In [53]:
```python
from os.path import basename, exists


def download(url):
    filename = basename(url)
    if not exists(filename):
        from urllib.request import urlretrieve

        local, _ = urlretrieve(url, filename)
        print("Downloaded " + local)


download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/thinkstats2.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/thinkplot.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/brfss.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/analytic.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/nsfg.py")
```

In [96]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import sys
import thinkplot
import thinkstats2
import scipy
import statsmodels.formula.api as smf
import brfss
import random
import analytic
import math
import locale
import hypothesis
from prettytable import PrettyTable
import textblob
from spellchecker import SpellChecker

import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
```

I currently work for a holding company with many subsidiaries. My functions include finance manager, data warehousing and management as well as risk analysis and claims reserve projections on ultimate loss ratios. Claims are the leading expense on an insuring business's profit statement outside of reinsurance and salaries. Much emphasis is placed on predicting how a product will perform. This leads to evaluating the reasonableness of the warranty cost and claims experience to present loss reserves. The subsidiary I will focus on for this project is a warranty group that specializes in servicing extended warranties on appliances (refrigerators, washers, dryers, stoves, small home appliances), TV's and other electronics (audio equipment, home wine coolers, portable air conditioners, mobile phones). These products can have different warranty periods from 12 months to 5 years. The reason I am choosing this subsidiary is due to the fact that their operating income has fallen in the past couple of years. Assumption is that this is due to an increase in claims experience since bringing on a large client. This particular buying group (many dealers under the same contract) product mix consists 99% of refrigerators, washers, TV's and small home appliances.

The data set below contains all sales and claim information for the last 3 years for the buying group. Including contract number, product sold, manufacturer, dealer name, warranty terms, sale date, warranty costs and retail costs.

In [55]:
```python
df = pd.read_excel(r'Sales_Original2.xlsx')
df.head(10)
```

Out[55]:

	ContractNumber	DealerNumber	DealerName	ProductDescription	ManufacturerDescription	ModelNumber	StateCode	ReceivedDate	Effec
0	AU48094	56596 A	BON MARCHE APPLIANCE CENTER	MICROWAVE	FRIGIDAIRE	FGMV17WNVF	LA	2021-09-30	[illegible]
1	AU48115	56596 A	BON MARCHE APPLIANCE CENTER	MICROWAVE	FRIGIDAIRE	FFMV1845VS	LA	2021-09-30	[illegible]
2	AU49973	57054 A	BOBCAT HOME FURNISHINGS CO	FREEZER	GALANZ	GLF70CWED0	MT	2021-09-30	[illegible]
3	AU48097	56596 A	BON MARCHE APPLIANCE CENTER	FREEZER	ASCOLI	ACCF0700W1	LA	2021-09-30	[illegible]
4	AU47695	56181 A	LYONS APPLIANCE	FREEZER	FRIGIDAIRE	FFCS0722AW	IA	2021-09-30	[illegible]
5	AU47946	56464 A	RW MCDONALD AND SONS	REFRIGERATOR	GE	GNE25JMKES	PA	2021-09-30	[illegible]
6	AU48170	56694 A	CHAVIS FURNITURE	REFRIGERATOR	GE	GNE27JYMFS	AL	2021-09-30	[illegible]
7	AU48171	56694 A	CHAVIS FURNITURE	RANGE	SAMSUNG	NX58T7511S	AL	2021-09-30	[illegible]
