Joining Hurricane and Housing Dataframes

In [1]:
```
#Importing libraries needed
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import pyplot
%matplotlib inline
import numpy as np
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
```

Obtaining Data

In [2]:
```
#opening dataframes
bottom =  pd.read_csv(r'data\bottom_housing.csv')
middle = pd.read_csv(r'data\middle_housing.csv')
top = pd.read_csv(r'data\top_housing.csv')
hurricane = pd.read_csv(r'data\hurricane_cleaned.csv')
```

In [3]:
```
#checking it out
bottom.head()
```

Out[3]:

	City	HurricaneName	SizeRank	before	after	percent	increase
0	Jacksonville	charley	12	46528.30349	52803.32790	13.486467	0
1	Orlando	charley	16	75863.27537	88560.22345	16.736620	0
2	Miami	charley	20	86752.55847	106338.70750	22.577028	0
3	Tampa	charley	50	51585.41060	61309.89329	18.851227	0
4	Saint Petersburg	charley	84	47796.13229	57880.05754	21.097785	0

In [4]:
```
#checking it out
middle.head()
```

Out[4]:

	City	HurricaneName	SizeRank	before	after	percent	increase
0	Jacksonville	charley	12	120287.1799	136338.2043	13.343919	0
1	Orlando	charley	16	153628.1167	178133.7990	15.951300	0
2	Miami	charley	20	196585.3564	242294.9810	23.251795	1
3	Tampa	charley	50	134130.4031	158405.6253	18.098225	0
4	Saint Petersburg	charley	84	112809.7002	134746.5950	19.445930	0

In [5]:
```
#checking it out
top.head()
```

Out[5]:

	City	HurricaneName	SizeRank	before	after	percent	increase
0	Jacksonville	charley	12	219711.2386	249137.7656	13.393273	0
1	Orlando	charley	16	268593.0990	311622.3096	16.020222	0
2	Miami	charley	20	438933.0461	531656.5319	21.124745	0
3	Tampa	charley	50	314461.3881	368173.9723	17.080820	0
4	Saint Petersburg	charley	84	245925.9512	292718.6866	19.027165	0

In [6]:
```
#checking it out
hurricane
```

Out[6]:

	DATE	AWND	WSF2	HurricaneName	City
0	8/14/2004	5.820000	13.00000	charley	Apalachicola
1	8/13/2004	7.380000	13.00000	charley	Brooksville
2	8/14/2004	4.700000	21.90000	charley	Brooksville
3	8/13/2004	9.620000	25.10000	charley	Clearwater
4	8/14/2004	7.380000	25.10000	charley	Clearwater
...	...	...	...	...	...
534	9/29/2022	29.527080	51.44870	ian	Tallahassee
535	9/28/2022	39.526023	82.54161	ian	Tampa
536	9/29/2022	57.040950	107.59489	ian	Vero Beach
537	9/28/2022	53.551386	85.00220	ian	West Palm Beach
538	9/28/2022	40.040510	71.58080	ian	Winter Haven

539 rows × 5 columns

Data Scrubbing

In [7]:
```
hurricane.isna().sum()
```

Out[7]:
```
DATE            0
AWND            0
WSF2            0
HurricaneName   0
City            0
dtype: int64
```

Joining Housing Values with Hurricanes

In order to do logistic regression on our data we need to join the datasets. We will use the join

In [8]:

```python
#setting the index to city and HurricaneName so that we use .join()
hurricane.set_index(['City', 'HurricaneName'], inplace = True)
```

In [9]:

```python
#function to join housing and hurricane datasets
def join(df):
    #setting the index
    df.set_index(['City', 'HurricaneName'], inplace = True)
    #joining the dataframe
    df = hurricane.join(df, how='inner')
    #reseting the index
    df.reset_index(inplace = True)
    return df
```

Joining Bottom Tier Home Values with Hurricane Data

In [10]:

```python
#applying function
bottom_hurricane = join(bottom)
#looking at results
bottom_hurricane
```

Out[10]:

	City	HurricaneName	DATE	AWND	WSF2	SizeRank	before	
0	Apalachicola	charley	8/14/2004	5.8200	13.00000	12877	33025.67901	41
1	Apalachicola	dennis	7/10/2005	19.4600	30.00000	12877	40369.46137	50
2	Apalachicola	dennis	7/11/2005	17.0000	32.00000	12877	40369.46137	50
3	Apalachicola	ian	9/28/2022	38.0273	57.93571	12877	65287.07867	76
4	Apalachicola	irma	9/11/2017	20.8000	36.90000	12877	52379.75722	63
...	...	...	...	...	...	...	...	
428	Winter Haven	matthew	10/7/2016	13.4200	25.90000	395	69267.39054	80
429	Winter Haven	matthew	10/8/2016	8.7200	18.10000	395	69267.39054	80
430	Winter Haven	michael	10/11/2018	7.3800	16.10000	395	94132.64063	110
431	Winter Haven	michael	10/10/2018	13.2000	25.10000	395	94132.64063	110
432	Winter Haven	michael	10/9/2018	11.6300	18.10000	395	94132.64063	110

