Canada Consumer Price Index

By: Tarun Kataria

In [31]:
```
import numpy as np
import pandas as pd
import sklearn as sk
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [32]:
```
cpi = pd.read_csv("canada_cpi.csv")
```

In [33]:
```
cpi.head(10)
```

Out[33]:

	Year	All-items	Food	Shelter	Household operations, furnishings and equipment	Clothing and footwear	Transportation	Gasoline	Health and personal care	Recreation, education and reading	Alcoholic beverages and tobacco products	All-items excluding food and energy	All-items excluding energy
0	1981	49.5	54.3	50.0	58.6	61.8	45.2	50.9	49.7	46.2	27.8	48.8	50.0
1	1982	54.9	58.2	56.8	64.8	65.3	51.6	61.8	55.0	50.2	32.1	54.1	54.9
2	1983	58.1	60.4	60.9	68.3	67.9	54.2	65.6	58.8	53.5	36.1	57.4	58.0
3	1984	60.6	63.7	63.3	70.5	69.5	56.5	69.4	61.1	55.3	39.1	59.6	60.4
4	1985	63.0	65.5	65.6	72.3	71.5	59.2	73.5	63.2	57.7	42.8	62.0	62.7
5	1986	65.6	68.8	67.5	74.5	73.4	61.0	65.4	65.9	60.7	47.9	65.3	65.9
6	1987	68.5	71.8	70.5	76.7	76.5	63.3	68.5	69.3	63.7	51.1	68.3	68.9
7	1988	71.2	73.7	73.8	79.6	80.5	64.5	67.9	72.3	67.3	54.9	71.5	71.9
8	1989	74.8	76.5	78.1	82.5	83.7	67.8	72.1	75.5	70.3	59.9	75.5	75.6

The Quantitative/Numerical variables is Year and all the items provided in the data such as all-items, Food and shelter Ordinal Variabls Is

the year as years are layed out in order from 1981 to 2018 in the entire dataset Ordinal data is the CPI scores that are between 40-100

In [34]:
```
#B)
pd.DataFrame({'mean' : cpi.mean(),
'Sd' : cpi.std(),
'min' : cpi.min(),
'max' : cpi.max(),
'median' : cpi.median(),
'length' : len(cpi),
'miss.val': cpi.isnull().sum(),
})
```

Out[34]:

	mean	Sd	min	max	median	length	miss.val
Year	1999.500000	11.113055	1981.0	2018.0	1999.50	38	0
All-items	95.144737	23.541243	49.5	133.4	94.15	38	0
Food	98.331579	26.386843	54.3	145.3	92.65	38	0
Shelter	98.652632	25.263720	50.0	140.9	93.95	38	0
Household operations, furnishings and equipment	95.236842	16.856075	58.6	123.2	96.25	38	0
Clothing and footwear	89.989474	10.919256	61.8	100.7	94.35	38	0
Transportation	94.352632	27.353460	45.2	139.1	94.90	38	0
Gasoline	109.647368	42.183664	50.9	183.8	92.60	38	0
Health and personal care	94.213158	21.328032	49.7	125.9	96.20	38	0
Recreation, education and reading	88.392105	19.851930	46.2	115.3	95.85	38	0
Alcoholic beverages and tobacco products	94.039474	40.799520	27.8	167.9	81.60	38	0
All-items excluding food and energy	93.707895	21.803934	48.8	127.9	94.75	38	0
All-items excluding energy	94.518421	22.512385	50.0	131.0	94.30	38	0
Fresh fruit and vegetables	92.621053	20.059522	57.2	135.8	89.40	38	0
Energy	103.405263	37.131948	46.8	165.3	91.90	38	0
Goods	93.815789	18.738262	53.8	121.1	94.55	38	0
Services	96.350000	28.567925	44.9	145.8	93.70	38	0

C.

i. Which variables have the largest variabilities?

Answer:Gasoline, Alcoholic beverages and tobacco products and Energy have the largest variablities. Data in 'Gasoline' varies from approximately 30 to 185 unit. Data in 'Alcoholic beverages and tobacco' varies from approximately 20 to 170 unit. Data in 'Energy' varies from approximately 20 to 165 unit.

ii. Which variables were seen skewed?