8	AU47753	56204 A	NIX HOME CENTER	REFRIGERATOR	GE	GSS25GMHES	AR	2021-09-30	[illegible]
9	AU48169	56694 A	CHAVIS FURNITURE	REFRIGERATOR	WHIRLPOOL	WRS321SDHW	AL	2021-09-30	[illegible]

10 rows × 22 columns

Choose a minimum of 5 variables in your dataset used during your analysis.

The vairables I am focusing within my dataset are:

1. Contract Number = Value assigned at purchase of extended warranty for policy identification.
2. Product Description = Description of item purchased that the warranty was placed for.
3. Manufacturer Description = Manufacturer of product sold.
4. State Code = State the product was purchased in.
5. Contract Cost Amount = Purchase price of warranty placed on product.
6. Claim Amount = If a claim was made on the product, the cost of the claim total.
7. Dealer Name = Store the product was purchased in.
8. Product Retail Amount = Cost of the product at time of purchase.

In [56]:
```python
df_variables = df[['ContractNumber', 'ProductDescription', 'ManufacturerDescription', 'StateCode',\
                   'ContractCostAmount', 'ClaimAmount', 'DealerName', 'ProductRetailAmount']]
```

In [98]:
```python
df_variables.head()
```

Out[98]:

	ContractNumber	ProductDescription	ManufacturerDescription	StateCode	ContractCostAmount	ClaimAmount	DealerName	ProductRetailA
0	AU48094	MICROWAVE	FRIGIDAIRE	LA	23.15	0.0	BON MARCHE APPLIANCE CENTER	
1	AU48115	MICROWAVE	FRIGIDAIRE	LA	23.15	0.0	BON MARCHE APPLIANCE CENTER	
2	AU49973	FREEZER	GALANZ	MT	20.15	0.0	BOBCAT HOME FURNISHINGS CO	
3	AU48097	FREEZER	ASCOLI	LA	14.01	0.0	BON MARCHE APPLIANCE CENTER	
4	AU47695	FREEZER	FRIGIDAIRE	IA	64.72	0.0	LYONS APPLIANCE	

In [58]:
```python
df_variables.describe()
```

Out[58]:

	ContractCostAmount	ClaimAmount	ProductRetailAmount
count	561962.000000	561962.000000	561962.000000
mean	75.458236	10.762085	1279.801189
std	33.728644	57.943497	1091.018191
min	3.840000	0.000000	0.000000
25%	57.040000	0.000000	679.000000
50%	69.630000	0.000000	909.000000
75%	92.210000	0.000000	1519.990000
max	703.410000	10068.810000	18999.000000

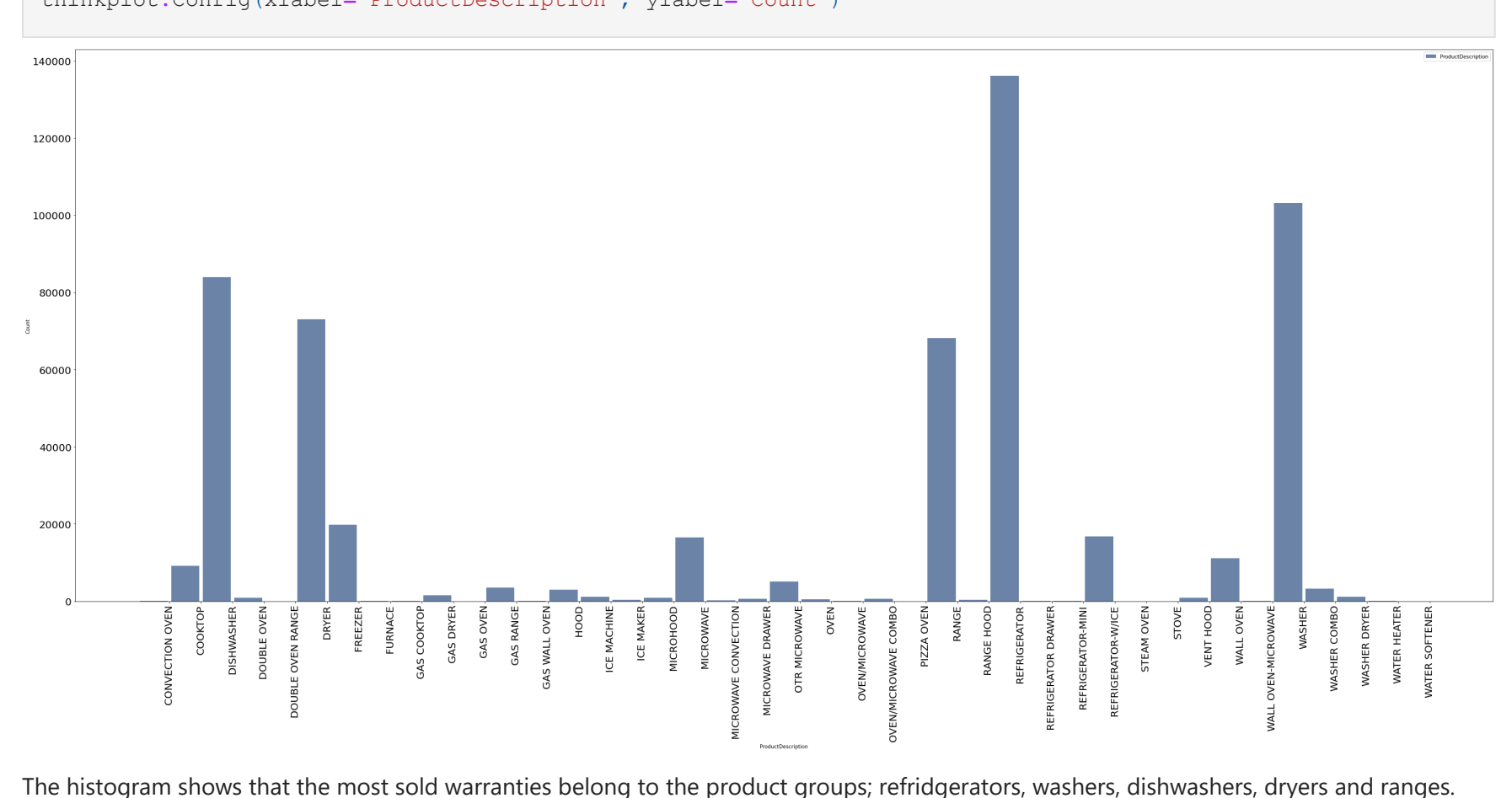
In [59]:
```python
df2 = pd.DataFrame(df_variables.groupby(['ProductDescription'])['ProductDescription'].count())
df2 = df2.rename(columns={'ProductDescription' : 'Count'})
df2 = df2.sort_values(by=['Count'], ascending=False)
df2
```

Out[59]:

ProductDescription	Count
REFRIGERATOR	136141
WASHER	103095
DISHWASHER	83966
DRYER	73021
RANGE	68216
FREEZER	19790
REFRIGERATOR-W/ICE	16831
MICROWAVE	16520
WALL OVEN	11173
COOKTOP	9142
OTR MICROWAVE	5016
GAS RANGE	3554
WASHER COMBO	3205
HOOD	2944
GAS DRYER	1548
WASHER DRYER	1131
ICE MACHINE	1117
DOUBLE OVEN	867
MICROHOOD	809
VENT HOOD	803
OVEN/MICROWAVE COMBO	641
MICROWAVE DRAWER	619
OVEN	438
RANGE HOOD	373
ICE MAKER	300
MICROWAVE CONVECTION	234
FURNACE	104
OVEN/MICROWAVE	96
GAS COOKTOP	82
REFRIGERATOR-MINI	73
REFRIGERATOR DRAWER	39
GAS WALL OVEN	24
WALL OVEN-MICROWAVE	16
CONVECTION OVEN	14
WATER HEATER	7
STOVE	3
WATER SOFTENER	3
PIZZA OVEN	2
GAS OVEN	2
DOUBLE OVEN RANGE	2
STEAM OVEN	1

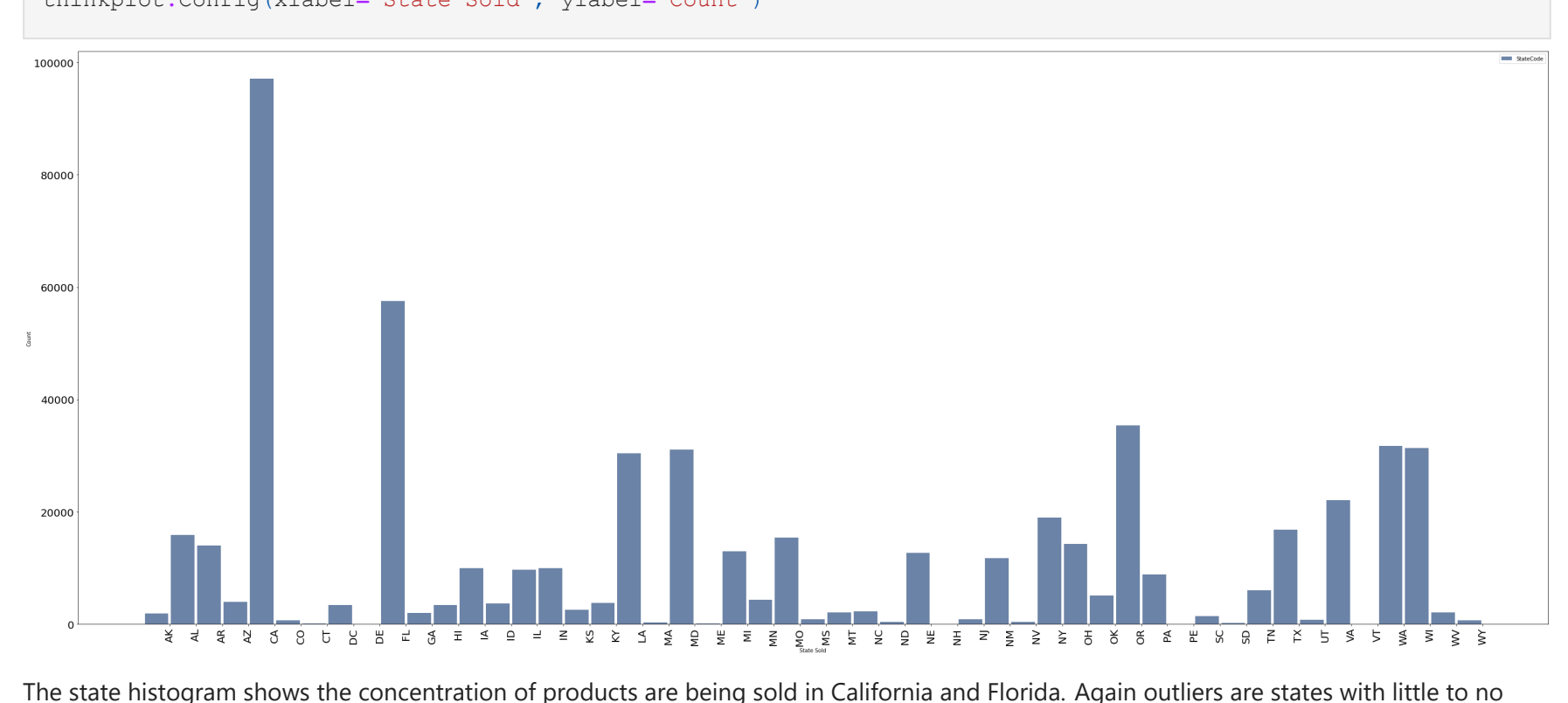
Include a histogram of each of the variables - in your summary and analysis, identify any outliers and explain the reasoning for them being outliers and how you believe they should be handled.

In [60]:
```python
plt.figure(figsize=(50,20))
histogram_product = thinkstats2.Hist(df_variables['ProductDescription'], label='ProductDescription')