433 rows × 10 columns

Joining Middle Tier Home Values with Hurricane Data

In [11]:

```
#applying function
middle_hurricane = join(middle)
#looking at results
middle_hurricane
```

Out[11]:

	City	HurricaneName	DATE	AWND	WSF2	SizeRank	before	
0	Apalachicola	charley	8/14/2004	5.8200	13.00000	12877	91915.39335	11
1	Apalachicola	dennis	7/10/2005	19.4600	30.00000	12877	112287.89680	14
2	Apalachicola	dennis	7/11/2005	17.0000	32.00000	12877	112287.89680	14
3	Apalachicola	ian	9/28/2022	38.0273	57.93571	12877	144565.87220	16
4	Apalachicola	irma	9/11/2017	20.8000	36.90000	12877	127923.42670	14
...	...	...	...	...	...	...	...	
421	West Palm Beach	matthew	10/7/2016	19.6900	31.10000	158	197641.97590	2
422	West Palm Beach	matthew	10/8/2016	10.5100	17.00000	158	197641.97590	2
423	West Palm Beach	michael	10/11/2018	6.9300	17.00000	158	235358.13210	25
424	West Palm Beach	michael	10/10/2018	12.7500	25.10000	158	235358.13210	25
425	West Palm Beach	michael	10/9/2018	13.6500	23.00000	158	235358.13210	25

426 rows × 10 columns

Joining Top Tier Home Values with Hurricane Data

In [12]:

```
#applying function
top_hurricane = join(top)
#looking at results
top_hurricane
```

Out[12]:

	City	HurricaneName	DATE	AWND	WSF2	SizeRank	before	
0	Apalachicola	charley	8/14/2004	5.8200	13.00000	12877	221794.3003	275
1	Apalachicola	dennis	7/10/2005	19.4600	30.00000	12877	269923.5452	339
2	Apalachicola	dennis	7/11/2005	17.0000	32.00000	12877	269923.5452	339
3	Apalachicola	ian	9/28/2022	38.0273	57.93571	12877	279871.2479	308
4	Apalachicola	irma	9/11/2017	20.8000	36.90000	12877	257605.2886	276
...	...	...	...	...	...	...	...	
430	West Palm Beach	matthew	10/7/2016	19.6900	31.10000	158	375111.3104	393
431	West Palm Beach	matthew	10/8/2016	10.5100	17.00000	158	375111.3104	393
432	West Palm Beach	michael	10/11/2018	6.9300	17.00000	158	414414.1815	434
433	West Palm Beach	michael	10/10/2018	12.7500	25.10000	158	414414.1815	434
434	West Palm Beach	michael	10/9/2018	13.6500	23.00000	158	414414.1815	434

435 rows × 10 columns

Creating a Dataset with Bottom, Middle, and Top Tier Homes

In [13]:

```
#concating the three dataframes into one
all_hurricane = hurricane = pd.concat([bottom_hurricane, middle_hurric
all_hurricane
```

Out[13]:

	City	HurricaneName	DATE	AWND	WSF2	SizeRank	before
0	Apalachicola	charley	8/14/2004	5.8200	13.00000	12877	33025.67901
1	Apalachicola	dennis	7/10/2005	19.4600	30.00000	12877	40369.46137
2	Apalachicola	dennis	7/11/2005	17.0000	32.00000	12877	40369.46137
3	Apalachicola	ian	9/28/2022	38.0273	57.93571	12877	65287.07867
4	Apalachicola	irma	9/11/2017	20.8000	36.90000	12877	52379.75722
...	...	...	...	...	...	...	...
1289	West Palm Beach	matthew	10/7/2016	19.6900	31.10000	158	375111.31040
1290	West Palm Beach	matthew	10/8/2016	10.5100	17.00000	158	375111.31040
1291	West Palm Beach	michael	10/11/2018	6.9300	17.00000	158	414414.18150
1292	West Palm Beach	michael	10/10/2018	12.7500	25.10000	158	414414.18150
1293	West Palm Beach	michael	10/9/2018	13.6500	23.00000	158	414414.18150

1294 rows × 10 columns

Data Exploration

Each dataset had a slightly different list of cities, which is why the wind speed mean values are not all the same. However, the max wind speed was the same across all datasets. We can also see from the pairplot that the wind features have a right handed tail which is expected because higher wind values only occur during strong storms. The most highly correlated variable to our target variable is before prices.

