Homework 02 - Exploratory Data Analysis in Python

Author: Sanjay Bhargav Siddi

1. Using data transformation to correct non-normality in numerical data

a) Load and explore a data set with publication quality tables

b) Quickly diagnose non-normality in data

c) Data transformation

1.1. Required Setup

In [1]:
```
# Import all required libraries
# Data analysis and manipulation
import pandas as pd
# Working with arrays
import numpy as np
# Statistical visualization
import seaborn as sns
# Matlab plotting for Python
import matplotlib.pyplot as plt
# Data analysis
import statistics as stat
# Predictive data analysis: process data
from sklearn import preprocessing as pproc
import scipy.stats as stats
# Visualizing missing values
import missingno as msno
# Statistical modeling
import statsmodels.api as sm

# Increase font size of all seaborn plot elements
sns.set(font_scale = 1.5, rc = {'figure.figsize':(8, 8)})

# Change theme to "white"
sns.set_style("white")
```

1.2 Loading a data set

In [2]:
```
tornadosData = pd.read_csv('C:/Users/sanja/OneDrive/Desktop/University of Arizona Classes/INFO 523 - Data Mining/HW/hw-02-SanjaySiddi/data/tornados.csv')
```

1.3 Examining the data set and trimming the data

In [3]:
```
tornadosData.describe()
```

Out[3]:

	om	yr	mo	dy	stf	mag	inj	fat	loss	slat	...	elat	elon	len	wid	ns	
count	68693.000000	68693.000000	68693.000000	68693.000000	68693.000000	67937.000000	68693.000000	68693.00000	4.152300e+04	68693.000000	...	68693.000000	68693.000000	68693.000000	68693.000000	68693.000000	68693
mean	113201.815542	1991.854061	5.968541	15.930881	29.220255	0.778721	1.418689	0.08931	2.020898e+06	37.129386	...	22.960651	-56.836090	3.489270	107.767633	1.008764	0
std	226621.993899	19.565158	2.444656	8.750070	15.013273	0.895790	18.114752	1.47212	3.039588e+07	5.099005	...	18.528144	45.340732	8.247115	206.851267	0.095060	0
min	1.000000	1950.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.00000	5.000000e+01	17.721200	...	0.000000	-163.530000	0.000000	0.000000	1.000000	0
25%	285.000000	1976.000000	4.000000	8.000000	18.000000	0.000000	0.000000	0.00000	1.000000e+04	33.180000	...	0.000000	-94.780000	0.120000	20.000000	1.000000	1
50%	588.000000	1995.000000	6.000000	16.000000	28.000000	1.000000	0.000000	0.00000	5.000000e+04	37.000000	...	32.550000	-84.720000	0.800000	50.000000	1.000000	1
75%	1118.000000	2008.000000	7.000000	24.000000	42.000000	1.000000	0.000000	0.00000	5.000000e+05	40.920000	...	38.650000	0.000000	3.210000	100.000000	1.000000	1
max	622080.000000	2022.000000	12.000000	31.000000	78.000000	5.000000	1740.000000	158.00000	2.800100e+09	61.020000	...	61.020000	0.000000	234.700000	4576.000000	3.000000	1

8 rows × 21 columns

In [4]:
```
tornadosData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68693 entries, 0 to 68692
Data columns (total 27 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   om            68693 non-null  int64  
 1   yr            68693 non-null  int64  
 2   mo            68693 non-null  int64  
 3   dy            68693 non-null  int64  
 4   date          68693 non-null  object 
 5   time          68693 non-null  object 
 6   tz            68693 non-null  object 
 7   datetime_utc  68693 non-null  object 
 8   st            68693 non-null  object 
 9   stf           68693 non-null  int64  
 10  mag           67937 non-null  float64
 11  inj           68693 non-null  int64  
 12  fat           68693 non-null  int64  
 13  loss          41523 non-null  float64
 14  slat          68693 non-null  float64
 15  slon          68693 non-null  float64
 16  elat          68693 non-null  float64
 17  elon          68693 non-null  float64
 18  len           68693 non-null  float64
 19  wid           68693 non-null  int64  
 20  ns            68693 non-null  int64  
 21  sn            68693 non-null  int64  
 22  f1            68693 non-null  int64  
 23  f2            68693 non-null  int64  
 24  f3            68693 non-null  int64  
 25  f4            68693 non-null  int64  
 26  fc            68693 non-null  bool   
dtypes: bool(1), float64(7), int64(14), object(5)
memory usage: 13.7+ MB
```

In [5]:
```
# creating a copy of the tornados data set
data = tornadosData.copy()

# renaming columns for readability
data = data.rename(columns={'om':'Tornado ID','yr':'Year','mo':'Month','dy':'Day','date':'Date','time':'Time','tz':'Timezone','st':'State','mag':'Magnitude','inj':'Injuries','fat':'Fatality','lo

# removing non-important columns
```

```
data = data.drop(columns=['datetime_utc','stf','slat','slon','elat','elon','f1','f2','f3','f4','sn','fc'])

# filling NaN with 0
data = data.fillna(0)
```

Original Data Set

In [6]:
```
tornadosData.head()
```

Out[6]:

	om	yr	mo	dy	date	time	tz	datetime_utc	st	stf	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
0	192	1950	10	1	1950-10-01	21:00:00	America/Chicago	1950-10-02T03:00:00Z	OK	40	...	-102.3	15.8	10	1	1	25	0	0	0	False
1	193	1950	10	9	1950-10-09	02:15:00	America/Chicago	1950-10-09T08:15:00Z	NC	37	...	0.0	2.0	880	1	1	47	0	0	0	False
2	195	1950	11	20	1950-11-20	02:20:00	America/Chicago	1950-11-20T08:20:00Z	KY	21	...	0.0	0.1	10	1	1	177	0	0	0	False
3	196	1950	11	20	1950-11-20	04:00:00	America/Chicago	1950-11-20T10:00:00Z	KY	21	...	0.0	0.1	10	1	1	209	0	0	0	False
4	197	1950	11	20	1950-11-20	07:30:00	America/Chicago	1950-11-20T13:30:00Z	MS	28	...	0.0	2.0	37	1	1	101	0	0	0	False

5 rows × 27 columns

Trimmed Data Set

In [7]:
```
data.head()
# Tornado ID = Tornado number. Effectively an ID for this tornado in this year.
# States Affected = Number of states affected by this tornado. 1, 2, or 3.
```

Out[7]:

	Tornado ID	Year	Month	Day	Date	Time	Timezone	State	Magnitude	Injuries	Fatality	Loss	Length	Width	States Affected
0	192	1950	10	1	1950-10-01	21:00:00	America/Chicago	OK	1.0	0	0	50000.0	15.8	10	1
1	193	1950	10	9	1950-10-09	02:15:00	America/Chicago	NC	3.0	3	0	500000.0	2.0	880	1
2	195	1950	11	20	1950-11-20	02:20:00	America/Chicago	KY	2.0	0	0	500000.0	0.1	10	1
3	196	1950	11	20	1950-11-20	04:00:00	America/Chicago	KY	1.0	0	0	500000.0	0.1	10	1
4	197	1950	11	20	1950-11-20	07:30:00	America/Chicago	MS	1.0	3	0	50000.0	2.0	37	1

Creating a sub group

In [8]:
```
def loss_group_data(data):
  if data.Loss >= 0 and data.Loss <= 1000: return "Low loss"
  elif data.Loss > 1000 and data.Loss <= 100000: return "Medium loss"
  else: return "Huge loss"

# Apply the function to data
data['Loss_group'] = data.apply(loss_group_data, axis = 1)

# What does the data look like
data.head(1000)
```

Out[8]:

	Tornado ID	Year	Month	Day	Date	Time	Timezone	State	Magnitude	Injuries	Fatality	Loss	Length	Width	States Affected	Loss_group
0	192	1950	10	1	1950-10-01	21:00:00	America/Chicago	OK	1.0	0	0	50000.0	15.8	10	1	Medium loss
1	193	1950	10	9	1950-10-09	02:15:00	America/Chicago	NC	3.0	3	0	500000.0	2.0	880	1	Huge loss
2	195	1950	11	20	1950-11-20	02:20:00	America/Chicago	KY	2.0	0	0	500000.0	0.1	10	1	Huge loss
3	196	1950	11	20	1950-11-20	04:00:00	America/Chicago	KY	1.0	0	0	500000.0	0.1	10	1	Huge loss
4	197	1950	11	20	1950-11-20	07:30:00	America/Chicago	MS	1.0	3	0	50000.0	2.0	37	1	Medium loss
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
995	216	1953	6	4	1953-06-04	15:00:00	America/Chicago	FL	1.0	0	0	50.0	0.1	10	1	Low loss
996	217	1953	6	5	1953-06-05	08:45:00	America/Chicago	FL	0.0	0	0	50.0	0.1	10	1	Low loss
997	218	1953	6	5	1953-06-05	10:00:00	America/Chicago	UT	0.0	0	0	0.0	8.0	147	1	Low loss
998	219	1953	6	5	1953-06-05	13:30:00	America/Chicago	TX	0.0	0	0	0.0	0.1	10	1	Low loss
999	220	1953	6	5	1953-06-05	15:05:00	America/Chicago	MI	0.0	0	0	500.0	1.0	50	1	Low loss