Answer: The variables were both positively and negatively skewed. They are listed below:

Positively skewed: All Items Foods Gasoline Alcoholic beverages and tobacco products Fresh fruit and vegetables Energy All-items excluding energy

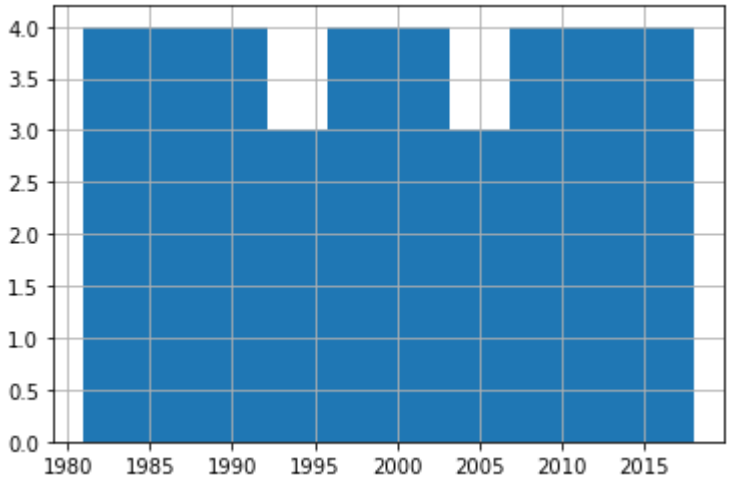
Negatively skewed: Shelter Household operations, furnishings and equipment Clothing and footwear Transportation Health and personal care Recreation, education and reading All-items excluding food and energy Goods

iii. Are there any values that seem extreme?

Answer:No, there were no extreme values found in any of the histograms.

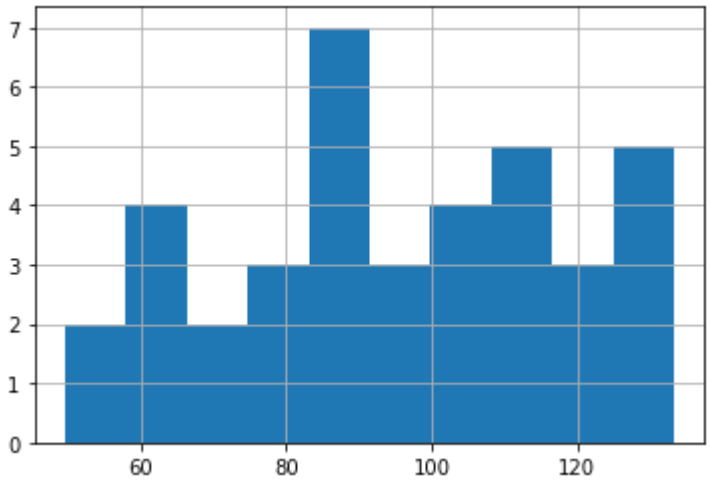
In [35]:
```
#C)#C) Creating histogrsms for years
