

Final Project

Course Name: Independent Study - Survival Analysis

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```
In [1]: # Libraries Utilized
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from lifelines import KaplanMeierFitter
from lifelines.statistics import logrank_test, pairwise_logrank_test
from tabulate import tabulate
import warnings
from lifelines import CoxPHFitter
import matplotlib as mpl
import numpy as np
from lifelines import CoxPHFitter
# !pip install scikit-survival
from sksurv.ensemble import RandomSurvivalForest
from sksurv.metrics import concordance_index_censored
from sklearn.inspection import permutation_importance
from sksurv.metrics import concordance_index_censored
```

```
In [2]: # Loading the CSV file
canine = pd.read_csv('Canine_Survival_Analysis.csv')

# Displaying the first few rows
print(canine.head())
```

	PatientID	site	Died	how died	Pre-ACTH	Post-ACTH	Insurance	weight	\
0	1.0	183.0	0.0	0	0.0	0.0	0	7.55	
1	2.0	284.0	0.0	0	0.0	0.0	0	7.20	
2	3.0	182.0	1.0	0	267.0	922.0	0	12.50	
3	4.0	284.0	1.0	0	0.0	0.0	0	19.00	
4	5.0	159.0	1.0	Euthanasia	145.0	684.0	Insured	34.25	

	BreedRelativeWeight	BirthDate	...	Complications	Hypertensive_Yes4	\
0	1.0	14-05-2003	...	Unknown	Unknown	
1	1.0	07-11-2002	...	Unknown	Unknown	
2	2.0	01-02-2005	...	Unknown	Unknown	
3	1.0	09-10-2003	...	Unknown	Unknown	
4	2.0	01-07-2004	...	Yes	Yes	

	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	\
0	Yes	Yes	Yes	
1	Yes	Unknown	Unknown	
2	Yes	Yes	No	
3	Yes	No	No	
4	Yes	Yes	Yes	

	Number_comorbidities	comorb_UTI	comorb_dm	comorb_hypot	Unnamed: 37
0	0.0	No	No	No	NaN
1	1.0	No	No	No	NaN
2	3.0	No	Yes	No	NaN
3	0.0	No	No	No	NaN
4	1.0	Yes	No	No	NaN

[5 rows x 38 columns]

Analyzing and Preprocessing - Part 1

```
In [3]: # Printing the column names
print(canine.columns)
print(f"Total number of columns: {len(canine.columns)}")
```

```
Index(['PatientID', 'site', 'Died', 'how died', 'Pre-ACTH', 'Post-ACTH',
      'Insurance', 'weight', 'BreedRelativeWeight', 'BirthDate', 'Sex',
      'Isneutered', 'Breed', 'KC_group', 'Purebreed_status',
      'Date of diagnosis_3', 'Failedate', 'Date of first suspicion_4',
      'Date trilostane started_5', 'Changes to trilostane_6', 'Stay_vs_stop',
      'Treated with trilostane_7', 'Trilostane starting dose (mg/kg)_8',
      'Trilostane SID/BID_9', 'Censored_10', 'Why censored_11',
      'Cause of death_13', 'Neuro signs', 'Complications',
      'Hypertensive_Yes4', 'Oversuppresion?', 'Cortisol stayed <250',
      'Cortisol went <40', 'Number_comorbidities', 'comorb_UTI', 'comorb_dm',
      'comorb_hypot', 'Unnamed: 37'],
      dtype='object')
Total number of columns: 38
```

```
In [4]: # Removing the last column
canine = canine.iloc[:, :-1]

# Verifying the number of columns after removal
print(f"Total number of columns after removal: {len(canine.columns)}")
```

Total number of columns after removal: 37

```
In [5]: # Displaying detailed information about the DataFrame
print(canine.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 393 entries, 0 to 392
Data columns (total 37 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   PatientID                            219 non-null    float64
1   site                                  219 non-null    float64
2   Died                                  219 non-null    float64
3   how died                             219 non-null    object
4   Pre-ACTH                             219 non-null    float64
5   Post-ACTH                            219 non-null    float64
6   Insurance                             219 non-null    object
7   weight                                219 non-null    float64
8   BreedRelativeWeight                  219 non-null    float64
9   BirthDate                            219 non-null    object
10  Sex                                   219 non-null    object
11  Isneutered                           219 non-null    object
12  Breed                                 219 non-null    object
13  KC_group                             219 non-null    object
14  Purebreed_status                     219 non-null    float64
15  Date of diagnosis_3                  219 non-null    object
16  Failedate                             219 non-null    object
17  Date of first suspicion_4             219 non-null    object
18  Date trilostane started_5             205 non-null    object
19  Changes to trilostane_6               206 non-null    float64
20  Stay_vs_stop                          219 non-null    float64
21  Treated with trilostane_7             219 non-null    float64
22  Trilostane starting dose (mg/kg)_8    199 non-null    float64
23  Trilostane SID/BID_9                  206 non-null    object
24  Censored_10                           45 non-null    object
25  Why censored_11                       40 non-null    object
26  Cause of death_13                     177 non-null    object
27  Neuro signs                           219 non-null    object
28  Complications                         219 non-null    object
29  Hypertensive_Yes4                     219 non-null    object
30  Oversuppresion?                       219 non-null    object
31  Cortisol stayed <250                   219 non-null    object
32  Cortisol went <40                     219 non-null    object
33  Number_comorbidities                  219 non-null    float64
34  comorb_UTI                            219 non-null    object
35  comorb_dm                             219 non-null    object
36  comorb_hypot                          219 non-null    object
dtypes: float64(13), object(24)
memory usage: 113.7+ KB
None
```

```
In [6]: # Creating a subset excluding PatientID
canine_subset = canine.iloc[:,219].drop('PatientID', axis=1)

# Total columns in subset
print(f"Total number of columns in the subset: {len(canine_subset.columns)}")
```

```
# Total rows in subset
print(f"Number of rows in canine_subset: {len(canine_subset)}")
print(canine_subset.head())
print(canine_subset.tail())

# Converting the 'Died' column from float to int
canine_subset['Died'] = canine_subset['Died'].astype(int)

# Printing the unique and the first few values to confirm the conversion
print("Unique values in 'Died' column:", canine_subset['Died'].unique())
print(canine_subset['Died'].head())
```

Total number of columns in the subset: 36

Number of rows in canine_subset: 219

	site	Died	how died	Pre-ACTH	Post-ACTH	Insurance	weight	\
0	183.0	0.0	0	0.0	0.0	0	7.55	
1	284.0	0.0	0	0.0	0.0	0	7.20	
2	182.0	1.0	0	267.0	922.0	0	12.50	
3	284.0	1.0	0	0.0	0.0	0	19.00	
4	159.0	1.0	Euthanasia	145.0	684.0	Insured	34.25	

	BreedRelativeWeight	BirthDate	Sex	...	Neuro signs	Complications	\
0	1.0	14-05-2003	male	...	No	Unknown	
1	1.0	07-11-2002	Female	...	No	Unknown	
2	2.0	01-02-2005	male	...	No	Unknown	
3	1.0	09-10-2003	Female	...	No	Unknown	
4	2.0	01-07-2004	male	...	No	Yes	

	Hypertensive_Yes4	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	\
0	Unknown	Yes	Yes	Yes	
1	Unknown	Yes	Unknown	Unknown	
2	Unknown	Yes	Yes	No	
3	Unknown	Yes	No	No	
4	Yes	Yes	Yes	Yes	

	Number_comorbidities	comorb_UTI	comorb_dm	comorb_hypot
0	0.0	No	No	No
1	1.0	No	No	No
2	3.0	No	Yes	No
3	0.0	No	No	No
4	1.0	Yes	No	No

[5 rows x 36 columns]

	site	Died	how died	Pre-ACTH	Post-ACTH	Insurance	weight	\
214	139.0	1.0	Euthanasia	0.0	0.0	Uninsured	9.10	
215	138.0	1.0	Euthanasia	0.0	0.0	Uninsured	9.00	
216	120.0	1.0	Unassisted	118.0	1380.0	Uninsured	9.20	
217	166.0	0.0	0	0.0	0.0	Uninsured	7.95	
218	123.0	1.0	Euthanasia	178.0	811.0	Insured	0.00	

	BreedRelativeWeight	BirthDate	Sex	...	Neuro signs	Complications	\
214	1.0	26-07-2003	male	...	No	Unknown	
215	1.0	08-03-2001	male	...	Yes	Unknown	
216	1.0	09-06-1995	Female	...	No	Unknown	
217	4.0	29-09-2004	Female	...	No	Unknown	
218	4.0	03-11-1999	male	...	Yes	Unknown	

	Hypertensive_Yes4	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	\
214	Unknown	No	No	No	
215	Unknown	No	Unknown	Unknown	
216	Unknown	No	Yes	No	
217	Unknown	No	Unknown	Unknown	
218	Unknown	No	Unknown	Unknown	

	Number_comorbidities	comorb_UTI	comorb_dm	comorb_hypot
214	0.0	No	No	No
215	1.0	No	No	No
216	0.0	No	No	No

217	0.0	No	No	No
218	1.0	No	No	No

[5 rows x 36 columns]

Unique values in 'Died' column: [0 1]

0 0

1 0

2 1

3 1

4 1

Name: Died, dtype: int32

```
In [7]: # Calculating the frequency table for 'site' column
site_freq = canine_subset['site'].value_counts()
site_percent = canine_subset['site'].value_counts(normalize=True, dropna=False) * 1

print("Frequency table for 'site':")
print("Value Frequency Percentage")
for value, count in site_freq.items():
    percentage = site_percent[value]
    print(f"{value:<6} {count:<10} {percentage:.2f}%")

print(f"\nTotal number of entries: {len(canine_subset)}")
print(f"Number of unique values: {canine_subset['site'].nunique()}")
print(f"Number of missing values: {canine_subset['site'].isnull().sum()}")
```

Frequency table for 'site':

Value	Frequency	Percentage
174.0	7	3.20%
120.0	7	3.20%
118.0	7	3.20%
132.0	6	2.74%
160.0	6	2.74%
196.0	6	2.74%
198.0	6	2.74%
135.0	6	2.74%
126.0	5	2.28%
178.0	5	2.28%
123.0	5	2.28%
115.0	5	2.28%
140.0	5	2.28%
173.0	4	1.83%
199.0	4	1.83%
133.0	4	1.83%
131.0	4	1.83%
136.0	4	1.83%
163.0	4	1.83%
197.0	4	1.83%
189.0	4	1.83%
151.0	4	1.83%
164.0	4	1.83%
157.0	3	1.37%
107.0	3	1.37%
122.0	3	1.37%
111.0	3	1.37%
145.0	3	1.37%
138.0	3	1.37%
108.0	3	1.37%
121.0	3	1.37%
139.0	3	1.37%
169.0	3	1.37%
144.0	3	1.37%
106.0	3	1.37%
166.0	3	1.37%
159.0	3	1.37%
110.0	3	1.37%
183.0	2	0.91%
168.0	2	0.91%
158.0	2	0.91%
187.0	2	0.91%
176.0	2	0.91%
113.0	2	0.91%
186.0	2	0.91%
143.0	2	0.91%
162.0	2	0.91%
154.0	2	0.91%
128.0	2	0.91%
165.0	2	0.91%
182.0	2	0.91%
124.0	2	0.91%
284.0	2	0.91%
134.0	2	0.91%

194.0	2	0.91%
152.0	2	0.91%
293.0	1	0.46%
127.0	1	0.46%
147.0	1	0.46%
172.0	1	0.46%
137.0	1	0.46%
142.0	1	0.46%
117.0	1	0.46%
179.0	1	0.46%
170.0	1	0.46%
292.0	1	0.46%
155.0	1	0.46%
295.0	1	0.46%
148.0	1	0.46%
156.0	1	0.46%
167.0	1	0.46%
294.0	1	0.46%
296.0	1	0.46%
188.0	1	0.46%
146.0	1	0.46%
181.0	1	0.46%
114.0	1	0.46%
130.0	1	0.46%

Total number of entries: 219

Number of unique values: 78

Number of missing values: 0

```
In [8]: # "site" column not so informative, thus dropping from the analysis
        canine_subset = canine_subset.iloc[:, 1:]
        # Total columns in subset
        print(f"Total number of columns in the subset: {len(canine_subset.columns)}")
        # Column names in subset
        print(f"Column names in the subset: {canine_subset.columns}")
```

Total number of columns in the subset: 35

Column names in the subset: Index(['Died', 'how died', 'Pre-ACTH', 'Post-ACTH', 'Insurance', 'weight', 'BreedRelativeWeight', 'BirthDate', 'Sex', 'Isneutered', 'Breed', 'KC_group', 'Purebreed_status', 'Date of diagnosis_3', 'Failedate', 'Date of first suspicion_4', 'Date trilostane started_5', 'Changes to trilostane_6', 'Stay_vs_stop', 'Treated with trilostane_7', 'Trilostane starting dose (mg/kg)_8', 'Trilostane SID/BID_9', 'Censored_10', 'Why censored_11', 'Cause of death_13', 'Neuro signs', 'Complications', 'Hypertensive_Yes4', 'Oversuppresion?', 'Cortisol stayed <250', 'Cortisol went <40', 'Number_comorbidities', 'comorb_UTI', 'comorb_dm', 'comorb_hypot'], dtype='object')

```
In [9]: # Printing the count of NaN values in each column
        print("Count of NaN values in each column before replacement:")
        print(canine_subset.isnull().sum())
        # There were a total of 393 rows initially.
        # Removing the nulls resulted in a dataset of 219 rows
```



```

Count of NaN values in each column before replacement:
Died                                0
how died                            0
Pre-ACTH                            0
Post-ACTH                           0
Insurance                           0
weight                              0
BreedRelativeWeight                 0
BirthDate                           0
Sex                                  0
Isneutered                           0
Breed                                0
KC_group                             0
Purebreed_status                    0
Date of diagnosis_3                  0
Failedate                            0
Date of first suspicion_4            0
Date trilostane started_5            14
Changes to trilostane_6              13
Stay_vs_stop                         0
Treated with trilostane_7            0
Trilostane starting dose (mg/kg)_8   20
Trilostane SID/BID_9                13
Censored_10                         174
Why censored_11                     179
Cause of death_13                    42
Neuro signs                          0
Complications                        0
Hypertensive_Yes4                    0
Oversuppresion?                      0
Cortisol stayed <250                 0
Cortisol went <40                    0
Number_comorbidities                 0
comorb_UTI                           0
comorb_dm                            0
comorb_hypot                         0
dtype: int64

```

```

In [10]: # Creating the categorical_columns
categorical_columns = [
    'Died',
    'how died',
    'Insurance',
    'Sex',
    'Isneutered',
    'Breed',
    'KC_group',
    'BreedRelativeWeight',
    'Purebreed_status',
    'Changes to trilostane_6',
    'Stay_vs_stop',
    'Treated with trilostane_7',
    'Trilostane SID/BID_9',
    'Censored_10',
    'Why censored_11',
    'Cause of death_13',

```

```

    'Neuro signs',
    'Complications',
    'Hypertensive_Yes4',
    'Oversuppresion?',
    'Cortisol stayed <250',
    'Cortisol went <40',
    'Number_comorbidities',
    'comorb_UTI',
    'comorb_dm',
    'comorb_hypot'
]

# Converting the specified columns to categorical (factor)
for col in categorical_columns:
    canine_subset[col] = canine_subset[col].astype('category')

# Generating the descriptive statistics for each categorical variable
descriptive_stats = {}
for col in categorical_columns:
    descriptive_stats[col] = canine_subset[col].value_counts(dropna=False)

# Printing the descriptive statistics
for col, stats in descriptive_stats.items():
    print(f"\nDescriptive statistics for '{col}':")
    print(stats)

```

Descriptive statistics for 'Died':

Died

1 179

0 40

Name: count, dtype: int64

Descriptive statistics for 'how died':

how died

Euthanasia 126

0 73

Unassisted 19

Unknown 1

Name: count, dtype: int64

Descriptive statistics for 'Insurance':

Insurance

Insured 126

Uninsured 52

0 41

Name: count, dtype: int64

Descriptive statistics for 'Sex':

Sex

male 115

Female 104

Name: count, dtype: int64

Descriptive statistics for 'Isneutered':

Isneutered

Yes 169

No 50

Name: count, dtype: int64

Descriptive statistics for 'Breed':

Breed

Crossbreed

47

Terrier - Jack Russell (JRT)

21

Terrier - Yorkshire (Yorkshire Terrier)

16

Bichon - Frise

13

Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)) 13

Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT))

12

Retriever - Labrador (Labrador Retriever)

8

Schnauzer

8

Spaniel - Cocker (unspecified) (Cocker Spaniel (unspecified))

6

Terrier - Border (Border Terrier)

5

Boxer (unspecified)

5
Shih-tzu
5
Dachshund, Miniature
5
Lhasa Apso
5
Terrier - Tibetan
4
Spaniel - Cavalier King Charles (CKCS) (Cavalier King Charles Spaniel (CKCS))
4
Terrier - Bull (unspecified) (Bull Terrier (unspecified))
4
Collie - Bearded
3
Terrier - Scottish
3
Shepherd Dog - German (Alsatian) (GSD) (unspecified) (German Shepherd Dog (Alsatian) (GSD) (unspecified)) 3
Dachshund, Standard
3
Terrier - Boston
2
Chihuahua, Short-Haired
2
Terrier - Patterdale
2
Terrier - Norfolk
2
Poodle, Standard
2
Retriever - Golden (Golden Retriever)
2
Retriever - Flat Coated
1
Terrier - Australian Silky
1
Spaniel - Springer, English (English Springer Spaniel)
1
Terrier - Cairn
1
Terrier - Fox (unspecified)
1
Collie - Border
1
Terrier - Lakeland
1
Spaniel - King Charles (KCS)
1
Sheepdog - Shetland (Sheltie)
1
Mastiff - Bull
1
Samoyed
1
Poodle, Miniature

```
1
Bulldog (unspecified)
1
Whippet (unspecified)
1
Name: count, dtype: int64
```

Descriptive statistics for 'KC_group':

```
KC_group
Terrier      65
Non-KC       47
Toy          47
Gundog       18
Utility      18
Hound        9
Pastoral     9
Working      6
Name: count, dtype: int64
```

Descriptive statistics for 'BreedRelativeWeight':

```
BreedRelativeWeight
1.0      81
2.0      73
4.0      45
3.0      20
Name: count, dtype: int64
```

Descriptive statistics for 'Purebreed_status':

```
Purebreed_status
1.0      172
2.0       47
Name: count, dtype: int64
```

Descriptive statistics for 'Changes to trilostane_6':

```
Changes to trilostane_6
3.0      94
1.0      55
4.0      34
2.0      23
NaN       13
Name: count, dtype: int64
```

Descriptive statistics for 'Stay_vs_stop':

```
Stay_vs_stop
1.0      172
2.0       47
Name: count, dtype: int64
```

Descriptive statistics for 'Treated with trilostane_7':

```
Treated with trilostane_7
1.0      206
2.0       13
Name: count, dtype: int64
```

Descriptive statistics for 'Trilostane SID/BID_9':

```
Trilostane SID/BID_9
```

SID 178
BID 16
NaN 13
Unknown 12
Name: count, dtype: int64

Descriptive statistics for 'Censored_10':

Censored_10
NaN 174
Yes 40
No 5
Name: count, dtype: int64

Descriptive statistics for 'Why censored_11':

Why censored_11
NaN 179
Moved practice 22
No record in last 3 months 11
Alive 6
Practice cannot contact 1
Name: count, dtype: int64

Descriptive statistics for 'Cause of death_13':

Cause of death_13
Unknown 55
NaN 42
Nervous 33
Digestive 24
Endocrine (Cushing's) 13
Renal/urinary 13
Circulatory 12
Respiratory 10
Musculoskeletal 7
Endocrine (not cushing's) 5
Immune system/Lymphatic 2
Integumental 2
Reproductive 1
Name: count, dtype: int64

Descriptive statistics for 'Neuro signs':

Neuro signs
No 174
Yes 45
Name: count, dtype: int64

Descriptive statistics for 'Complications':

Complications
Unknown 169
Yes 50
Name: count, dtype: int64

Descriptive statistics for 'Hypertensive_Yes4':

Hypertensive_Yes4
Unknown 177
Yes 27
No 15

Name: count, dtype: int64

Descriptive statistics for 'Oversuppresion?':

Oversuppresion?

No 191

Yes 28

Name: count, dtype: int64

Descriptive statistics for 'Cortisol stayed <250':

Cortisol stayed <250

Unknown 119

Yes 68

No 32

Name: count, dtype: int64

Descriptive statistics for 'Cortisol went <40':

Cortisol went <40

Unknown 119

No 79

Yes 21

Name: count, dtype: int64

Descriptive statistics for 'Number_comorbidities':

Number_comorbidities

1.0 86

0.0 78

2.0 37

3.0 14

4.0 3

5.0 1

Name: count, dtype: int64

Descriptive statistics for 'comorb_UTI':

comorb_UTI

No 200

Yes 19

Name: count, dtype: int64

Descriptive statistics for 'comorb_dm':

comorb_dm

No 197

Yes 22

Name: count, dtype: int64

Descriptive statistics for 'comorb_hypot':

comorb_hypot

No 213

Yes 6

Name: count, dtype: int64

```
In [11]: # Creating the continuous_columns
continuous_columns = [
    'Pre-ACTH',
    'Post-ACTH',
    'weight',
    'Trilostane starting dose (mg/kg)_8'
```

```

]

# Generating descriptive statistics for continuous variables
descriptive_stats = canine_subset[continuous_columns].describe()

# Printing the descriptive statistics
print("Descriptive Statistics for Continuous Variables:")
print(descriptive_stats)

# Calculating the correlation matrix
correlation_matrix = canine_subset[continuous_columns].corr()

# Setting up the matplotlib figure
plt.figure(figsize=(10, 8))

# Generating the heatmap with the mask and correct aspect ratio
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)

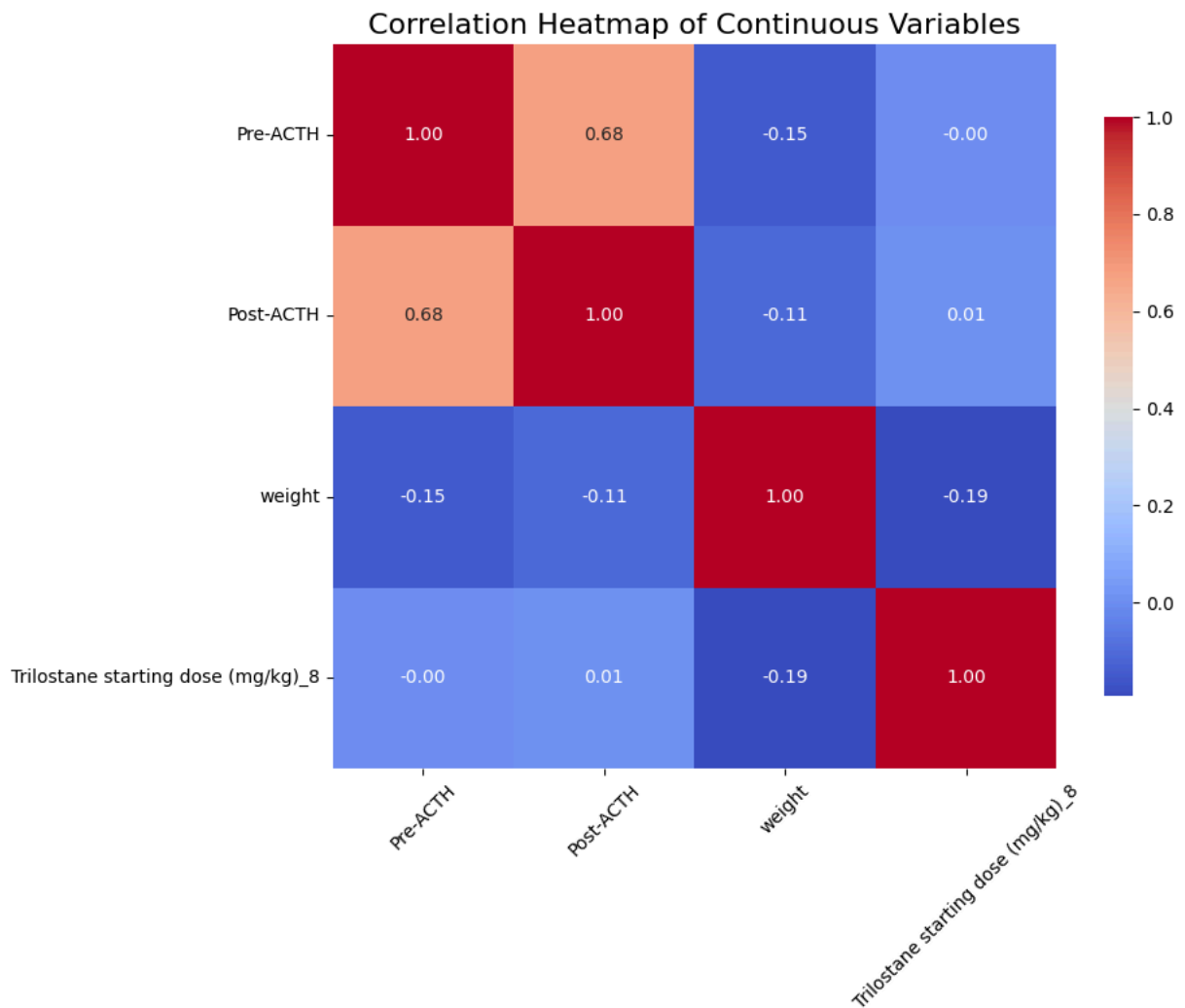
# Setting titles and labels
plt.title('Correlation Heatmap of Continuous Variables', fontsize=16)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()

# Showing the plot
plt.show()

```

Descriptive Statistics for Continuous Variables:

	Pre-ACTH	Post-ACTH	weight	Trilostane starting dose (mg/kg)_8
count	219.000000	219.000000	219.000000	199.000000
mean	53.794064	301.045662	16.314064	3.301508
std	101.191170	440.164489	10.872733	1.275695
min	0.000000	0.000000	0.000000	1.000000
25%	0.000000	0.000000	9.200000	2.500000
50%	0.000000	0.000000	12.750000	3.000000
75%	88.850000	682.500000	20.350000	4.000000
max	508.000000	1380.000000	65.600000	8.000000



```
In [12]: # Converting date columns to datetime format
date_columns = [
    'BirthDate',
    'Date of first suspicion_4',
    'Date of diagnosis_3',
    'Date trilostane started_5',
    'Failedate'
]

for col in date_columns:
    canine_subset[col] = pd.to_datetime(canine_subset[col], format='%d-%m-%Y', error

# Filtering for uncensored data (Died = 1)
uncensored_data = canine_subset[canine_subset['Died'] == 1].copy() # Using .copy()

# Counting of the uncensored entries
count_uncensored = len(uncensored_data)

# Earliest and latest dates
earliest_dates = uncensored_data[date_columns].min()
latest_dates = uncensored_data[date_columns].max()