thinkplot.Hist(histogram_product, align='center')
plt.xticks(rotation=90, fontsize=20)
plt.yticks(fontsize=20)
thinkplot.Config(xlabel='ProductDescription', ylabel='Count')
```



The histogram shows that the most sold warranties belong to the product groups; refridgerators, washers, dishwashers, dryers and ranges. The outliers could be the least sold product warranties such as water softeners and pizza ovens, making them insignificant to the study.

In [61]:
```python
plt.figure(figsize=(50,20))
histogram_product = thinkstats2.Hist(df_variables['StateCode'], label='StateCode')
thinkplot.Hist(histogram_product, align='center')
plt.xticks(rotation=90, fontsize=20)
plt.yticks(fontsize=20)
thinkplot.Config(xlabel='State Sold', ylabel='Count')
```

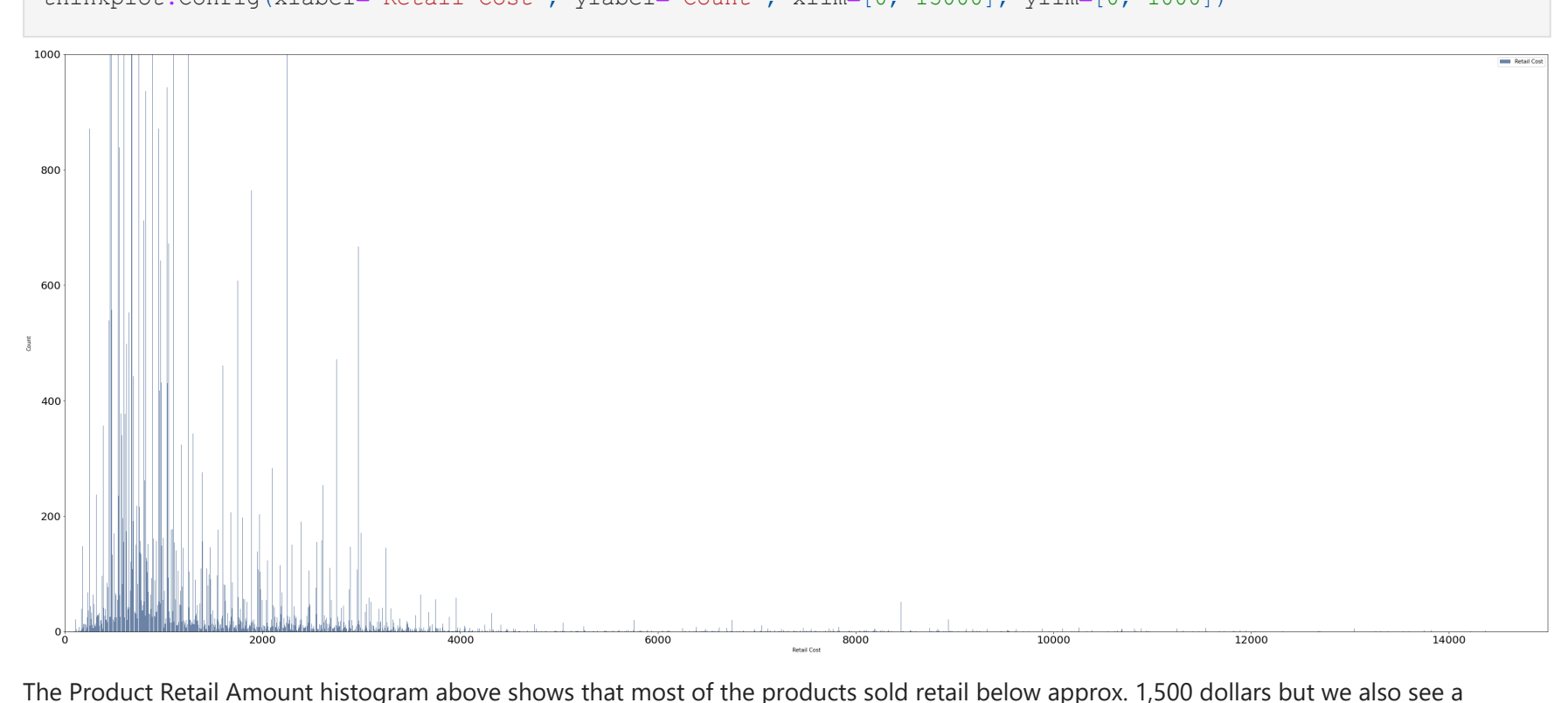


The state histogram shows the concentration of products are being sold in California and Florida. Again outliers are states with little to no sales. Would be insignificant to study and excluded if needed.

In [62]:
```python
plt.figure(figsize=(50,20))
flr_cost = np.floor(df_variables['ContractCostAmount'])
hist_prem = thinkstats2.Hist(flr_cost, label='Premiums')
thinkplot.Hist(hist_prem)
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
thinkplot.Config(xlabel='Premium', ylabel='Count', xlim=[0, 500], ylim=[0, 70000])
```

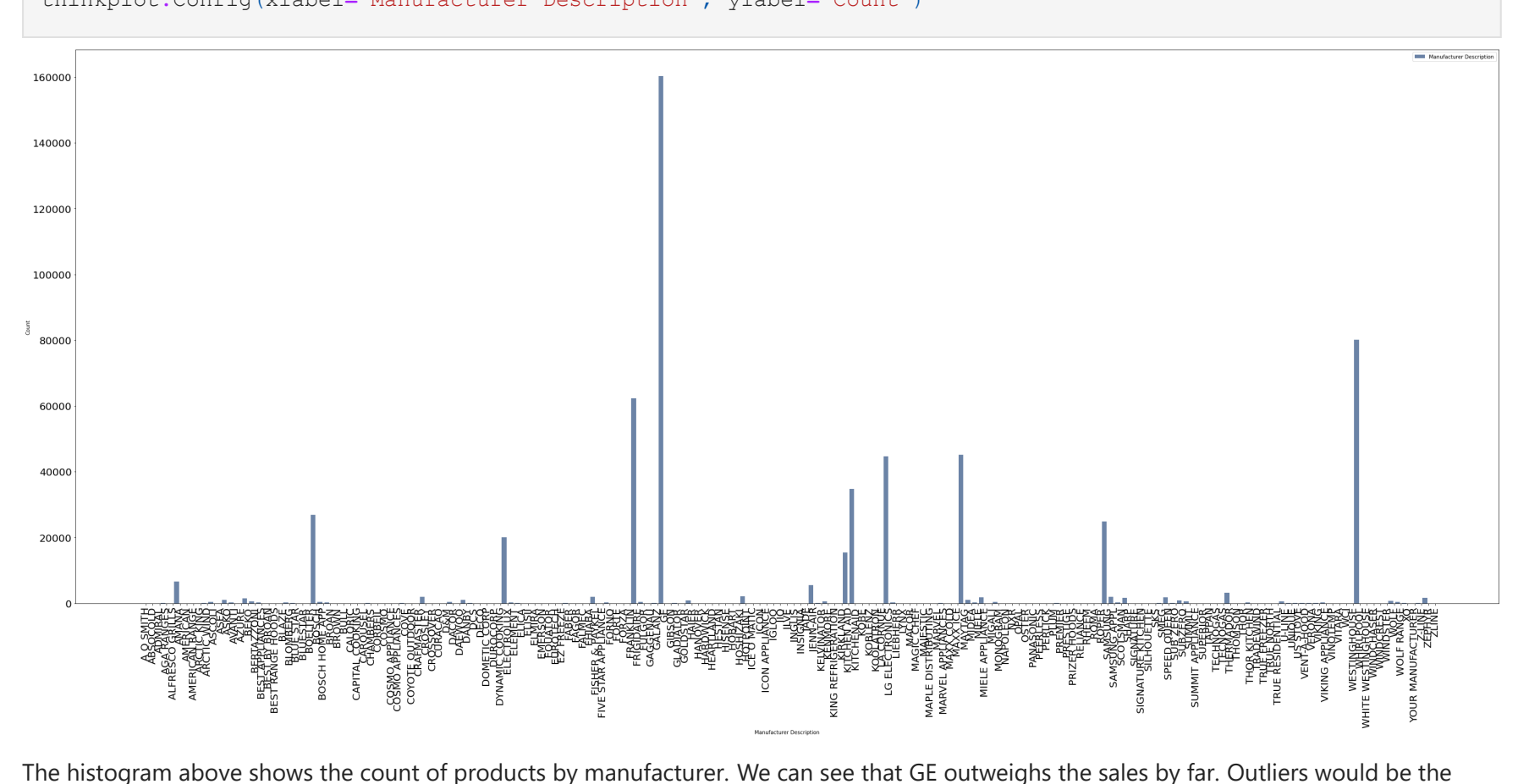
The Premium histogram above shows the concentration of warranty policy cost amounts fall mainly between 50 and 100 dollars. Outliers in this chart would be high end products with larger waranty policy costs. I would want to see if there was any significance in the warranty costs and the claim amounts.

In [63]:
```python
plt.figure(figsize=(50,20))
flr_retail = np.floor(df_variables['ProductRetailAmount'])
hist_prem = thinkstats2.Hist(flr_retail, label='Retail Cost')
thinkplot.Hist(hist_prem)
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
thinkplot.Config(xlabel='Retail Cost', ylabel='Count', xlim=[0, 15000], ylim=[0, 1000])
```



The Product Retail Amount histogram above shows that most of the products sold retail below approx. 1,500 dollars but we also see a spike around 2,500 to 3,500. This could be speciality refridgerators etc. The outliers in the retail costs are high end products, some, I found during EDA, were input incorrectly into the system of record.

In [64]:
```python
plt.figure(figsize=(50,20))
df3 = df_variables.sort_values(by=['ManufacturerDescription'], ascending=False)
histogram_manufacturer = thinkstats2.Hist(df3['ManufacturerDescription'], label='Manufacturer Description')
thinkplot.Hist(histogram_manufacturer, align='center', width=0.7)
plt.xticks(rotation=90)
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
thinkplot.Config(xlabel='Manufacturer Description', ylabel='Count')
```



The histogram above shows the count of products by manufacturer. We can see that GE outweighs the sales by far. Outliers would be the brands with very low sells.

The table below adds a column for a new variable, Current Loss Ratio. Which is the ratio of claims to premium over the period in question (past 3 years). There is also a ratio called "Ultimate Loss Ratio" which I will touch on later in the project.

In [65]:
```python
Calc_pivot = df.pivot_table(index =['ProductDescription'],
                      values = ['ContractCostAmount', 'ClaimAmount'],
                      aggfunc = 'sum')