- The mean value for homes six months before the hurricanes for the bottom tier dataset was 95,603USD and 110,462USD six months after the hurricanes. And the 75th percentile increase was 20%.
- The mean value for homes six months before the hurricanes for the middle tier dataset was 179,521USD and 200,815USD six months after the hurricanes. And the 75th percentile increase was 17%.

In [14]:

```
#checking descriptive stats
bottom_hurricane.describe()
```

Out[14]:

	AWND	WSF2	SizeRank	before	after	percent	i
count	433.000000	433.000000	433.000000	433.000000	433.000000	433.000000	433
mean	17.050417	32.820248	836.427252	95603.235456	110462.544534	16.765446	(
std	13.009195	22.912817	2127.208992	33766.654876	35707.591357	7.402668	(
min	4.030000	0.000000	12.000000	33025.679010	41196.088340	1.715556	(
25%	9.170000	19.900000	84.000000	71026.657360	83003.431000	11.465540	(
50%	13.200000	25.100000	190.000000	90687.074960	107991.152200	16.018972	(
75%	19.460000	36.900000	704.000000	117150.037000	135916.268400	20.412881	1
max	91.064199	194.610300	12877.000000	217713.978800	246535.290800	38.720009	1

In [15]:

```
#checking descriptive stats
middle_hurricane.describe()
```

Out[15]:

	AWND	WSF2	SizeRank	before	after	percent	i
count	426.000000	426.000000	426.000000	426.000000	426.000000	426.000000	426
mean	16.965034	32.618184	1202.546948	179521.587759	200815.463231	12.660287	(
std	13.043998	22.723287	2868.716634	55801.125522	58971.129387	8.220775	(
min	2.910000	0.000000	12.000000	38971.285380	48205.342730	-0.304135	(
25%	9.170000	19.900000	84.000000	142852.541600	161515.927500	6.577412	(
50%	13.200000	25.100000	190.000000	170976.149100	189263.549000	10.233490	(
75%	19.460000	36.000000	744.000000	213419.907300	235282.792000	17.158423	(
max	91.064199	194.610300	12877.000000	370849.443700	390533.139700	34.925821	1

In [16]:

```
#checking descriptive stats
top_hurricane.describe()
```

Out[16]:

	AWND	WSF2	SizeRank	before	after	percent	i
count	435.000000	435.000000	435.000000	435.000000	435.000000	435.000000	435
mean	17.004029	32.631220	1179.839080	322761.896341	354399.169863	10.175128	(
std	13.036412	22.842738	2843.121543	112297.390629	122555.225444	8.649244	(
min	2.910000	0.000000	12.000000	98118.000900	119490.997200	-4.161603	(
25%	9.170000	19.900000	84.000000	244929.739400	264040.439200	5.033413	(
50%	13.200000	25.100000	190.000000	302316.013900	336663.041800	5.964686	(
75%	19.460000	36.000000	744.000000	372909.443500	405177.683500	16.495062	(
max	91.064199	194.610300	12877.000000	671004.028700	768214.341700	33.863819	1

In [17]:

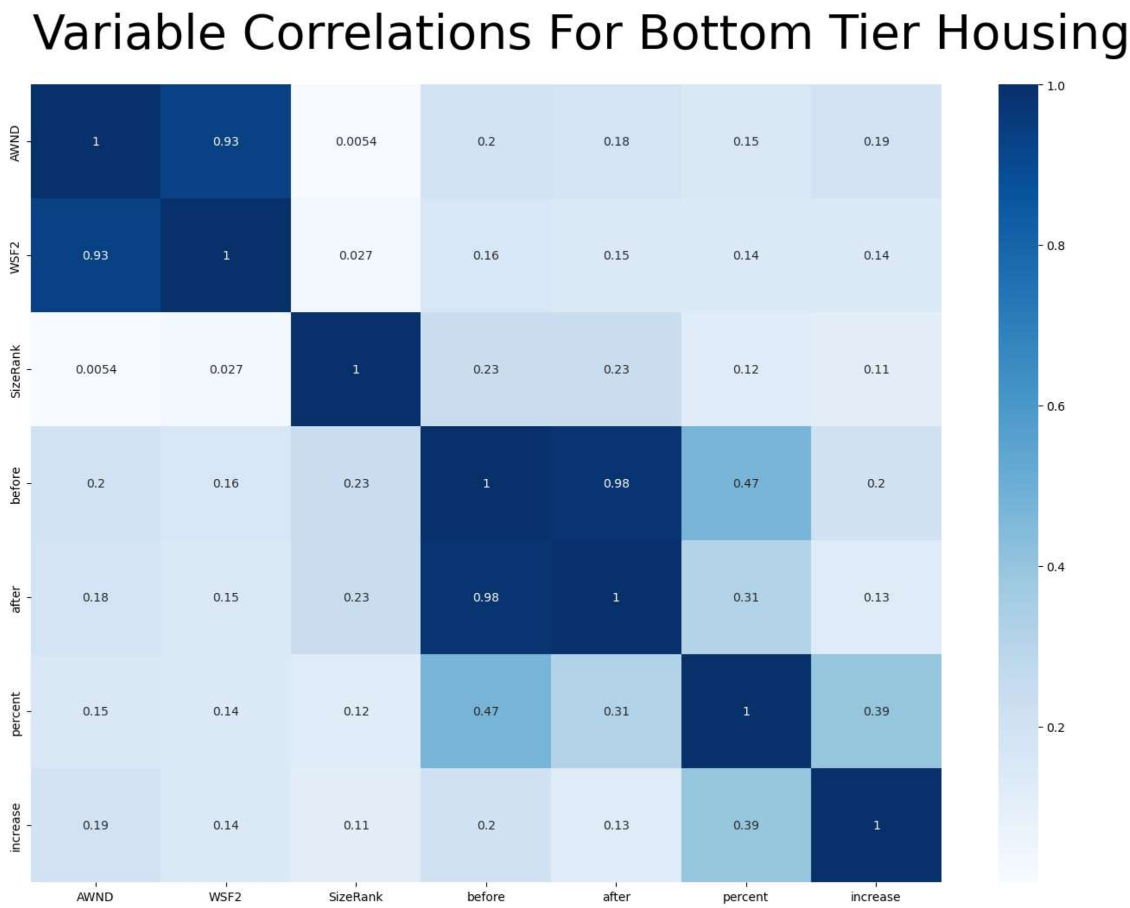
```
#checking descriptive stats
all_hurricane.describe()
```