# Date ranges
date_ranges = latest_dates - earliest_dates
```

```

# Calculating the time intervals using .loc to avoid warnings
uncensored_data.loc[:, 'Time_Birth_to_Suspicion'] = (uncensored_data['Date of first
uncensored_data.loc[:, 'Time_Suspicion_to_Diagnosis'] = (uncensored_data['Date of d
uncensored_data.loc[:, 'Time_Diagnosis_to_Treatment'] = (uncensored_data['Date tril
uncensored_data.loc[:, 'Time_Treatment_to_Failure'] = (uncensored_data['Failedate

# Mean and median time intervals
mean_intervals = uncensored_data[['Time_Birth_to_Suspicion',
                                'Time_Suspicion_to_Diagnosis',
                                'Time_Diagnosis_to_Treatment',
                                'Time_Treatment_to_Failure']].mean()
median_intervals = uncensored_data[['Time_Birth_to_Suspicion',
                                'Time_Suspicion_to_Diagnosis',
                                'Time_Diagnosis_to_Treatment',
                                'Time_Treatment_to_Failure']].median()

# Printing the results
print(f"Count of Uncensored Entries: {count_uncensored}")
print("\nEarliest Dates:")
print(earliest_dates)
print("\nLatest Dates:")
print(latest_dates)
print("\nDate Ranges:")
print(date_ranges)
print("\nMean Time Intervals (days):")
print(mean_intervals)
print("\nMedian Time Intervals (days):")
print(median_intervals)

```

Count of Uncensored Entries: 179

Earliest Dates:

BirthDate	1993-11-11
Date of first suspicion_4	2010-03-08
Date of diagnosis_3	2010-03-12
Date trilostane started_5	2010-03-15
Failedate	2010-09-03

dtype: datetime64[ns]

Latest Dates:

BirthDate	2009-02-12
Date of first suspicion_4	2014-08-21
Date of diagnosis_3	2014-08-29
Date trilostane started_5	2014-08-29
Failedate	2018-02-27

dtype: datetime64[ns]

Date Ranges:

BirthDate	5572 days
Date of first suspicion_4	1627 days
Date of diagnosis_3	1631 days
Date trilostane started_5	1628 days
Failedate	2734 days

dtype: timedelta64[ns]

Mean Time Intervals (days):

Time_Birth_to_Suspicion	4020.620112
Time_Suspicion_to_Diagnosis	45.664804
Time_Diagnosis_to_Treatment	10.396450
Time_Treatment_to_Failure	503.834320

dtype: float64

Median Time Intervals (days):

Time_Birth_to_Suspicion	4024.0
Time_Suspicion_to_Diagnosis	12.0
Time_Diagnosis_to_Treatment	0.0
Time_Treatment_to_Failure	402.0

dtype: float64

```
In [13]: # Creating a new column 'Censored' based on 'Censored_10'
# Using .map() to convert 'Yes' to 1 and 'No' to 0, treating nulls as 0
canine_subset['Censored'] = canine_subset['Censored_10'].map({'Yes': 1, 'No': 0}).f

# Printing the updated DataFrame to verify the changes
print(canine_subset[['Censored_10', 'Censored']].head())

# Calculating survival time from diagnosis to failure
canine_subset['Days_Diagnosis_to_Failure'] = (canine_subset['Failedate'] - canine

# Printing the updated DataFrame to verify the changes
print(canine_subset['Days_Diagnosis_to_Failure'].head())

# Dropping the Censored_10 column
canine_subset.drop(columns=['Censored_10'], inplace=True)
```

```
# Printing the Length of the DataFrame and the remaining column names
num_rows = len(canine_subset)
num_cols = canine_subset.shape[1] # Number of columns

print(f"Length of DataFrame: {num_rows}")
print(f"Number of Columns: {num_cols}")
print("Remaining Column Names:", canine_subset.columns.tolist())
```

	Censored_10	Censored
0	Yes	1
1	Yes	1
2	NaN	0
3	NaN	0
4	NaN	0

0	1778
1	1842
2	1260
3	942
4	779

Name: Days_Diagnosis_to_Failure, dtype: int64

Length of DataFrame: 219

Number of Columns: 36

Remaining Column Names: ['Died', 'how died', 'Pre-ACTH', 'Post-ACTH', 'Insurance', 'weight', 'BreedRelativeWeight', 'BirthDate', 'Sex', 'Isneutered', 'Breed', 'KC_group', 'Purebreed_status', 'Date of diagnosis_3', 'Failedate', 'Date of first suspicion_4', 'Date trilostane started_5', 'Changes to trilostane_6', 'Stay_vs_stop', 'Treated with trilostane_7', 'Trilostane starting dose (mg/kg)_8', 'Trilostane SID/BID_9', 'Why censored_11', 'Cause of death_13', 'Neuro signs', 'Complications', 'Hypertensive_Yes4', 'Oversuppression?', 'Cortisol stayed <250', 'Cortisol went <40', 'Number_comorbidities', 'comorb_UTI', 'comorb_dm', 'comorb_hypot', 'Censored', 'Days_Diagnosis_to_Failure']

```
In [14]: # Displaying detailed information about the DataFrame
print(canine_subset.info())
print(canine_subset['Died'].head())
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 219 entries, 0 to 218
Data columns (total 36 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   Died                                     219 non-null    category
1   how died                               219 non-null    category
2   Pre-ACTH                               219 non-null    float64
3   Post-ACTH                              219 non-null    float64
4   Insurance                              219 non-null    category
5   weight                                 219 non-null    float64
6   BreedRelativeWeight                    219 non-null    category
7   BirthDate                             219 non-null    datetime64[ns]
8   Sex                                    219 non-null    category
9   Isneutered                             219 non-null    category
10  Breed                                  219 non-null    category
11  KC_group                               219 non-null    category
12  Purebreed_status                       219 non-null    category
13  Date of diagnosis_3                     219 non-null    datetime64[ns]
14  Failedate                              219 non-null    datetime64[ns]
15  Date of first suspicion_4               219 non-null    datetime64[ns]
16  Date trilostane started_5               205 non-null    datetime64[ns]
17  Changes to trilostane_6                 206 non-null    category
18  Stay_vs_stop                            219 non-null    category
19  Treated with trilostane_7               219 non-null    category
20  Trilostane starting dose (mg/kg)_8      199 non-null    float64
21  Trilostane SID/BID_9                    206 non-null    category
22  Why censored_11                         40 non-null     category
23  Cause of death_13                       177 non-null    category
24  Neuro signs                             219 non-null    category
25  Complications                           219 non-null    category
26  Hypertensive_Yes4                       219 non-null    category
27  Oversuppresion?                         219 non-null    category
28  Cortisol stayed <250                     219 non-null    category
29  Cortisol went <40                       219 non-null    category
30  Number_comorbidities                    219 non-null    category
31  comorb_UTI                              219 non-null    category
32  comorb_dm                               219 non-null    category
33  comorb_hypot                            219 non-null    category
34  Censored                                219 non-null    int32
35  Days_Diagnosis_to_Failure                219 non-null    int64
dtypes: category(25), datetime64[ns](5), float64(4), int32(1), int64(1)
memory usage: 28.6 KB
None
0    0
1    0
2    1
3    1
4    1
Name: Died, dtype: category
Categories (2, int32): [0, 1]

```

```

In [15]: # The following preprocessing is done for fitting CoxPH and Random Survival Forests
# Calculating Age at diagnosis
canine_subset['Age_at_diagnosis(Years)'] = (canine_subset['Date of diagnosis_3'] -

```

```

# Calculating Time from first suspicion to diagnosis
canine_subset['Time_suspicion_to_diagnosis(Days)'] = (canine_subset['Date of diagno

# Rounding the results to 2 decimal places for better readability
canine_subset['Age_at_diagnosis(Years)'] = canine_subset['Age_at_diagnosis(Years)']
canine_subset['Time_suspicion_to_diagnosis(Days)'] = canine_subset['Time_suspicion_

# Displaying the first few rows of the new columns to verify
print(canine_subset[['Age_at_diagnosis(Years)', 'Time_suspicion_to_diagnosis(Days)']

# Getting the basic statistics of the new variables
print("\nStatistics for Age at diagnosis(Years):")
print(canine_subset['Age_at_diagnosis(Years)'].describe())
print("\nStatistics for Time from suspicion to diagnosis(Days):")
print(canine_subset['Time_suspicion_to_diagnosis(Days)'].describe())

```

	Age_at_diagnosis(Years)	Time_suspicion_to_diagnosis(Days)
0	10.04	7
1	10.36	22
2	8.66	6
3	10.79	35
4	10.03	60

Statistics for Age at diagnosis(Years):

```

count    219.000000
mean      10.991461
std        2.488682
min        4.450000
25%        9.120000
50%       11.010000
75%       12.855000
max       18.000000

```

Name: Age_at_diagnosis(Years), dtype: float64

Statistics for Time from suspicion to diagnosis(Days):

```

count    219.000000
mean      41.963470
std       81.534866
min        0.000000
25%        6.000000
50%       12.000000
75%       29.500000
max       548.000000

```

Name: Time_suspicion_to_diagnosis(Days), dtype: float64

```

In [16]: # Displaying detailed information about the DataFrame
print(canine_subset.info())

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 219 entries, 0 to 218
Data columns (total 38 columns):
 #   Column                                     Non-Null Count  Dtype
---  -
 0   Died                                     219 non-null    category
 1   how died                               219 non-null    category
 2   Pre-ACTH                               219 non-null    float64
 3   Post-ACTH                              219 non-null    float64
 4   Insurance                              219 non-null    category
 5   weight                                 219 non-null    float64
 6   BreedRelativeWeight                    219 non-null    category
 7   BirthDate                             219 non-null    datetime64[ns]
 8   Sex                                    219 non-null    category
 9   Isneutered                            219 non-null    category
10   Breed                                  219 non-null    category
11   KC_group                               219 non-null    category
12   Purebreed_status                       219 non-null    category
13   Date of diagnosis_3                     219 non-null    datetime64[ns]
14   Failedate                              219 non-null    datetime64[ns]
15   Date of first suspicion_4               219 non-null    datetime64[ns]
16   Date trilostane started_5              205 non-null    datetime64[ns]
17   Changes to trilostane_6                206 non-null    category
18   Stay_vs_stop                           219 non-null    category
19   Treated with trilostane_7               219 non-null    category
20   Trilostane starting dose (mg/kg)_8      199 non-null    float64
21   Trilostane SID/BID_9                   206 non-null    category
22   Why censored_11                        40 non-null     category
23   Cause of death_13                      177 non-null    category
24   Neuro signs                            219 non-null    category
25   Complications                          219 non-null    category
26   Hypertensive_Yes4                      219 non-null    category
27   Oversuppresion?                        219 non-null    category
28   Cortisol stayed <250                    219 non-null    category
29   Cortisol went <40                      219 non-null    category
30   Number_comorbidities                   219 non-null    category
31   comorb_UTI                             219 non-null    category
32   comorb_dm                              219 non-null    category
33   comorb_hypot                           219 non-null    category
34   Censored                               219 non-null    int32
35   Days_Diagnosis_to_Failure              219 non-null    int64
36   Age_at_diagnosis(Years)                 219 non-null    float64
37   Time_suspicion_to_diagnosis(Days)       219 non-null    int64
dtypes: category(25), datetime64[ns](5), float64(5), int32(1), int64(2)
memory usage: 32.1 KB
None

```

```
In [44]: ##### Preprocessing - 1 ends here
```

Kaplan - Meier Estimator

```
In [18]: # Fitting the Kaplan-Meier estimator
kmf = KaplanMeierFitter()
kmf.fit(durations=canine_subset['Days_Diagnosis_to_Failure'], event_observed=canine
```

```

# Plotting the Kaplan-Meier survival function
plt.figure(figsize=(10, 6))
kmf.plot_survival_function()
plt.title('Kaplan-Meier Survival Curve for Dogs Diagnosed with Hyperadrenocorticism')
plt.xlabel('Days from Diagnosis to Failure')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.show()

# Extracting survival probabilities and time points
survival_function = kmf.survival_function_
time_points = survival_function.index.values
survival_probabilities = survival_function.values.flatten()

# Calculating expected survivors at specific probabilities from 1.0 to 0.0
total_dogs = len(canine_subset) # Total number of dogs
thresholds = [round(i * 0.1, 1) for i in range(11)] # Creating [1.0, 0.9, ..., 0.0]

# Initializing a list to store results
results = []

for threshold in thresholds:
    # Finding the closest survival probability to the threshold
    closest_index = (survival_probabilities <= threshold).argmax() # Getting index
    days_at_threshold = time_points[closest_index]
    expected_survivors = round(total_dogs * threshold) # Rounding the expected survivors

    results.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold,
        'Expected Survivors': expected_survivors
    })

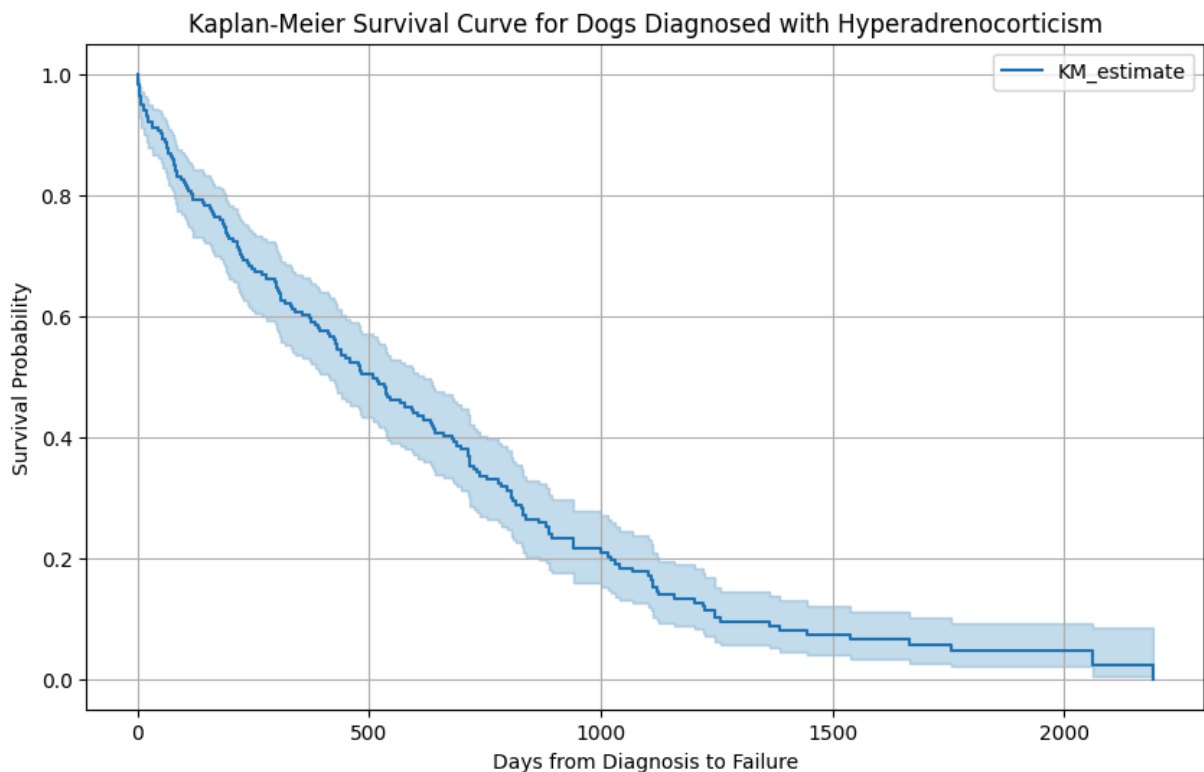
# Converting results to a DataFrame for better display
results_df = pd.DataFrame(results)

# Sorting the DataFrame by Survival Probability in descending order
results_df.sort_values(by='Survival Probability', ascending=False, inplace=True)

# Printing the results table
print(results_df)

print("-----")
# Calculating median survival time
median_survival_time = kmf.median_survival_time_
print(f"Median Survival Time for Dogs Diagnosed with Hyperadrenocorticism: {median_

```

	Survival Probability	Days	Expected Survivors
10	1.0	0.0	219
9	0.9	54.0	197
8	0.8	119.0	175
7	0.7	224.0	153
6	0.6	373.0	131
5	0.5	510.0	110
4	0.4	681.0	88
3	0.3	807.0	66
2	0.2	1023.0	44
1	0.1	1260.0	22
0	0.0	2192.0	0

 Median Survival Time for Dogs Diagnosed with Hyperadrenocorticism: 510.00 days

Log Rank Tests

Based on Neutered Status

```
In [19]: # Grouping data based on Isneutered status
group1 = canine_subset[canine_subset['Isneutered'] == 'Yes']
group2 = canine_subset[canine_subset['Isneutered'] == 'No']

# Performing Log-Rank test between the two groups
results_isneutered = logrank_test(group1['Days_Diagnosis_to_Failure'], group2['Days
                                event_observed_A=group1['Died'], event_observed_B

# Printing the p-value for the comparison
print(f"Log-rank test between Neutered and Non-neutered: p-value = {results_isneute

# Calculating the Bonferroni-corrected threshold (only one comparison here)
```

```

alpha = 0.05
n_comparisons = 1 # Since we are only comparing two groups
bonferroni_threshold = alpha / n_comparisons
print(f"\nBonferroni-corrected significance threshold: {bonferroni_threshold:.4f}")

# Calculating the survival probabilities for both groups
kmf_yes = KaplanMeierFitter()
kmf_no = KaplanMeierFitter()

kmf_yes.fit(group1['Days_Diagnosis_to_Failure'], group1['Died'], label="Neutered")
kmf_no.fit(group2['Days_Diagnosis_to_Failure'], group2['Died'], label="Non-neutered")

# Plotting Kaplan-Meier survival curves
plt.figure(figsize=(10, 6))
kmf_yes.plot()
kmf_no.plot()

plt.title('Kaplan-Meier Survival Curves by Neutering Status')
plt.xlabel('Days from Diagnosis to Failure')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.legend()
plt.show()

# Defining the thresholds (from 1.0 to 0.0)
thresholds = [round(i * 0.1, 1) for i in range(11)][::-1] # Creates [1.0, 0.9, ...

# Initializing the lists to store results
results_yes = []
results_no = []

for threshold in thresholds:
    # For Neutered group
    closest_index_yes = (kmf_yes.survival_function_.values <= threshold).argmax()
    days_at_threshold_yes = kmf_yes.survival_function_.index[closest_index_yes]
    expected_survivors_yes = round(len(group1) * threshold)

    results_yes.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold_yes,
        'Expected Survivors': expected_survivors_yes
    })

    # For Non-neutered group
    closest_index_no = (kmf_no.survival_function_.values <= threshold).argmax()
    days_at_threshold_no = kmf_no.survival_function_.index[closest_index_no]
    expected_survivors_no = round(len(group2) * threshold)

    results_no.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold_no,
        'Expected Survivors': expected_survivors_no
    })

# Converting the results to DataFrames for better display
results_df_yes = pd.DataFrame(results_yes)

```

```

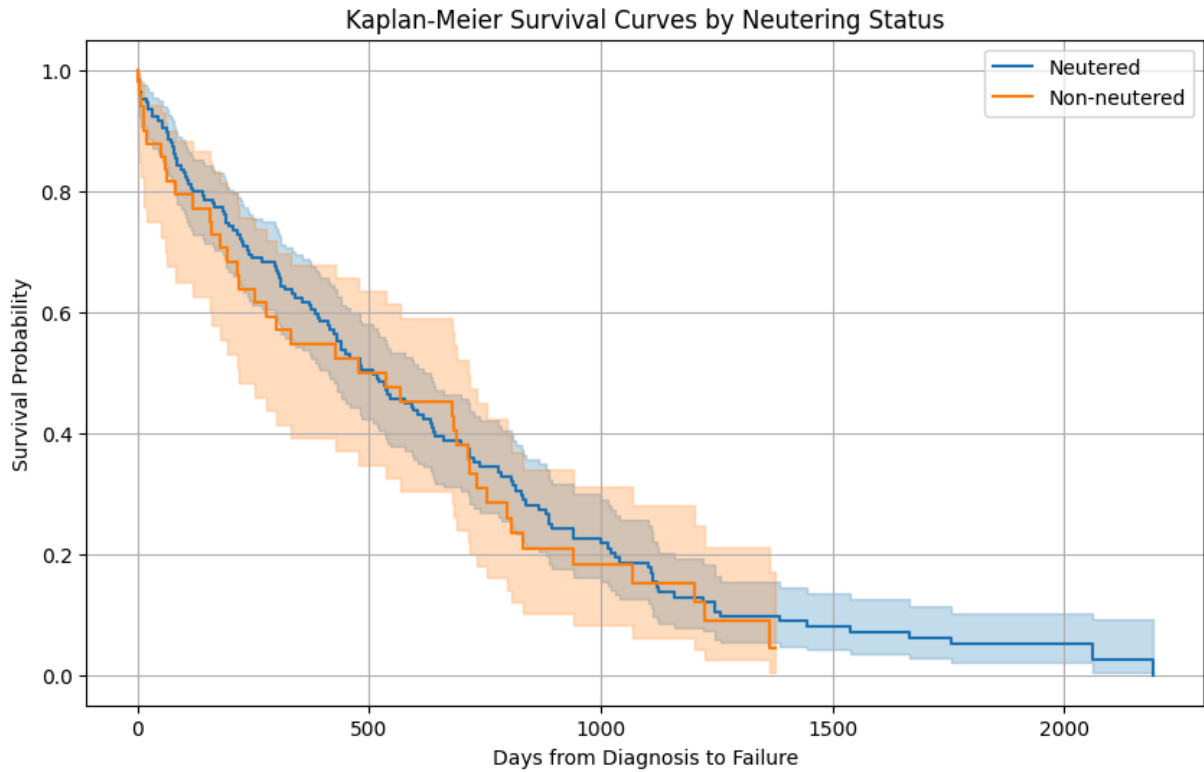
results_df_no = pd.DataFrame(results_no)

# Printing the results tables of survival probabilities
print("\nExpected Survival Probabilities for Neutered Dogs:")
print(results_df_yes)
print("\nExpected Survival Probabilities for Non-neutered Dogs:")
print(results_df_no)

```

Log-rank test between Neutered and Non-neutered: p-value = 0.4999

Bonferroni-corrected significance threshold: 0.0500



Expected Survival Probabilities for Neutered Dogs:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	169
1	0.9	63.0	152
2	0.8	119.0	135
3	0.7	240.0	118
4	0.6	385.0	101
5	0.5	510.0	84
6	0.4	643.0	68
7	0.3	829.0	51
8	0.2	1031.0	34
9	0.1	1260.0	17
10	0.0	2192.0	0

Expected Survival Probabilities for Non-neutered Dogs:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	50
1	0.9	15.0	45
2	0.8	82.0	40
3	0.7	194.0	35
4	0.6	279.0	30
5	0.5	536.0	25
6	0.4	688.0	20
7	0.3	754.0	15
8	0.2	940.0	10
9	0.1	1224.0	5
10	0.0	0.0	0

Based on Purebreed Status

```
In [20]: # Grouping data based on 'Purebreed_status'
group1 = canine_subset[canine_subset['Purebreed_status'] == 1] # Purebred
group2 = canine_subset[canine_subset['Purebreed_status'] == 2] # Crossbred

# Performing Log-Rank test between the two groups
results_purebred = logrank_test(group1['Days_Diagnosis_to_Failure'], group2['Days_
                                event_observed_A=group1['Died'], event_observed_B=

# Printing the p-value for the comparison
print(f"Log-rank test between Purebred and Crossbred: p-value = {results_purebred.

# Calculating the Bonferroni-corrected threshold (only one comparison here)
alpha = 0.05
n_comparisons = 1 # Since we are only comparing two groups
bonferroni_threshold = alpha / n_comparisons
print(f"\nBonferroni-corrected significance threshold: {bonferroni_threshold:.4f}")

# Calculating the survival probabilities for both groups
kmf_purebred = KaplanMeierFitter()
kmf_crossbred = KaplanMeierFitter()

kmf_purebred.fit(group1['Days_Diagnosis_to_Failure'], group1['Died'], label="Purebr
kmf_crossbred.fit(group2['Days_Diagnosis_to_Failure'], group2['Died'], label="Cross

# Plotting Kaplan-Meier survival curves
```

```

plt.figure(figsize=(10, 6))
kmf_purebred.plot()
kmf_crossbred.plot()

plt.title('Kaplan-Meier Survival Curves by Breed Status')
plt.xlabel('Days from Diagnosis to Failure')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.legend()
plt.show()

# Defining the thresholds (from 1.0 to 0.0)
thresholds = [round(i * 0.1, 1) for i in range(11)][::-1] # Creates [1.0, 0.9, ...