Calc_pivot['CurrentLosssRatio'] = (Calc_pivot['ClaimAmount'] / Calc_pivot['ContractCostAmount']).round(4)


Calc_pivot
```

Out[65]:

ProductDescription	ClaimAmount	ContractCostAmount	CurrentLosssRatio
CONVECTION OVEN	0.00	1.037010e+03	0.0000
COOKTOP	29802.87	6.592025e+05	0.0452
DISHWASHER	702077.16	4.660735e+06	0.1506
DOUBLE OVEN	7733.90	8.163108e+04	0.0947
DOUBLE OVEN RANGE	0.00	1.585000e+02	0.0000
DRYER	440861.14	3.945050e+06	0.1118
FREEZER	66478.68	1.146319e+06	0.0580
FURNACE	0.00	3.890290e+03	0.0000
GAS COOKTOP	194.80	6.204400e+03	0.0314
GAS DRYER	7806.22	8.643537e+04	0.0903
GAS OVEN	0.00	2.303600e+02	0.0000
GAS RANGE	21446.16	2.515021e+05	0.0853
GAS WALL OVEN	0.00	1.675340e+03	0.0000
HOOD	5227.36	1.787593e+05	0.0292
ICE MACHINE	16914.58	2.289832e+05	0.0739
ICE MAKER	5012.52	6.230069e+04	0.0805
MICROHOOD	2945.02	3.160041e+04	0.0932
MICROWAVE	101416.39	7.334923e+05	0.1383
MICROWAVE CONVECTION	2577.49	1.383896e+04	0.1862
MICROWAVE DRAWER	2506.68	4.265194e+04	0.0588
OTR MICROWAVE	35497.91	2.157286e+05	0.1645
OVEN	5333.54	4.224535e+04	0.1263
OVEN/MICROWAVE	1110.57	8.755420e+03	0.1268
OVEN/MICROWAVE COMBO	7441.69	6.258252e+04	0.1189
PIZZA OVEN	0.00	2.258000e+02	0.0000
RANGE	444165.49	4.835476e+06	0.0919
RANGE HOOD	817.28	2.380745e+04	0.0343
REFRIGERATOR	2661399.56	1.389412e+07	0.1915
REFRIGERATOR DRAWER	632.71	4.502820e+03	0.1405
REFRIGERATOR-MINI	183.33	6.583690e+03	0.0278
REFRIGERATOR-W/ICE	295732.59	1.820135e+06	0.1625
STEAM OVEN	0.00	1.904100e+02	0.0000
STOVE	0.00	1.793700e+02	0.0000
VENT HOOD	195.00	4.918289e+04	0.0040
WALL OVEN	84943.15	1.010563e+06	0.0841
WALL OVEN-MICROWAVE	438.10	1.514020e+03	0.2894
WASHER	1049951.33	7.965474e+06	0.1318
WASHER COMBO	38155.24	2.385862e+05	0.1599
WASHER DRYER	8884.19	8.876701e+04	0.1001
WATER HEATER	0.00	2.641700e+02	0.0000
WATER SOFTENER	0.00	8.648000e+01	0.0000

Summarizing by the Product Description and calculate current loss ratio. Created new variable, Current Loss Ratio, which tells us the likelihood of a loss happening on a product: Refrigerator = LR of 0.1915, loss will happen at least 19% of the time within the first 3 years of the gross written premium. This will only increase with calculating on earned premium, which is the contract cost earned over the contract term. Typically a factor of 4x. You want to see a gross loss ratio around .15 or lower.

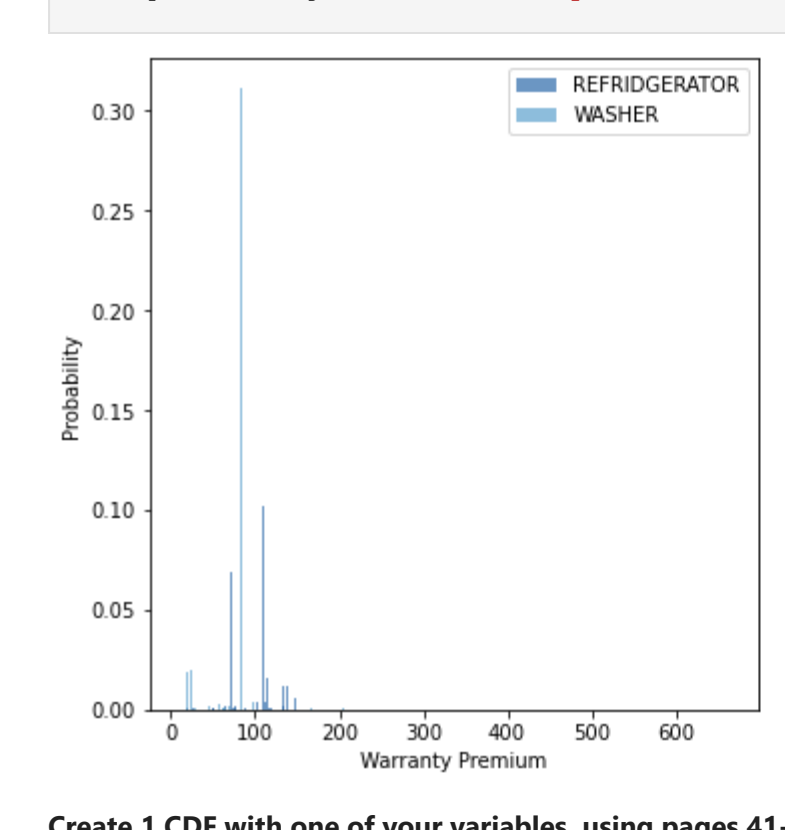
Summarizing the claims and premium totals by year sold, shows there has been an increase year over year. Per the claim data, most are incurred within years 2 and 3 of the contract term.

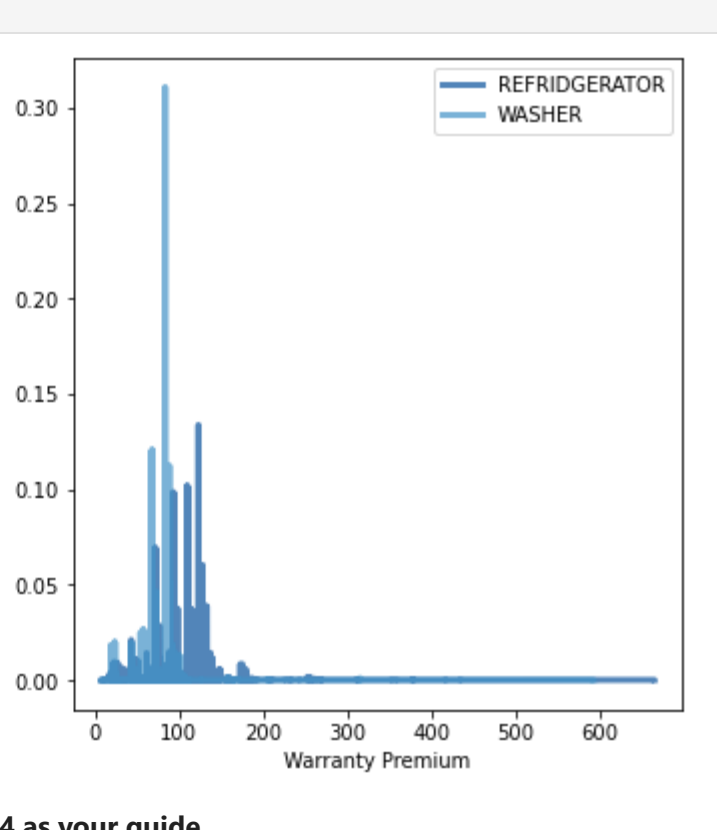
Using Pg.29 of your text as an example, compare two scenarios in your data using PMF.

In [66]:
```python
df_variables_fridge = df_variables.loc[df_variables['ProductDescription'] == 'REFRIGERATOR']
df_variables_washer = df_variables.loc[df_variables['ProductDescription'] == 'WASHER']
```

In [67]:
```python
fridge_pmf = thinkstats2.Pmf(df_variables_fridge['ContractCostAmount'], label='REFRIDGERATOR')
washer_pmf = thinkstats2.Pmf(df_variables_washer['ContractCostAmount'], label='WASHER')
```

In [68]:
```python
thinkplot.PrePlot(2, cols=2)
width = 0.45
thinkplot.Hist(fridge_pmf, align='right', width=width)
thinkplot.Hist(washer_pmf, align='right', width=width)
thinkplot.Config(xlabel='Warranty Premium',
                 ylabel='Probability')