Out[17]:

	AWND	WSF2	SizeRank	before	after	percent
count	1294.000000	1294.000000	1294.000000	1294.000000	1294.000000	1294.000000
mean	17.006714	32.690181	1072.401855	199593.371133	222211.211755	13.198532
std	13.019776	22.809524	2637.829032	120395.657710	129699.018906	8.547732
min	2.910000	0.000000	12.000000	33025.679010	41196.088340	-4.161603
25%	9.170000	19.900000	84.000000	107382.952600	127738.626975	6.043874
50%	13.200000	25.100000	190.000000	170976.149100	188779.652850	10.375848
75%	19.460000	36.000000	704.000000	259185.661000	289155.432400	19.081084
max	91.064199	194.610300	12877.000000	671004.028700	768214.341700	38.720009

In [18]:

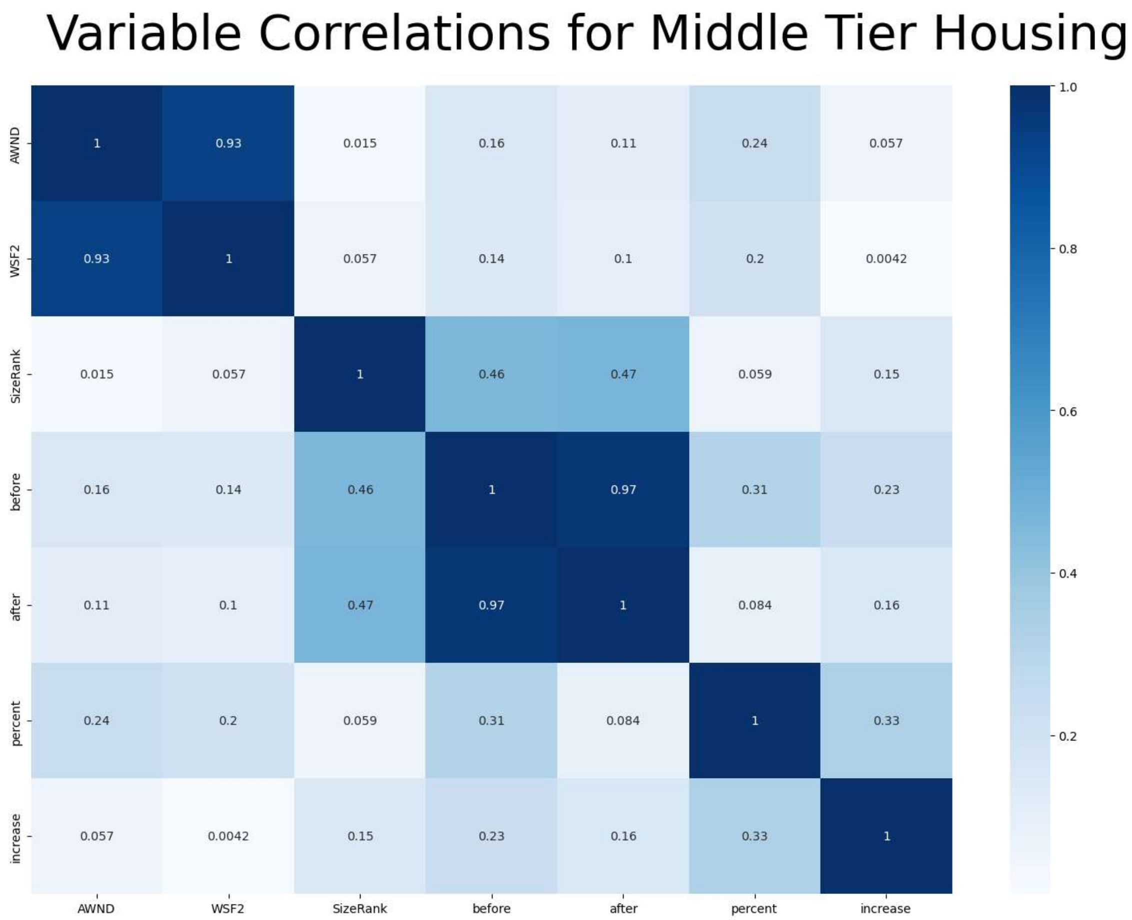
```
#checking variable correlations for bottom tier housing
#high correlation between AWND and WSF2
#high crrelation between before and after
corr = bottom_hurricane.corr().abs()
fig, ax=plt.subplots(figsize=(17,12))
fig.suptitle('Variable Correlations For Bottom Tier Housing', fontsize
heatmap = sns.heatmap(corr, cmap='Blues', annot=True)
```