cpi['Year'].hist()
```

Out[35]: <AxesSubplot:>



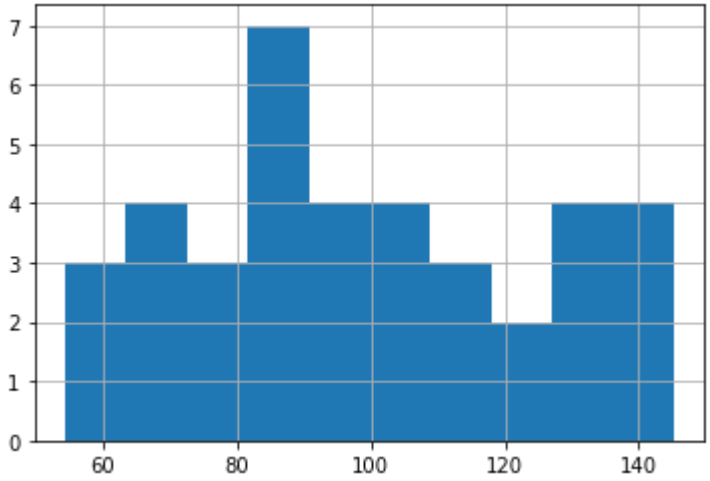
In [36]:
```
#C) Creating histogrsms for all items
cpi['All-items'].hist()
```

Out[36]: <AxesSubplot:>



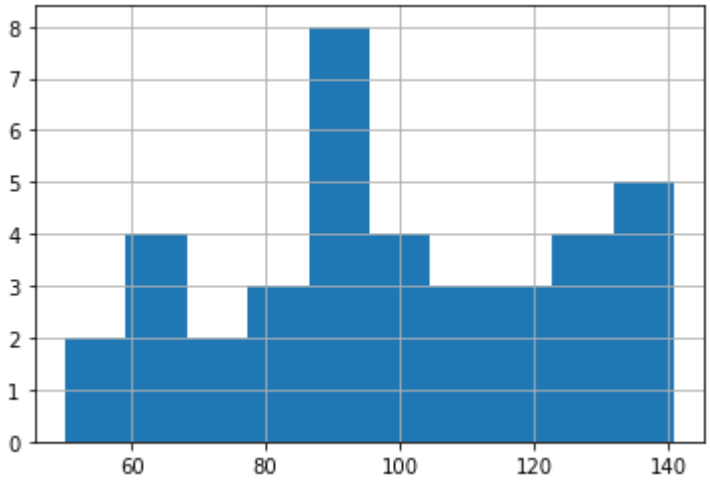
In [37]:
```
#C) Creating histogrsms for food
cpi['Food'].hist()
```

Out[37]: <AxesSubplot:>



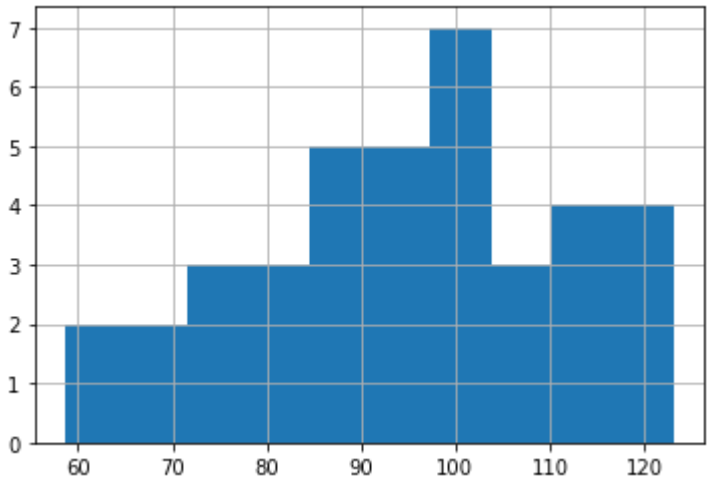
In [38]:
```
#C) Creating histogrsms for shelter
cpi['Shelter'].hist()
```

Out[38]: <AxesSubplot:>



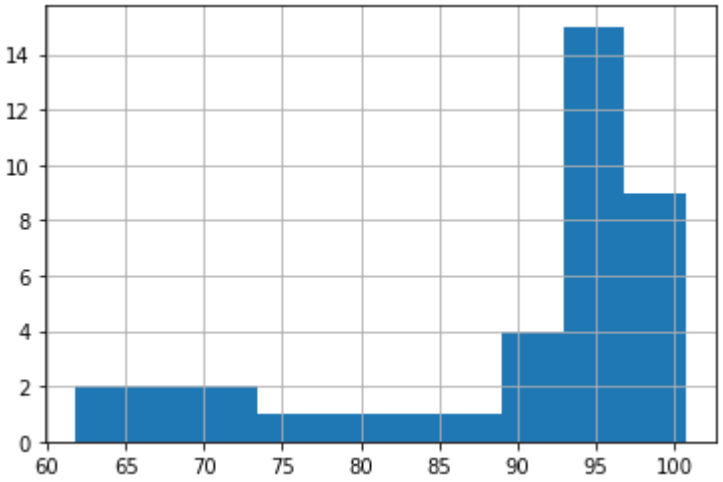
In [39]:
```
#C) Creating histogrsms for Household operations, furnishings and equipment
cpi['Household operations, furnishings and equipment'].hist()
```

