CPU
resources and might reduce performance.

NOTE: PROCEDURE CONTENTS used (Total process time):
      real time       0.07 seconds
      user cpu time   0.07 seconds
      system cpu time 0.01 seconds
      memory          1951.50k
      OS Memory       32936.00k
      Timestamp       04/07/2025 04:25:29 PM

92    Proc Contents Data = SurvMedi.mbsf_ab_2010;
93    Run;

NOTE: PROCEDURE CONTENTS used (Total process time):
      real time       0.06 seconds
      user cpu time   0.06 seconds
      system cpu time 0.00 seconds
      memory          2349.21k
      OS Memory       33964.00k
      Timestamp       04/07/2025 04:25:29 PM

94
95    Proc Print Data = SurvMedi.ICD9DX(Obs=25);
NOTE: Data file SURVMEDI.ICD9DX.DATA is in a format that is native to another host, or the file encoding does not
match the session encoding. Cross Environment Data Access will be used, which might require additional CPU
resources and might reduce performance.
96    Run;

NOTE: There were 25 observations read from the data set SURVMEDI.ICD9DX.
NOTE: PROCEDURE PRINT used (Total process time):
      real time       0.02 seconds
      user cpu time   0.02 seconds
      system cpu time 0.00 seconds
      memory          1500.59k
      OS Memory       33448.00k
      Timestamp       04/07/2025 04:25:29 PM



98    /* Join IP Claims File with Diagnosis Code Lookup Table to add Diagnosis Description */
99    Data ip2010claim;
100     Length DXCD1-DXCD10 $6;
101
102   Set SURVMEDI.ip2010claim;
NOTE: Data file SURVMEDI.IP2010CLAIM.DATA is in a format that is native to another host, or the file encoding does
not match the session encoding. Cross Environment Data Access will be used, which might require additional CPU
resources and might reduce performance.
103
104    Array ICDDX{10} $ ICD_DGNS_CD1-ICD_DGNS_CD10;
```

```
105     Array DXCode {10} $ DXCD1-DXCD10;
106
107     Do I = 1 to 10;
108     DXCode{i} = Substr(ICDDX{I}, 1, 3)||'.'||Substr(ICDDX{I}, 4, 2);
109     End;
110
111     Drop ICD_DGNS_CD1-ICD_DGNS_CD10;
112     Run;

NOTE: There were 13916 observations read from the data set SURVMEDI.IP2010CLAIM.
NOTE: The data set WORK.IP2010CLAIM has 13916 observations and 37 variables.
NOTE: DATA statement used (Total process time):
          real time          0.06 seconds
          user cpu time      0.06 seconds
          system cpu time    0.00 seconds
          memory             2423.53k
          OS Memory          34472.00k
          Timestamp          04/07/2025 04:25:29 PM
113
114     Proc Sql;
115       Create Table IPClaim_v2 as
116       Select A.*, B.Description
117       From ip2010claim as A Left Join SurvMedi.ICD9DX as B
118       On A.DXCD1=B.Code;
NOTE: Data file SURVMEDI.ICD9DX.DATA is in a format that is native to another host, or the file encoding does not
match the session encoding. Cross Environment Data Access will be used, which might require additional CPU
resources and might reduce performance.

NOTE: Table WORK.IPCLAIM_V2 created, with 13916 rows and 38 columns.

119     Quit;

NOTE: PROCEDURE SQL used (Total process time):
          real time          0.04 seconds
          user cpu time      0.03 seconds
          system cpu time    0.02 seconds
          memory             26113.78k
          OS Memory          57784.00k
          Timestamp          04/07/2025 04:25:29 PM

121     Proc Print Data=IPClaim_v2(Obs=25);
122       Var DXCD1 Description;
123     Run;

NOTE: There were 25 observations read from the data set WORK.IPCLAIM_V2.
NOTE: PROCEDURE PRINT used (Total process time):
          real time          0.02 seconds
          user cpu time      0.02 seconds
          system cpu time    0.00 seconds
          memory             2030.62k
          OS Memory          35496.00k
          Timestamp          04/07/2025 04:25:29 PM

124
125     Proc Freq Data=IPClaim_v2 Order=FREQ;
```

```
126         Tables Description / List Missing;
127       Run;

NOTE: There were 13916 observations read from the data set WORK.IPCLAIM_V2.
NOTE: PROCEDURE FREQ used (Total process time):
              real time        1.20 seconds
              user cpu time    1.20 seconds
              system cpu time  0.00 seconds
              memory           12701.68k
              OS Memory        45740.00k
              Timestamp        04/07/2025 04:25:30 PM