thinkplot.PrePlot(2)
thinkplot.SubPlot(2)
thinkplot.Pmfs([fridge_pmf, washer_pmf])
thinkplot.Config(xlabel='Warranty Premium')
```

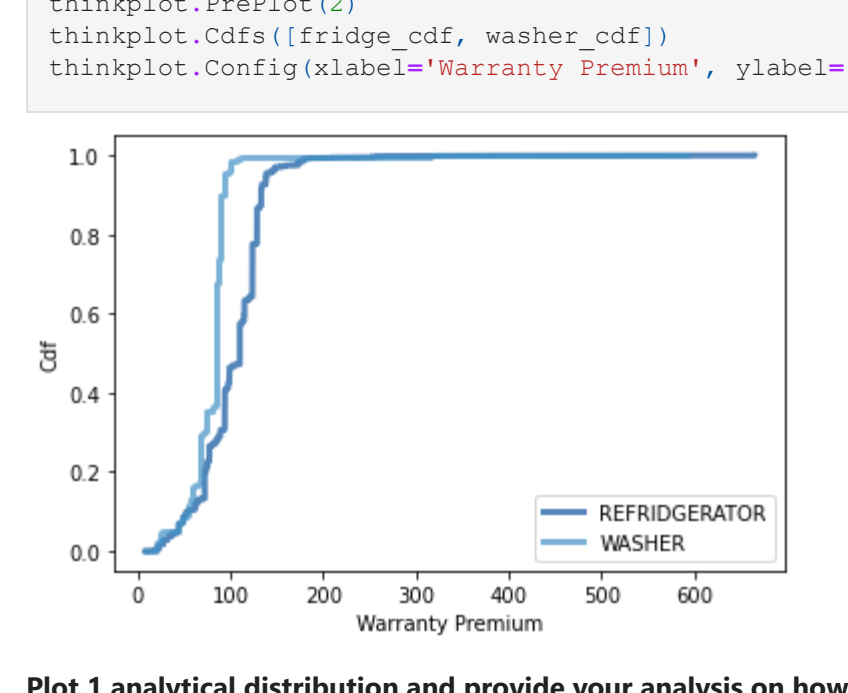




Create 1 CDF with one of your variables, using pages 41-44 as your guide.

In [69]:
```python
fridge_cdf = thinkstats2.Cdf(df_variables_fridge['ContractCostAmount'], label='REFRIDGERATOR')
washer_cdf = thinkstats2.Cdf(df_variables_washer['ContractCostAmount'], label='WASHER')
```

In [70]:
```python
thinkplot.PrePlot(2)
thinkplot.Cdfs([fridge_cdf, washer_cdf])
thinkplot.Config(xlabel='Warranty Premium', ylabel='Cdf')
```



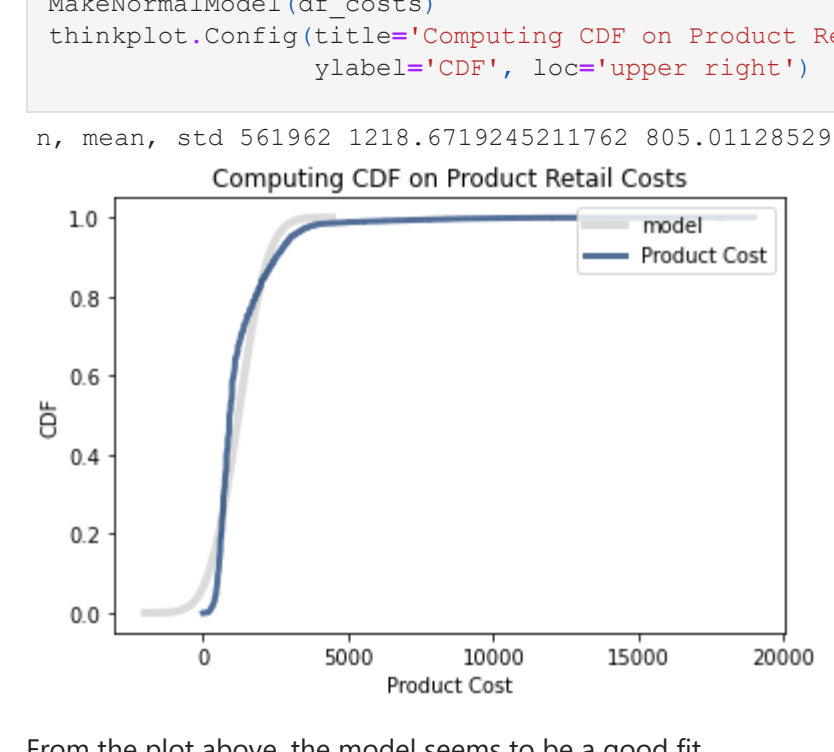
Plot 1 analytical distribution and provide your analysis on how it applies to the dataset you have chosen.

In [71]:
```python
def MakeNormalModel(ProductCost):