1000 rows × 16 columns

1.4. Describing Properties of our Data (Refined)

Measures of describing the shape of a distribution, usually compared to a normal distribution (bell-curve)

Skewness: The symmetry of the distribution

Kurtosis: The tailedness of the distribution

In [9]:

```
# Make a copy of the data
dataCopy = data.copy()

# Select only numerical columns
dataRed = dataCopy.select_dtypes(include = np.number)

# List of numerical columns
dataRedColsList = dataRed.columns[...]

# For all values in the numerical column list from above
for i_col in dataRedColsList:
  # List of the values in i_col
  dataRed_i = dataRed.loc[:,i_col]

  # Skewness: The symmetry of the distribution
  skewness = round((dataRed_i.skew()), 3)

  # Kurtosis: The tailedness of the distribution
  kurtosis = round((dataRed_i.kurt()), 3)

  # Print a blank row
  print('')

  # Print the column name
  print(i_col)

  # Print skewness and kurtosis
  print('skewness =', skewness, 'kurtosis =', kurtosis)
```

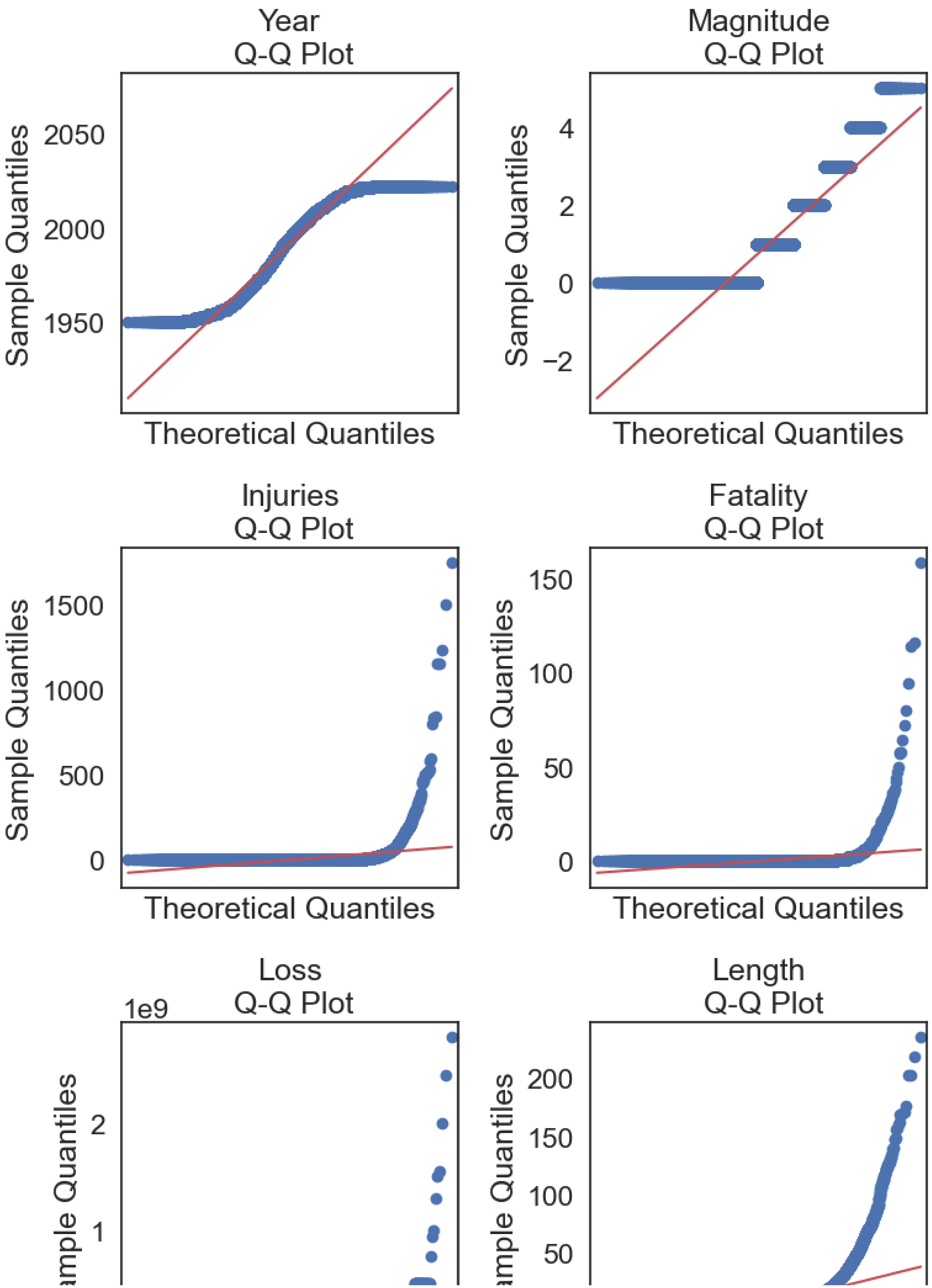
```
Tornado ID
skewness = 1.598 kurtosis = 0.693

Year
skewness = -0.317 kurtosis = -1.001

Month
skewness = 0.536 kurtosis = 0.032

Day
skewness = -0.011 kurtosis = -1.197

Magnitude
skewness = 1.136 kurtosis = 1.076

Injuries
skewness = 45.494 kurtosis = 3063.365

Fatality
skewness = 50.365 kurtosis = 3758.323

Loss
skewness = 67.02 kurtosis = 6102.314

Length
skewness = 7.415 kurtosis = 95.365

Width
skewness = 5.479 kurtosis = 46.394

States Affected
skewness = 11.146 kurtosis = 130.128
```