# Initializing the lists to store results
results_purebred = []
results_crossbred = []

for threshold in thresholds:
    # For Purebred group
    closest_index_purebred = (kmf_purebred.survival_function_.values <= threshold).
    days_at_threshold_purebred = kmf_purebred.survival_function_.index[closest_index_purebred]
    expected_survivors_purebred = round(len(group1) * threshold)

    results_purebred.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold_purebred,
        'Expected Survivors': expected_survivors_purebred
    })

    # For Crossbred group
    closest_index_crossbred = (kmf_crossbred.survival_function_.values <= threshold)
    days_at_threshold_crossbred = kmf_crossbred.survival_function_.index[closest_index_crossbred]
    expected_survivors_crossbred = round(len(group2) * threshold)

    results_crossbred.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold_crossbred,
        'Expected Survivors': expected_survivors_crossbred
    })

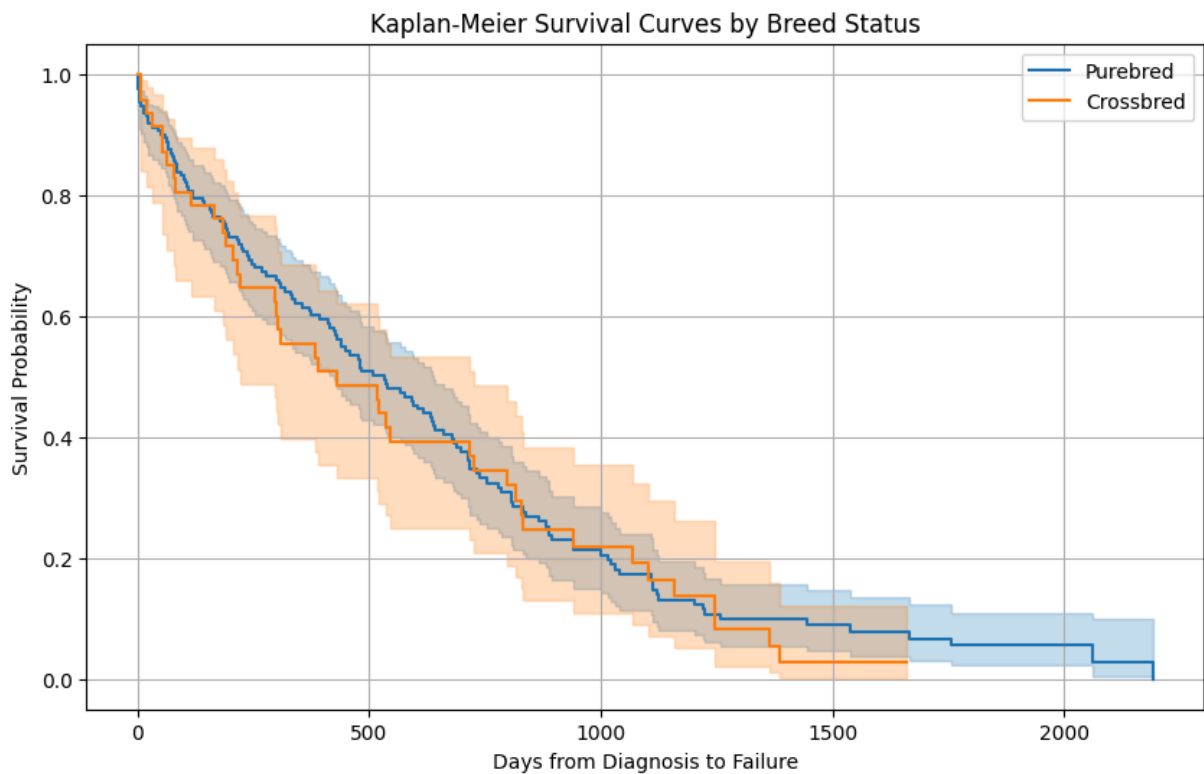
# Converting the results to DataFrames for better display
results_df_purebred = pd.DataFrame(results_purebred)
results_df_crossbred = pd.DataFrame(results_crossbred)

# Printing the results tables of survival probabilities
print("\nExpected Survival Probabilities for Purebred Dogs:")
print(results_df_purebred)
print("\nExpected Survival Probabilities for Crossbred Dogs:")
print(results_df_crossbred)

```

Log-rank test between Purebred and Crossbred: p-value = 0.6397

Bonferroni-corrected significance threshold: 0.0500



Expected Survival Probabilities for Purebred Dogs:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	172
1	0.9	50.0	155
2	0.8	119.0	138
3	0.7	237.0	120
4	0.6	395.0	103
5	0.5	533.0	86
6	0.4	681.0	69
7	0.3	807.0	52
8	0.2	1015.0	34
9	0.1	1260.0	17
10	0.0	2192.0	0

Expected Survival Probabilities for Crossbred Dogs:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	47
1	0.9	54.0	42
2	0.8	118.0	38
3	0.7	208.0	33
4	0.6	304.0	28
5	0.5	432.0	24
6	0.4	545.0	19
7	0.3	817.0	14
8	0.2	1069.0	9
9	0.1	1245.0	5
10	0.0	0.0	0

Based on treated with trilostane

```
In [21]: # Grouping data based on 'Treated with trilostane_7' status
group1 = canine_subset[canine_subset['Treated with trilostane_7'] == 1] # Treated
```

```

group2 = canine_subset[canine_subset['Treated with trilostane_7'] == 2] # Not trea

# Performing Log-Rank test between the two groups
results_trilostane = logrank_test(group1['Days_Diagnosis_to_Failure'], group2['Days
                                event_observed_A=group1['Died'], event_observed_B

# Printing the p-value for the comparison
print(f"Log-rank test between Treated and Not Treated with trilostane: p-value = {r

# Calculating the Bonferroni-corrected threshold (only one comparison here)
alpha = 0.05
n_comparisons = 1 # Since we are only comparing two groups
bonferroni_threshold = alpha / n_comparisons
print(f"\nBonferroni-corrected significance threshold: {bonferroni_threshold:.4f}")

# Calculating the survival probabilities for both groups
kmf_treated = KaplanMeierFitter()
kmf_not_treated = KaplanMeierFitter()

kmf_treated.fit(group1['Days_Diagnosis_to_Failure'], group1['Died'], label="Treated
kmf_not_treated.fit(group2['Days_Diagnosis_to_Failure'], group2['Died'], label="Not

# Plotting Kaplan-Meier survival curves
plt.figure(figsize=(10, 6))
kmf_treated.plot()
kmf_not_treated.plot()

plt.title('Kaplan-Meier Survival Curves by Trilostane Treatment Status')
plt.xlabel('Days from Diagnosis to Failure')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.legend()
plt.show()

# Defining the thresholds (from 1.0 to 0.0)
thresholds = [round(i * 0.1, 1) for i in range(11)][::-1] # Creates [1.0, 0.9, ...

# Initializing the lists to store results
results_treated = []
results_not_treated = []

for threshold in thresholds:
    # For Treated group
    closest_index_treated = (kmf_treated.survival_function_.values <= threshold).ar
    days_at_threshold_treated = kmf_treated.survival_function_.index[closest_index_
    expected_survivors_treated = round(len(group1) * threshold)

    results_treated.append({
        'Survival Probability': threshold,
        'Days': days_at_threshold_treated,
        'Expected Survivors': expected_survivors_treated
    })

    # For Not Treated group
    closest_index_not_treated = (kmf_not_treated.survival_function_.values <= thres
    days_at_threshold_not_treated = kmf_not_treated.survival_function_.index[closes

```

```

expected_survivors_not_treated = round(len(group2) * threshold)

results_not_treated.append({
    'Survival Probability': threshold,
    'Days': days_at_threshold_not_treated,
    'Expected Survivors': expected_survivors_not_treated
})

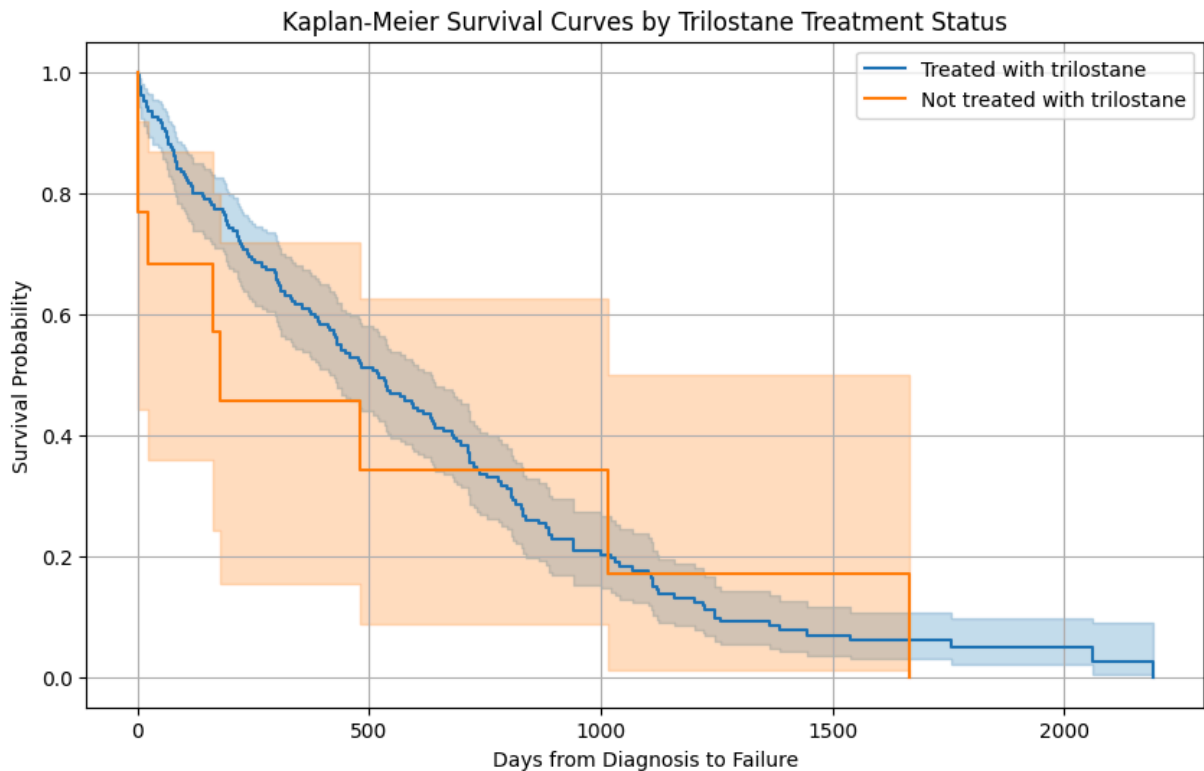
# Converting the results to DataFrames for better display
results_df_treated = pd.DataFrame(results_treated)
results_df_not_treated = pd.DataFrame(results_not_treated)

# Printing the results tables of survival probabilities
print("\nExpected Survival Probabilities for Dogs Treated with Trilostane:")
print(results_df_treated)
print("\nExpected Survival Probabilities for Dogs Not Treated with Trilostane:")
print(results_df_not_treated)

```

Log-rank test between Treated and Not Treated with trilostane: p-value = 0.5896

Bonferroni-corrected significance threshold: 0.0500



Expected Survival Probabilities for Dogs Treated with Trilostane:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	206
1	0.9	63.0	185
2	0.8	119.0	165
3	0.7	240.0	144
4	0.6	376.0	124
5	0.5	520.0	103
6	0.4	683.0	82
7	0.3	807.0	62
8	0.2	1023.0	41
9	0.1	1245.0	21
10	0.0	2192.0	0

Expected Survival Probabilities for Dogs Not Treated with Trilostane:

	Survival Probability	Days	Expected Survivors
0	1.0	0.0	13
1	0.9	1.0	12
2	0.8	3.0	10
3	0.7	24.0	9
4	0.6	163.0	8
5	0.5	178.0	6
6	0.4	481.0	5
7	0.3	1015.0	4
8	0.2	1015.0	3
9	0.1	1665.0	1
10	0.0	1665.0	0

Based on Breeds

```
In [22]: # Counting the number of samples for each breed
breed_counts = canine_subset['Breed'].value_counts()
print(breed_counts)

# Filtering breeds with sufficient representation
sufficient_breeds = breed_counts[breed_counts >= 10].index.tolist()
print("Breeds with sufficient representation:", sufficient_breeds)
```

Breed
 Crossbreed
 47
 Terrier - Jack Russell (JRT)
 21
 Terrier - Yorkshire (Yorkshire Terrier)
 16
 Bichon - Frise
 13
 Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified))
 13
 Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT))
 12
 Retriever - Labrador (Labrador Retriever)
 8
 Schnauzer
 8
 Spaniel - Cocker (unspecified) (Cocker Spaniel (unspecified))
 6
 Terrier - Border (Border Terrier)
 5
 Boxer (unspecified)
 5
 Shih-tzu
 5
 Dachshund, Miniature
 5
 Lhasa Apso
 5
 Terrier - Tibetan
 4
 Spaniel - Cavalier King Charles (CKCS) (Cavalier King Charles Spaniel (CKCS))
 4
 Terrier - Bull (unspecified) (Bull Terrier (unspecified))
 4
 Collie - Bearded
 3
 Terrier - Scottish
 3
 Shepherd Dog - German (Alsatian) (GSD) (unspecified) (German Shepherd Dog (Alsatian) (GSD) (unspecified))
 3
 Dachshund, Standard
 3
 Terrier - Boston
 2
 Chihuahua, Short-Haired
 2
 Terrier - Patterdale
 2
 Terrier - Norfolk
 2
 Poodle, Standard
 2
 Retriever - Golden (Golden Retriever)
 2
 Retriever - Flat Coated

```

1
Terrier - Australian Silky
1
Spaniel - Springer, English (English Springer Spaniel)
1
Terrier - Cairn
1
Terrier - Fox (unspecified)
1
Collie - Border
1
Terrier - Lakeland
1
Spaniel - King Charles (KCS)
1
Sheepdog - Shetland (Sheltie)
1
Mastiff - Bull
1
Samoyed
1
Poodle, Miniature
1
Bulldog (unspecified)
1
Whippet (unspecified)
1
Name: count, dtype: int64
Breeds with sufficient representation: ['Crossbreed', 'Terrier - Jack Russell (JR
T)', 'Terrier - Yorkshire (Yorkshire Terrier)', 'Bichon - Frise', 'Terrier - Staffor
dshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified))', 'Terrier - We
st Highland White (WHWT) (West Highland White Terrier (WHWT))']

```

```

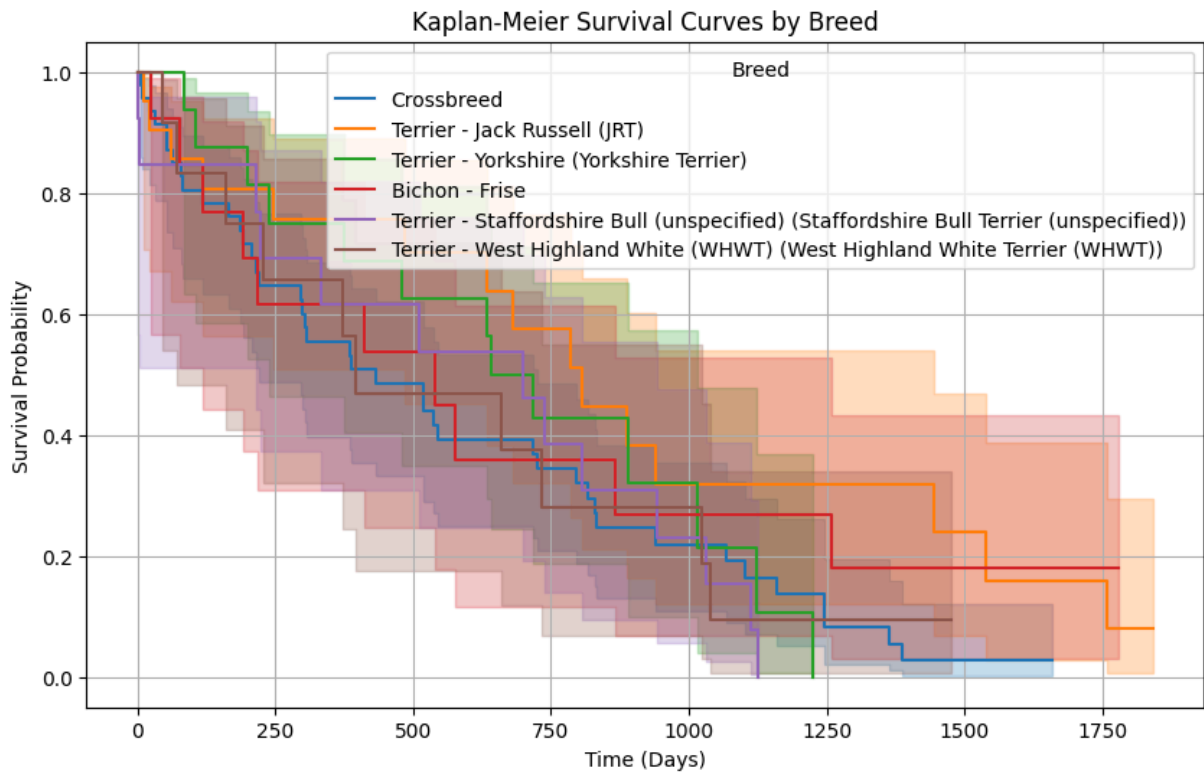
In [23]: # Creating a dictionary to hold subsets for each breed
breed_data = {breed: canine_subset[canine_subset['Breed'] == breed] for breed in su

# Fitting and Plotting Kaplan-Meier curves for each breed
kmf = KaplanMeierFitter()

plt.figure(figsize=(10, 6))
for breed, data in breed_data.items():
    kmf.fit(data['Days_Diagnosis_to_Failure'], event_observed=data['Died'], label=b
    kmf.plot_survival_function()

plt.title('Kaplan-Meier Survival Curves by Breed')
plt.xlabel('Time (Days)')
plt.ylabel('Survival Probability')
plt.legend(title='Breed')
plt.grid(True)
plt.show()

```



```
In [24]: # Performing Log-rank tests between pairs of breeds
breeds_to_compare = list(sufficient_breeds) # List of breeds to compare
for i in range(len(breeds_to_compare)):
    for j in range(i + 1, len(breeds_to_compare)):
        group1 = breed_data[breeds_to_compare[i]]
        group2 = breed_data[breeds_to_compare[j]]

        results = logrank_test(
            group1['Days_Diagnosis_to_Failure'],
            group2['Days_Diagnosis_to_Failure'],
            event_observed_A=group1['Died'],
            event_observed_B=group2['Died']
        )

        print(f"Log-Rank Test between {breeds_to_compare[i]} and {breeds_to_compare[j]}")
```

Log-Rank Test between Crossbreed and Terrier - Jack Russell (JRT): p-value = 0.03642641759435863

Log-Rank Test between Crossbreed and Terrier - Yorkshire (Yorkshire Terrier): p-value = 0.6692473130343376

Log-Rank Test between Crossbreed and Bichon - Frise: p-value = 0.36841829323395925

Log-Rank Test between Crossbreed and Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)): p-value = 0.7709627160434211

Log-Rank Test between Crossbreed and Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT)): p-value = 0.8337970167715292

Log-Rank Test between Terrier - Jack Russell (JRT) and Terrier - Yorkshire (Yorkshire Terrier): p-value = 0.2577114515491709

Log-Rank Test between Terrier - Jack Russell (JRT) and Bichon - Frise: p-value = 0.5158772885275844

Log-Rank Test between Terrier - Jack Russell (JRT) and Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)): p-value = 0.12143454232807871

Log-Rank Test between Terrier - Jack Russell (JRT) and Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT)): p-value = 0.24664745778391245

Log-Rank Test between Terrier - Yorkshire (Yorkshire Terrier) and Bichon - Frise: p-value = 0.87309074220082

Log-Rank Test between Terrier - Yorkshire (Yorkshire Terrier) and Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)): p-value = 0.539480393516573

Log-Rank Test between Terrier - Yorkshire (Yorkshire Terrier) and Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT)): p-value = 0.7400404656913269

Log-Rank Test between Bichon - Frise and Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)): p-value = 0.4652353594419921

Log-Rank Test between Bichon - Frise and Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT)): p-value = 0.7182020624984118

Log-Rank Test between Terrier - Staffordshire Bull (unspecified) (Staffordshire Bull Terrier (unspecified)) and Terrier - West Highland White (WHWT) (West Highland White Terrier (WHWT)): p-value = 0.9723712953533593

Preprocessing - Part 2 : For CoxPH and Random Survival Forests

```
In [25]: # Categorical columns summary function
def categorical_column_summary(df, column_name):
    column = df[column_name]
    unique_values = column.unique()
    value_counts = column.value_counts()
    null_count = column.isnull().sum()

    # Preparing the data for tabulation
    summary_data = {
        'Unique Values': unique_values,
        'Count': [value_counts.get(val, 0) for val in unique_values],
        'Percentage': [round(value_counts.get(val, 0) / len(column) * 100, 2) for val in unique_values]
    }

    # Creating the DataFrame for the column
    summary_df = pd.DataFrame(summary_data)

    print(f"\nSummary for Categorical Column: {column_name}")
```

```

print(f"Total Entries: {len(column)}")
print(f"Null Count: {null_count}")
print(tabulate(summary_df, headers='keys', tablefmt='pretty', showindex=False))

# Continuous columns summary function
def continuous_column_summary(df, column_name):
    column = df[column_name]
    null_count = column.isnull().sum()

    summary_data = {
        'Statistic': ['Null Count', 'Total Entries', 'Mean', 'Median', 'Min', 'Max']
        'Value': [
            null_count,
            len(column),
            round(column.mean(), 2),
            round(column.median(), 2),
            round(column.min(), 2),
            round(column.max(), 2),
            round(column.std(), 2)
        ]
    }

    summary_df = pd.DataFrame(summary_data)

    print(f"\nSummary for Continuous Column: {column_name}")
    print(tabulate(summary_df, headers='keys', tablefmt='pretty', showindex=False))

# Categorical columns
cat_columns = [
    'Died', 'Neuro signs', 'Complications', 'Hypertensive_Yes4', 'Oversuppresion?',
    'Cortisol stayed <250', 'Cortisol went <40', 'Number_comorbidities',
    'comorb_UTI', 'comorb_dm', 'comorb_hypot', 'Sex', 'Isneutered',
    'BreedRelativeWeight', 'Purebreed_status', 'Changes to trilostane_6',
    'Stay_vs_stop', 'Treated with trilostane_7', 'Trilostane SID/BID_9'
]

# Continuous columns
cont_columns = [
    'Days_Diagnosis_to_Failure', 'Pre-ACTH', 'Post-ACTH', 'weight', 'Trilostane sta
    'Age_at_diagnosis(Years)', 'Time_suspicion_to_diagnosis(Days)'
]

# Generating the summaries for categorical columns
print("CATEGORICAL COLUMNS SUMMARY")
print("=" * 50)
for column in cat_columns:
    categorical_column_summary(canine_subset, column)

# Generating the summaries for continuous columns
print("\n\nCONTINUOUS COLUMNS SUMMARY")
print("=" * 50)
for column in cont_columns:
    continuous_column_summary(canine_subset, column)

```

CATEGORICAL COLUMNS SUMMARY

=====

Summary for Categorical Column: Died

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
0.0	40.0	18.26
1.0	179.0	81.74

Summary for Categorical Column: Neuro signs

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
No	174	79.45
Yes	45	20.55

Summary for Categorical Column: Complications

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Unknown	169	77.17
Yes	50	22.83

Summary for Categorical Column: Hypertensive_Yes4

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Unknown	177	80.82
Yes	27	12.33
No	15	6.85

Summary for Categorical Column: Oversuppresion?

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Yes	28	12.79
No	191	87.21

Summary for Categorical Column: Cortisol stayed <250

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Yes	68	31.05
Unknown	119	54.34
No	32	14.61

Summary for Categorical Column: Cortisol went <40

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Yes	21	9.59
Unknown	119	54.34
No	79	36.07

Summary for Categorical Column: Number_comorbidities

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
0.0	78.0	35.62
1.0	86.0	39.27
3.0	14.0	6.39
2.0	37.0	16.89
4.0	3.0	1.37
5.0	1.0	0.46

Summary for Categorical Column: comorb_UTI

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
No	200	91.32
Yes	19	8.68

Summary for Categorical Column: comorb_dm

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
No	197	89.95
Yes	22	10.05

Summary for Categorical Column: comorb_hypot

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
No	213	97.26
Yes	6	2.74

Summary for Categorical Column: Sex

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
male	115	52.51
Female	104	47.49

Summary for Categorical Column: Isneutered

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
Yes	169	77.17
No	50	22.83

Summary for Categorical Column: BreedRelativeWeight

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
1.0	81.0	36.99
2.0	73.0	33.33
4.0	45.0	20.55
3.0	20.0	9.13

Summary for Categorical Column: Purebreed_status

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
1.0	172.0	78.54
2.0	47.0	21.46

Summary for Categorical Column: Changes to trilostane_6

Total Entries: 219

Null Count: 13

Unique Values	Count	Percentage

1.0	55.0	25.11
2.0	23.0	10.5
4.0	34.0	15.53
nan	0.0	0.0
3.0	94.0	42.92

Summary for Categorical Column: Stay_vs_stop

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
1.0	172.0	78.54
2.0	47.0	21.46

Summary for Categorical Column: Treated with trilostane_7

Total Entries: 219

Null Count: 0

Unique Values	Count	Percentage
1.0	206.0	94.06
2.0	13.0	5.94

Summary for Categorical Column: Trilostane SID/BID_9

Total Entries: 219

Null Count: 13

Unique Values	Count	Percentage
SID	178	81.28
BID	16	7.31
Unknown	12	5.48
nan	0	0.0

CONTINUOUS COLUMNS SUMMARY

=====

Summary for Continuous Column: Days_Diagnosis_to_Failure

Statistic	Value
Null Count	0.0
Total Entries	219.0
Mean	517.79
Median	424.0
Min	1.0
Max	2192.0
Standard Deviation	465.73

Summary for Continuous Column: Pre-ACTH

Statistic	Value
Null Count	0.0
Total Entries	219.0
Mean	53.79
Median	0.0
Min	0.0
Max	508.0
Standard Deviation	101.19

Summary for Continuous Column: Post-ACTH

Statistic	Value
Null Count	0.0
Total Entries	219.0
Mean	301.05
Median	0.0
Min	0.0
Max	1380.0
Standard Deviation	440.16

Summary for Continuous Column: weight

Statistic	Value
Null Count	0.0
Total Entries	219.0
Mean	16.31
Median	12.75
Min	0.0
Max	65.6
Standard Deviation	10.87

Summary for Continuous Column: Trilostane starting dose (mg/kg)_8

Statistic	Value
Null Count	20.0
Total Entries	219.0
Mean	3.3
Median	3.0
Min	1.0
Max	8.0
Standard Deviation	1.28

Summary for Continuous Column: Age_at_diagnosis(Years)

Statistic	Value
-----------	-------

Null Count	0.0
Total Entries	219.0
Mean	10.99
Median	11.01
Min	4.45
Max	18.0
Standard Deviation	2.49

Summary for Continuous Column: Time_suspicion_to_diagnosis(Days)

Statistic	Value
Null Count	0.0
Total Entries	219.0
Mean	41.96
Median	12.0
Min	0.0
Max	548.0
Standard Deviation	81.53

```
In [26]: # Creating a list of columns to include in cox_data
columns_to_include = [
    # Clinical factors
    'Pre-ACTH', 'Post-ACTH', 'weight',
    'Neuro signs', 'Complications', 'Hypertensive_Yes4', 'Oversuppresion?',
    'Cortisol stayed <250', 'Cortisol went <40', 'Number_comorbidities',
    'comorb_UTI', 'comorb_dm', 'comorb_hypot',

    # Demographic factors
    'Sex', 'Isneutered', 'BreedRelativeWeight', 'Purebreed_status',

    # Treatment-related factors
    'Stay_vs_stop', 'Treated with trilostane_7',

    # Time-related factors
    'Age_at_diagnosis(Years)', 'Time_suspicion_to_diagnosis(Days)',

    # Outcome and event indicator
    'Days_Diagnosis_to_Failure', 'Died'
]

# Copying the selected columns to cox_data
cox_data = canine_subset[columns_to_include].copy()

# Displaying the first few rows of cox_data to verify
print(cox_data.head())

# Print the column names of cox_data one by one
print("Column names in cox_data:")
for col in cox_data.columns:
    print(col)

# Print the number of columns
num_cols = len(cox_data.columns)
```

```
print("\nTotal number of columns in cox_data:", num_cols)
```

```
# Get the number of rows in cox_subset
```

```
num_rows = len(cox_data)
```

```
print("Number of rows in cox_subset:", num_rows)
```

	Pre-ACTH	Post-ACTH	weight	Neuro signs	Complications	Hypertensive_Yes4	\
0	0.0	0.0	7.55	No	Unknown	Unknown	
1	0.0	0.0	7.20	No	Unknown	Unknown	
2	267.0	922.0	12.50	No	Unknown	Unknown	
3	0.0	0.0	19.00	No	Unknown	Unknown	
4	145.0	684.0	34.25	No	Yes	Yes	

	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	Number_comorbidities	\
0	Yes	Yes	Yes	0.0	
1	Yes	Unknown	Unknown	1.0	
2	Yes	Yes	No	3.0	
3	Yes	No	No	0.0	
4	Yes	Yes	Yes	1.0	

	...	Sex	Isneutered	BreedRelativeWeight	Purebreed_status	Stay_vs_stop	\
0	...	male	Yes	1.0	1.0	1.0	
1	...	Female	Yes	1.0	1.0	1.0	
2	...	male	Yes	2.0	1.0	1.0	
3	...	Female	Yes	1.0	1.0	2.0	
4	...	male	Yes	2.0	1.0	2.0	

	Treated with trilostane_7	Age_at_diagnosis(Years)	\
0	1.0	10.04	
1	1.0	10.36	
2	1.0	8.66	
3	1.0	10.79	
4	1.0	10.03	

	Time_suspicion_to_diagnosis(Days)	Days_Diagnosis_to_Failure	Died
0	7	1778	0
1	22	1842	0
2	6	1260	1
3	35	942	1
4	60	779	1

[5 rows x 23 columns]
Column names in cox_data:
Pre-ACTH
Post-ACTH
weight
Neuro signs
Complications
Hypertensive_Yes4
Oversuppresion?
Cortisol stayed <250
Cortisol went <40
Number_comorbidities
comorb_UTI
comorb_dm
comorb_hypot
Sex
Isneutered
BreedRelativeWeight
Purebreed_status
Stay_vs_stop
Treated with trilostane_7