Out[39]: <AxesSubplot:>



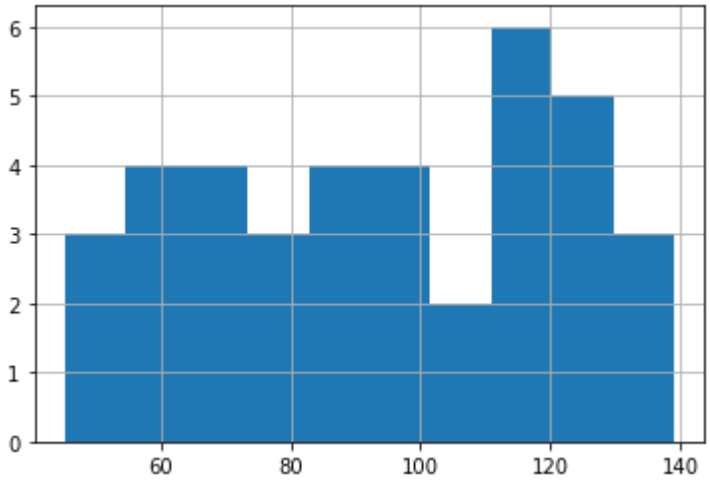
In [40]:
```
#C) Creating histogrsms for Clothing and footwear
cpi['Clothing and footwear'].hist()
```

Out[40]: <AxesSubplot:>



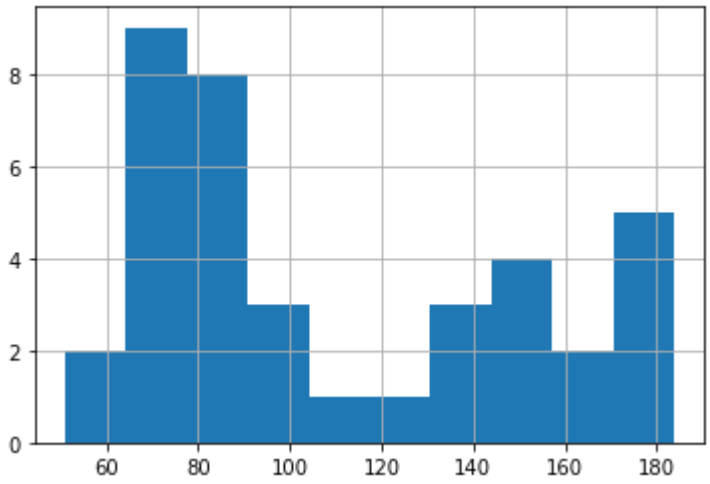
In [41]:
```
#C) Creating histogrsms for Transportation
cpi['Transportation'].hist()
```

Out[41]: <AxesSubplot:>



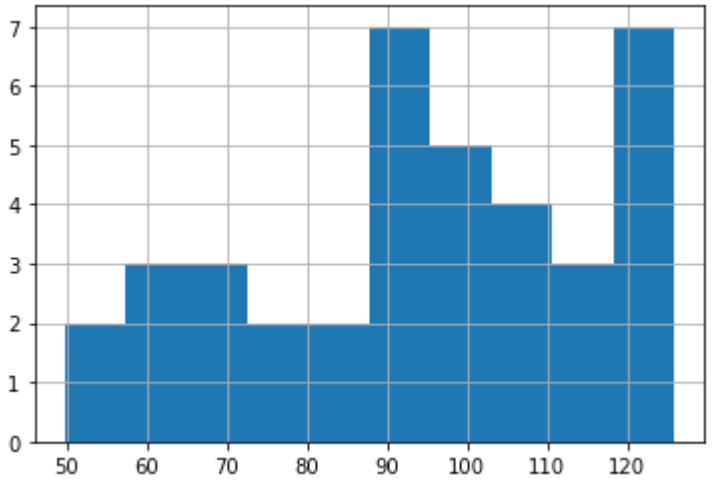
In [42]:
```
#C) Creating histogrsms for Gasoline
cpi['Gasoline'].hist()
```

Out[42]: <AxesSubplot:>



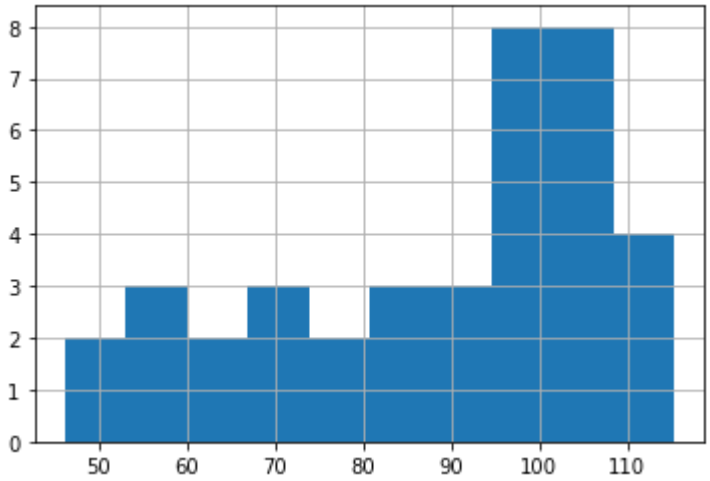
In [43]:
```
#C) Creating histogrsms for Health and personal care
cpi['Health and personal care'].hist()
```

Out[43]: <AxesSubplot:>