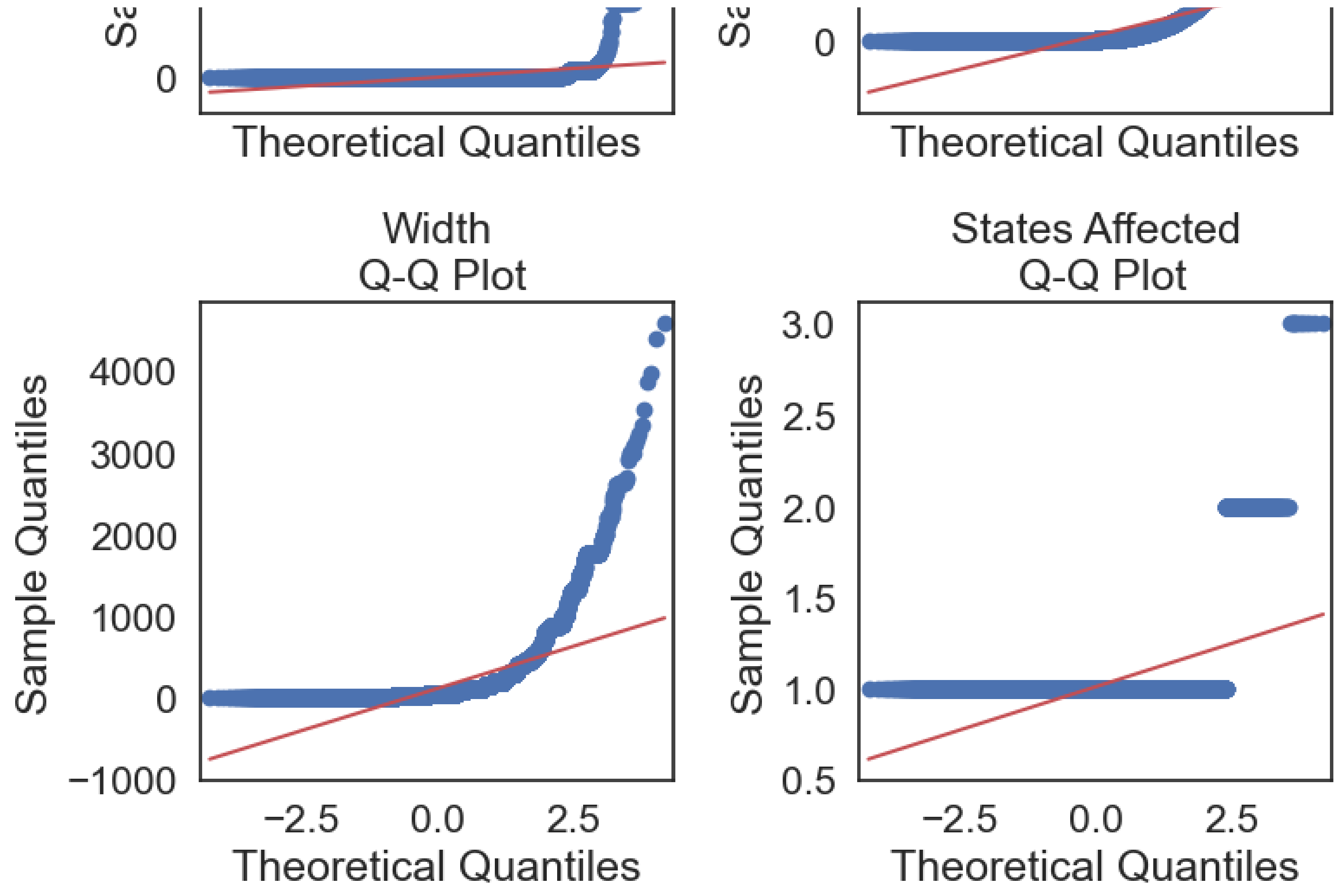
1.5. Testing Normality

Testing overall normality of numerical columns

In [10]:

```
# Make a copy of the data
dataCopy = data.copy()

# Remove NAs
dataCopyFin = dataCopy.dropna()

# Removing unnecessary columns for QQ plot
dataCopyFin1 = dataCopyFin.drop(columns=['Tornado ID','Month','Day',])

# Select only numerical columns
dataRed = dataCopyFin1.select_dtypes(include = np.number)

# Combine multiple plots, the number of columns and rows is derived from the number of numerical columns from above.
fig, axes = plt.subplots(ncols = 2, nrows = 4, sharex = True, figsize = (2 * 4, 4 * 4))

# Generate figures for all numerical grouped data subsets
for k, ax in zip(dataRed.columns, np.ravel(axes)):
    sm.qqplot(dataRed[k], line = 's', ax = ax)
    ax.set_title(f'{k}\n Q-Q Plot')
plt.tight_layout()
plt.show()
```


Year
Q-Q Plot
Sample Quantiles
2050
2000
1950
Theoretical Quantiles
Magnitude
Q-Q Plot
Sample Quantiles
4
2
0
−2
Theoretical Quantiles
Injuries
Q-Q Plot
Sample Quantiles
1500
1000
500
0
Theoretical Quantiles
Fatality
Q-Q Plot
Sample Quantiles
150
100
50
0
Theoretical Quantiles
Loss
Q-Q Plot
1e9
2
1
Length
Q-Q Plot
200
150
100
50



Magnitude Q-Q Plot - light tailed, right skewed

Injuries Q-Q Plot - right skewed, heavy tailed, can observe a spike in the values with a spread from around 750

Fatality Q-Q Plot - right skewed, heavy tailed, can observe a spike in the values, can observe a gap from around 110

Loss Q-Q Plot - right skewed, heavy tailed, can observe a spike in the values with a spread

Length Q-Q Plot - right skewed, heavy tailed, observed a sudden spike in the values

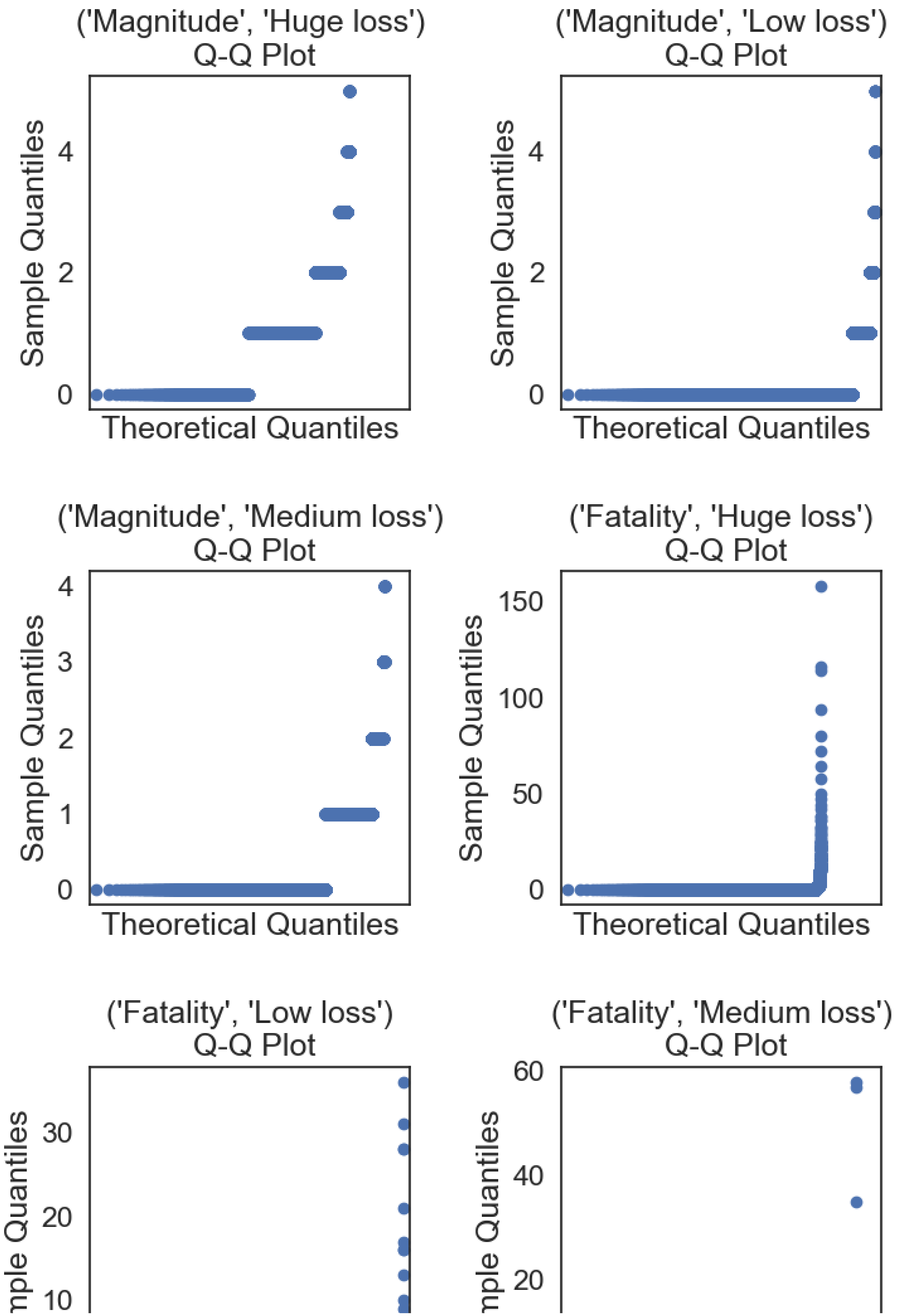
Width Q-Q Plot - right skewed, heavy tailed, observed a spike in the values similar to that of lenght qq plot