	AWND	WSF2	SizeRank	before	after	percent	increase
AWND	1	0.93	0.0054	0.2	0.18	0.15	0.19
WSF2	0.93	1	0.027	0.16	0.15	0.14	0.14
SizeRank	0.0054	0.027	1	0.23	0.23	0.12	0.11
before	0.2	0.16	0.23	1	0.98	0.47	0.2
after	0.18	0.15	0.23	0.98	1	0.31	0.13
percent	0.15	0.14	0.12	0.47	0.31	1	0.39
increase	0.19	0.14	0.11	0.2	0.13	0.39	1

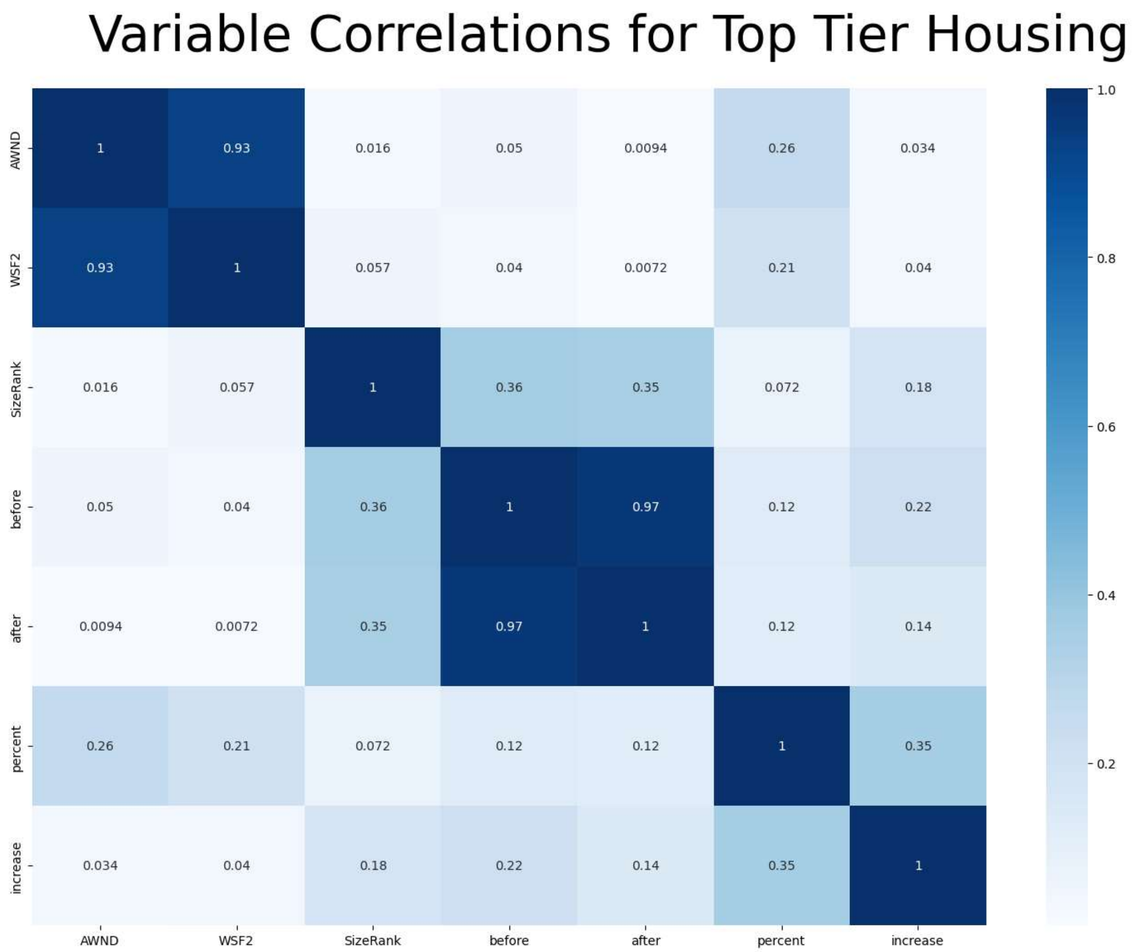
In [19]:

```
#checking variable correlations for middle tier housing
#high correlation between AWND and WSF2
#high crrelation between before and after
corr = middle_hurricane.corr().abs()
fig, ax=plt.subplots(figsize=(17,12))
fig.suptitle('Variable Correlations for Middle Tier Housing', fontsize
heatmap = sns.heatmap(corr, cmap='Blues', annot=True)
```