128
129       /* Join New IP Claim File with Membership File */
130       Data mbsf_ab_2010;
131          Set SurvMedi.mbsf_ab_2010(Rename=(Race=RaceGrp));
132
133       /* Create Race and Gender variables with formatted values */
134       Race = Put(RaceGrp, $RaceCat.);
135       Gender = Put(Sex, $Gender.);
136
137       If Death_Dt^=. Then
138                DeathStatus='Y';
139       Else
140                DeathStatus='N';
141
142              Drop RaceGrp Sex;
143       Run;

NOTE: There were 112754 observations read from the data set SURVMEDI.MBSF_AB_2010.
NOTE: The data set WORK.MBSF_AB_2010 has 112754 observations and 33 variables.

NOTE: DATA statement used (Total process time):
              real time        0.05 seconds
              user cpu time    0.03 seconds
              system cpu time  0.02 seconds
              memory           3704.28k
              OS Memory        39596.00k
              Timestamp        04/07/2025 04:25:30 PM

144
145       Proc Sort Data = mbsf_ab_2010 Nodupkey;
146        By Bene_ID;
147       Run;

NOTE: There were 112754 observations read from the data set WORK.MBSF_AB_2010.
NOTE: 0 observations with duplicate key values were deleted.
NOTE: The data set WORK.MBSF_AB_2010 has 112754 observations and 33 variables.
NOTE: PROCEDURE SORT used (Total process time):
              real time        0.04 seconds
              user cpu time    0.03 seconds
              system cpu time  0.02 seconds
              memory           26497.68k
              OS Memory        61676.00k
              Timestamp        04/07/2025 04:25:30 PM
```

```
149     Proc Sql;
150       Create Table Claim_MBSF as
151         Select A.*,
152                B.Race,
153                B.Gender,
154                B.State_Cd,
155                B.Cnty_Cd,
156                B.Death_Dt,
157                B.DeathStatus,
158                B.Bene_Dob
159       From IPClaim_v2 as A, mbsf_ab_2010 as B
160     Where A.Bene_ID=B.Bene_ID;
NOTE: Table WORK.CLAIM_MBSF created, with 13916 rows and 45 columns.

161     Quit;
NOTE: PROCEDURE SQL used (Total process time):
          real time        0.03 seconds
          user cpu time    0.02 seconds
          system cpu time  0.02 seconds
          memory           22728.31k
          OS Memory        57528.00k
          Timestamp        04/07/2025 04:25:30 PM

163     Proc Freq Data=Claim_MBSF;
164           Tables DeathStatus / List Missing;
165     Run;

NOTE: There were 13916 observations read from the data set WORK.CLAIM_MBSF.
NOTE: PROCEDURE FREQ used (Total process time):
          real time        0.01 seconds
          user cpu time    0.01 seconds
          system cpu time  0.00 seconds
          memory           2241.25k
          OS Memory        37804.00k
          Timestamp        04/07/2025 04:25:30 PM

167     Data Claim_MBSF_v2;
168               Length Condition $20;
169       Set Claim_MBSF;
170
171       Array DXCode {10} $ DXCD1-DXCD10;
172
173       Do I=1 to 10;
174
175       If Substr(DXCode{i}, 1, 3)='250' or DXCode{i}='253.5'
176           Then Condition='Diabetes';
177
178       Else If Substr(DXCode{i}, 1, 3)='428'
179     Then Condition='CHF';
180
181       Else If Substr(DXCode{i}, 1, 3) In ('580', '581', '582', '583', '584',
182                                           '585', '586', '587', '588', '589',
183                                           '590', '591', '592', '593')
184     Then Condition='CKD';
```

```
185     End;
186
187     Keep Bene_ID Clm_ID From_Dt Thru_Dt Admsn_Dt DschrgDt Race Gender Bene_Dob
188             State_Cd Cnty_Cd Death_Dt DeathStatus Description Condition DXCD1-DXCD10;
189
190       If Condition In ('Diabetes', 'CHF', 'CKD');
191     Run;