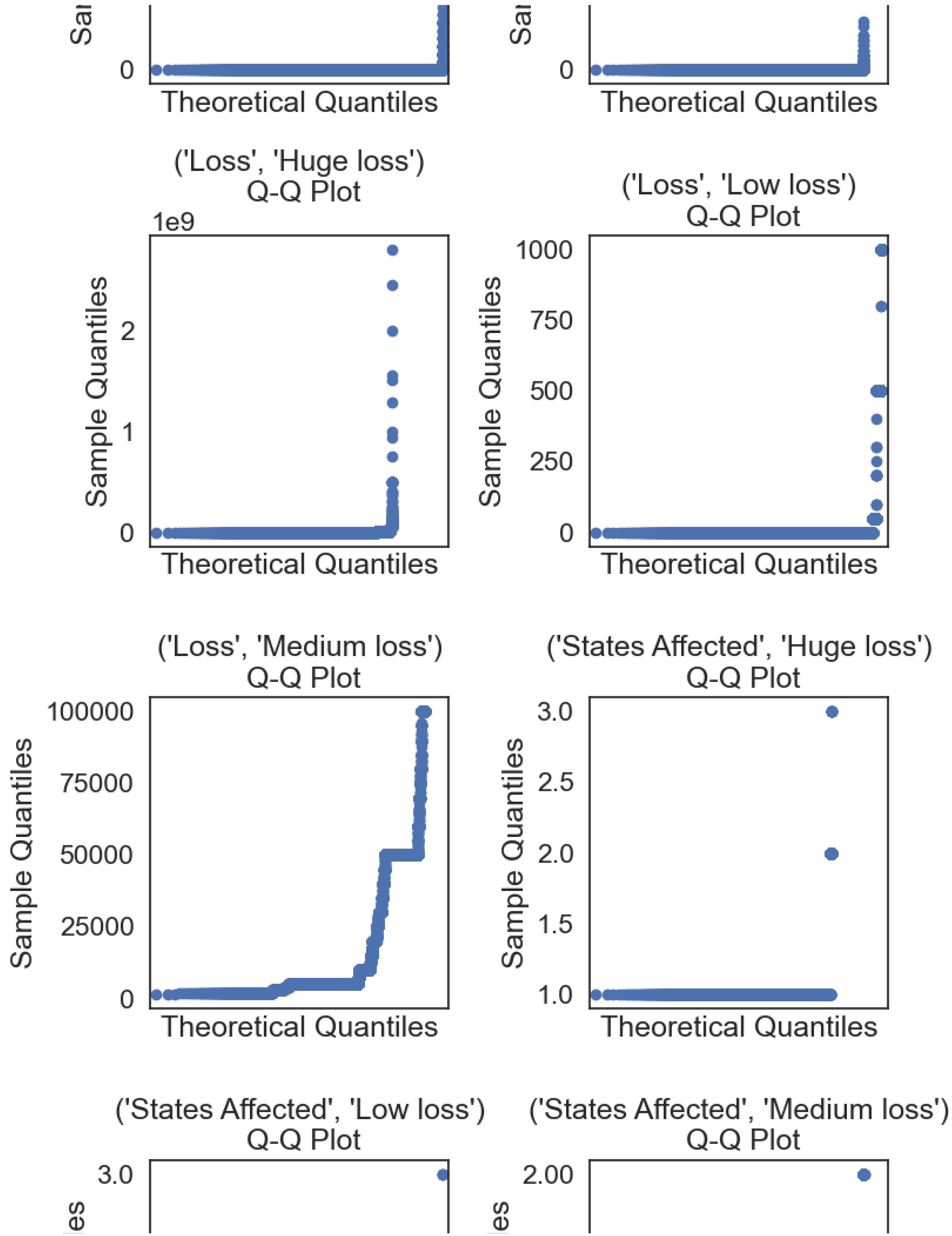
States Affected Q-Q Plot - right skewed, heavy tailed, huge gap in the values

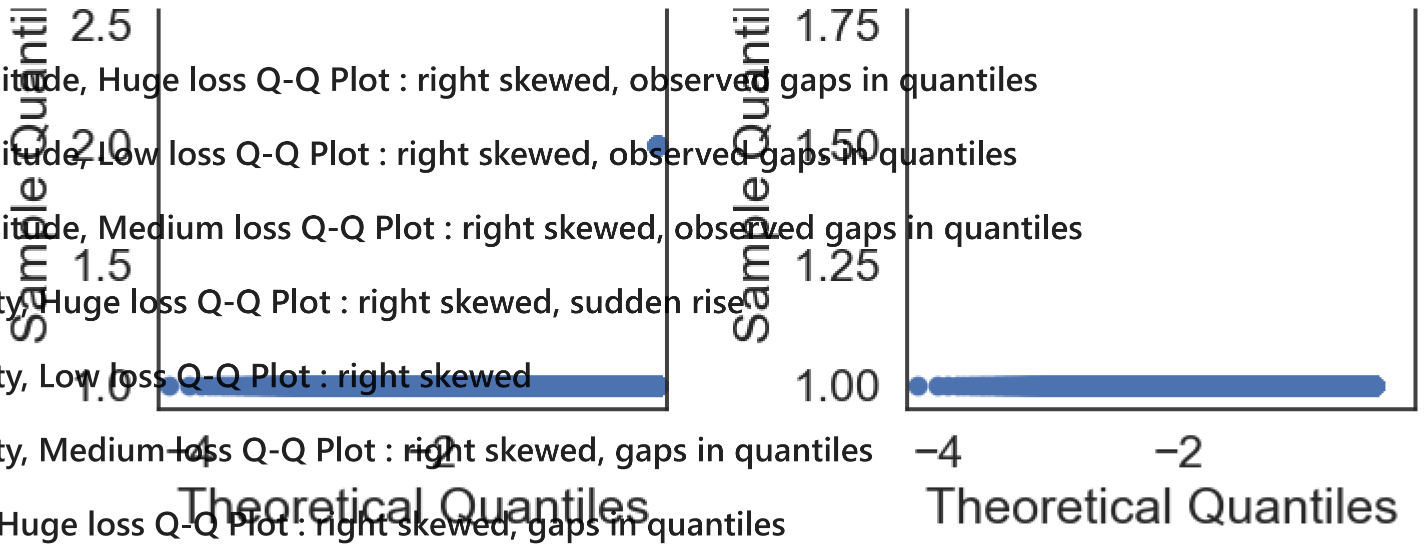
Testing normality of groups

In [11]:
```
# Make a copy of the data
dataCopy = data.copy()

# Remove NAs
dataCopyFin = dataCopy.dropna()

# Create a new column named in x, which is filled with the dataset rownames
dataCopyFin.index.name = 'Index'

# Reset the rownames index (not a column)
dataCopyFin.reset_index(inplace = True)
```

```python
# Pivot the data from long-to-wide with pivot, using Date as the index, so that a column is created for each Group and numerical column subset
dataPivot = dataCopyFin.pivot(index = 'Index', columns = 'Loss_group', values = ['Magnitude', 'Fatality', 'Loss', 'States Affected'])

# Select only numerical columns
dataRed = dataPivot.select_dtypes(include = np.number)

# Combine multiple plots, the number of columns and rows is derived from the number of numerical columns from above.
fig, axes = plt.subplots(ncols = 2, nrows = 6, sharex = True, figsize = (2 * 4, 6 * 4))

# Generate figures for all numerical grouped data subsets
for k, ax in zip(dataRed.columns, np.ravel(axes)):
    sm.qqplot(dataRed[k], line = 's', ax = ax)
    ax.set_title(f'{k}\n Q-Q Plot')
plt.tight_layout()
plt.show()
```


('Magnitude', 'Huge loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('Magnitude', 'Low loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('Magnitude', 'Medium loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('Fatality', 'Huge loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('Fatality', 'Low loss')
Q-Q Plot
('Fatality', 'Medium loss')
Q-Q Plot


Theoretical Quantiles
Theoretical Quantiles
('Loss', 'Huge loss')
Q-Q Plot
1e9
Sample Quantiles
Theoretical Quantiles
('Loss', 'Low loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('Loss', 'Medium loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('States Affected', 'Huge loss')
Q-Q Plot
Sample Quantiles
Theoretical Quantiles
('States Affected', 'Low loss')
Q-Q Plot
('States Affected', 'Medium loss')
Q-Q Plot