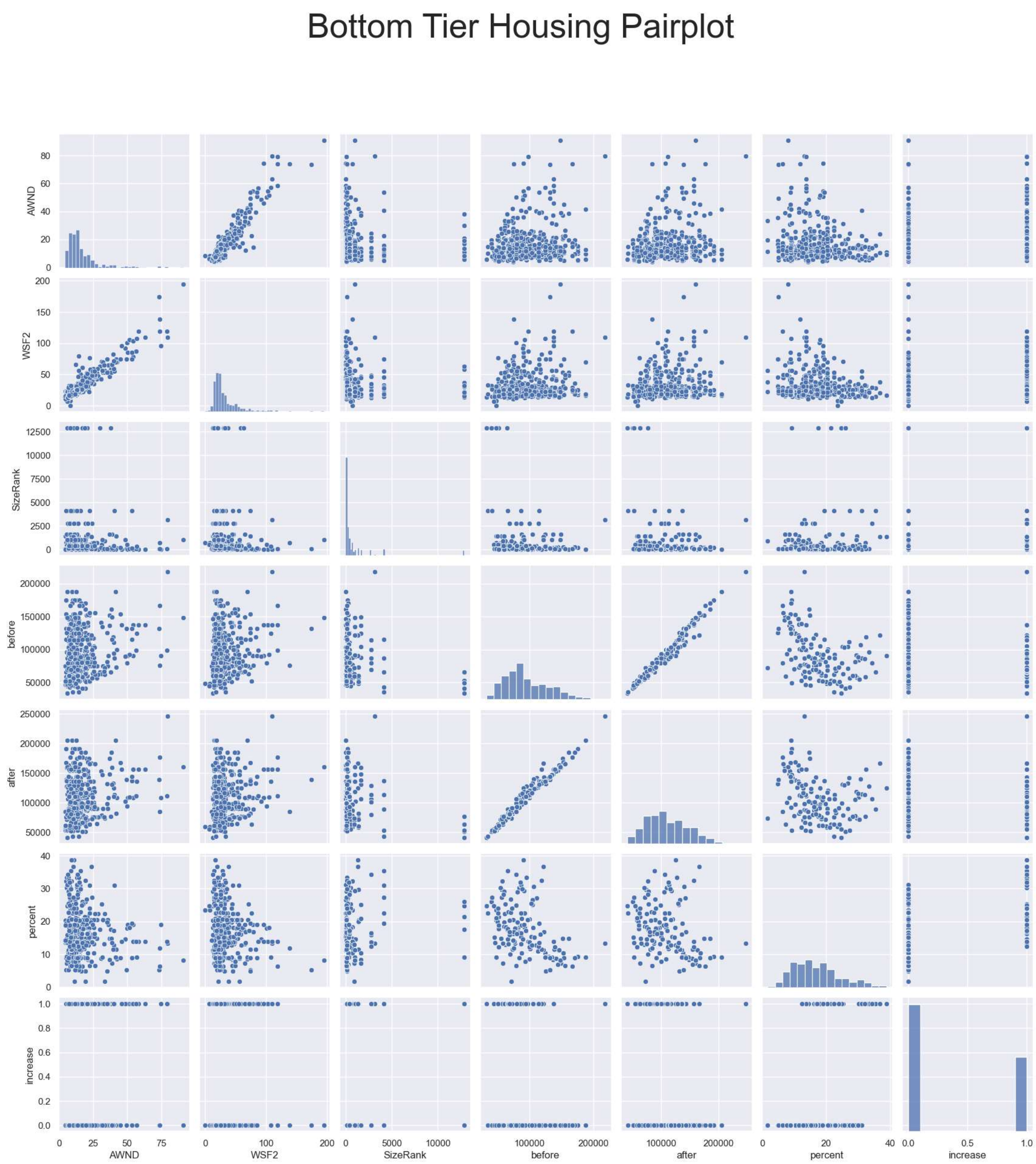
In [20]:

```
#checking variable correlations for top tier housing
#high correlation between AWND and WSF2
#high crrelation between before and after
corr = top_hurricane.corr().abs()
fig, ax=plt.subplots(figsize=(17,12))
fig.suptitle('Variable Correlations for Top Tier Housing', fontsize=40
heatmap = sns.heatmap(corr, cmap='Blues', annot=True)
```