```
Age_at_diagnosis(Years)
Time_suspicion_to_diagnosis(Days)
Days_Diagnosis_to_Failure
Died
```

Total number of columns in cox_data: 23

Number of rows in cox_subset: 219

```
In [27]: # Encoding Sex: Male as 0 and Female as 1
cox_data['Sex'] = (cox_data['Sex'].str.lower() == 'female').astype(int)

# Displaying the unique values and their counts for the new encoded columns
print("Encoded Sex column:")
print(cox_data['Sex'].value_counts(dropna=False))

# Checking for remaining null values
print("\nNull values in encoded columns:")
print(cox_data[['Sex']].isnull().sum())

# Get the number of rows in cox_subset
num_rows = len(cox_data)
print("Number of rows in cox_subset:", num_rows)
```

Encoded Sex column:

Sex

0 115

1 104

Name: count, dtype: int64

Null values in encoded columns:

Sex 0

dtype: int64

Number of rows in cox_subset: 219

```
In [28]: # Converting specified columns from float to int, keeping NaNs as is
cox_data['Died'] = cox_data['Died'].astype('Int64')
print("Died unique values:", cox_data['Died'].unique())

cox_data['Number_comorbidities'] = cox_data['Number_comorbidities'].astype('Int64')
print("Number_comorbidities unique values:", cox_data['Number_comorbidities'].unique())

cox_data['BreedRelativeWeight'] = cox_data['BreedRelativeWeight'].astype('Int64')
print("BreedRelativeWeight unique values:", cox_data['BreedRelativeWeight'].unique())

cox_data['Purebreed_status'] = cox_data['Purebreed_status'].astype('Int64')
print("Purebreed_status unique values:", cox_data['Purebreed_status'].unique())

cox_data['Stay_vs_stop'] = cox_data['Stay_vs_stop'].astype('Int64')
print("Stay_vs_stop unique values:", cox_data['Stay_vs_stop'].unique())

cox_data['Treated with trilostane_7'] = cox_data['Treated with trilostane_7'].astype('Int64')
print("Treated with trilostane_7 unique values:", cox_data['Treated with trilostane_7'].unique())

# Get the number of rows in cox_subset
num_rows = len(cox_data)
print("Number of rows in cox_subset:", num_rows)
```

```

Died unique values: <IntegerArray>
[0, 1]
Length: 2, dtype: Int64
Number_comorbidities unique values: <IntegerArray>
[0, 1, 3, 2, 4, 5]
Length: 6, dtype: Int64
BreedRelativeWeight unique values: <IntegerArray>
[1, 2, 4, 3]
Length: 4, dtype: Int64
Purebreed_status unique values: <IntegerArray>
[1, 2]
Length: 2, dtype: Int64
Stay_vs_stop unique values: <IntegerArray>
[1, 2]
Length: 2, dtype: Int64
Treated with trilostane_7 unique values: <IntegerArray>
[1, 2]
Length: 2, dtype: Int64
Number of rows in cox_subset: 219

```

```

In [29]: # Suppressing specific warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Encoding Neuro_signs: No as 0, Yes as 1
cox_data['Neuro_signs'] = cox_data['Neuro_signs'].replace({'Yes': 1, 'No': 0})
print("Neuro_signs unique values:", cox_data['Neuro_signs'].unique())

# Encoding Complications: No as 0, Yes as 1
cox_data['Complications'] = cox_data['Complications'].replace({'Yes': 1, 'Unknown': 0})
print("Complications unique values:", cox_data['Complications'].unique())

# Encoding Hypertensive_Yes4: No as 0, Yes as 1
cox_data['Hypertensive_Yes4'] = cox_data['Hypertensive_Yes4'].replace({'Yes': 1, 'No': 0})
print("Hypertensive_Yes4 unique values:", cox_data['Hypertensive_Yes4'].unique())

# Encoding Oversuppresion: No as 0, Yes as 1
cox_data['Oversuppresion?'] = cox_data['Oversuppresion?'].replace({'Yes': 1, 'No': 0})
print("Oversuppresion unique values:", cox_data['Oversuppresion?'].unique())

# Encoding Cortisol stayed <250: No as 0, Yes as 1
cox_data['Cortisol stayed <250'] = cox_data['Cortisol stayed <250'].replace({'Yes': 1, 'No': 0})
print("Cortisol stayed <250 unique values:", cox_data['Cortisol stayed <250'].unique())

# Encoding Cortisol went <40: No as 0, Yes as 1
cox_data['Cortisol went <40'] = cox_data['Cortisol went <40'].replace({'Yes': 1, 'No': 0})
print("Cortisol went <40 unique values:", cox_data['Cortisol went <40'].unique())

# Encoding comorb_UTI: No as 0, Yes as 1
cox_data['comorb_UTI'] = cox_data['comorb_UTI'].replace({'Yes': 1, 'No': 0})
print("comorb_UTI unique values:", cox_data['comorb_UTI'].unique())

# Encoding comorb_dm: No as 0, Yes as 1
cox_data['comorb_dm'] = cox_data['comorb_dm'].replace({'Yes': 1, 'No': 0})
print("comorb_dm unique values:", cox_data['comorb_dm'].unique())

# Encoding comorb_hypot: No as 0, Yes as 1

```



```

cox_data['comorb_hypot'] = cox_data['comorb_hypot'].replace({'Yes': 1, 'No': 0})
print("comorb_hypot unique values:", cox_data['comorb_hypot'].unique())

# Encoding Isneutered: No as 0, Yes as 1
cox_data['Isneutered'] = cox_data['Isneutered'].replace({'Yes': 1, 'No': 0})
print("Isneutered unique values:", cox_data['Isneutered'].unique())

# Get the number of rows in cox_subset
num_rows = len(cox_data)
print("Number of rows in cox_subset:", num_rows)

# 'Changes to trilostane_6', 'Trilostane SID/BID_9' 'Trilostane starting dose (mg/kg

```

```

Neuro_signs unique values: [0, 1]
Categories (2, int64): [0, 1]
Complications unique values: [2, 1]
Categories (2, int64): [2, 1]
Hypertensive_Yes4 unique values: [2, 1, 0]
Categories (3, int64): [0, 2, 1]
Oversuppresion unique values: [1, 0]
Categories (2, int64): [0, 1]
Cortisol stayed <250 unique values: [1, 2, 0]
Categories (3, int64): [0, 2, 1]
Cortisol went <40 unique values: [1, 2, 0]
Categories (3, int64): [0, 2, 1]
comorb_UTI unique values: [0, 1]
Categories (2, int64): [0, 1]
comorb_dm unique values: [0, 1]
Categories (2, int64): [0, 1]
comorb_hypot unique values: [0, 1]
Categories (2, int64): [0, 1]
Isneutered unique values: [1, 0]
Categories (2, int64): [0, 1]
Number of rows in cox_subset: 219

```

```

In [30]: # Printing the column names of cox_data
print("Column names in cox_data:")
for col in cox_data.columns:
    print(col)

# Printing the number of columns
num_cols = len(cox_data.columns)
print("\nTotal number of columns in cox_data:", num_cols)
print(cox_data.head(2))

# Getting the number of rows in cox_subset
num_rows = len(cox_data)
print("Number of rows in cox_subset:", num_rows)

```

Column names in cox_data:

Pre-ACTH
Post-ACTH
weight
Neuro signs
Complications
Hypertensive_Yes4
Oversuppresion?
Cortisol stayed <250
Cortisol went <40
Number_comorbidities
comorb_UTI
comorb_dm
comorb_hypot
Sex
Isneutered
BreedRelativeWeight
Purebreed_status
Stay_vs_stop
Treated with trilostane_7
Age_at_diagnosis(Years)
Time_suspicion_to_diagnosis(Days)
Days_Diagnosis_to_Failure
Died

Total number of columns in cox_data: 23

	Pre-ACTH	Post-ACTH	weight	Neuro signs	Complications	Hypertensive_Yes4	\
0	0.0	0.0	7.55	0	2	2	
1	0.0	0.0	7.20	0	2	2	

	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	\
0	1	1	1	
1	1	2	2	

	Number_comorbidities	...	Sex	Isneutered	BreedRelativeWeight	\
0	0	...	0	1	1	
1	1	...	1	1	1	

	Purebreed_status	Stay_vs_stop	Treated with trilostane_7	\
0	1	1	1	
1	1	1	1	

	Age_at_diagnosis(Years)	Time_suspicion_to_diagnosis(Days)	\
0	10.04	7	
1	10.36	22	

	Days_Diagnosis_to_Failure	Died
0	1778	0
1	1842	0

[2 rows x 23 columns]

Number of rows in cox_subset: 219

Subset : final_cox_data is used for CoxPH Models

```

In [31]: # Preparing the DataFrame for fitting CoxPH Model
final_cox_data = cox_data[['Days_Diagnosis_to_Failure',
    'Died', 'Neuro signs', 'Complications', 'Hypertensive_Yes4', 'Oversuppresion',
    'Cortisol stayed <250', 'Cortisol went <40', 'Number_comorbidities',
    'comorb_UTI', 'comorb_dm', 'comorb_hypot', 'Sex', 'Isneutered',
    'BreedRelativeWeight', 'Purebreed_status',
    'Stay_vs_stop', 'Treated with trilostane_7', 'Pre-ACTH', 'Post-ACTH', 'weig',
    'Age_at_diagnosis(Years)', 'Time_suspicion_to_diagnosis(Days)']]

# Getting the number of rows in cox_subset
num_rows = len(final_cox_data)
print("Number of rows in cox_subset:", num_rows)

# Creating an instance of the CoxPHFitter
cph = CoxPHFitter()
cph.fit(final_cox_data, duration_col='Days_Diagnosis_to_Failure', event_col='Died')

# Printing the summary of the model
cph.print_summary()

```

Number of rows in cox_subset: 219

model	lifelines.CoxPHFitter
duration col	'Days_Diagnosis_to_Failure'
event col	'Died'
baseline estimation	breslow
number of observations	219
number of events observed	179
partial log-likelihood	-766.83
time fit was run	2024-11-23 18:25:33 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%
Neuro signs	0.49	1.64	0.20	0.10	0.89	1.10	
Complications	-0.14	0.87	0.30	-0.72	0.44	0.49	
Hypertensive_Yes4	-0.13	0.88	0.16	-0.44	0.19	0.64	
Oversuppresion?	-0.42	0.65	0.24	-0.90	0.05	0.41	
Cortisol stayed <250	0.37	1.45	0.23	-0.09	0.83	0.91	
Cortisol went <40	-0.01	0.99	0.18	-0.36	0.34	0.70	
Number_comorbidities	-0.19	0.82	0.10	-0.39	0.01	0.68	
comorb_UTI	0.92	2.50	0.28	0.37	1.46	1.45	
comorb_dm	0.21	1.23	0.33	-0.45	0.87	0.64	
comorb_hypot	-0.39	0.67	0.54	-1.45	0.66	0.23	
Sex	-0.06	0.94	0.17	-0.40	0.28	0.67	
Isneutered	-0.11	0.89	0.20	-0.50	0.27	0.61	
BreedRelativeWeight	-0.11	0.89	0.13	-0.36	0.14	0.70	
Purebreed_status	0.20	1.22	0.33	-0.45	0.85	0.64	
Stay_vs_stop	0.16	1.18	0.22	-0.27	0.59	0.76	
Treated with trilostane_7	-0.35	0.70	0.46	-1.26	0.55	0.28	
Pre-ACTH	0.00	1.00	0.00	-0.00	0.00	1.00	
Post-ACTH	-0.00	1.00	0.00	-0.00	0.00	1.00	
weight	0.01	1.01	0.01	-0.00	0.03	1.00	
Age_at_diagnosis(Years)	0.16	1.18	0.04	0.09	0.24	1.09	
Time_suspicion_to_diagnosis(Days)	-0.00	1.00	0.00	-0.00	0.00	1.00	

Concordance	0.66
Partial AIC	1575.65
log-likelihood ratio test	53.45 on 21 df
-log2(p) of ll-ratio test	13.04

```
In [32]: mpl.rcParams['figure.max_open_warning'] = 50
# Check proportional hazards assumption
cph.check_assumptions(final_cox_data, show_plots=True)
```

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

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Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

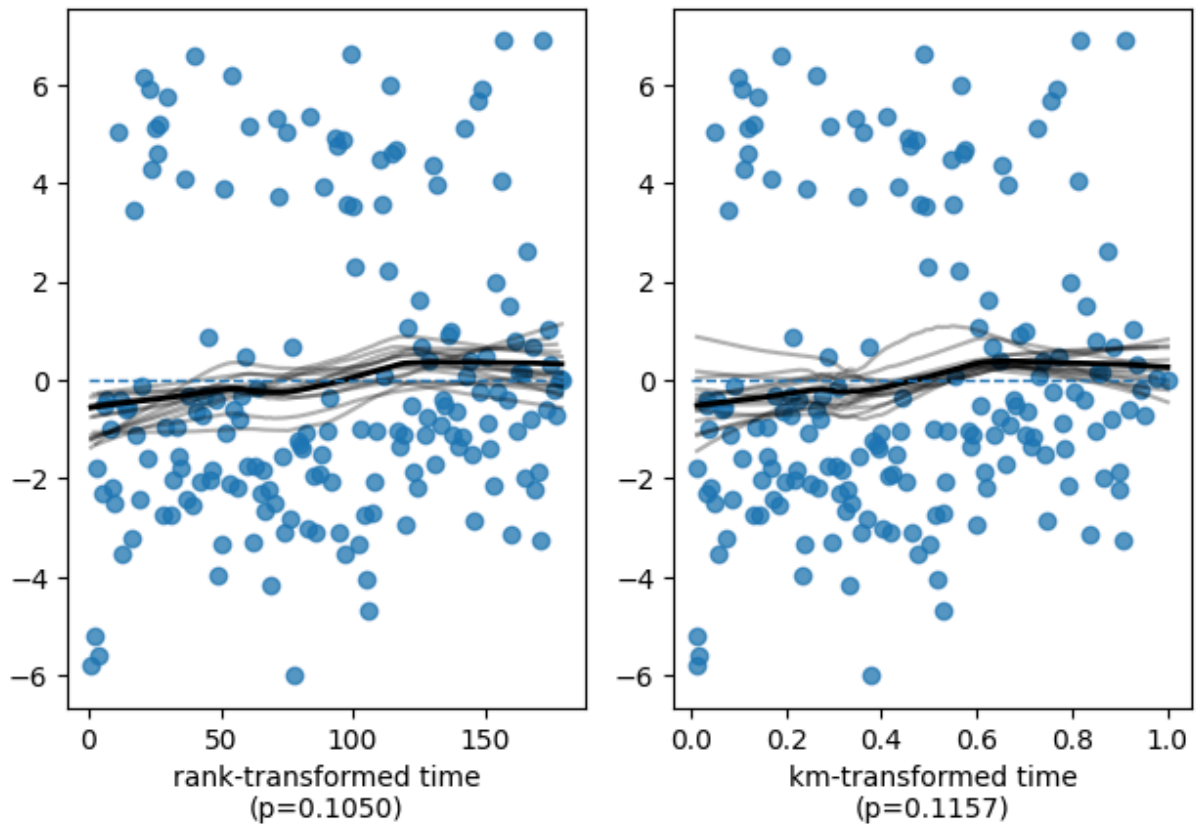
Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

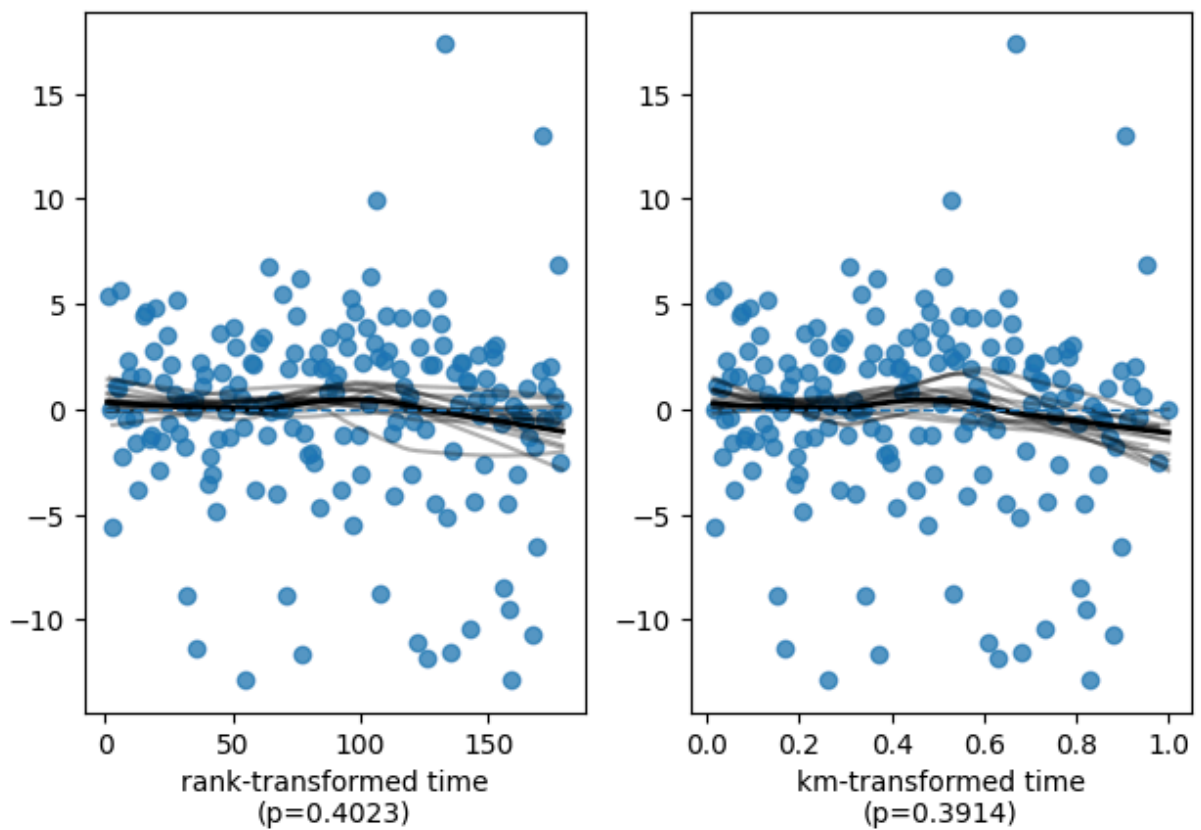
Proportional hazard assumption looks okay.