NOTE: There were 13916 observations read from the data set WORK.CLAIM_MBSF.
NOTE: The data set WORK.CLAIM_MBSF_V2 has 7714 observations and 25 variables.
NOTE: DATA statement used (Total process time):
            real time         0.02 seconds
            user cpu time     0.02 seconds
            system cpu time   0.01 seconds
            memory            3666.81k
            OS Memory         39596.00k
            Timestamp         04/07/2025 04:25:30 PM
192
193     Data Claim_MBSF_KidDis;
194       Set Claim_MBSF_v2(Where=(Condition='CKD'));
195
196       If (225<=_N_<=275 or 325<=_N_<=340 or
197         401<=_N_<=422 or 1501<=_N_<=2000) Then Death_Dt='31DEC2010'D;
198
199       Else If (275<_N_<=291 Or 340<_N_<=354 Or
200         422<_N_<=451 Or 2001<_N_<=2878) Then Death_Dt='31DEC2011'D;
201
202       If (225<=_N_<=291 or 325<=_N_<=354 or 401<=_N_<=451 or 1501<=_N_<=2878)
203         Then DeathStatus='N';
204       Else DeathStatus='Y';
205
206     Run;

NOTE: There were 2878 observations read from the data set WORK.CLAIM_MBSF_V2.
          WHERE Condition='CKD';
NOTE: The data set WORK.CLAIM_MBSF_KIDDIS has 2878 observations and 25 variables.
NOTE: DATA statement used (Total process time):
            real time         0.00 seconds
            user cpu time     0.01 seconds
            system cpu time   0.00 seconds
            memory            2686.06k
            OS Memory         38316.00k
            Timestamp         04/07/2025 04:25:30 PM

207
208     Proc Freq Data = Claim_MBSF_KidDis;
209       Tables Condition / List Missing;
210       Tables Condition*DeathStatus / List Missing;
211     Run;

NOTE: There were 2878 observations read from the data set WORK.CLAIM_MBSF_KIDDIS.
NOTE: PROCEDURE FREQ used (Total process time):
            real time         0.02 seconds
            user cpu time     0.02 seconds
            system cpu time   0.00 seconds
```

```
            memory          2216.46k
            OS Memory       38200.00k
            Timestamp       04/07/2025 04:25:30 PM

213     Proc Sql;
214       Create Table Claim_Sum As
215       Select Bene_ID, Count(Bene_ID) as Num_Visits
216       From Claim_MBSF_KidDis
217       Group By Bene_ID
218       Having Num_Visits>1;
NOTE: Table WORK.CLAIM_SUM created, with 96 rows and 2 columns.

219     Quit;
NOTE: PROCEDURE SQL used (Total process time):
            real time       0.00 seconds
            user cpu time     0.01 seconds
            system cpu time   0.00 seconds
            memory          6250.56k
            OS Memory       42284.00k
            Timestamp       04/07/2025 04:25:30 PM

220
221     Data KidDis;
222           Set Claim_MBSF_KidDis;
223
224     *Use Death Date or Discharge Date to Compute Age;
225     *Compute Survival Time Based on Death Date and Admission Date;
226     *Create CENSOR flag variable for Censored patients;
227
228     *Compute Survival time based on Death Date and Admission date;
229      SurvTime=Death_Dt-Admsn_Dt;
230
231     If DeathStatus='Y' Then Do; *Recorded Death Dates;
232      Age=Floor((Death_Dt-Bene_Dob)/365.25);
233               Censor=0;
234     End;

235       /* Death Date Missing;   */
236       /* Patients lossed to followup */
237     Else Do;
238      Age=Floor((DschrgDt-Bene_Dob)/365.25);
239      Censor=1;
240     End;
241
242     If _N_<=10 Then Put ADMSN_DT= DSCHRGDT= DEATH_DT= BENE_DOB= AGE= SURVTIME=
                            CENSOR=;
243     Run;
```

```
ADMSN_DT=20100522 DSCHRGDT=20100612 DEATH_DT=20110901 BENE_DOB=19190901 Age=92 SurvTime=467 Censor=0
ADMSN_DT=20100830 DSCHRGDT=20100907 DEATH_DT=20150901 BENE_DOB=19531201 Age=61 SurvTime=1828 Censor=0
ADMSN_DT=20100114 DSCHRGDT=20100119 DEATH_DT=20150101 BENE_DOB=19571101 Age=57 SurvTime=1813 Censor=0
ADMSN_DT=20100703 DSCHRGDT=20100712 DEATH_DT=20130101 BENE_DOB=19251001 Age=87 SurvTime=913 Censor=0
ADMSN_DT=20100222 DSCHRGDT=20100302 DEATH_DT=20121201 BENE_DOB=19620601 Age=50 SurvTime=1013 Censor=0
ADMSN_DT=20100129 DSCHRGDT=20100208 DEATH_DT=20130101 BENE_DOB=19410501 Age=71 SurvTime=1068 Censor=0
ADMSN_DT=20100708 DSCHRGDT=20100710 DEATH_DT=20150401 BENE_DOB=19431101 Age=71 SurvTime=1728 Censor=0
ADMSN_DT=20100518 DSCHRGDT=20100523 DEATH_DT=20150101 BENE_DOB=19370201 Age=77 SurvTime=1689 Censor=0
ADMSN_DT=20100713 DSCHRGDT=20100722 DEATH_DT=20150101 BENE_DOB=19370201 Age=77 SurvTime=1633 Censor=0
ADMSN_DT=20101002 DSCHRGDT=20101020 DEATH_DT=20151101 BENE_DOB=19420901 Age=73 SurvTime=1856 Censor=0