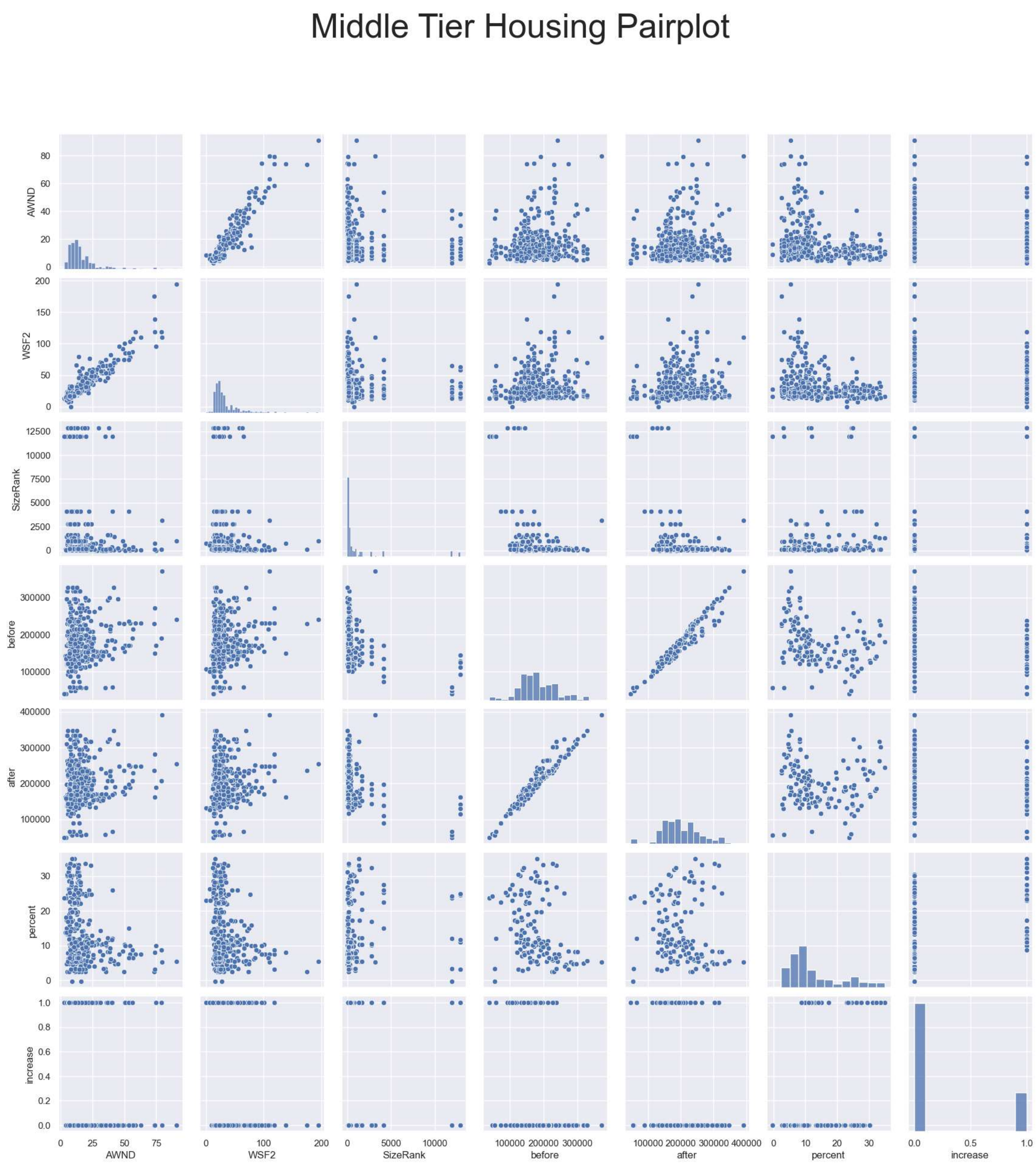
In [21]:

```
#plotting bottom_hurricane
#long tail on AWND and WSF2
sns.set()
s = sns.pairplot(bottom_hurricane, size = 2.5)
s.fig.suptitle("Bottom Tier Housing Pairplot", y= 1.1, fontsize=40)
plt.show();
```



In [22]:

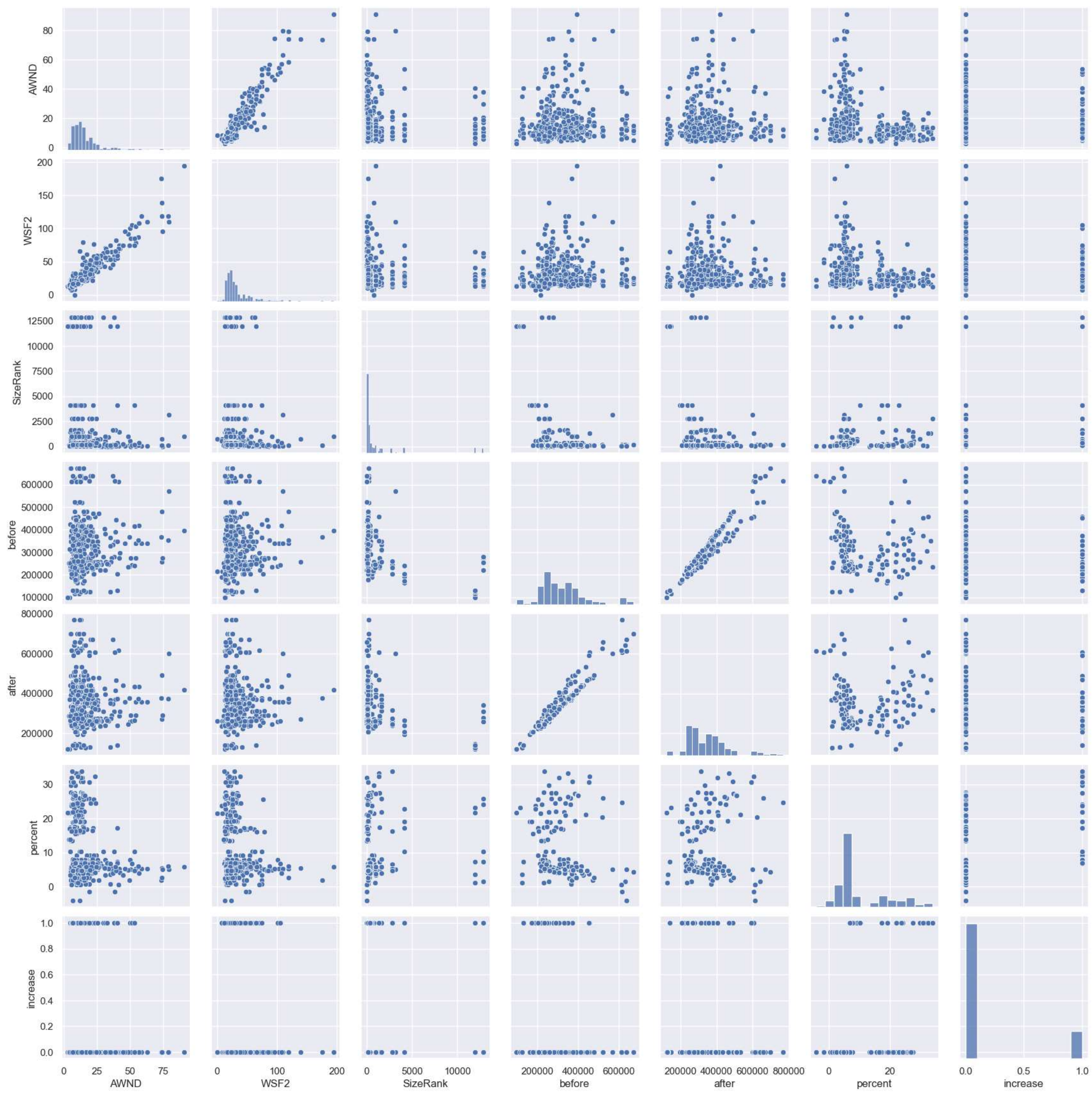
```
#plotting middle_hurricane
#long tail on AWND and WSF2
sns.set()
s = sns.pairplot(middle_hurricane, size = 2.5)
s.fig.suptitle("Middle Tier Housing Pairplot", y= 1.1, fontsize=40)
plt.show();
```



In [23]:

```
#plotting top_hurricane
#long tail on AWND and WSF2
sns.set()
s = sns.pairplot(top_hurricane, size = 2.5)
s.fig.suptitle("Top Tier Housing Pairplot", y= 1.1, fontsize=40)
plt.show();
```

Top Tier Housing Pairplot



Saving the Datasets

In [24]:

```
#saving the dataframes
bottom_hurricane.to_csv(r'data\bottom_hurricane.csv', index=False)
middle_hurricane.to_csv(r'data\middle_hurricane.csv', index=False)
top_hurricane.to_csv(r'data\top_hurricane.csv', index=False)
all_hurricane.to_csv(r'data\all_hurricane.csv', index=False)
```