Magnitude, Huge loss Q-Q Plot : right skewed, observed gaps in quantiles

Magnitude, Low loss Q-Q Plot : right skewed, observed gaps in quantiles

Magnitude, Medium loss Q-Q Plot : right skewed, observed gaps in quantiles

Fatality, Huge loss Q-Q Plot : right skewed, sudden rise

Fatality, Low loss Q-Q Plot : right skewed

Fatality, Medium loss Q-Q Plot : right skewed, gaps in quantiles

Loss, Huge loss Q-Q Plot : right skewed, gaps in quantiles

Loss, Low loss Q-Q Plot : right skewed, gaps in quantiles

Loss, Medium loss Q-Q Plot : right skewed, heavy tailed

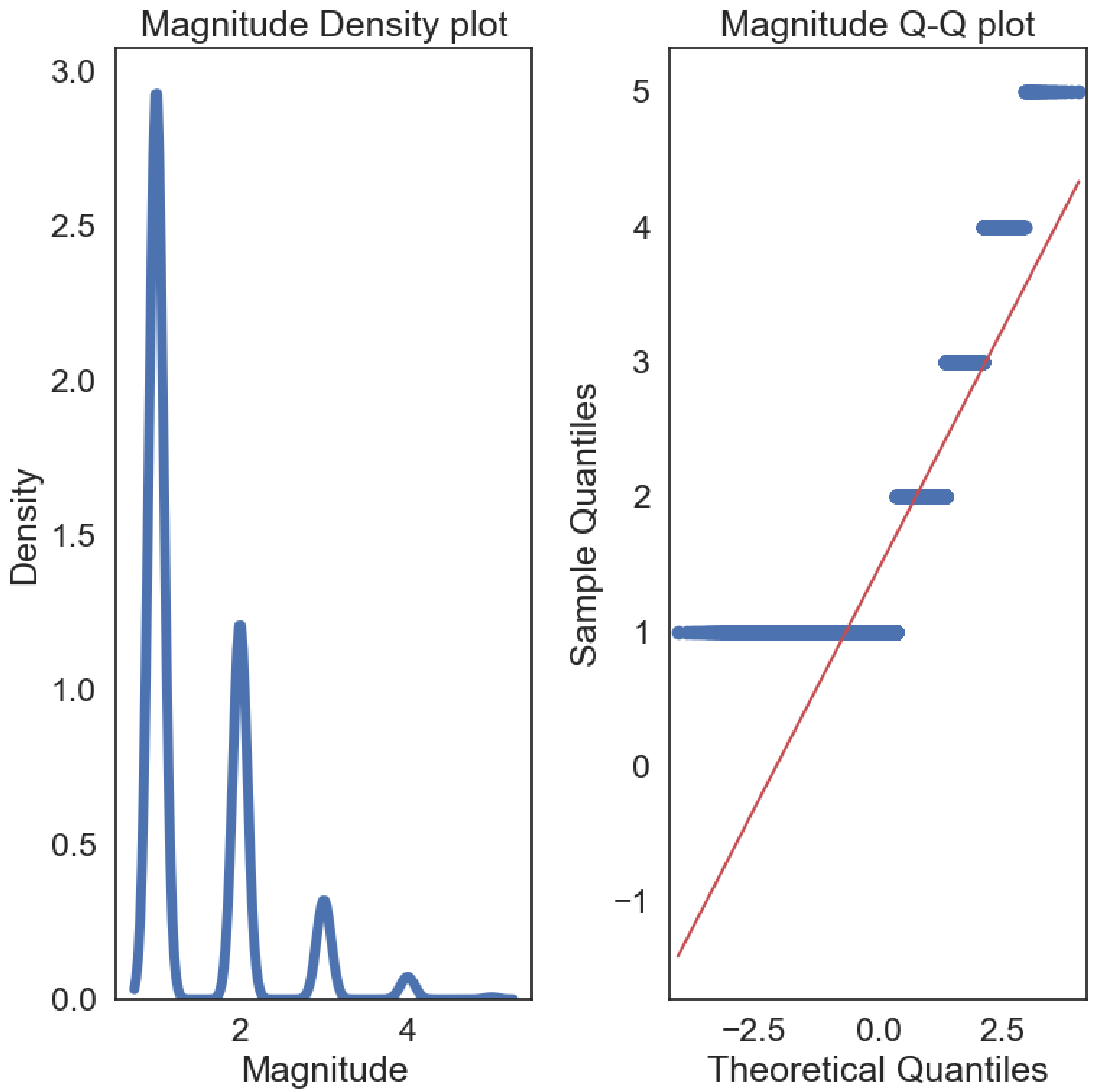
States Affected, Huge loss Q-Q Plot : discrete data, right skewed

1.6. Transforming Data

In [12]:
```
# Filter magnitude greater than 0
Mag = data[data.Magnitude > 0]

# Select only Magnitude
MagMod = Mag.filter(["Magnitude"], axis = "columns")
```

Square-root Transformation

In [13]:
```
# Square-root transform the data in a new column
MagMod['Mag_Sqrt'] = np.sqrt(MagMod['Magnitude'])

# Specify desired column
col = MagMod.Magnitude

# Specify desired column
i_col = MagMod.Mag_Sqrt

# ORIGINAL
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(col, linewidth = 5, ax = ax1)
ax1.set_title('Magnitude Density plot')

# Q-Q plot
sm.qqplot(col, line='s', ax = ax2)
ax2.set_title('Magnitude Q-Q plot')
plt.tight_layout()
plt.show()
```

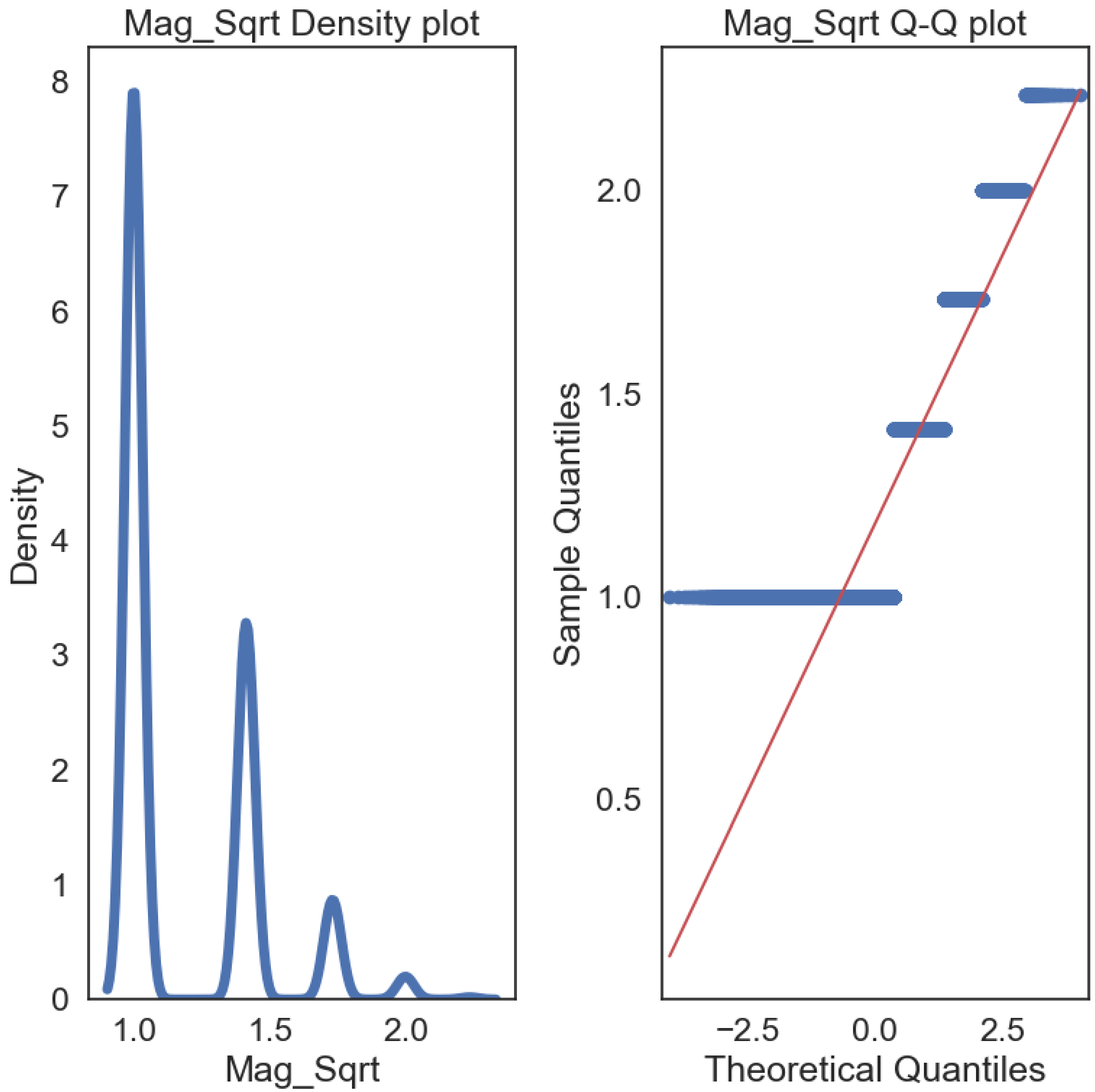


Magnitude density plot - Right skewed, multimodal distributions

Magnitude Q-Q plot - right skewed, with gaps

In [14]:
```
# TRANSFORMED
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(i_col, linewidth = 5, ax = ax1)
ax1.set_title('Mag_Sqrt Density plot')

# Q-Q plot
sm.qqplot(i_col, line='s', ax = ax2)
ax2.set_title('Mag_Sqrt Q-Q plot')
```

```
plt.tight_layout()
plt.show()
```