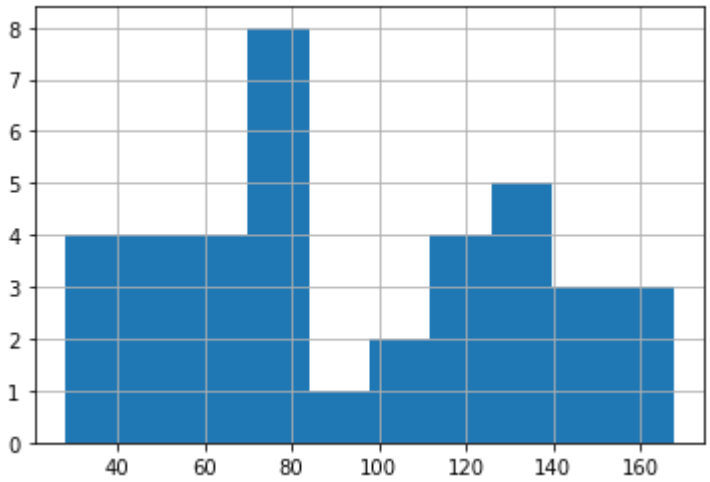
In [44]:
```
#C) Creating histogrsms for Recreation, education and reading
cpi['Recreation, education and reading'].hist()
```

Out[44]: <AxesSubplot:>



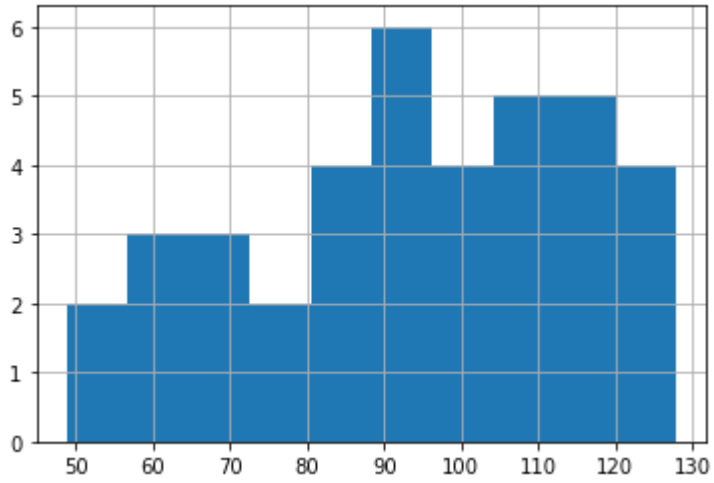
In [45]:
```
#C) Creating histogrsms for Alcoholic beverages and tobacco products
cpi['Alcoholic beverages and tobacco products'].hist()
```

Out[45]: <AxesSubplot:>



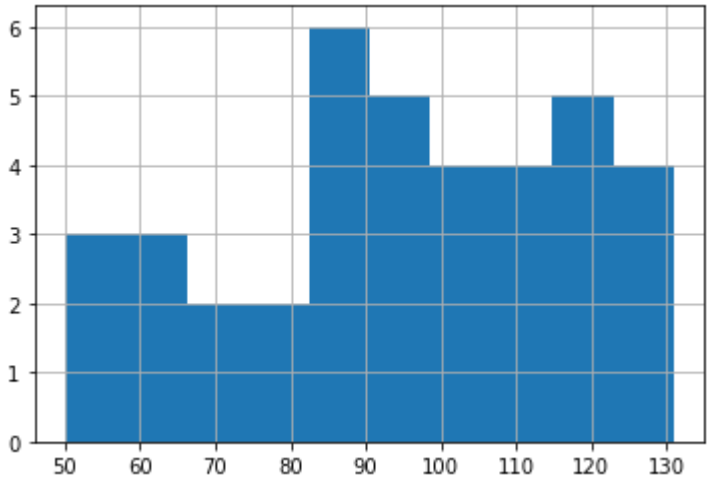
In [46]:
```
#C) Creating histogrsms for All-items excluding food and energy
cpi['All-items excluding food and energy'].hist()
```

Out[46]: <AxesSubplot:>



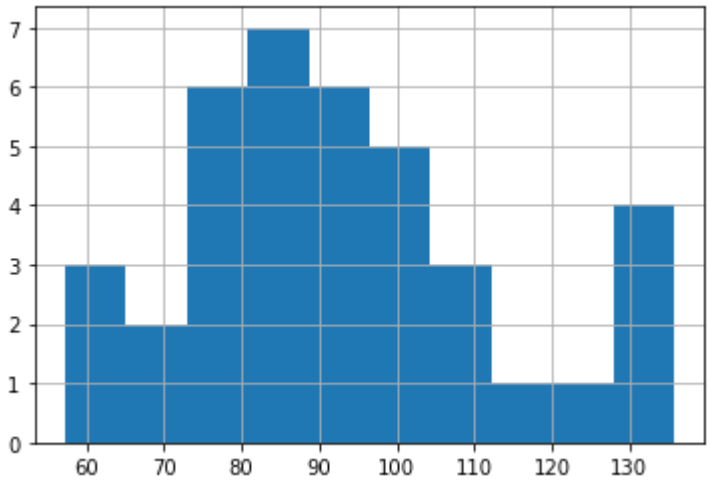
In [47]:
```
#C) Creating histogrsms for All-items excluding energy