```
Out[32]: [[<Axes: xlabel='rank-transformed time\n(p=0.1050)'\>,
<Axes: xlabel='km-transformed time\n(p=0.1157)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.4023)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.5798)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.1004)'\>,
<Axes: xlabel='km-transformed time\n(p=0.1057)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.3749)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.1995)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.0920)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.4158)'\>,
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[<Axes: xlabel='rank-transformed time\n(p=0.6103)'\>,
<Axes: xlabel='km-transformed time\n(p=0.6213)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.3416)'\>,
<Axes: xlabel='km-transformed time\n(p=0.3359)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.0410)'\>,
<Axes: xlabel='km-transformed time\n(p=0.0451)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.0181)'\>,
<Axes: xlabel='km-transformed time\n(p=0.0267)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.9159)'\>,
<Axes: xlabel='km-transformed time\n(p=0.7953)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.3657)'\>,
<Axes: xlabel='km-transformed time\n(p=0.3343)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.3457)'\>,
<Axes: xlabel='km-transformed time\n(p=0.3371)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.6208)'\>,
<Axes: xlabel='km-transformed time\n(p=0.6098)'\>],
[<Axes: xlabel='rank-transformed time\n(p=0.0274)'\>,
<Axes: xlabel='km-transformed time\n(p=0.0322)'\>]]
```

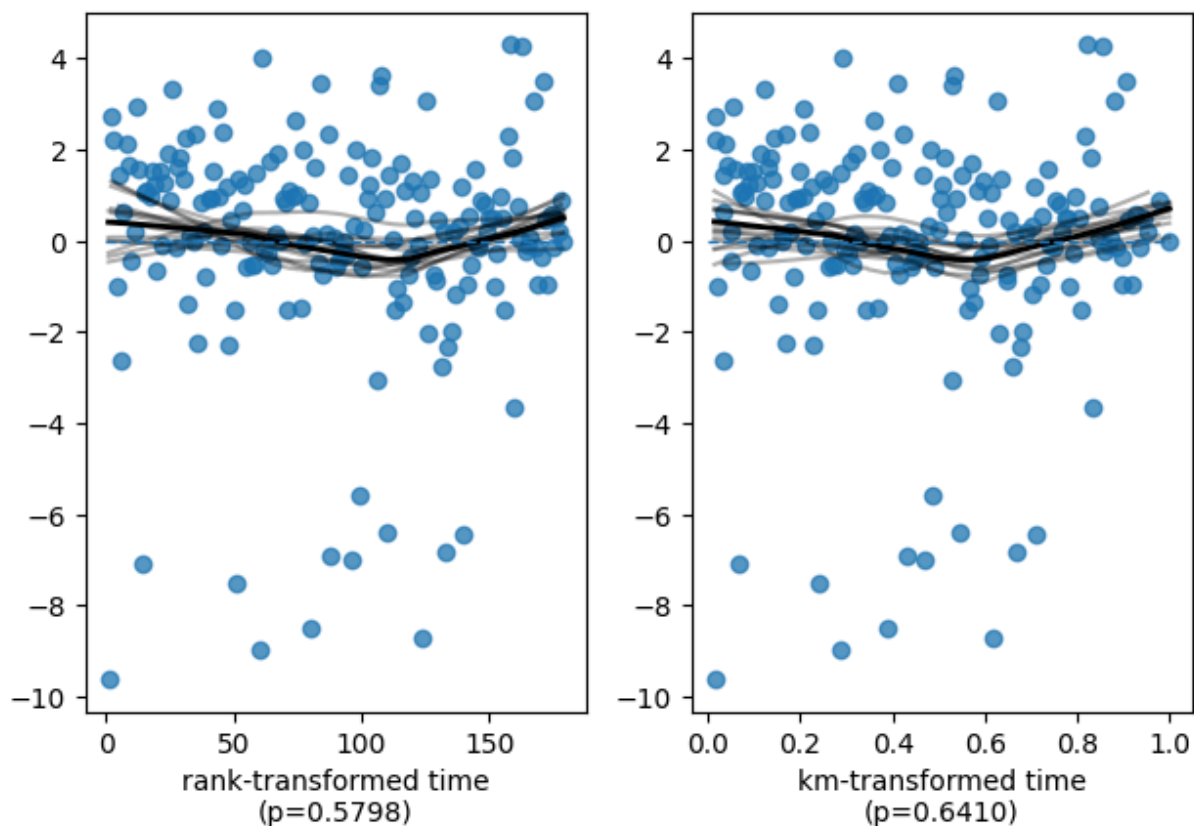
Scaled Schoenfeld residuals of 'Neuro signs'



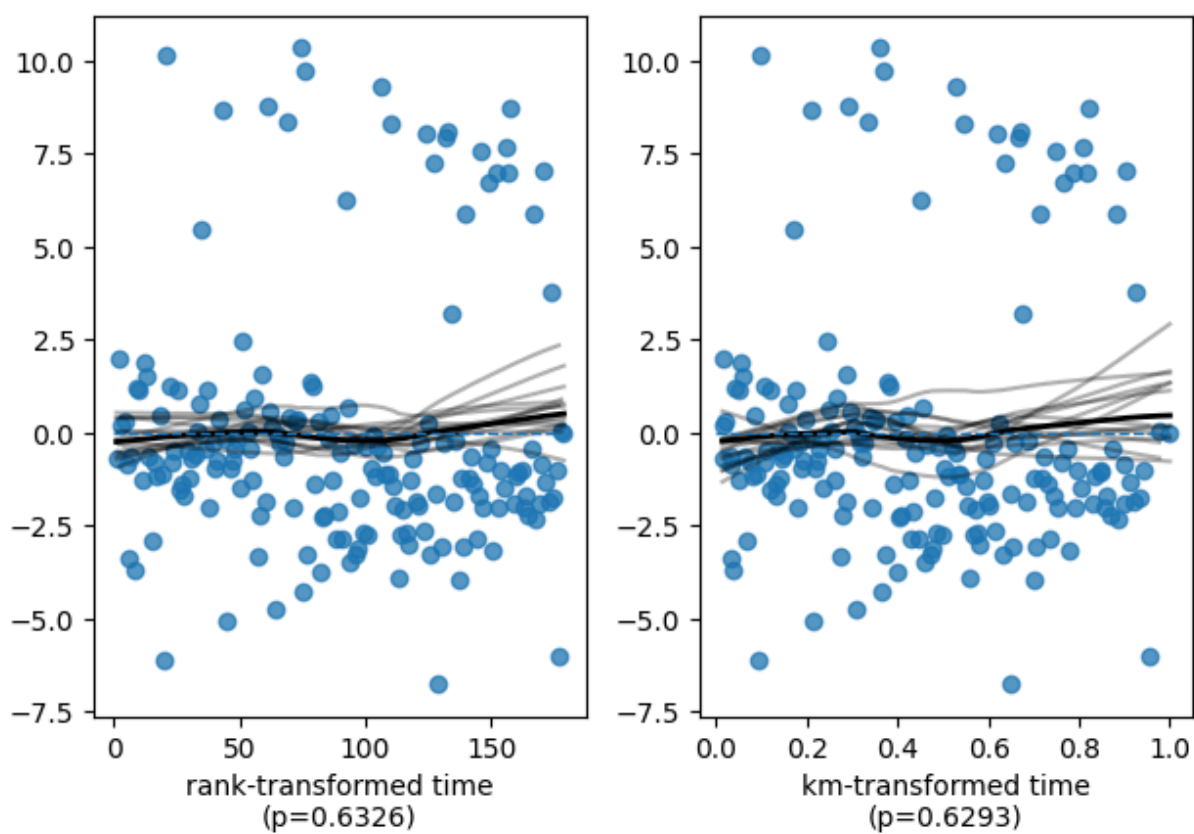
Scaled Schoenfeld residuals of 'Complications'



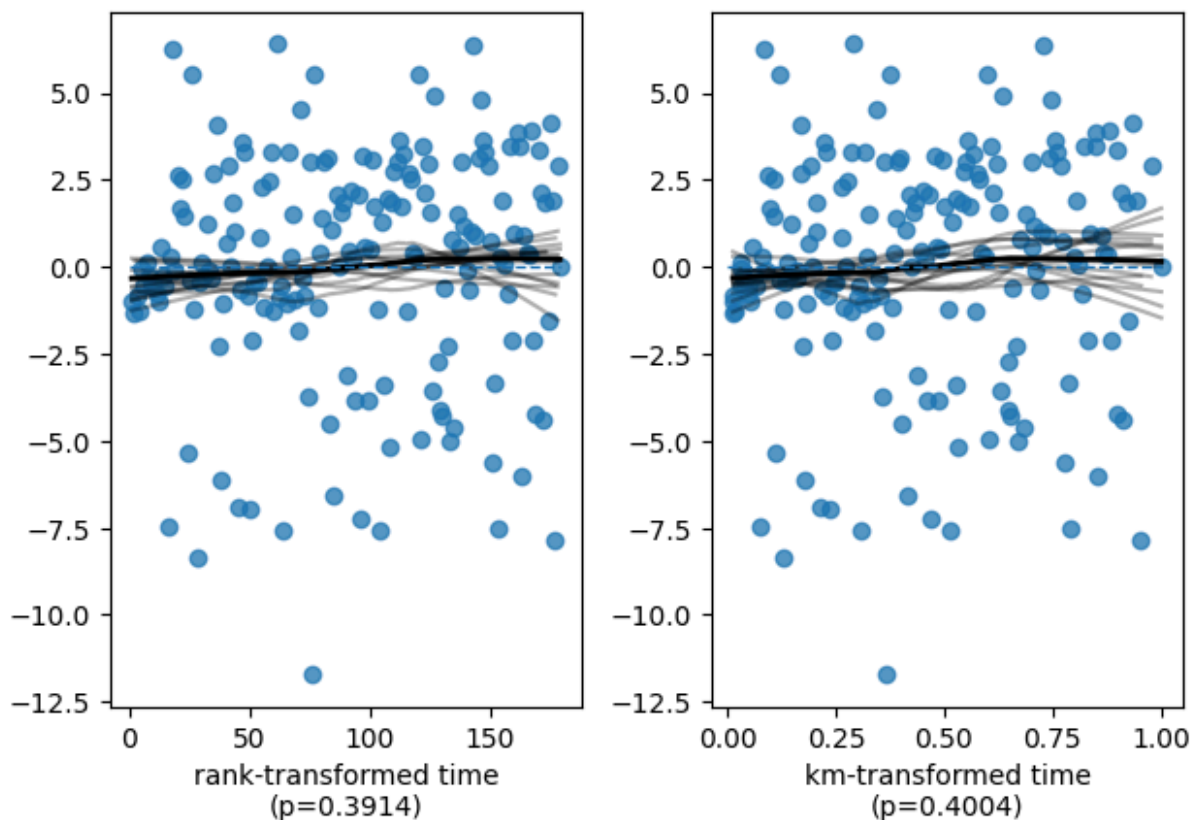
Scaled Schoenfeld residuals of 'Hypertensive_Yes4'



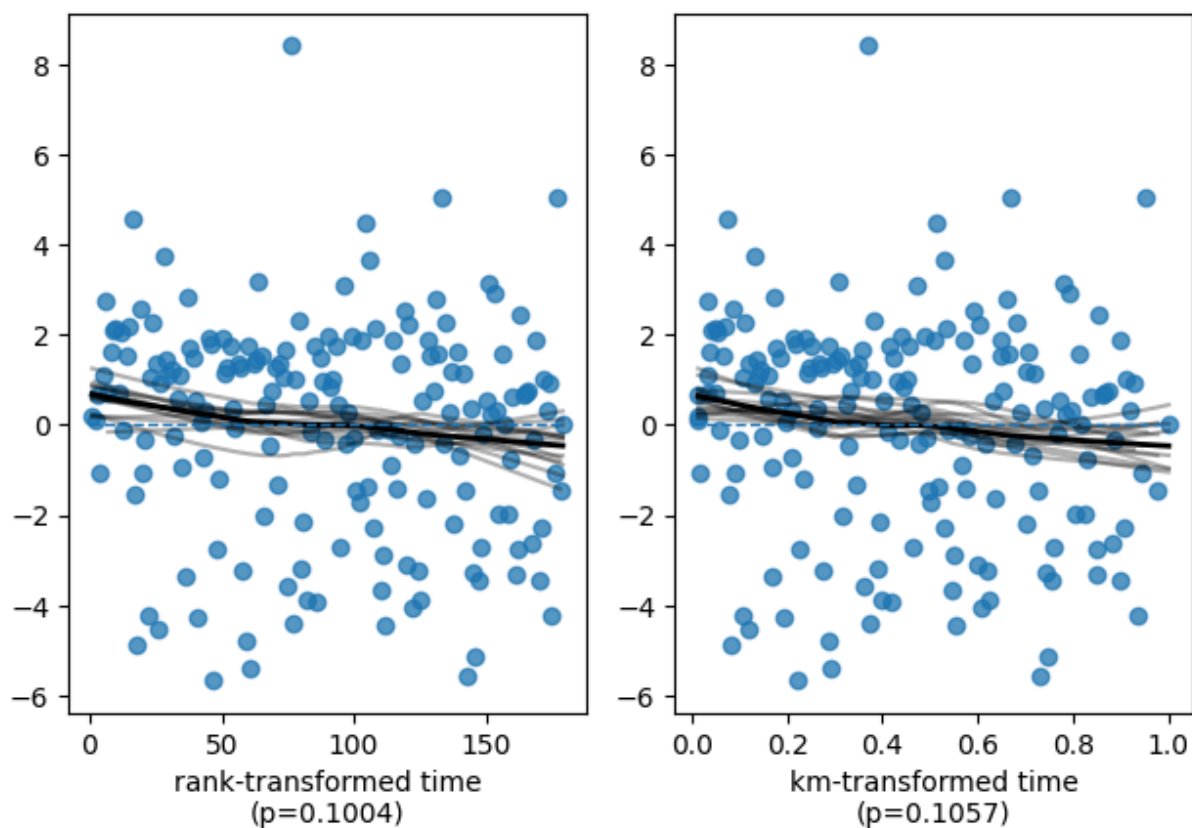