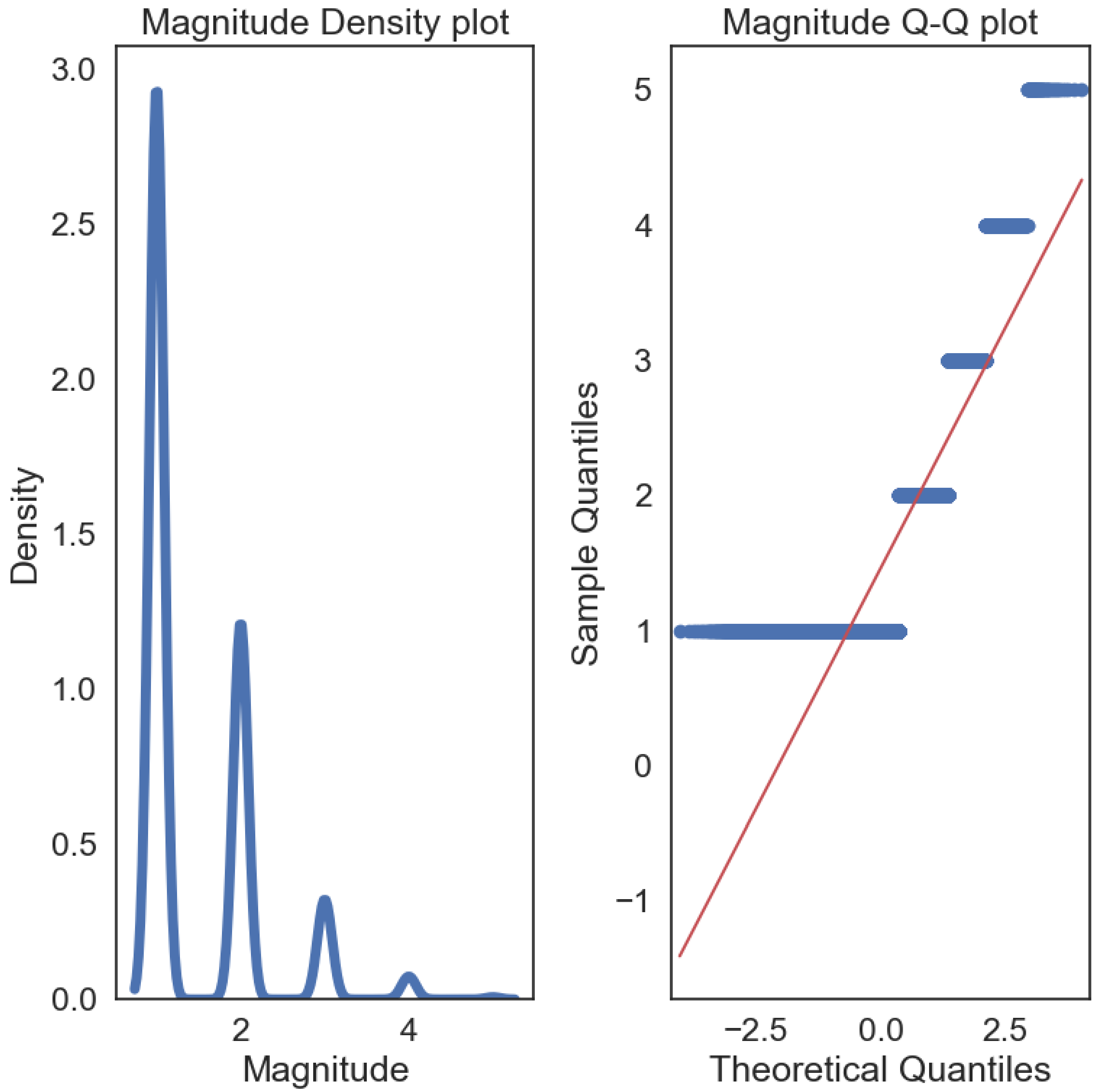
Magnitude square root density plot - multimodal distribution, right skewed

Magnitude square root QQ plot - right skewed, with gaps

Logarithmic (+1) Transformation

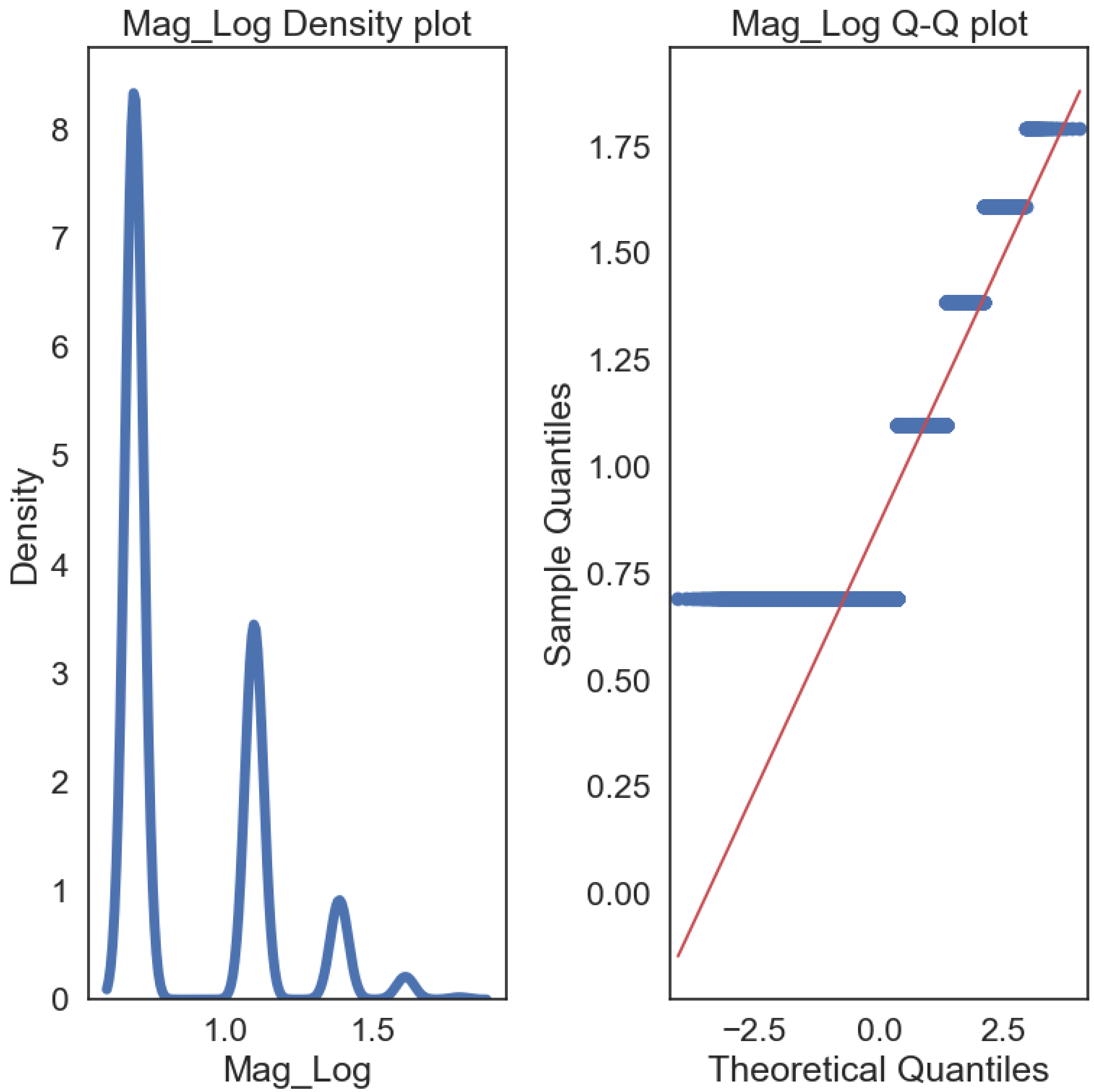
In [15]:
```
# Logarithmic transform the data in a new column
MagMod['Mag_Log'] = np.log(MagMod['Magnitude'] + 1)

# Specify desired column
col = MagMod.Magnitude
```

```
# Specify desired column
i_col = MagMod.Mag_Log

# ORIGINAL
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(col, linewidth = 5, ax = ax1)
ax1.set_title('Magnitude Density plot')

# Q-Q plot
sm.qqplot(col, line='s', ax = ax2)
ax2.set_title('Magnitude Q-Q plot')
plt.tight_layout()
plt.show()
```



In [16]:

```
# TRANSFORMED
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(i_col, linewidth = 5, ax = ax1)
ax1.set_title('Mag_Log Density plot')

# Q-Q plot
sm.qqplot(i_col, line='s', ax = ax2)
ax2.set_title('Mag_Log Q-Q plot')
plt.tight_layout()
plt.show()
```