cpi['All-items excluding energy'].hist()
```

Out[47]: <AxesSubplot:>



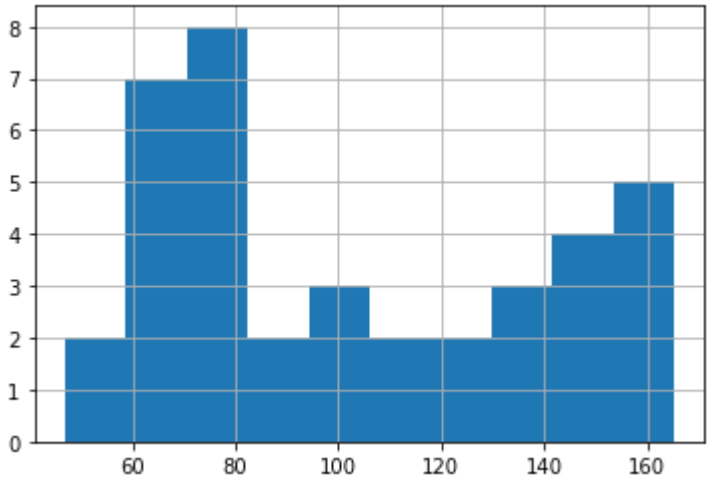
In [48]:
```
#C) Creating histogrsms for Fresh fruit and vegetables
cpi['Fresh fruit and vegetables'].hist()
```

Out[48]: <AxesSubplot:>



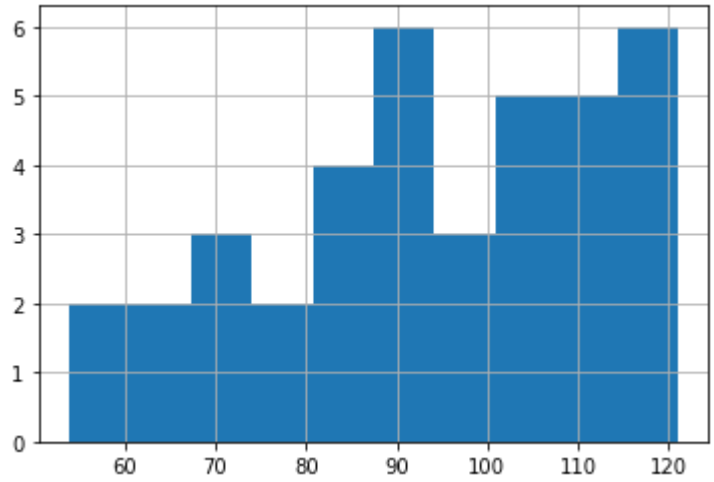
In [49]:
```
#C) Creating histogrsms for Energy
cpi['Energy'].hist()
```

Out[49]: <AxesSubplot:>



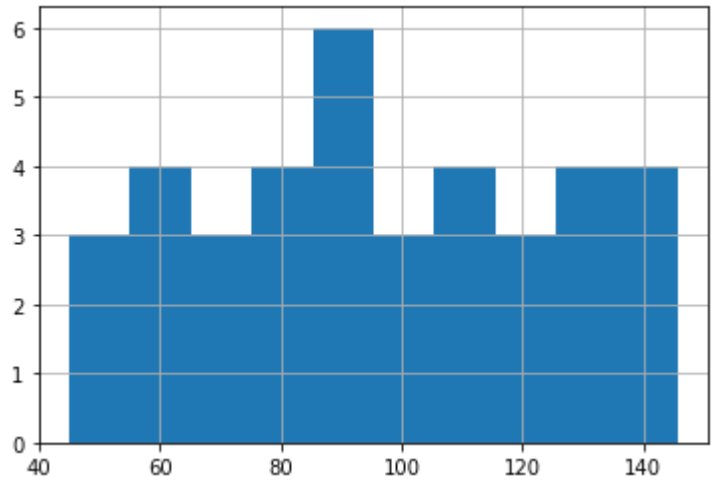
In [50]:
```
#C) Creating histogrsms for Goods
cpi['Goods'].hist()
```

Out[50]: <AxesSubplot:>



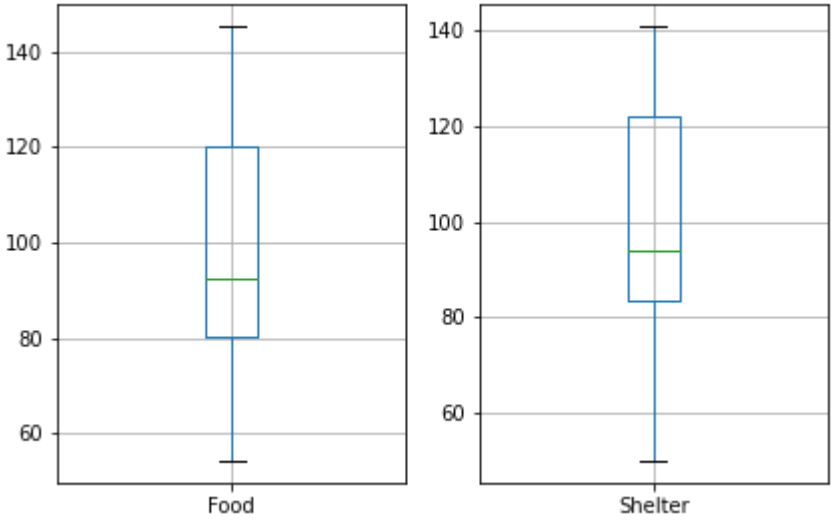
In [51]:
```
#C) Creating histogrsms for Services
cpi['Services'].hist()
```

Out[51]: <AxesSubplot:>



D.