    cdf = thinkstats2.Cdf(ProductCost, label='Product Cost')

    mean, var = thinkstats2.TrimmedMeanVar(ProductCost)
    std = np.sqrt(var)
    print('n, mean, std', len(ProductCost), mean, std)

    xmin = mean - 4 * std
    xmax = mean + 4 * std

    xs, ps = thinkstats2.RenderNormalCdf(mean, std, xmin, xmax)
    thinkplot.Plot(xs, ps, label='model', linewidth=4, color='0.8')
    thinkplot.Cdf(cdf)
```

In [72]:
```python
df_costs = df_variables['ProductRetailAmount']
```

In [73]:
```python
MakeNormalModel(df_costs)
thinkplot.Config(title='Computing CDF on Product Retail Costs', xlabel='Product Cost',
                 ylabel='CDF', loc='upper right')
```

```
n, mean, std 561962 1218.6719245211762 805.0112852985548
```

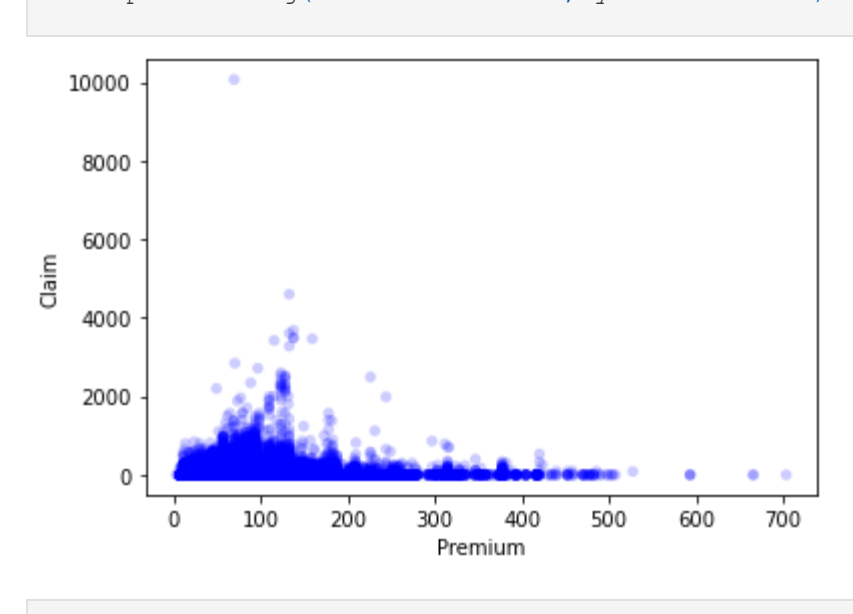


From the plot above, the model seems to be a good fit.

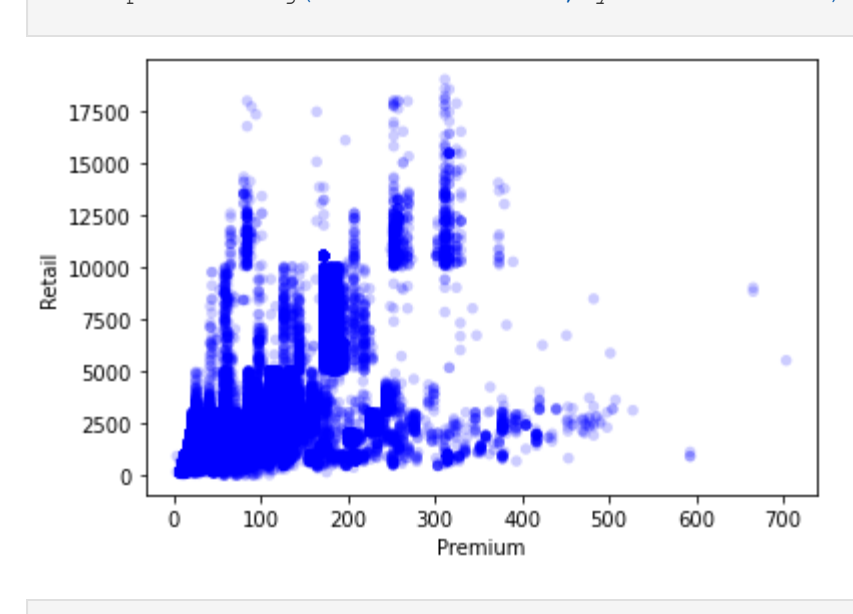
Create two scatter plots comparing two variables and provide your analysis on correlation and causation. Remeber, covariance, Pearson's correlation, and Non-Linear Relationships should be considered during your analysis.

In [74]:
```python
df_contract = df_variables['ContractCostAmount']
df_claim = df_variables['ClaimAmount']
df_retail = df_variables['ProductRetailAmount']
```

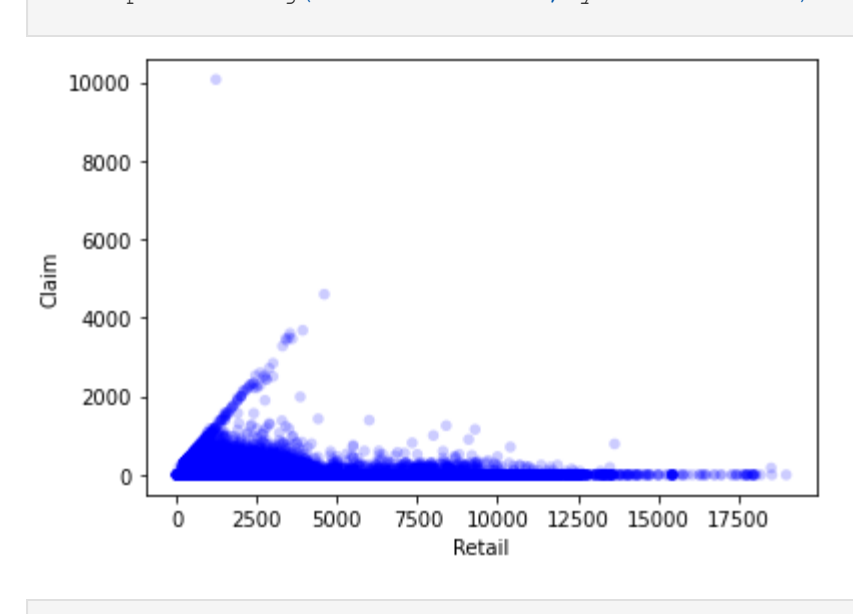
In [75]:
```python
thinkplot.Scatter(df_contract, df_claim)
thinkplot.Config(xlabel='Premium', ylabel='Claim')
```



In [76]:
```python
thinkplot.Scatter(df_contract, df_retail)
thinkplot.Config(xlabel='Premium', ylabel='Retail')
```



In [77]:
```python
thinkplot.Scatter(df_retail, df_claim)
thinkplot.Config(xlabel='Retail', ylabel='Claim')
```



In [78]:
```python
def Cov(xs, ys, meanx=None, meany=None):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    if meanx is None:
        meanx = np.mean(xs)
    if meany is None:
        meany = np.mean(ys)