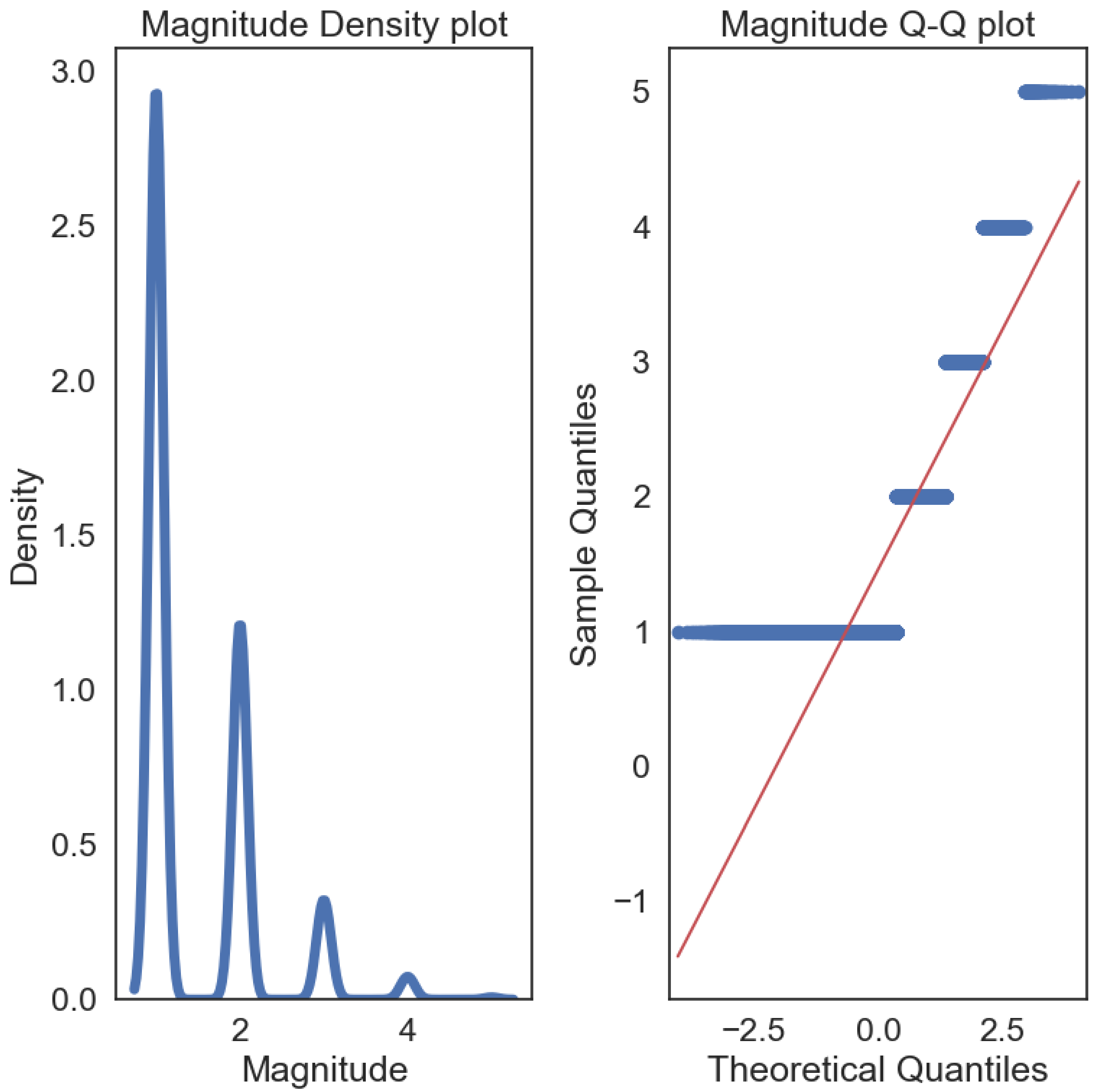


Magnitude log density plot - Right skewed, multimodal distributions

Magnitude log Q-Q plot - Left skewed, with gaps

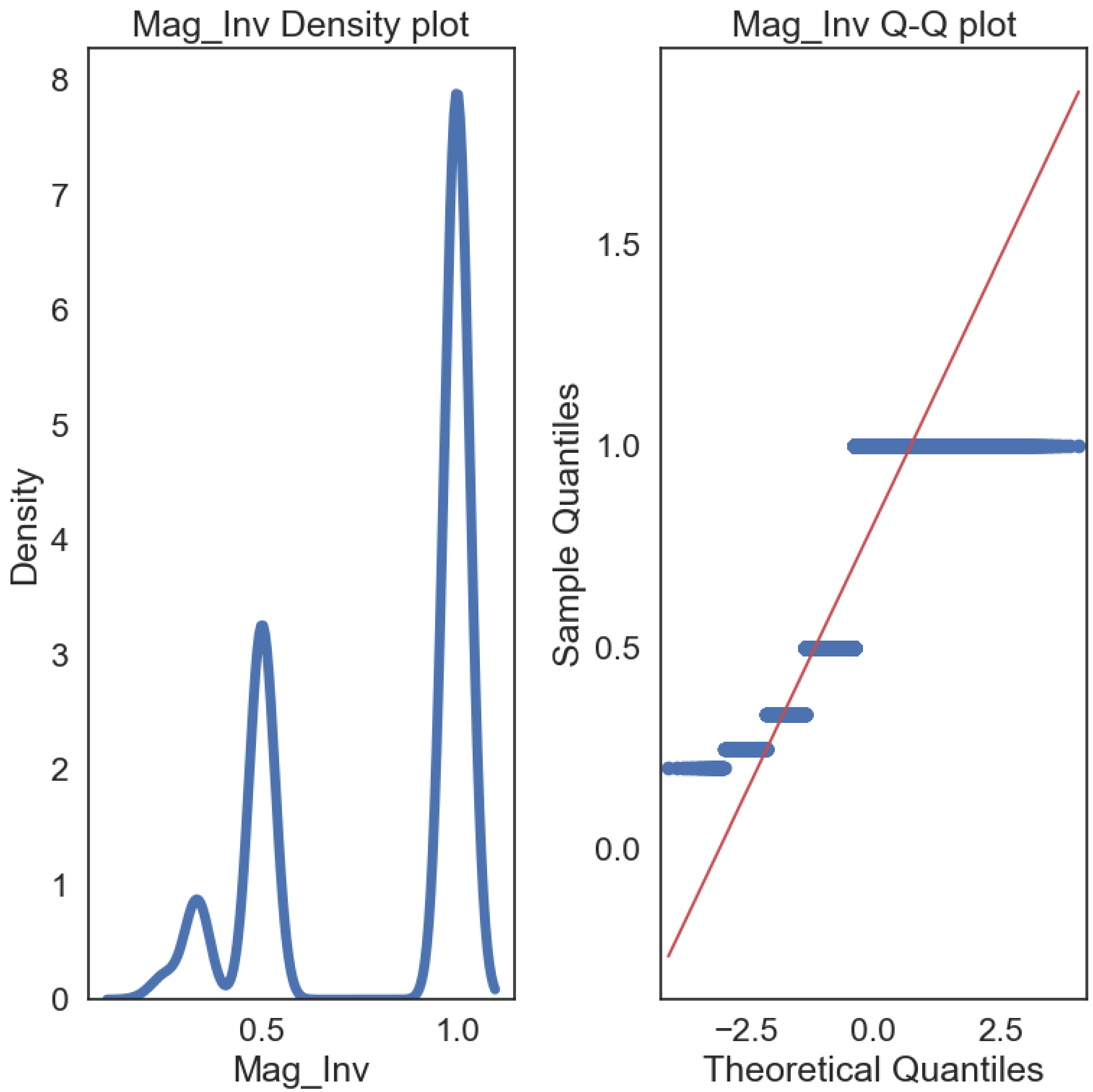
Inverse Transformation

In [17]:
```
# Inverse transform the data in a new column
MagMod['Mag_Inv'] = 1/MagMod.Magnitude

# Specify desired column
col = MagMod.Magnitude

# Specify desired column
i_col = MagMod.Mag_Inv

# ORIGINAL
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(col, linewidth = 5, ax = ax1)
ax1.set_title('Magnitude Density plot')

# Q-Q plot
sm.qqplot(col, line='s', ax = ax2)
ax2.set_title('Magnitude Q-Q plot')
plt.tight_layout()
plt.show()
```



In [18]:

```python
# TRANSFORMED
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(i_col, linewidth = 5, ax = ax1)
ax1.set_title('Mag_Inv Density plot')

# Q-Q plot
sm.qqplot(i_col, line='s', ax = ax2)
ax2.set_title('Mag_Inv Q-Q plot')
plt.tight_layout()
plt.show()
```