Scaled Schoenfeld residuals of 'Oversuppresion?'



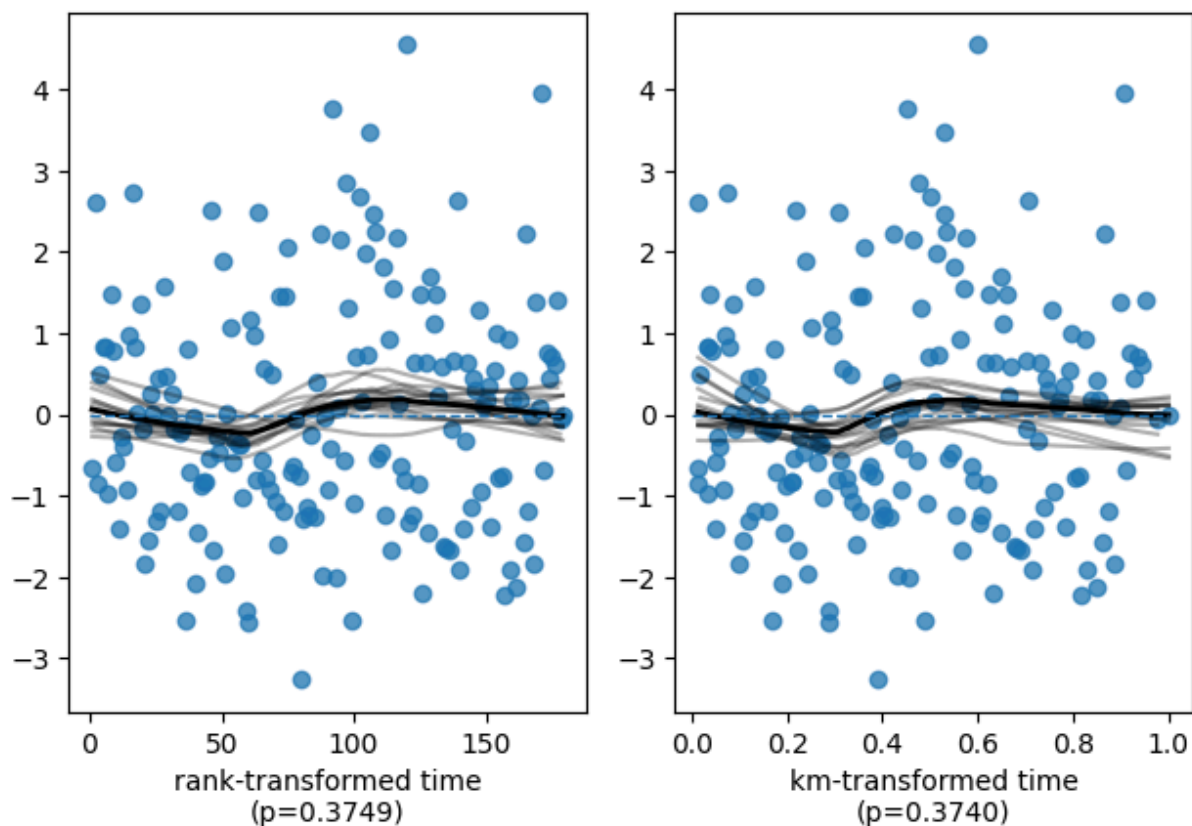
Scaled Schoenfeld residuals of 'Cortisol stayed <250'



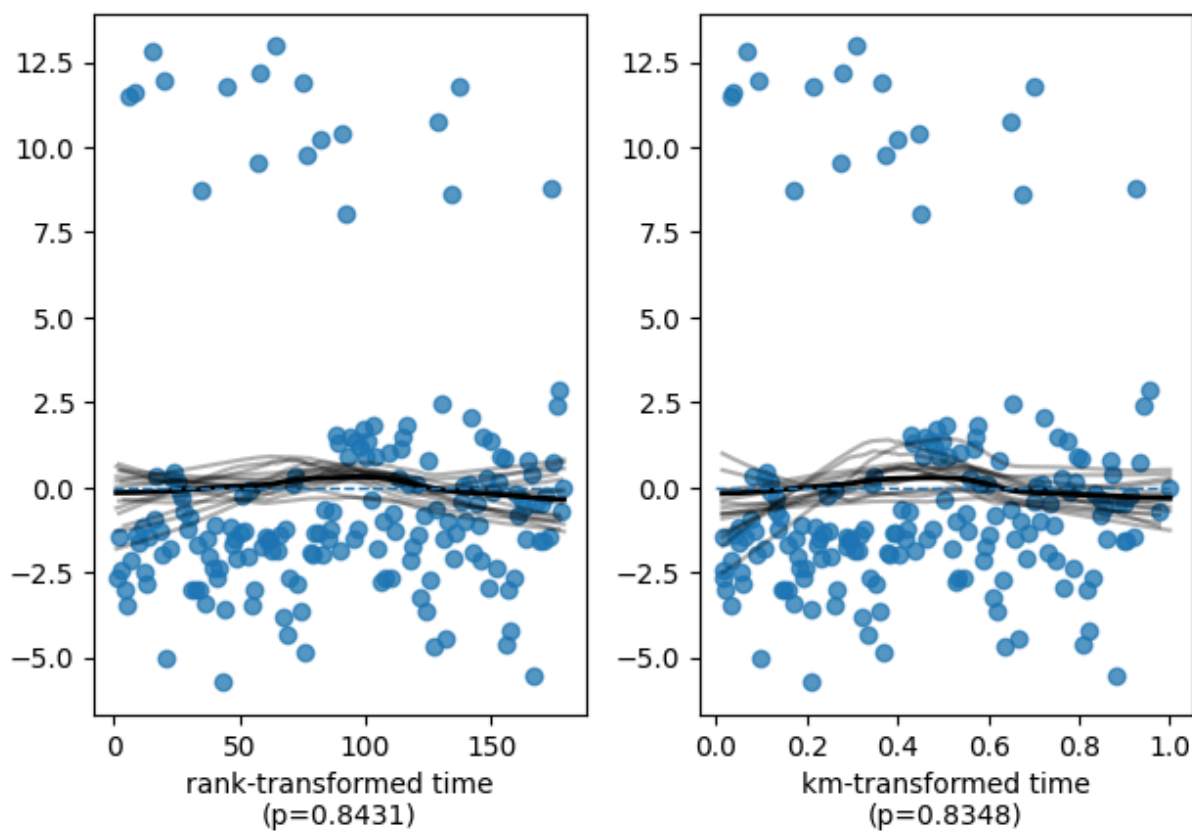
Scaled Schoenfeld residuals of 'Cortisol went <40'



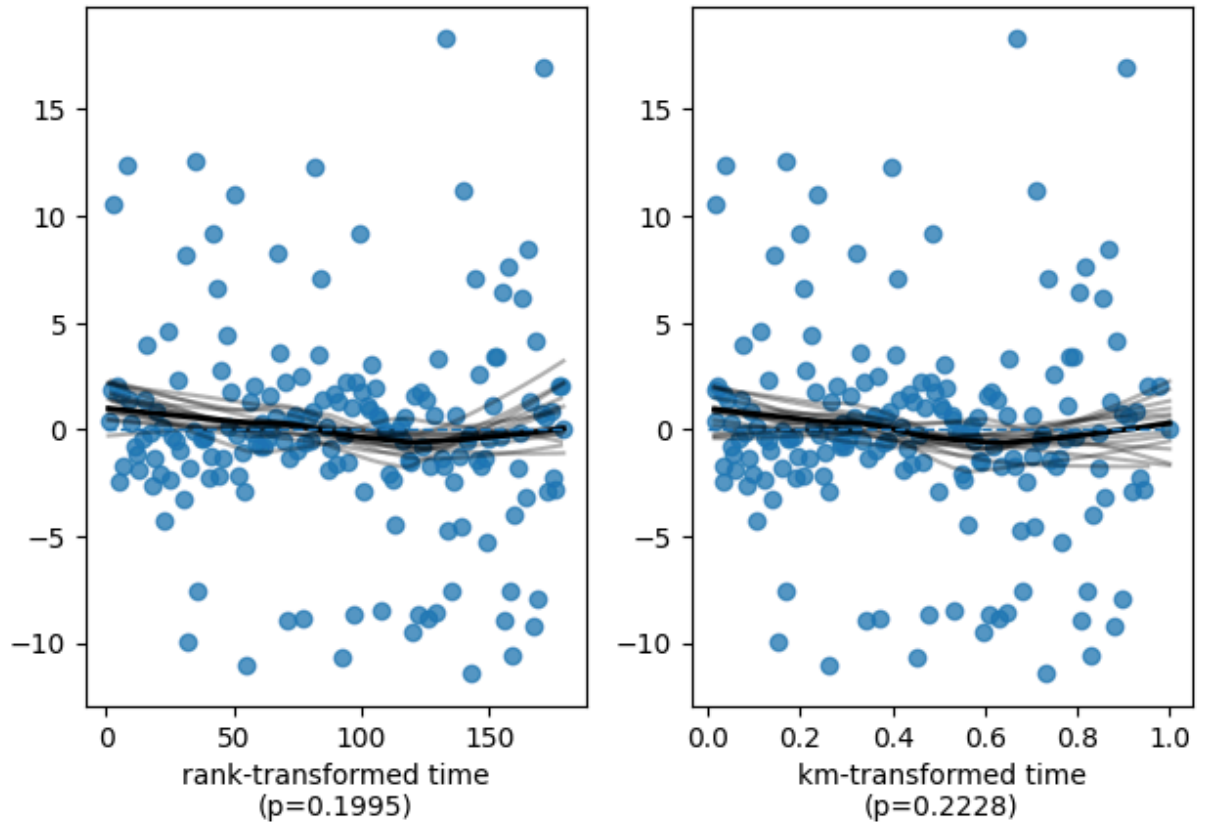
Scaled Schoenfeld residuals of 'Number_comorbidities'



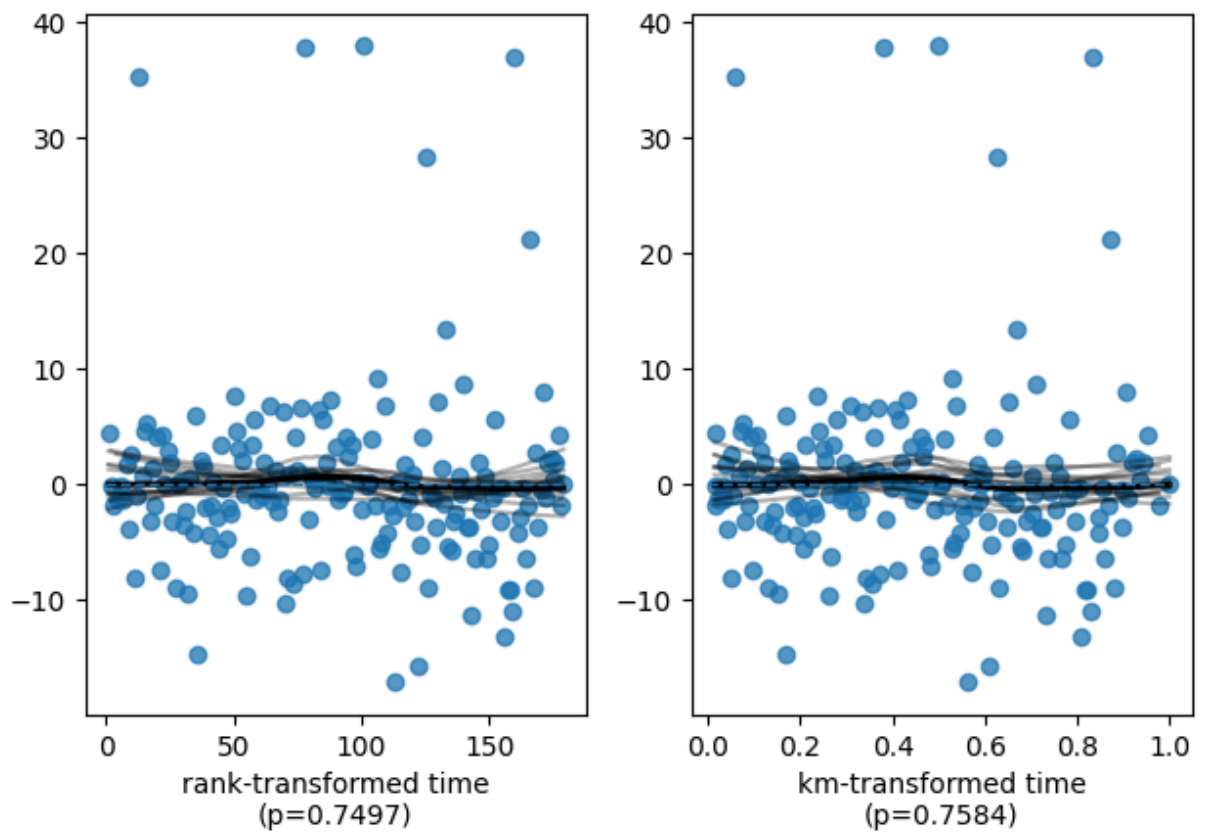
Scaled Schoenfeld residuals of 'comorb_UTI'



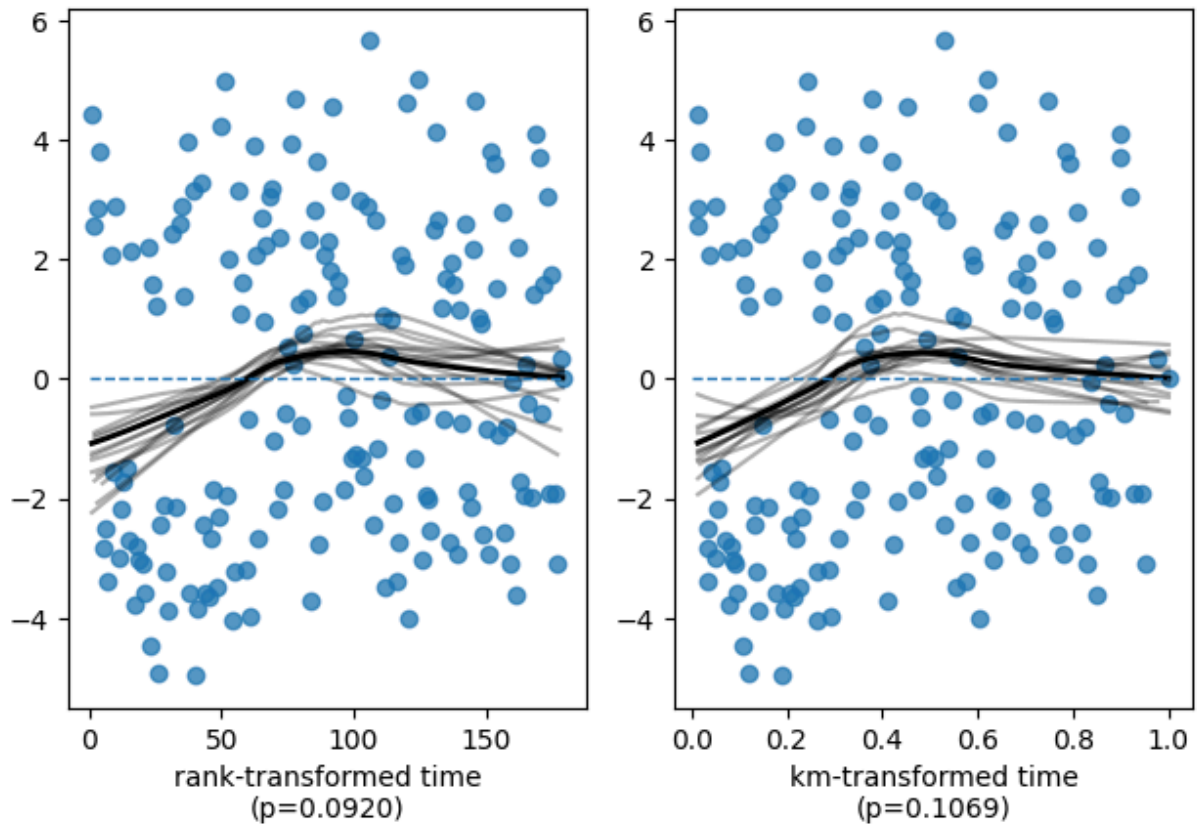
Scaled Schoenfeld residuals of 'comorb_dm'



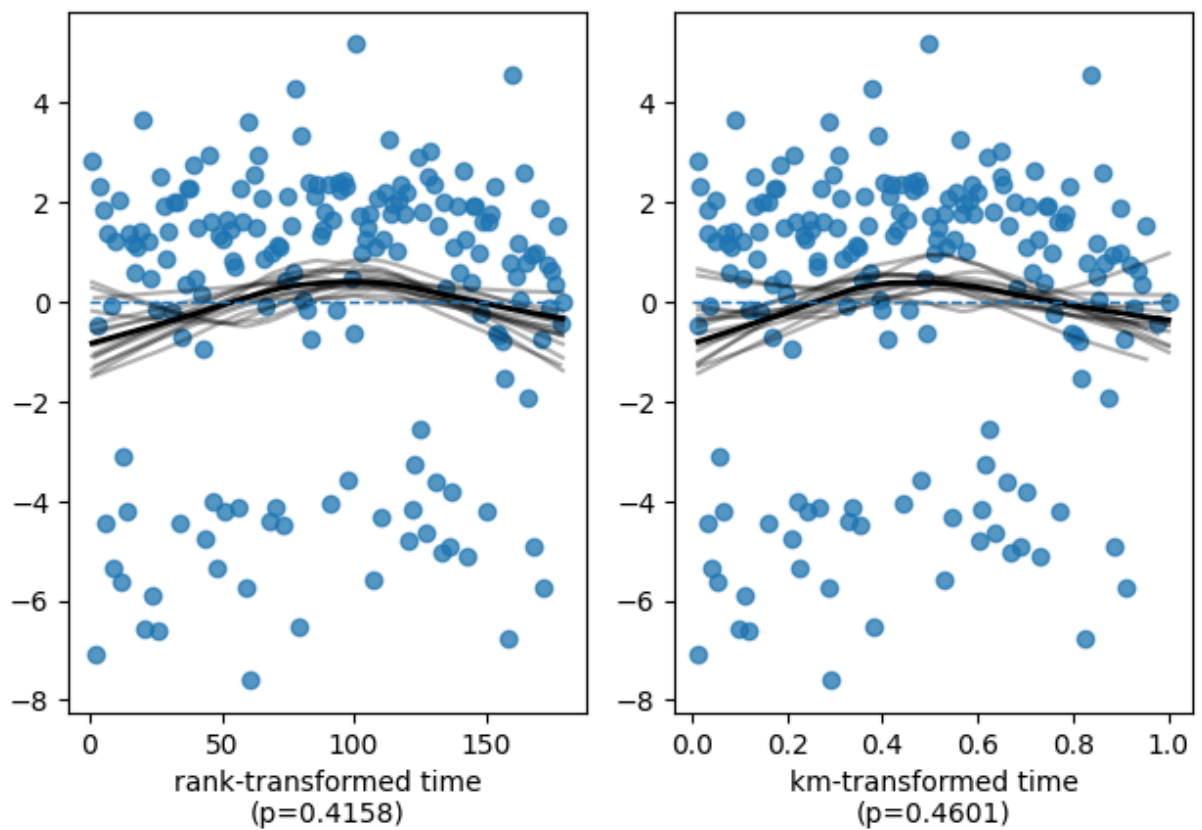
Scaled Schoenfeld residuals of 'comorb_hypot'



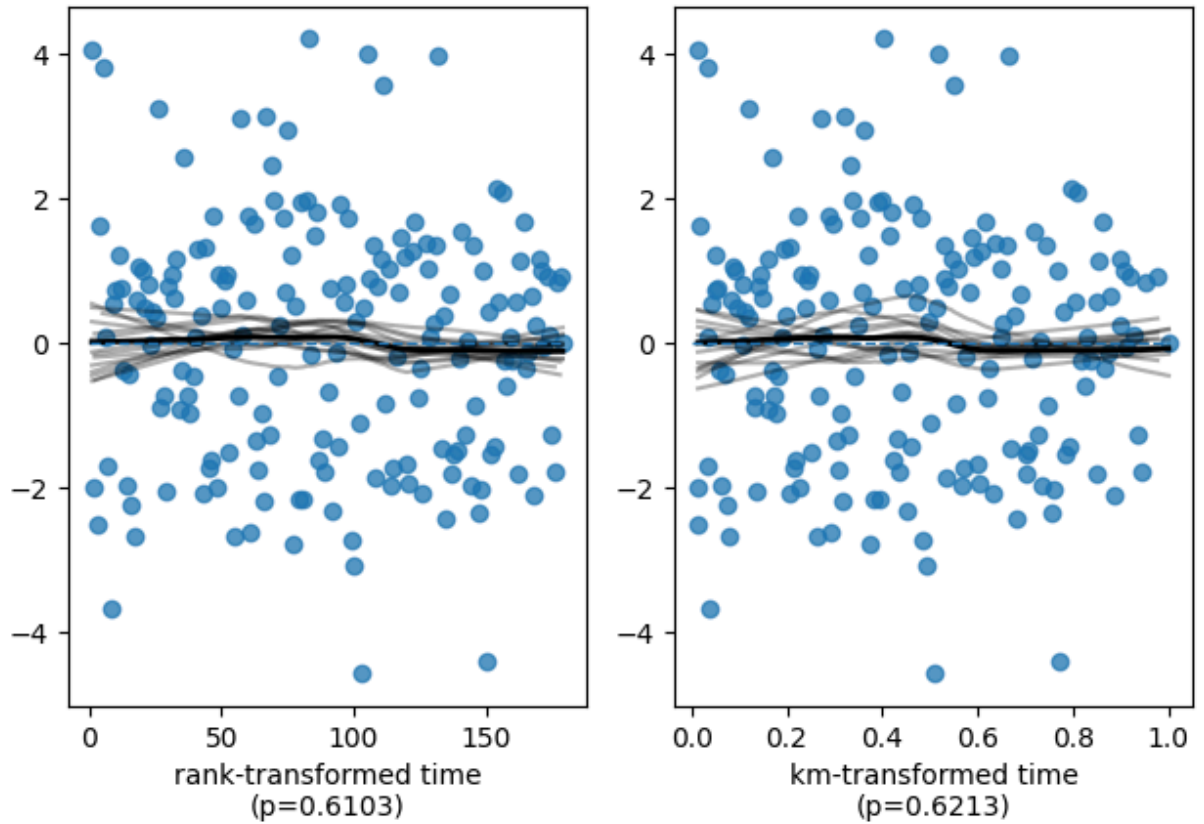
Scaled Schoenfeld residuals of 'Sex'



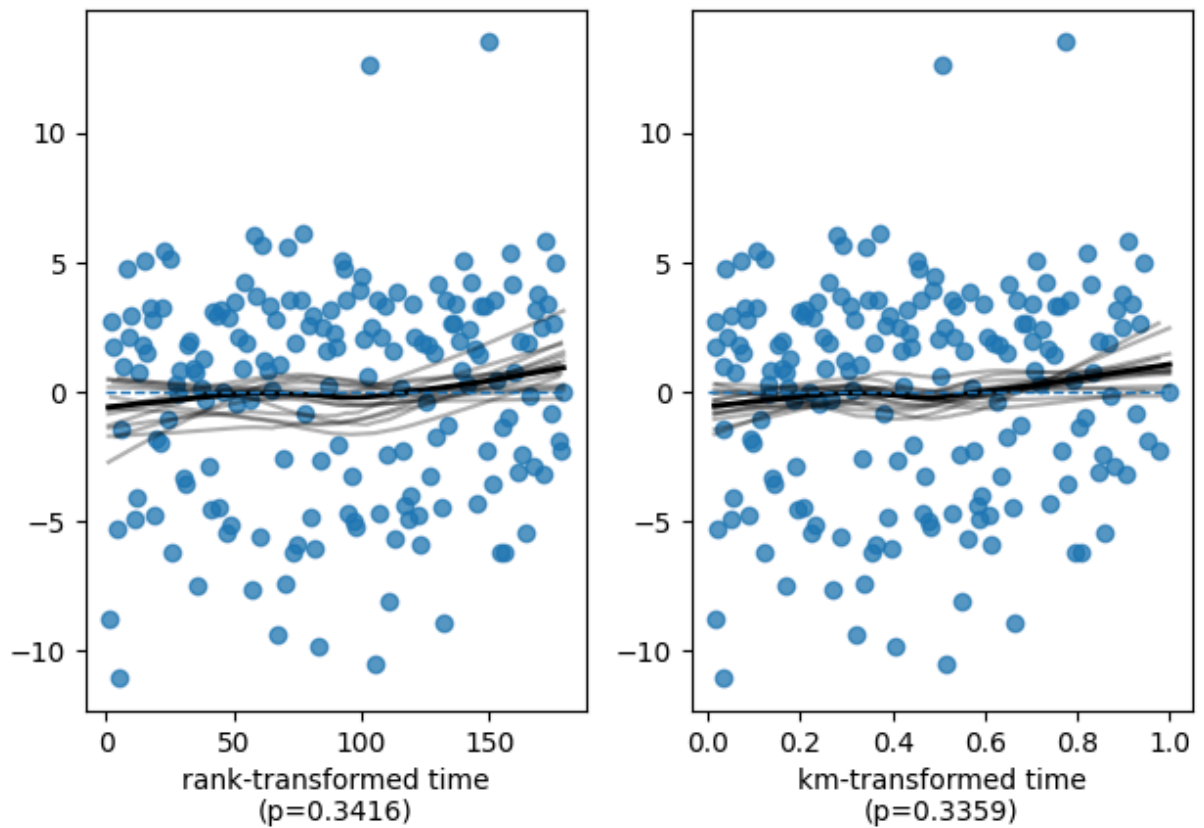
Scaled Schoenfeld residuals of 'Isneutered'



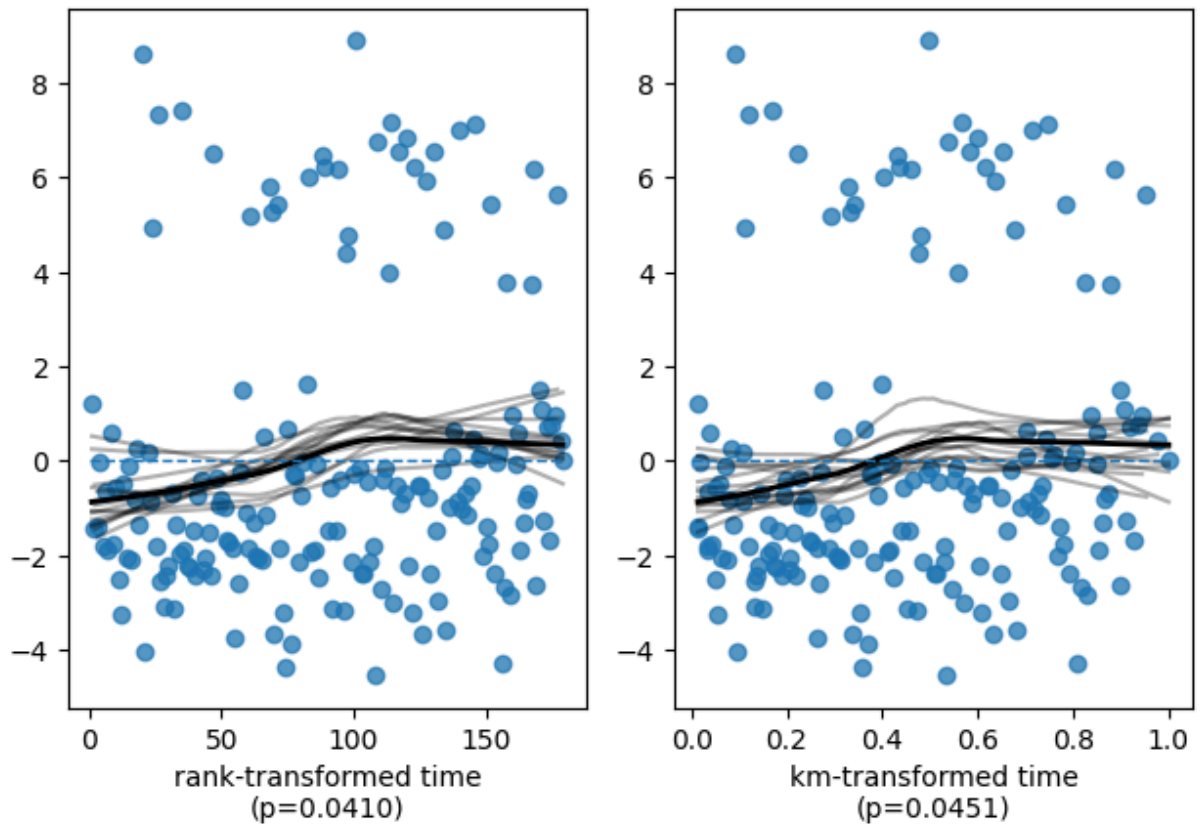
Scaled Schoenfeld residuals of 'BreedRelativeWeight'



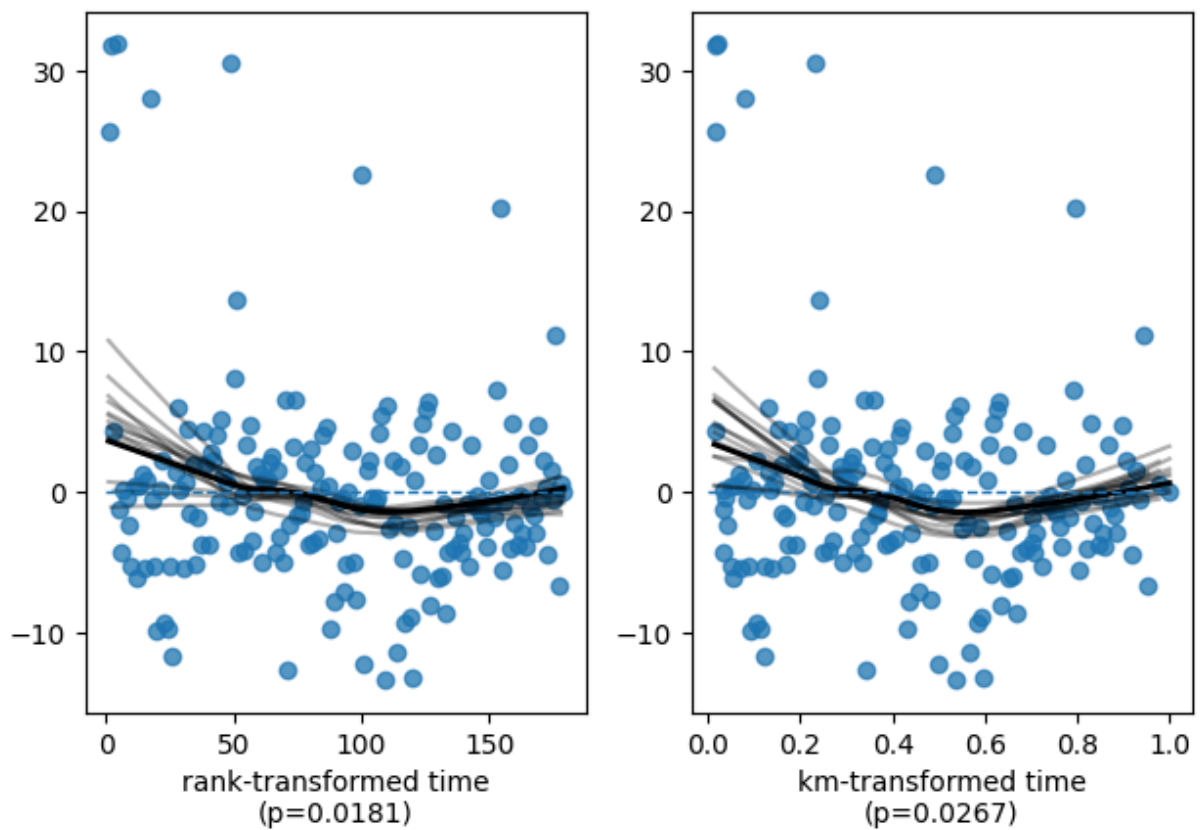
Scaled Schoenfeld residuals of 'Purebreed_status'



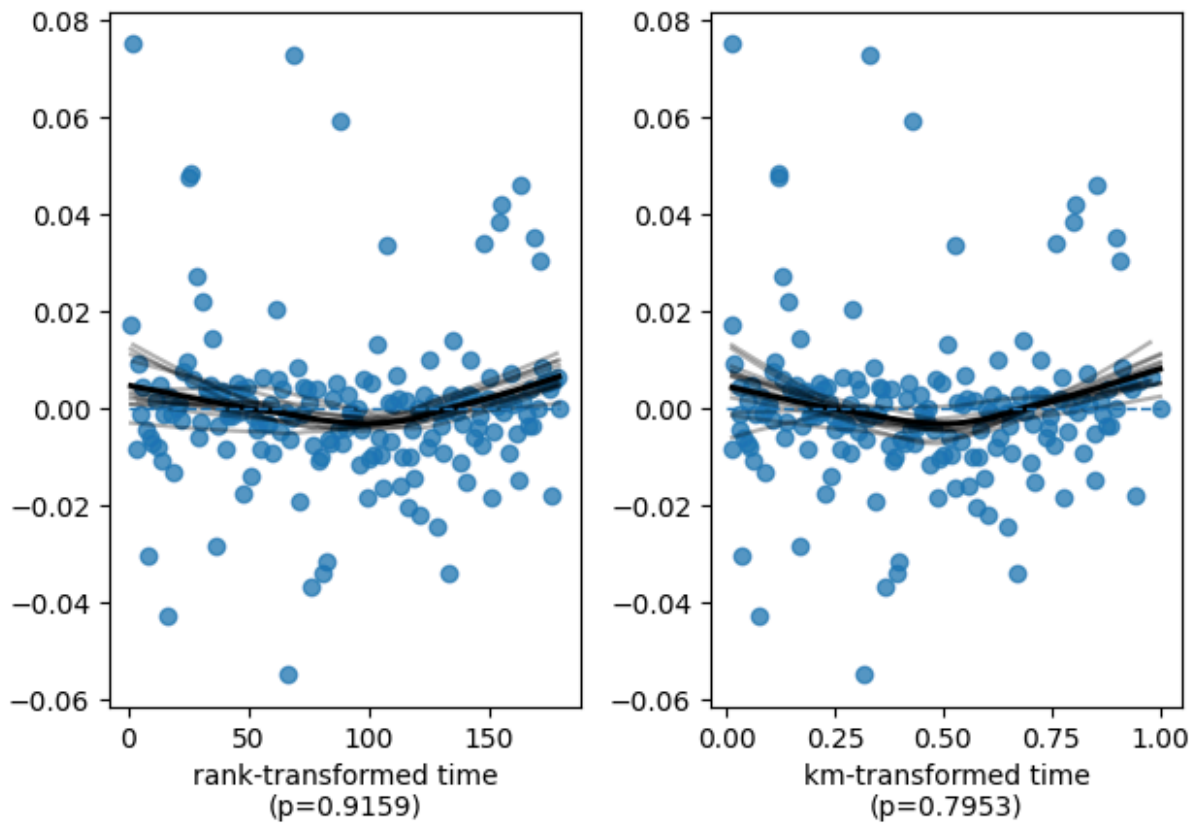
Scaled Schoenfeld residuals of 'Stay_vs_stop'



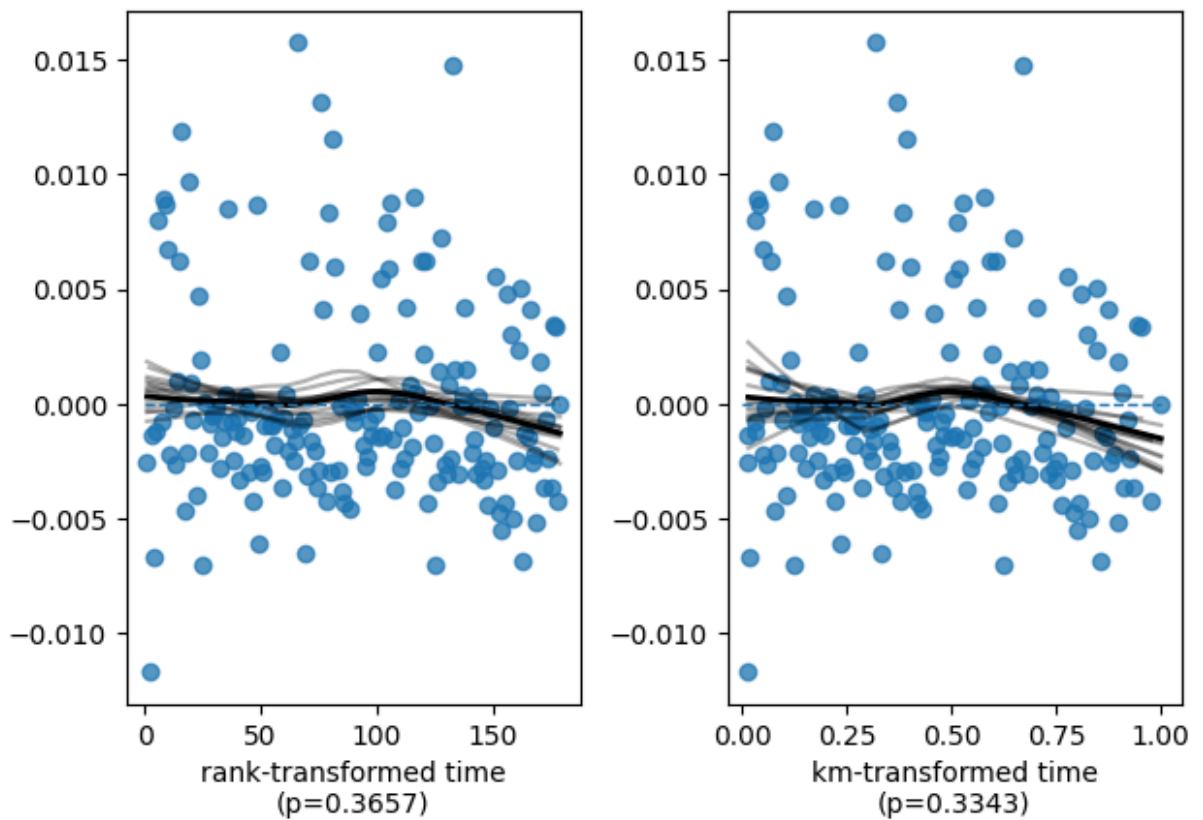
Scaled Schoenfeld residuals of 'Treated with trilostane_7'



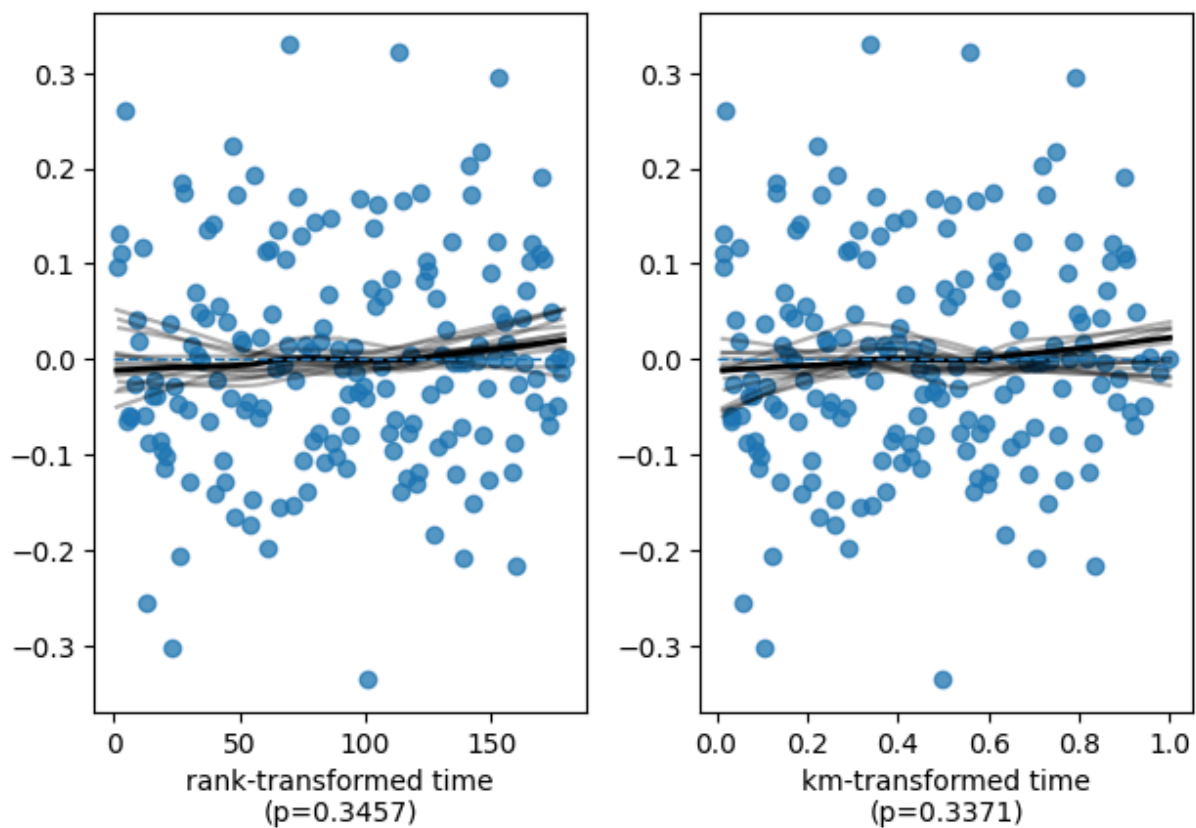
Scaled Schoenfeld residuals of 'Pre-ACTH'



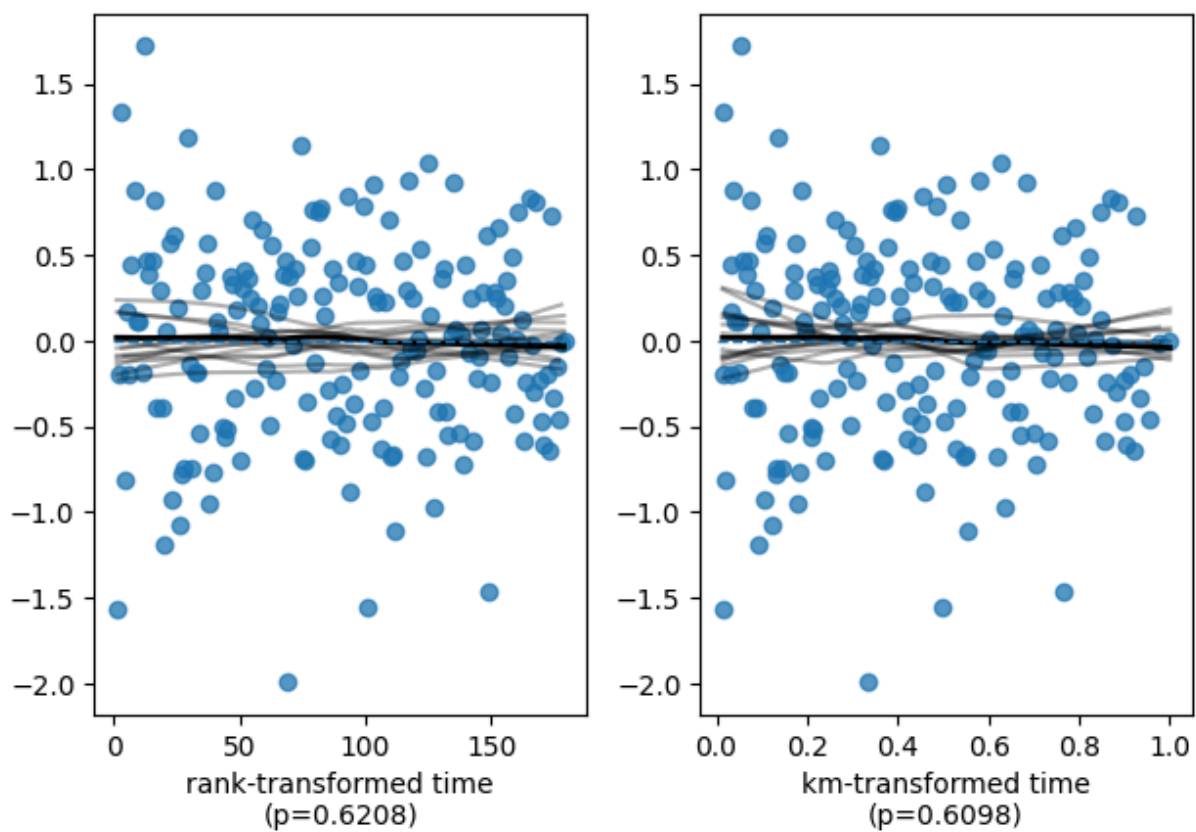
Scaled Schoenfeld residuals of 'Post-ACTH'



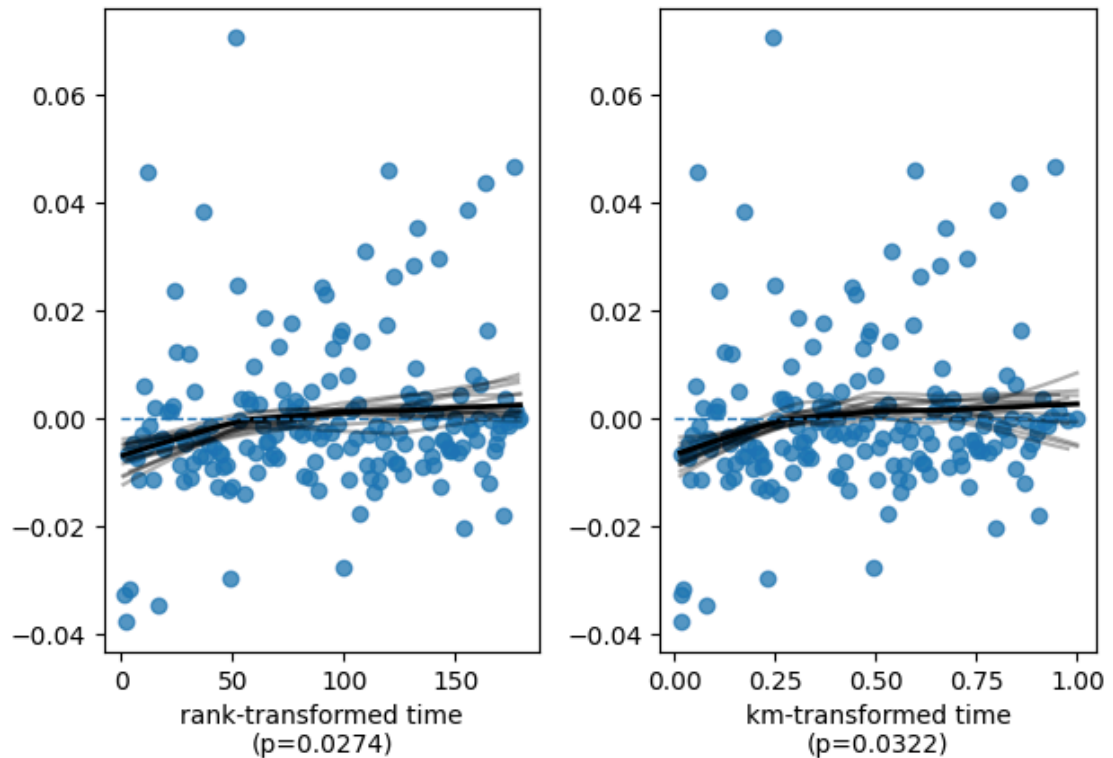
Scaled Schoenfeld residuals of 'weight'



Scaled Schoenfeld residuals of 'Age_at_diagnosis(Years)'



Scaled Schoenfeld residuals of 'Time_suspicion_to_diagnosis(Days)'



Proportional Hazards Assumption is Satisfied: The absence of any systematic trend in the residuals implies that the proportional hazards assumption is met. This is good news as it validates that the model is correctly specified in terms of the proportional hazards assumption.

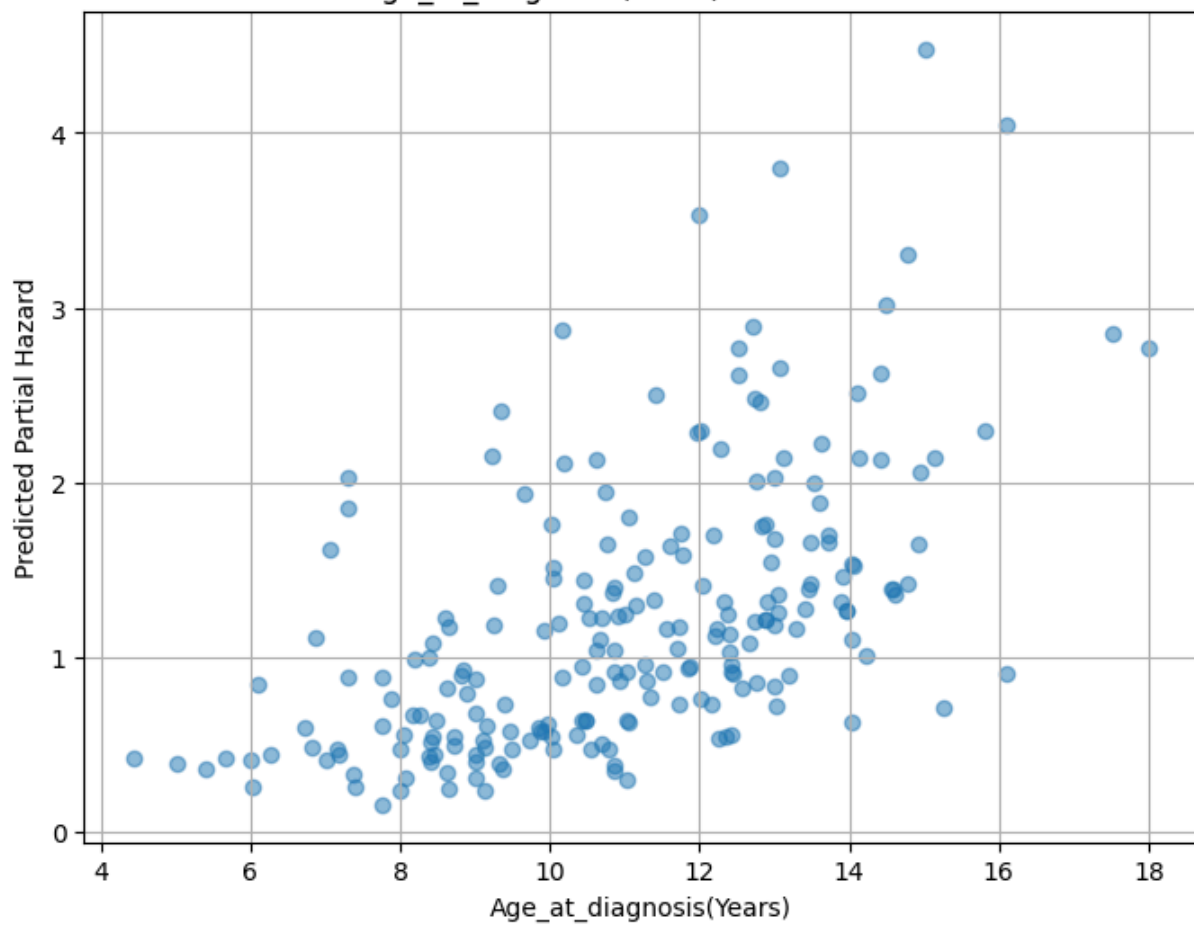
```
In [33]: cph = CoxPHFitter()
cph.fit(final_cox_data, duration_col='Days_Diagnosis_to_Failure', event_col='Died')