    cov = np.dot(xs-meanx, ys-meany) / len(xs)
    return cov
```

In [79]:
```python
def Corr(xs, ys):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    meanx, varx = thinkstats2.MeanVar(xs)
    meany, vary = thinkstats2.MeanVar(ys)

    corr = Cov(xs, ys, meanx, meany) / np.sqrt(varx * vary)
    return corr
```

In [80]:
```python
def SpearmanCorr(xs, ys):
    xranks = pd.Series(xs).rank()
    yranks = pd.Series(ys).rank()
    return Corr(xranks, yranks)
```

Covariance, Correlation and Spearman Correlation when testing the cost of the warranty contract to claims on the product:

In [81]:
```python
Cov(df_contract, df_claim)
```

Out[81]: 149.30988418245076

With the positive covariance, there will be more claims as we sell more warranties, both variables will move in the same direction as they change.

In [82]:
```python
Corr(df_contract, df_claim)
```

Out[82]: 0.07639866230030148

Since the correltaion is pretty low, it's showing that not all contracts will product a claim. Which is positive thing. To test further, you could run the correlations between each product to claims experience to find the product or even manufacturer with most potential to produce a claim. The look at the possibility of not covering that particular item.

In [83]:
```python
SpearmanCorr(df_contract, df_claim)
```

Out[83]: 0.09263744970197775

Again, shows the correlation is low when looking at the popualtion as a whole.

Covariance, Correlation and Spearman Correlation when testing the cost of the warranty contract to retail price of the product:

In [84]:
```python
Cov(df_contract, df_retail)
```

Out[84]: 25962.373506807635

In [85]:
```python
Corr(df_contract, df_retail)
```

Out[85]: 0.7055280698915519

In [86]:
```python
SpearmanCorr(df_contract, df_retail)
```

Out[86]: 0.7333165225840887

Covariance, Correlation and Spearman Correlation when testing retail price of the product to claims:

In [87]:
```python
Cov(df_retail, df_claim)
```

Out[87]: 3054.644804140891

In [88]:
```python
Corr(df_retail, df_claim)
```

Out[88]: 0.048319763400857176

In [89]:
```python
SpearmanCorr(df_retail, df_claim)
```

Out[89]: 0.06733096051930627

Conduct a test on your hypothesis using on the methonds covered in Chapter 9.

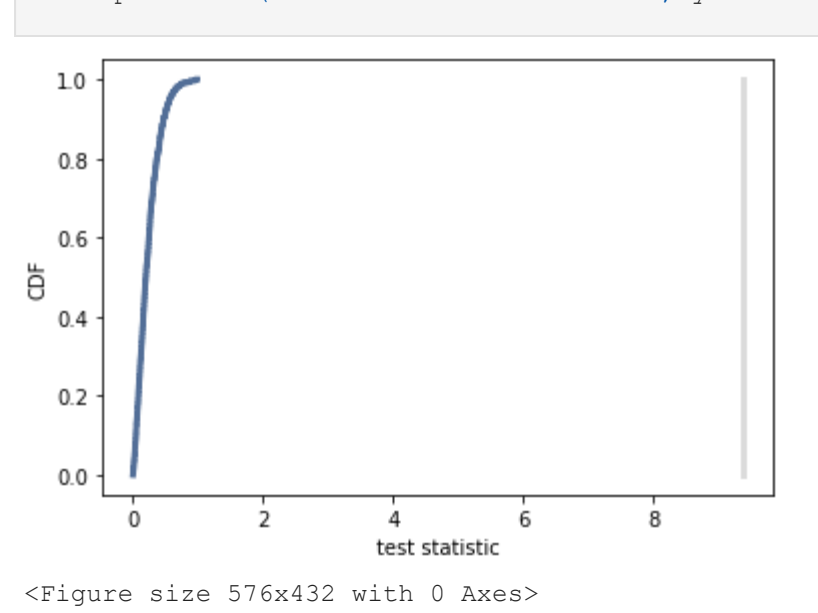
In [90]:
```python
class DiffMeansPermute(thinkstats2.HypothesisTest):

    def TestStatistic(self, data):
        group1, group2 = data
        test_stat = abs(group1.mean() - group2.mean())
        return test_stat

    def MakeModel(self):
        group1, group2 = self.data
        self.n, self.m = len(group1), len(group2)
        self.pool = np.hstack((group1, group2))

    def RunModel(self):
        np.random.shuffle(self.pool)
        data = self.pool[:self.n], self.pool[self.n:]
        return data
```

In [91]:
```python
df_claim_ = df_variables_fridge['ClaimAmount'].values, df_variables_washer['ClaimAmount'].values
```

In [92]:
```python
ht = DiffMeansPermute(df_claim_)
pvalue = ht.PValue()
pvalue
```

Out[92]: 0.0

In [93]:
```python
ht.PlotCdf()
thinkplot.Show(xlabel = 'test statistic', ylabel = 'CDF')
```