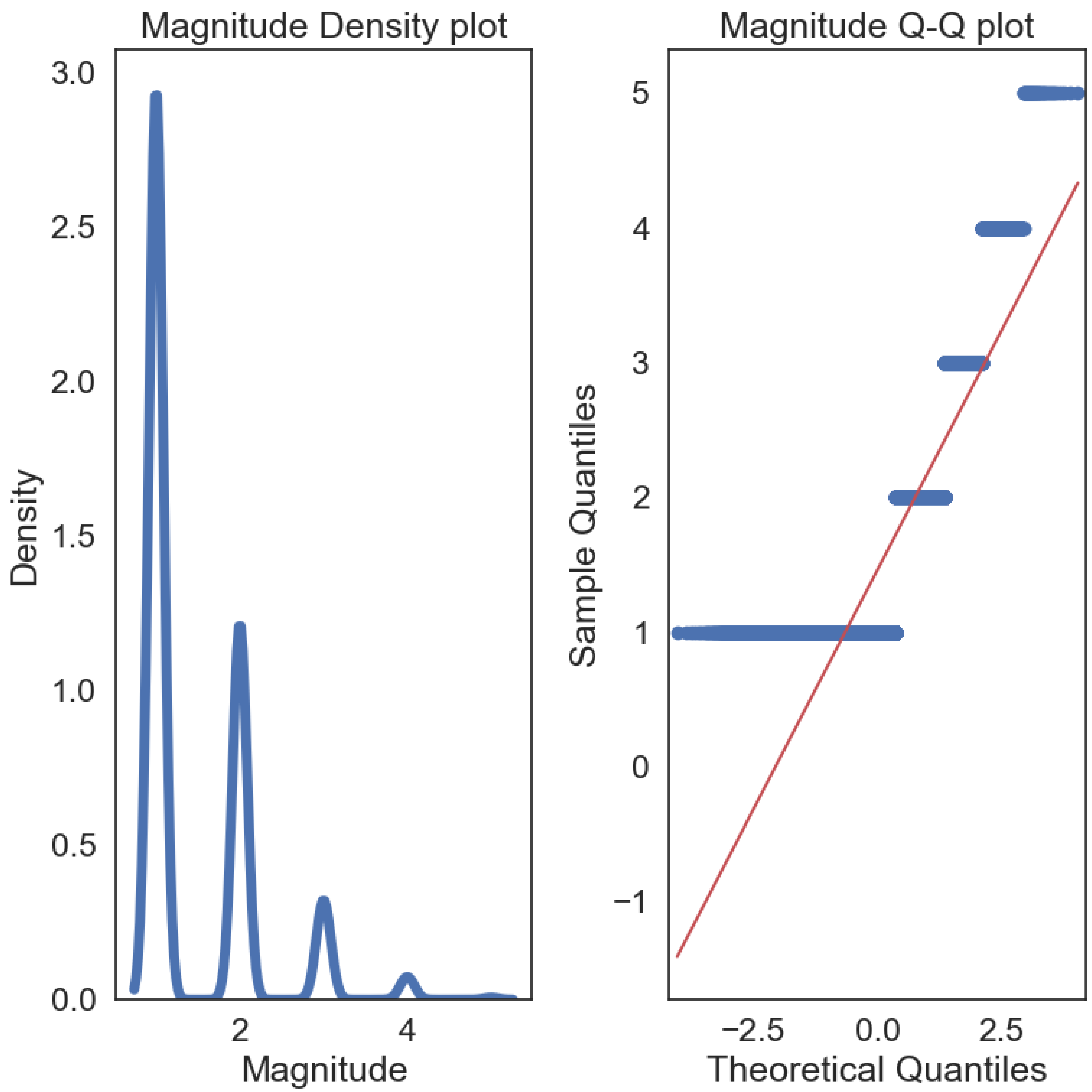
Magnitude inverse density plot - Left skewed, multimodal distributions (3)

Magnitude inverse Q-Q plot - Right skewed, with gaps

Box-Con Transformation

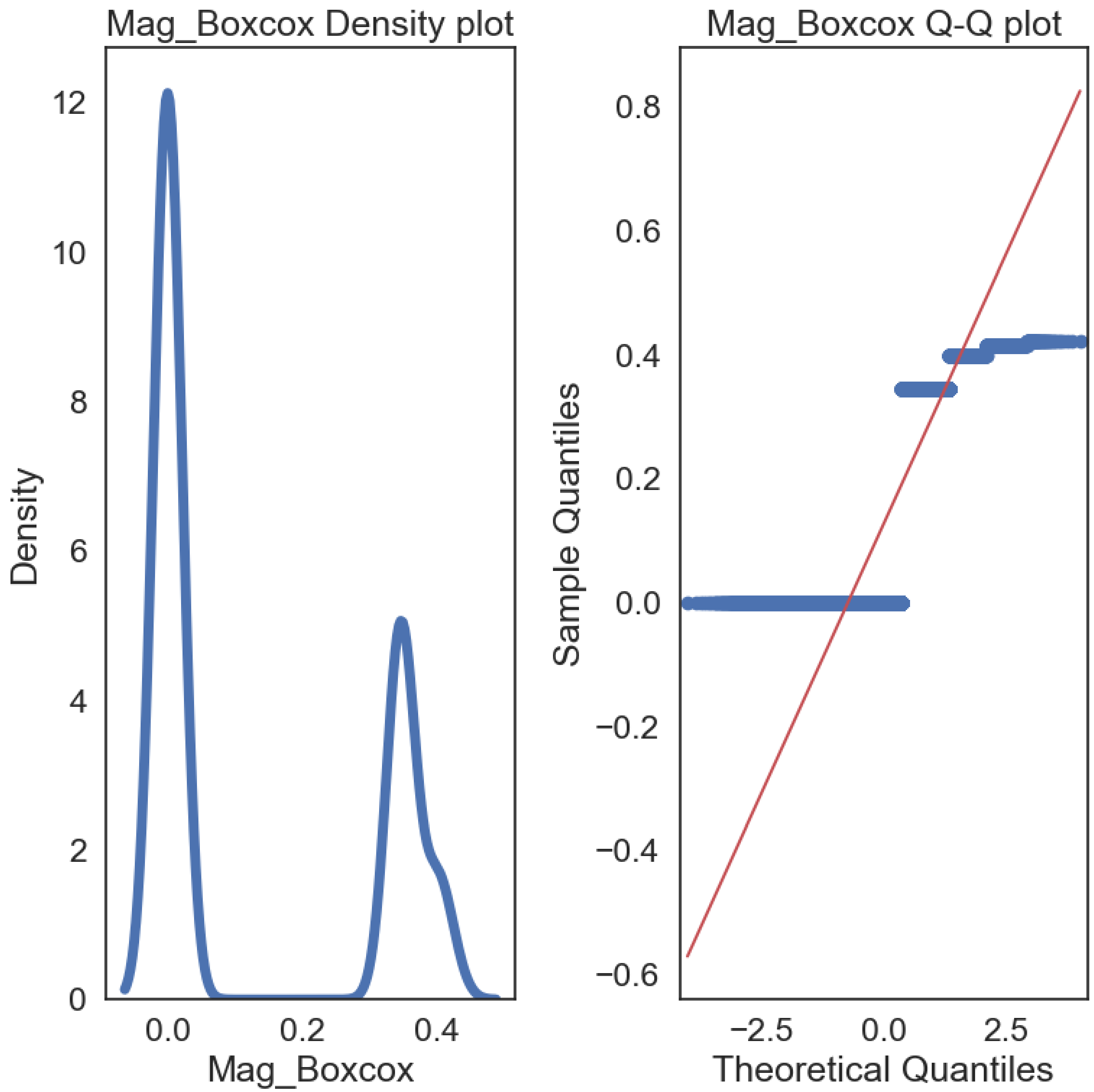
In [19]:
```
# Box-cox transform the data in a new column
MagMod['Mag_Boxcox'], parameters = stats.boxcox(MagMod['Magnitude'])

# Specify desired column
col = MagMod.Magnitude

# Specify desired column
i_col = MagMod.Mag_Boxcox
```

```
# ORIGINAL
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(col, linewidth = 5, ax = ax1)
ax1.set_title('Magnitude Density plot')

# Q-Q plot
sm.qqplot(col, line='s', ax = ax2)
ax2.set_title('Magnitude Q-Q plot')
plt.tight_layout()
plt.show()
```



In [20]:

```
# TRANSFORMED
# Subplots
fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows = 1)

# Density plot
sns.kdeplot(i_col, linewidth = 5, ax = ax1)
ax1.set_title('Mag_Boxcox Density plot')

# Q-Q plot
sm.qqplot(i_col, line='s', ax = ax2)
ax2.set_title('Mag_Boxcox Q-Q plot')
plt.tight_layout()
plt.show()
```



Magnitude Boxcon density plot - right skewed, bimodal distribution

Magnitude Boxcon QQ plot - left skewed, bimodal

```
In [ ]:
```