# Calculating the predicted partial hazards for each individual
partial_hazards = cph.predict_partial_hazard(final_cox_data)

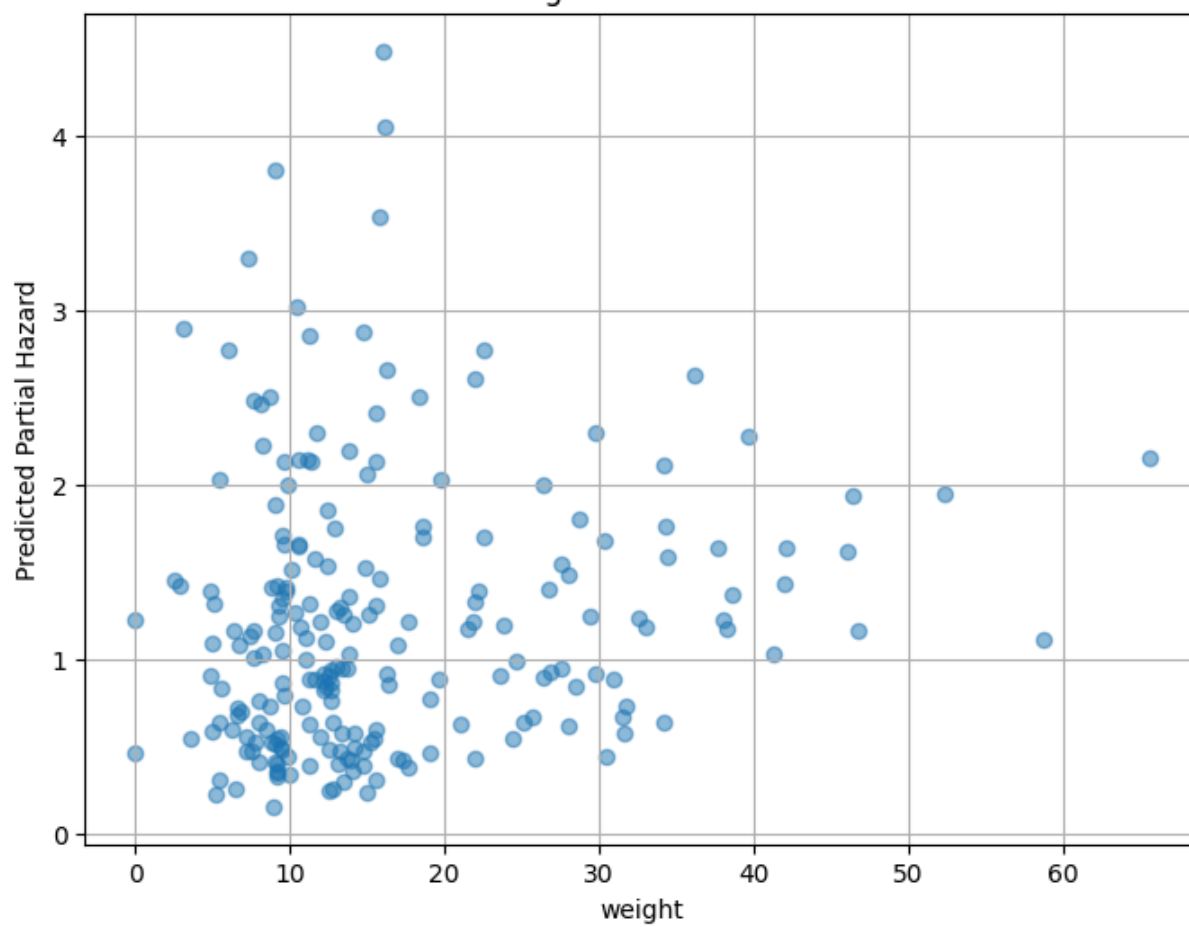
# Plotting for each continuous variable
continuous_vars = ['Age_at_diagnosis(Years)', 'weight', 'Pre-ACTH', 'Post-ACTH', 'w
                  'Age_at_diagnosis(Years)', 'Time_suspicion_to_diagnosis(Days)' ]

for var in continuous_vars:
    plt.figure(figsize=(8, 6))
    plt.scatter(final_cox_data[var], partial_hazards, alpha=0.5)
    plt.title(f'Scatter Plot of {var} vs. Predicted Partial Hazard')
    plt.xlabel(var)
    plt.ylabel('Predicted Partial Hazard')
    plt.grid(True)
    plt.show()
```

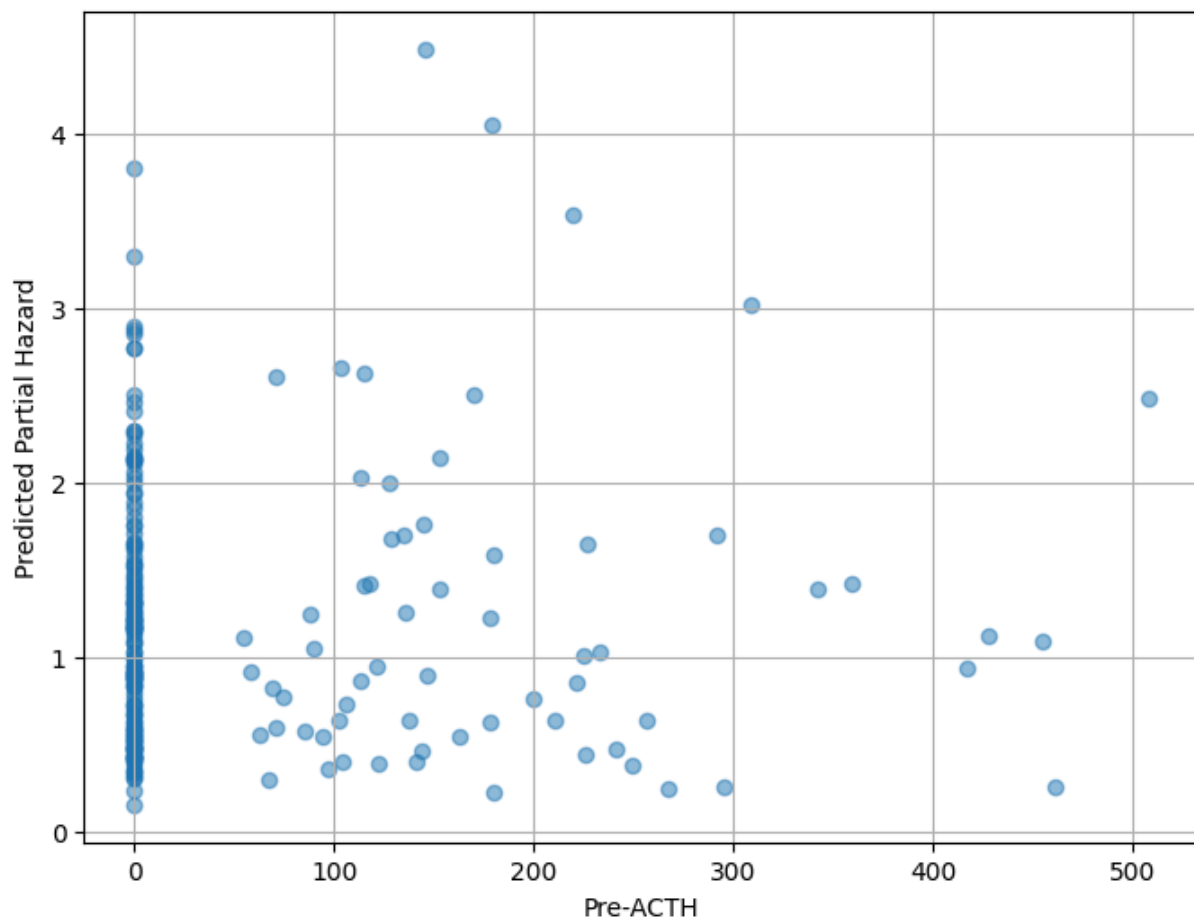
Scatter Plot of Age_at_diagnosis(Years) vs. Predicted Partial Hazard



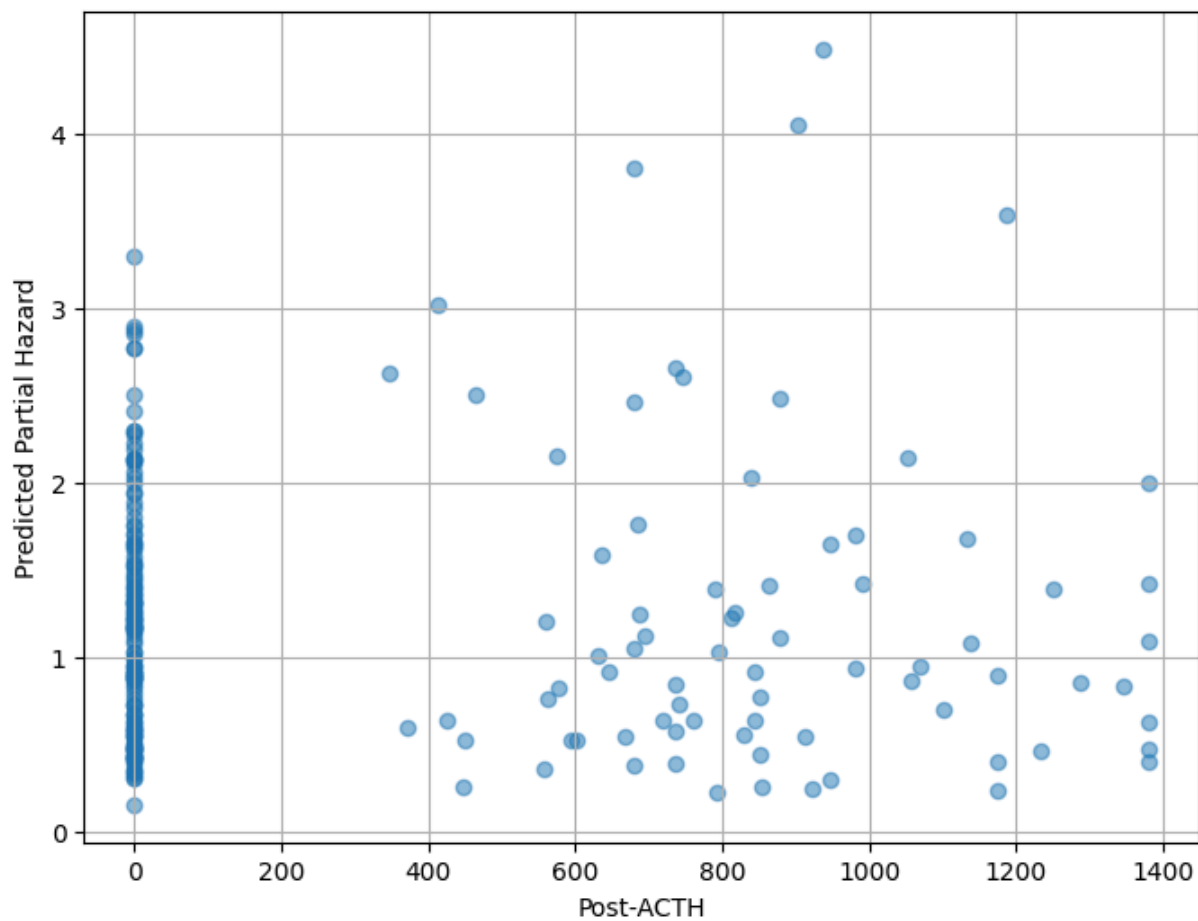
Scatter Plot of weight vs. Predicted Partial Hazard



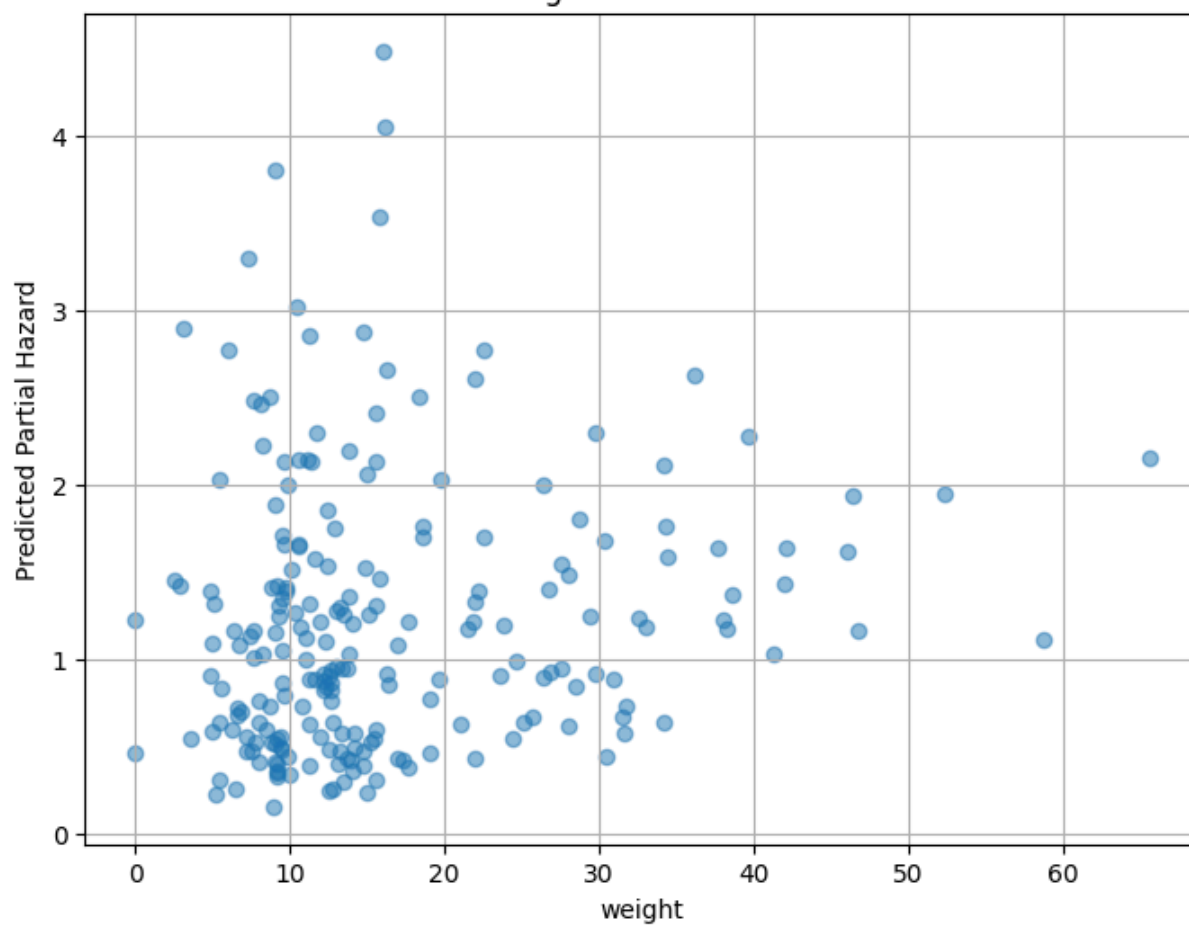
Scatter Plot of Pre-ACTH vs. Predicted Partial Hazard



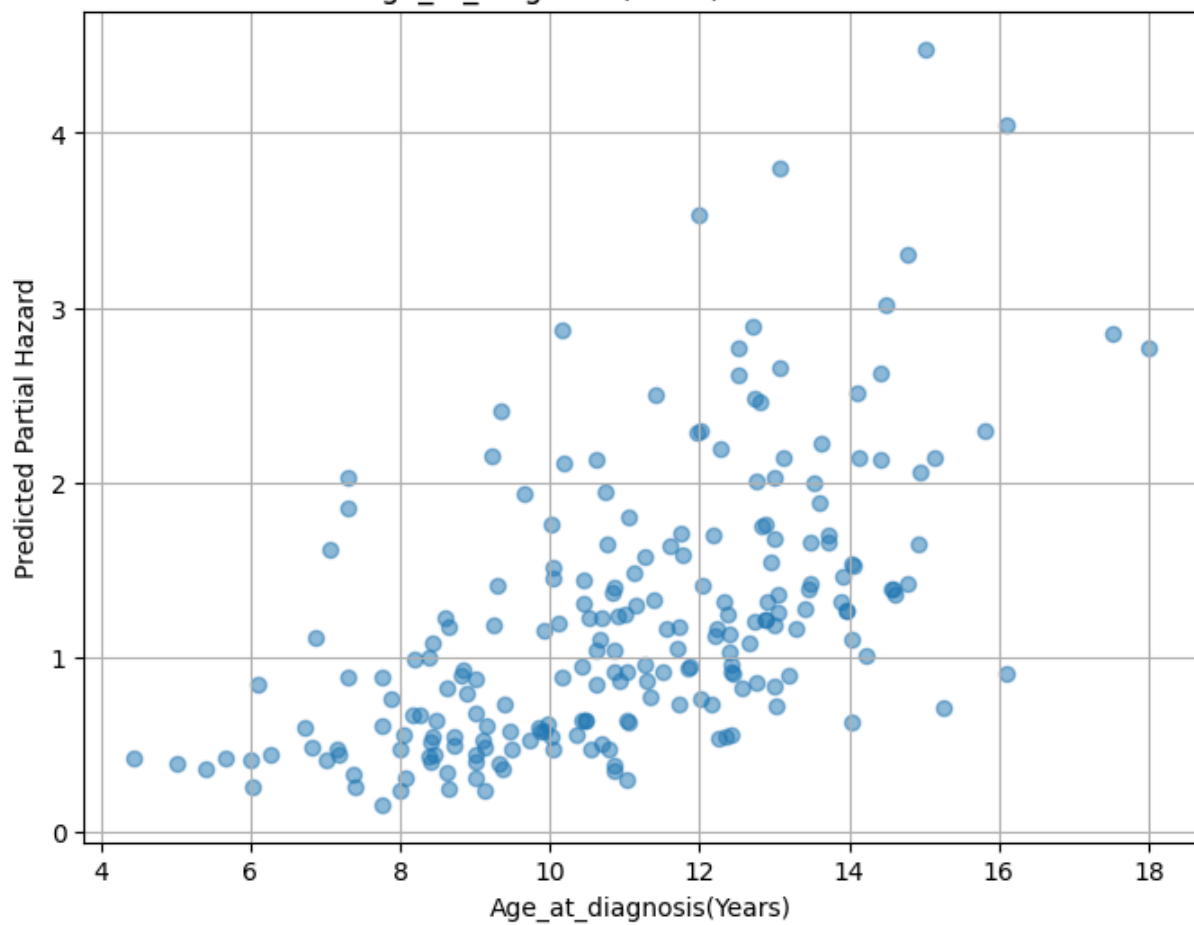
Scatter Plot of Post-ACTH vs. Predicted Partial Hazard

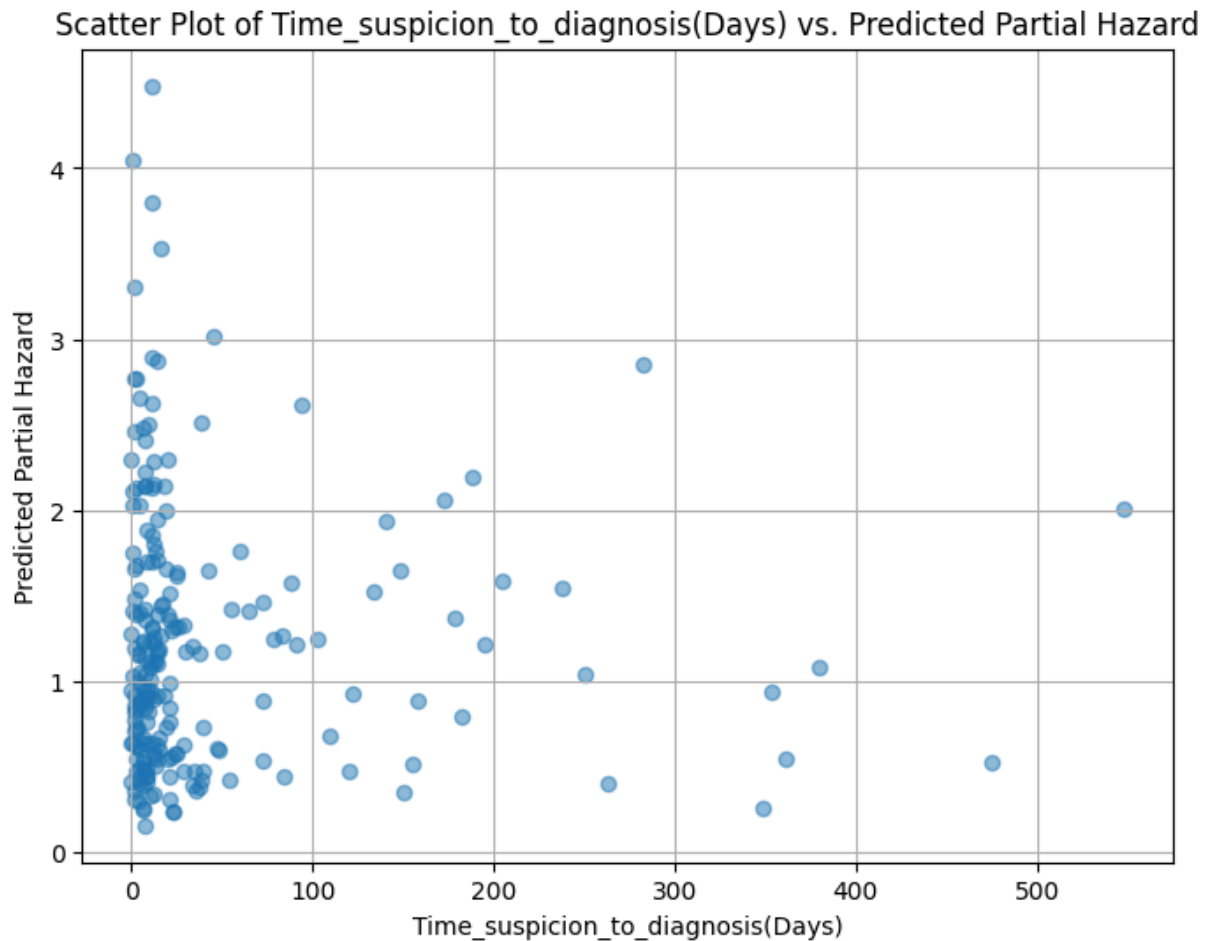


Scatter Plot of weight vs. Predicted Partial Hazard



Scatter Plot of Age_at_diagnosis(Years) vs. Predicted Partial Hazard





CoxPH for Comorbidities

Subset : canine_comorb is used for the Analysis

```
In [34]: # Creating a new DataFrame for comorbidities
canine_comorb = pd.DataFrame()

# Converting the categorical variables to binary
canine_comorb['comorb_UTI'] = canine_subset['comorb_UTI'].map({'Yes': 1, 'No': 0})
canine_comorb['comorb_dm'] = canine_subset['comorb_dm'].map({'Yes': 1, 'No': 0})
canine_comorb['comorb_hypot'] = canine_subset['comorb_hypot'].map({'Yes': 1, 'No': 0})
canine_comorb['Number_comorbidities'] = canine_subset['Number_comorbidities']
canine_comorb['Days_Diagnosis_to_Failure'] = canine_subset['Days_Diagnosis_to_Failure']
canine_comorb['Died'] = canine_subset['Died']