In [52]:
```
#D)
ig, axes = plt.subplots(nrows = 1, ncols = 2)
cpi.boxplot(column='Food', ax=axes[0])
cpi.boxplot(column='Shelter', ax=axes[1])
plt.suptitle('') # Suppress the overall title
plt.tight_layout() #Increase the separation between the plots
```



This plot shows us that Food has a lower median value than shelter in the consumer price index. Food cpi is left-skewed while Shelter's CPI is right-skewed. For the box and whiskers, the top quartile of the data for food exceeds the range provided by shelter. While the bottom quartile is vice versa as the shelter's CPI range is higher than the food's CPI. In the consumer price index, the first 25 percent of shelter's data is more volatile and with lower values than the food's. Therefore the plot shows that the food's cpi range is more volatile and high. This illustrates the price of food having more dramatic increases, and shelter's prices have more dramatic decreases despite having an upward trend in the data.

In [53]:
```
corr = cpi.corr()
corr
```

Out[53]:

	Year	All-items	Food	Shelter	Household operations, furnishings and equipment	Clothing and footwear	Transportation	Gasoline	Health and personal care	Recreation, education and reading	Alcoholic beverages and tobacco products
Year	1.000000	0.995701	0.991260	0.992346	0.987645	0.667444	0.995014	0.933601	0.986205	0.962644	0.982641
All-items	0.995701	1.000000	0.988266	0.996935	0.994182	0.710931	0.992888	0.925837	0.995467	0.972545	0.983584
Food	0.991260	0.988266	1.000000	0.992703	0.983085	0.610632	0.979374	0.940707	0.974231	0.931149	0.986648
Shelter	0.992346	0.996935	0.992703	1.000000	0.988631	0.673143	0.987267	0.937754	0.988620	0.954091	0.988657
Household operations, furnishings and equipment	0.987645	0.994182	0.983085	0.988631	1.000000	0.737199	0.979990	0.893442	0.993794	0.975327	0.969071
Clothing and footwear	0.667444	0.710931	0.610632	0.673143	0.737199	1.000000	0.680540	0.456926	0.765219	0.838812	0.612204
Transportation	0.995014	0.992888	0.979374	0.987267	0.979990	0.680540	1.000000	0.944660	0.983986	0.965796	0.975756
Gasoline	0.933601	0.925837	0.940707	0.937754	0.893442	0.456926	0.944660	1.000000	0.898211	0.837325	0.940957
Health and personal care	0.986205	0.995467	0.974231	0.988620	0.993794	0.765219	0.983986	0.898211	1.000000	0.984694	0.967046
Recreation, education and reading	0.962644	0.972545	0.931149	0.954091	0.975327	0.838812	0.965796	0.837325	0.984694	1.000000	0.925606
Alcoholic beverages and tobacco products	0.982641	0.983584	0.986648	0.988657	0.969071	0.612204	0.975756	0.940957	0.967046	0.925606	1.000000
All-items excluding food and energy	0.988728	0.997068	0.975791	0.990249	0.994817	0.760596	0.986884	0.898575	0.998523	0.985630	0.972246
All-items excluding energy	0.993447	0.999299	0.985068	0.994890	0.996270	0.730962	0.989443	0.911664	0.997354	0.977907	0.979497

	Year	All-items	Food	Shelter	Household operations, furnishings and equipment	Clothing and footwear	Transportation	Gasoline	Health and personal care	Recreation, education and reading	Alcoholic beverages and tobacco products
Fresh fruit and vegetables	0.946020	0.948535	0.971481	0.956083	0.958614	0.592555	0.920237	0.868496	0.934988	0.885650	0.956424
Energy	0.968036	0.961120	0.968333	0.968621	0.934241	0.531441	0.974361	0.991099	0.937770	0.889230	0.970650
Goods	0.985586	0.995455	0.970613	0.987889	0.991051	0.764518	0.987743	0.905194	0.996684	0.985128	0.970869
Services	0.997506	0.998043	0.994896	0.997856	0.991414	0.672694	0.991422	0.934373	0.989785	0.959775	0.986890

In [54]:
```
# E) correlation plot
corr = cpi.head(10).corr()
sns.heatmap(corr)
```

Out[54]: <AxesSubplot:>

Which pair of variables are most strongly correlated?