```
<Figure size 576x432 with 0 Axes>
```

For this project, conduct a regression analysis on either one dependent and one explanatory variable, or multiple explanatory variables (Chapter 10 & 11).

In [94]:
```python
formula = 'df_variables["ContractCostAmount"] ~ df_variables["ClaimAmount"]'
model = smf.ols(formula, data=df_variables)
results = model.fit()
results.summary()
```

Out[94]:

OLS Regression Results

Dep. Variable:	df_variables["ContractCostAmount"]	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	0.006
Method:	Least Squares	**F-statistic:**	3299.
Date:	Sat, 19 Nov 2022	**Prob (F-statistic):**	0.00
Time:	00:15:35	**Log-Likelihood:**	-2.7729e+06
No. Observations:	561962	**AIC:**	5.546e+06
Df Residuals:	561960	**BIC:**	5.546e+06
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	74.9796	0.046	1643.251	0.000	74.890	75.069
df_variables["ClaimAmount"]	0.0445	0.001	57.439	0.000	0.043	0.046

Omnibus:	216644.764	**Durbin-Watson:**	1.738
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2157554.731
Skew:	1.577	**Prob(JB):**	0.00
Kurtosis:	12.066	**Cond. No.**	59.9

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Outcome of EDA

The below questions will help address the main question of: *How can we make dealers and products more profitable by determinig the relationships of the data points collected?*

1. Can a predictive model help project claims assumptions using historical data and trends?
2. Has there been in an increase in claims volume, or a decrease?
3. Are there regional concentrations of dealers that are performing under contract terms?
4. Can we pinpoint ill performing dealers with the model?
5. Are the claims increasing or decreasing in a certain product group?
6. Are the claims increasing or decreasing in relation to a certain product and manufacturer?
7. Is there sufficient reserves for future claims?
8. Are the warranty products priced correctly?

Within the warranty business, the process of claims is approaching real time acceptance and denial. The certificate to replace a product, service a product and pay any associated costs with the claim needs to happen within a set time frame according to contract terms. Usually within 72 hours. An example within this project case with appliances would be to determine if the product is serviceable, start the process to get a tech out to the house. If determined to be a total loss, send certificate for full replacement and any associated costs with that replacement such as food loss. I began with EDA on my data sets, determining if I have sufficient volume with 3 years of sales and claims historical. I then calculated the ultimate loss ratio to determine if the premiums outweigh the loss projections. With this information I then conducted a correlation exercise to determine what data point has the most impact on the ultimate loss ratio. These steps lead to the regression analysis on how the products will perform in the future and whether the business model is sustainable.

The earnings pattern of the warranties sold should more than cover the cost to service the product over the life of the warranty. My approach addressed many aspects of what determines to be a good profit margin (15% or greater) and an ultimate loss ratio of 73%. I can not say it will be fully addressed as there may be factors outside of my approach that I can address in future project work. When complete, a recommendation can be given as to the areas that need to be addressed to improve the products performance within the pricing model, claims costs and cost sharing.

In [95]:

```
myTable = PrettyTable(["Product", "Net Adjusted Premium", "Paid claims", "Future Claim Liability",\
                       "Ulitmate Losses", "Ultimate Loss Ratio"])

myTable.add_row(["Refridgerators", "$13,027,882", "$1,025,254", "$11,777,503", "$12,802,756", "98.3%"])
myTable.add_row(["Washers", "$6,552,717", "$463,709", "$4,942,869", "$5,406,578", "82.5%"])
myTable.add_row(["Other Appliances", "$14,911,779", "$836,660", "$9,090,615", "$9,927,275", "66.7%"])
myTable.add_row(["Television", "$495,786", "$70,009", "$335,904", "$405,912", "81.9%"])
myTable.add_row(["TOTAL", "$34,988,163", "$2,395,632", "$26,146,890", "$28,542,521", "81.6%"])

print(myTable)
```

```
+------------------+----------------------+-------------+------------------------+-----------------+-----------
----------+
|     Product      | Net Adjusted Premium | Paid claims | Future Claim Liability | Ulitmate Losses | Ultimate L
oss Ratio |
+------------------+----------------------+-------------+------------------------+-----------------+-----------
----------+
|  Refridgerators  |     $13,027,882      |  $1,025,254 |      $11,777,503       |   $12,802,756   |         98.
3%        |
|     Washers      |      $6,552,717      |   $463,709  |       $4,942,869       |    $5,406,578   |         82.
5%        |
| Other Appliances |     $14,911,779      |   $836,660  |       $9,090,615       |    $9,927,275   |         66.
7%        |
|    Television    |       $495,786       |   $70,009   |        $335,904        |     $405,912    |         81.
9%        |
|      TOTAL       |     $34,988,163      |  $2,395,632 |      $26,146,890       |   $28,542,521   |         81.
6%        |
+------------------+----------------------+-------------+------------------------+-----------------+-----------
----------+
```

We can see here from the summary table above that the Ultimate Loss Ratio is above the target 73% for the book of business. The formula = Ultimate Losses/Net Adjusted Premium = Ultimate Loss Ratio.

There are several further investigations to determine next steps but we can conclude:

1. Refrigerators are number one in all categories: total premium sold, total claims and loss ratio. Followed by washers, number 2 in sales and number 3 in loss ratio. These 2 products make up more than 50% of the top 15 product groups in terms of number sold, premium collected and losses incurred.
2. Whirlpool and Frigidaire are the lowest performing manufacturers in these product groups.
3. Bray & Scarff followed by Good Deals are lowest performing dealers in the top 15.
4. Sales and claims concentration fall in 2 states, CA followed by FL.
5. The product retail price correlates to the loss amount incurred, meaning the higher the price of the item, the higher the loss claim amount is.

What do you feel was missed during the analysis?

From my EDA above, I was not able to address the reserving issues that could happen with future claim liabilites to the extent I would have liked. For Future Discovery.

Were there any variables you felt could have helped in the analysis?

There were a few limitations on how the overall operating income performance is scored. The largest being, I did not have access to the overhead expenses on servicing these dealers and products. Assumption is, as long as the Ultimate Loss Ratio remains at or below 73%, the company will be profitable. This is a big assumption as salaries and related is the second largest expense for this business model outside of losses.

Were there any assumptions made you feel were incorrect?

The assumptions I presumed, the greater the value of the product the higher the claims will be, was verified. However, I did expect a higher correlation between the product groups and claims.

What challenges did you face, what did you not fully understand?

One of the challenges I faced during this project included cleaning the data set once it was quereied from an internal SQL Database. I found that some free form data points were keyed incorrectly such as the product retail amount being $20,000 for a television etc. Another challenge I faced that I did not fullly understand was my PValue coming out as 0.0. From my understanding, a PValue of 0.0 says to reject my null hypothesis.

After reviewing all the data and performing the analysis above, the buying group in question is performing below the contractual expectation. The next steps will be to take a deeper dive into the lowest performing dealers and their product mix (large appliances seem to be the highest claims producers) to either drop coverage on certain manufacturers products or instill loss sharing within the contract per dealer. Where if their ultimate loss ratio goes above a certain threshold, such as 73%, they will share the cost of those claims. As well as review the pricing models to ensure the warranty premium is adjusting with current inflation models.