# Displaying the modified DataFrame
print(canine_comorb[['comorb_UTI', 'comorb_dm', 'comorb_hypot']])

# Displaying the modified DataFrame
print(canine_subset[['comorb_UTI', 'comorb_dm', 'comorb_hypot']])

print("-----")
print(canine_comorb.head())
```

	comorb_UTI	comorb_dm	comorb_hypot
0	0	0	0
1	0	0	0
2	0	1	0
3	0	0	0
4	1	0	0
..
214	0	0	0
215	0	0	0
216	0	0	0
217	0	0	0
218	0	0	0

[219 rows x 3 columns]

	comorb_UTI	comorb_dm	comorb_hypot
0	No	No	No
1	No	No	No
2	No	Yes	No
3	No	No	No
4	Yes	No	No
..
214	No	No	No
215	No	No	No
216	No	No	No
217	No	No	No
218	No	No	No

[219 rows x 3 columns]

	comorb_UTI	comorb_dm	comorb_hypot	Number_comorbidities \
0	0	0	0	0.0
1	0	0	0	1.0
2	0	1	0	3.0
3	0	0	0	0.0
4	1	0	0	1.0

	Days_Diagnosis_to_Failure	Died
0	1778	0
1	1842	0
2	1260	1
3	942	1
4	779	1

```
In [35]: # Checking the data types
print("Data types before fitting:")
print(canine_comorb.dtypes)

# Convert all categorical columns to numeric
for col in canine_comorb.select_dtypes(include=['category']).columns:
    canine_comorb[col] = canine_comorb[col].cat.codes # Convert categorical to num

# Checking the data types
print("Data types after fitting:")
print(canine_comorb.dtypes)
```

```

Data types before fitting:
comorb_UTI          category
comorb_dm           category
comorb_hypot        category
Number_comorbidities category
Days_Diagnosis_to_Failure int64
Died                category
dtype: object
Data types after fitting:
comorb_UTI          int8
comorb_dm           int8
comorb_hypot        int8
Number_comorbidities int8
Days_Diagnosis_to_Failure int64
Died                int8
dtype: object

```

```

In [36]: # Fit multivariate model including all comorbidities and number of comorbidities
cph.fit(canine_comorb[['Days_Diagnosis_to_Failure', 'Died',
                      'comorb_UTI', 'comorb_dm',
                      'comorb_hypot', 'Number_comorbidities']],
        duration_col='Days_Diagnosis_to_Failure', event_col='Died')

print("Multivariate analysis including all comorbidities:")
cph.print_summary()

```

Multivariate analysis including all comorbidities:

model	lifelines.CoxPHFitter
duration col	'Days_Diagnosis_to_Failure'
event col	'Died'
baseline estimation	breslow
number of observations	219
number of events observed	179
partial log-likelihood	-790.24
time fit was run	2024-11-23 18:26:10 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to
comorb_UTI	0.60	1.82	0.25	0.10	1.09	1.11	2.97	0.00
comorb_dm	0.02	1.02	0.25	-0.47	0.51	0.62	1.66	0.00
comorb_hypot	0.10	1.11	0.42	-0.73	0.93	0.48	2.53	0.00
Number_comorbidities	-0.10	0.90	0.08	-0.26	0.05	0.77	1.06	0.00

Concordance	0.57
Partial AIC	1588.49
log-likelihood ratio test	6.62 on 4 df
-log2(p) of ll-ratio test	2.67

```
In [37]: mpl.rcParams['figure.max_open_warning'] = 50
# Check proportional hazards assumption
cph.check_assumptions(canine_comorb, show_plots=True)
```

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

Bootstrapping lowess lines. May take a moment...

The ``p_value_threshold`` is set at 0.01. Even under the null hypothesis of no violations, some covariates will be below the threshold by chance. This is compounded when there are many covariates. Similarly, when there are lots of observations, even minor deviances from the proportional hazard assumption will be flagged.

With that in mind, it's best to use a combination of statistical tests and visual tests to determine the most serious violations. Produce visual plots using ``check_assumptions(..., show_plots=True)`` and looking for non-constant lines. See link [A] below for a full example.

null_distribution		chi squared		
degrees_of_freedom		1		
model		<lifelines.CoxPHFitter: fitted with 219 total ...		
test_name		proportional_hazard_test		
		test_statistic	p	-log2(p)
Number_comorbidities	km	9.92	<0.005	9.26
	rank	10.21	<0.005	9.48
comorb_UTI	km	0.05	0.82	0.28
	rank	0.05	0.83	0.27
comorb_dm	km	0.43	0.51	0.97
	rank	0.57	0.45	1.15
comorb_hypot	km	0.06	0.81	0.31
	rank	0.04	0.84	0.26

1. Variable 'Number_comorbidities' failed the non-proportional test: p-value is 0.0014.

Advice 1: the functional form of the variable 'Number_comorbidities' might be incorrect. That is, there may be non-linear terms missing. The proportional hazard test used is very sensitive to incorrect functional forms. See documentation in link [D] below on how to specify a functional form.

Advice 2: try binning the variable 'Number_comorbidities' using `pd.cut`, and then specify it in ``strata=['Number_comorbidities', ...]`` in the call in ``.fit``. See documentation in link [B] below.

Advice 3: try adding an interaction term with your time variable. See documentation in link [C] below.

[A] https://lifelines.readthedocs.io/en/latest/jupyter_notebooks/Proportional%20hazard%20assumption.html

[B] https://lifelines.readthedocs.io/en/latest/jupyter_notebooks/Proportional%20hazard%20assumption.html#Bin-variable-and-stratify-on-it

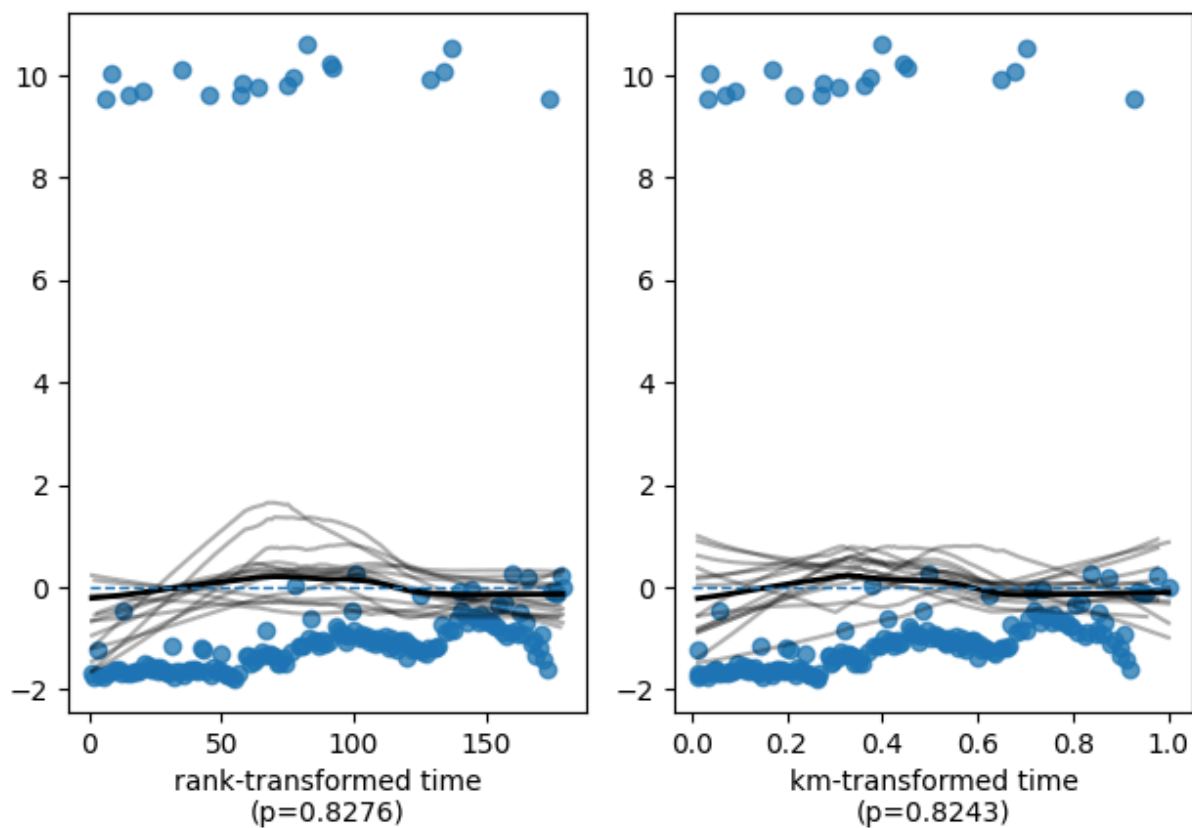
[C] https://lifelines.readthedocs.io/en/latest/jupyter_notebooks/Proportional%20hazard%20assumption.html#Introduce-time-varying-covariates

[D] https://lifelines.readthedocs.io/en/latest/jupyter_notebooks/Proportional%20hazard%20assumption.html#Modify-the-functional-form

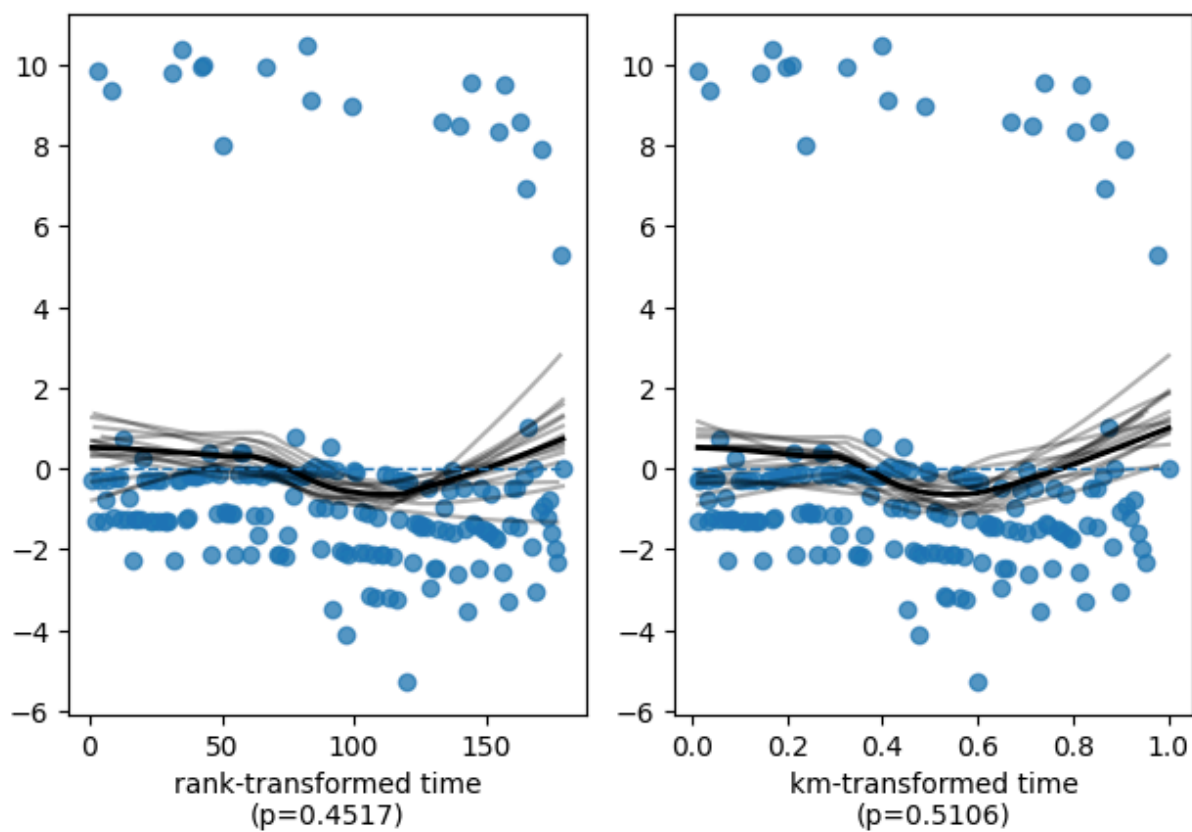
[E] https://lifelines.readthedocs.io/en/latest/jupyter_notebooks/Proportional%20hazard%20assumption.html#Stratification

```
Out[37]: [[<Axes: xlabel='rank-transformed time\n(p=0.8276)'\>,
  <Axes: xlabel='km-transformed time\n(p=0.8243)'\>],
  [<Axes: xlabel='rank-transformed time\n(p=0.4517)'\>,
  <Axes: xlabel='km-transformed time\n(p=0.5106)'\>],
  [<Axes: xlabel='rank-transformed time\n(p=0.8377)'\>,
  <Axes: xlabel='km-transformed time\n(p=0.8063)'\>],
  [<Axes: xlabel='rank-transformed time\n(p=0.0014)'\>,
  <Axes: xlabel='km-transformed time\n(p=0.0016)'\>]]
```

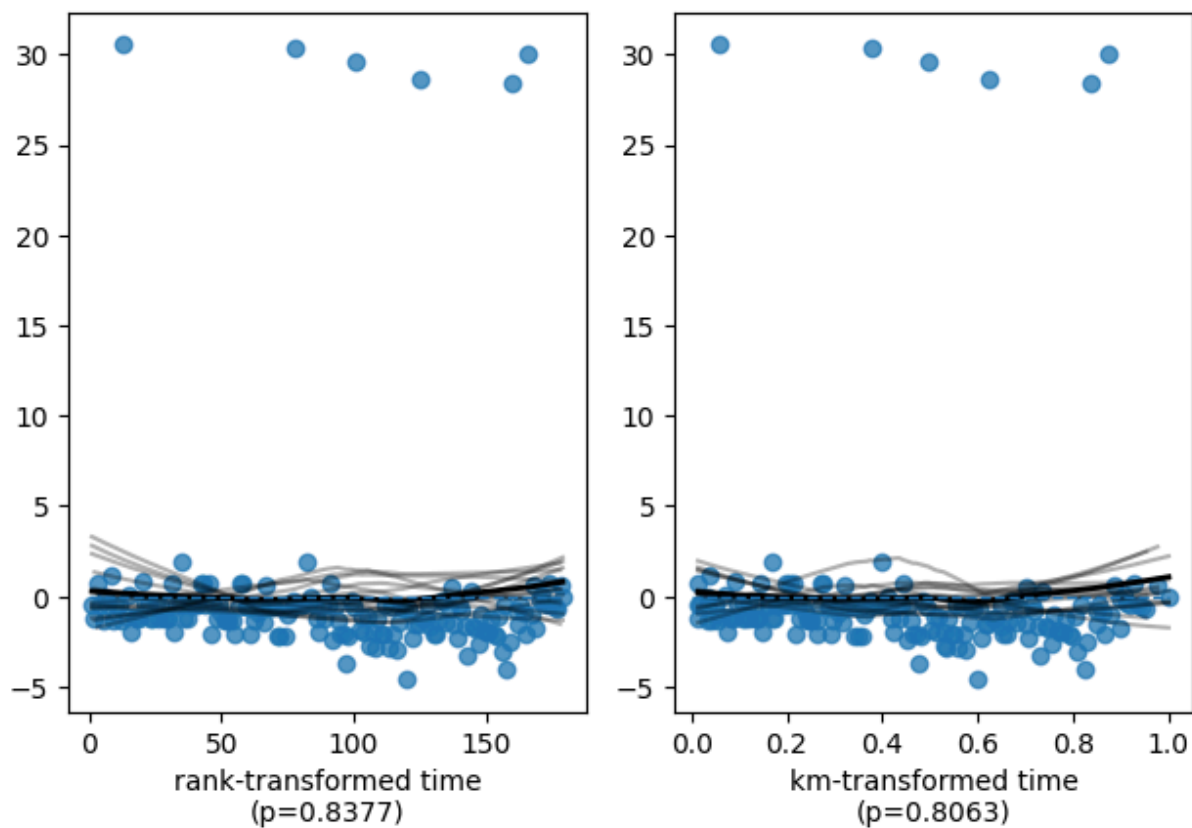
Scaled Schoenfeld residuals of 'comorb_UTI'



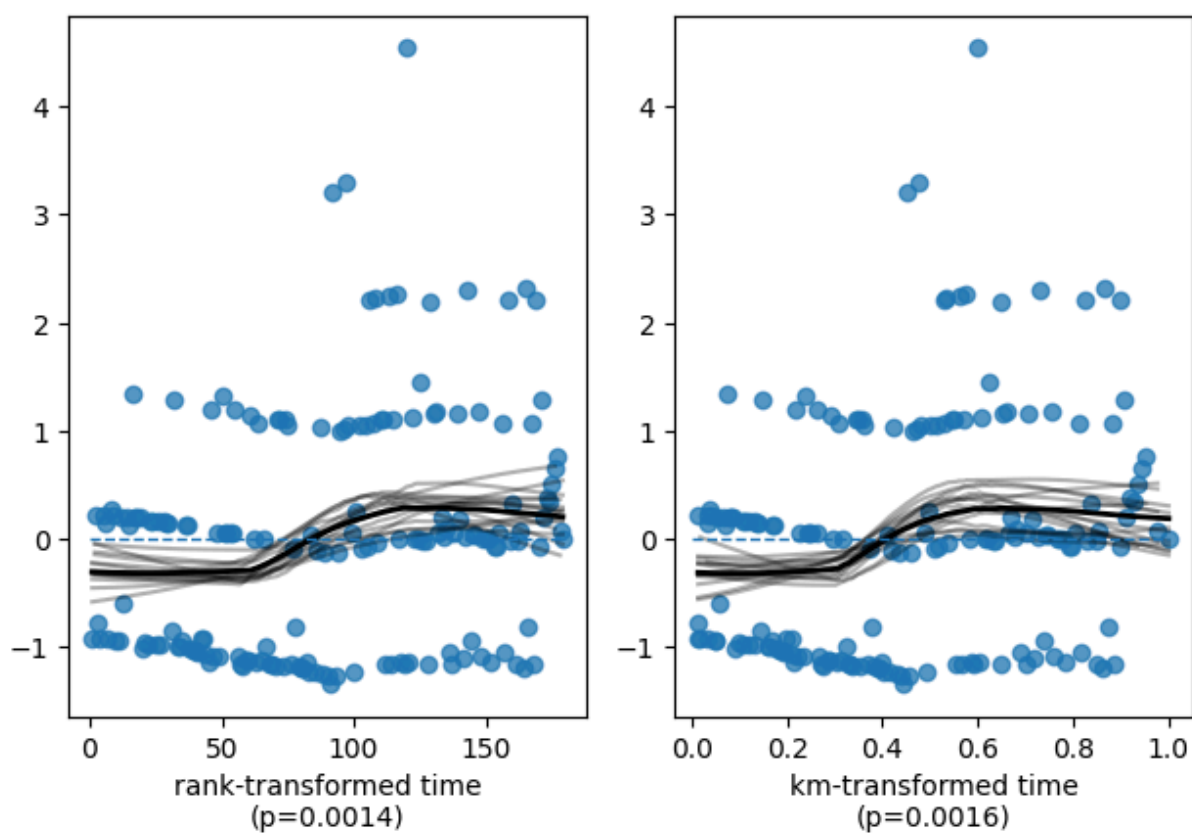
Scaled Schoenfeld residuals of 'comorb_dm'



Scaled Schoenfeld residuals of 'comorb_hypot'



Scaled Schoenfeld residuals of 'Number_comorbidities'



Random Survival Forests

Subset : random_data is used for the analysis

```
In [38]: # Creating random_data df for the Random Survival Forest Model
random_data = cox_data[['Days_Diagnosis_to_Failure',
                        'Died', 'Neuro signs', 'Complications',
                        'Hypertensive_Yes4', 'Oversuppresion?',
                        'Cortisol stayed <250', 'Cortisol went <40',
                        'Number_comorbidities', 'comorb_UTI',
                        'comorb_dm', 'comorb_hypot', 'Sex',
                        'Isneutered', 'BreedRelativeWeight',
                        'Purebreed_status', 'Stay_vs_stop',
                        'Treated with trilostane_7', 'Pre-ACTH',
                        'Post-ACTH', 'weight',
                        'Age_at_diagnosis(Years)',
                        'Time_suspicion_to_diagnosis(Days)']]

# Checking the first few rows to ensure it's set up correctly
print(random_data.head())
```

	Days_Diagnosis_to_Failure	Died	Neuro signs	Complications	\
0	1778	0	0	2	
1	1842	0	0	2	
2	1260	1	0	2	
3	942	1	0	2	
4	779	1	0	1	

	Hypertensive_Yes4	Oversuppresion?	Cortisol stayed <250	Cortisol went <40	\
0	2	1	1	1	
1	2	1	2	2	
2	2	1	1	0	
3	2	1	0	0	
4	1	1	1	1	

	Number_comorbidities	comorb_UTI	... Isneutered	BreedRelativeWeight	\
0	0	0	...	1	1
1	1	0	...	1	1
2	3	0	...	1	2
3	0	0	...	1	1
4	1	1	...	1	2

	Purebreed_status	Stay_vs_stop	Treated with trilostane_7	Pre-ACTH	\
0	1	1	1	0.0	
1	1	1	1	0.0	
2	1	1	1	267.0	
3	1	2	1	0.0	
4	1	2	1	145.0	

	Post-ACTH	weight	Age_at_diagnosis(Years)	\
0	0.0	7.55	10.04	
1	0.0	7.20	10.36	
2	922.0	12.50	8.66	
3	0.0	19.00	10.79	
4	684.0	34.25	10.03	

	Time_suspicion_to_diagnosis(Days)
0	7
1	22
2	6
3	35
4	60

[5 rows x 23 columns]

```
In [39]: # Preparing the features (X) and target (y)
X = random_data.drop(columns=['Days_Diagnosis_to_Failure', 'Died'])

# Creating the target variable with duration and event indicator
y = pd.DataFrame({'event': random_data['Died'].astype(bool), 'time': random_data['Time_suspicion_to_diagnosis(Days)']})
y = y.to_records(index=False)

# Creating and fitting the Random Survival Forest model
rsf = RandomSurvivalForest(n_estimators=1000, min_samples_split=10, min_samples_leaf=10)
rsf.fit(X, y)
```

Out[39]:

```
RandomSurvivalForest
RandomSurvivalForest(min_samples_leaf=15, min_samples_split=10,
                      n_estimators=1000, random_state=55)
```

In [40]:

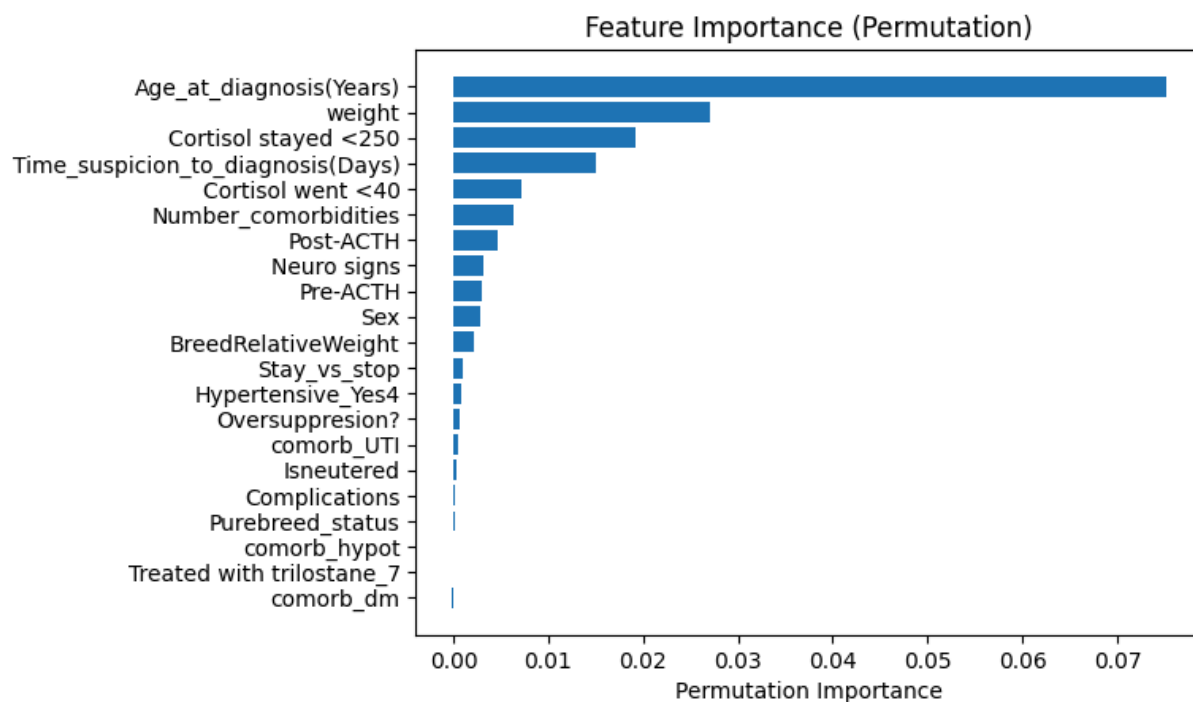
```
# Calculating the concordance index
c_index = concordance_index_censored(y['event'], y['time'], rsf.predict(X))
print(f"Concordance Index: {c_index[0]}")
```

Concordance Index: 0.7055767054223686

In [41]:

```
# Calculating the permutation importance
result = permutation_importance(rsf, X, y, n_repeats=10, random_state=55)

# Displaying the feature importance from permutation importance
sorted_idx = result.importances_mean.argsort()
plt.barh(range(len(sorted_idx)), result.importances_mean[sorted_idx], align='center')
plt.yticks(range(len(sorted_idx)), X.columns[sorted_idx])
plt.xlabel("Permutation Importance")
plt.title("Feature Importance (Permutation)")
plt.show()
```



In [42]:

```
# Calculating the permutation importance
# Feature Importance not available in this package
result = permutation_importance(rsf, X, y, n_repeats=10, random_state=55)

# Creating a DataFrame to display the results
importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance Mean': result.importances_mean,
    'Importance Std': result.importances_std
})
```

```

# Sorting by importance
importance_df = importance_df.sort_values(by='Importance Mean', ascending=False)

# Displaying the feature importance
print(importance_df)

```

	Feature	Importance Mean	Importance Std
19	Age_at_diagnosis(Years)	0.075152	0.018984
18	weight	0.027076	0.008896
4	Cortisol stayed <250	0.019158	0.011958
20	Time_suspicion_to_diagnosis(Days)	0.015084	0.004379
5	Cortisol went <40	0.007233	0.009773
6	Number_comorbidities	0.006354	0.002053
17	Post-ACTH	0.004651	0.001002
0	Neuro signs	0.003097	0.002291
16	Pre-ACTH	0.002974	0.000757
10	Sex	0.002799	0.000702
12	BreedRelativeWeight	0.002120	0.000745
14	Stay_vs_stop	0.001065	0.000501
2	Hypertensive_Yes4	0.000859	0.000336
3	Oversuppresion?	0.000720	0.001124
7	comorb_UTI	0.000540	0.000252
11	Isneutered	0.000417	0.000500
1	Complications	0.000180	0.000766
13	Purebreed_status	0.000129	0.000457
9	comorb_hypot	0.000000	0.000000
15	Treated with trilostane_7	0.000000	0.000000
8	comorb_dm	-0.000159	0.000071

```

In [43]: # Predicting the survival function for each individual in X
predicted_survival = rsf.predict_survival_function(X)

# Visualization of survival functions for each individual
for i in range(len(predicted_survival)):
    plt.step(predicted_survival[i].x, predicted_survival[i].y, where="post", label=

plt.title("Random Survival Forest - Survival Function")
plt.xlabel("Time")
plt.ylabel("Survival Probability")
plt.show()

```

Random Survival Forest - Survival Function