The pair of variables where the correlation coefficient (r) value is greater than 0.7 are generally considered the most strongly correlated variables. E.g., (Food, Shelter)

How can we reduce the number of variables based on these correlations?

we can remove the variables that are highly correlated.

How would the correlations change if we normalized the data first?

Normalization does not affect the correlation between variables. They remain exactly the same. The correlation captures the synchronization of the direction of the variables. There is nothing in normalization that does change the direction of the variables.

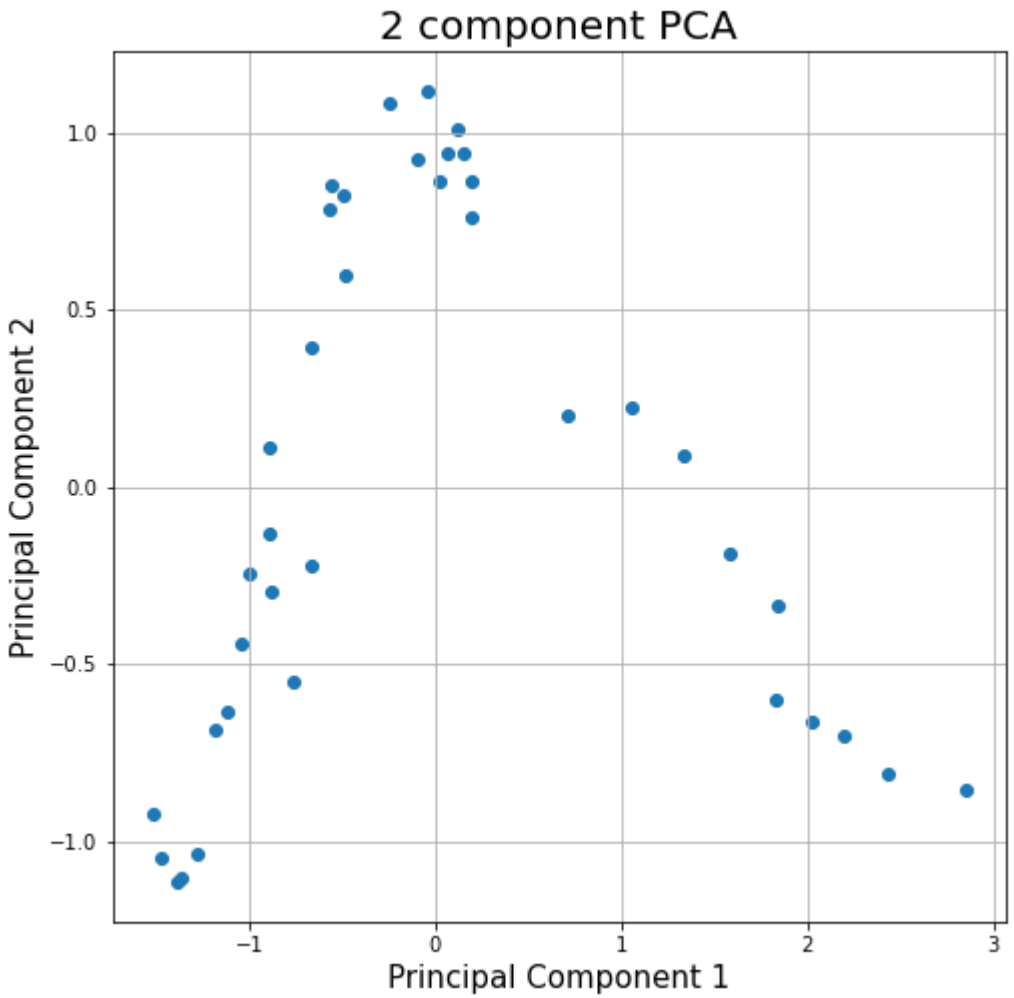
PCA

In [55]:
```
features = ['Gasoline', 'Clothing and footwear']
# Separating out the features
x = cpi.loc[:, features].values
# Standardizing the features
x = StandardScaler().fit_transform(x)
```

In [56]:
```
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
```

In [57]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
ax.scatter(principalDf['principal component 1']
               , principalDf['principal component 2'])
ax.grid()
```



In [58]:
```
1 principalDf.tail()
```

Out[58]:

	principal component 1	principal component 2
33	-1.470372	-1.048977
34	-1.045827	-0.440676
35	-0.876416	-0.297516
36	-1.119266	-0.632244
37	-1.516615	-0.924590

In [59]:
```
1 print('Explained variation per principal component: {}'.format(pca.explained_variance_ratio_))
```

```
Explained variation per principal component: [0.72846312 0.27153688]
```

From the above output, we can observe that the principal component 1 holds 72.8% of the information while the principal component 2 holds only 27.2% of the information.