NOTE: There were 2878 observations read from the data set WORK.CLAIM_MBSF_KIDDIS.
NOTE: The data set WORK.KIDDIS has 2878 observations and 28 variables.
NOTE: DATA statement used (Total process time):
      real time          0.00 seconds
      user cpu time      0.00 seconds
      system cpu time    0.00 seconds
      memory             2337.12k
      OS Memory          37420.00k
      Timestamp          04/07/2025 04:25:30 PM

244
245     /* Graph Survival time Group by Sex and Race for each Condition/Disease */
246     /* use PROC SGPLOT */
247
248     Proc Freq Data=KidDis;
249     Tables DeathStatus / List Missing;
250     Run;

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.
NOTE: PROCEDURE FREQ used (Total process time):
      real time          0.01 seconds
      user cpu time      0.01 seconds
      system cpu time    0.00 seconds
      memory             1492.09k
      OS Memory          37548.00k
      Timestamp          04/07/2025 04:25:30 PM
250
251
252     /* Kidney Disease */
253     /* By Race, Gender, and Race & Gender */
254
255     Proc Means Data=KidDis N Mean Std Min Max Maxdec=2;
256       Var SurvTime;
257       Class Race;
258       Title'Chronic Kidney Disease by Race';
259     Run;

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.
NOTE: PROCEDURE MEANS used (Total process time):
      real time          0.02 seconds
      user cpu time      0.02 seconds
      system cpu time    0.00 seconds
      memory             8654.34k
      OS Memory          43452.00k
      Timestamp          04/07/2025 04:25:30 PM
```

```
261     Proc SGPanel Data=KidDis;
262                 Panelby Race;
263                 Histogram SurvTime;
264                 Title'Chronic Kidney Disease by Race';
265     Run;

NOTE: PROCEDURE SGPANEL used (Total process time):
            real time        2.88 seconds
            user cpu time    0.16 seconds
            system cpu time  0.03 seconds
            memory           21619.79k
            OS Memory        55212.00k
            Timestamp        04/07/2025 04:25:33 PM

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.

266
267     Proc Means Data=KidDis N Mean Std Min Max;
268       Var SurvTime;
269       Class Gender;
270       Title'Chronic Kidney Disease by Gender';
271     Run;

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.
NOTE: PROCEDURE MEANS used (Total process time):
            real time        0.02 seconds
            user cpu time    0.02 seconds
            system cpu time  0.01 seconds
            memory           9736.96k
            OS Memory        63932.00k
            Timestamp        04/07/2025 04:25:33 PM
271
272
273     Proc SGPanel Data=KidDis;
274      Panelby Gender;
275                 Histogram SurvTime;
276                 Title'Chronic Kidney Disease by Gender';
277     Run;

NOTE: PROCEDURE SGPANEL used (Total process time):
            real time        0.38 seconds
            user cpu time    0.09 seconds
            system cpu time  0.01 seconds
            memory           5439.07k
            OS Memory        57776.00k
            Timestamp        04/07/2025 04:25:34 PM

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.

278
279     Proc Means Data=KidDis N Mean Std Min Max;
280       Var SurvTime;
281       Class Race Gender;
282      Title'Chronic Kidney Disease by Race and Gender';
```

```
283      Run;

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.
NOTE: PROCEDURE MEANS used (Total process time):
            real time        0.04 seconds
            user cpu time    0.04 seconds
            system cpu time  0.01 seconds
            memory           8679.15k
            OS Memory        62908.00k
            Timestamp        04/07/2025 04:25:34 PM

284
285      Proc SGPanel Data=KidDis;
286      Panelby Race Gender;
287      Histogram SurvTime;
288      Title'Chronic Kidney Disease by Race and Gender';
289      Run;

NOTE: PROCEDURE SGPANEL used (Total process time):
            real time        0.85 seconds
            user cpu time    0.24 seconds
            system cpu time  0.02 seconds
            memory           5476.21k
            OS Memory        57952.00k
            Timestamp        04/07/2025 04:25:34 PM

NOTE: There were 2878 observations read from the data set WORK.KIDDIS.
```