# Commodity Prices and EM's Political, Country, Sovereign Risk Analysis

**This analysis will delve into the impact the risk variables explored in the original analysis regarding EM's Economic Output and focus how a certain EM's Country, Political, and Sovereign risk impact commodity prices.**

# Data Importing and Visualization and Exploring Key Variables

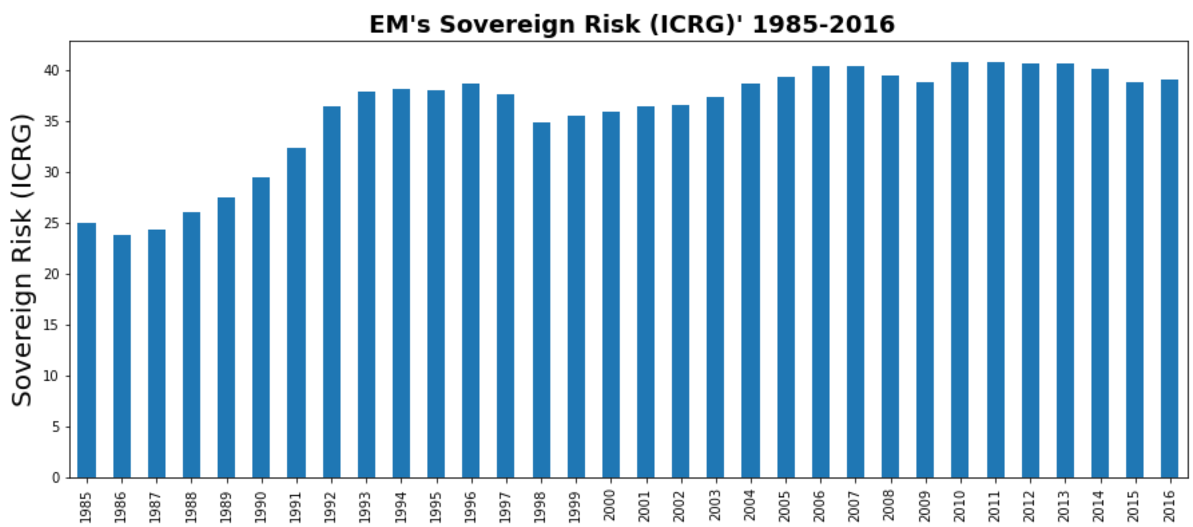
In [164]:
```
import pandas as pd
import numpy as np

year=[1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,19
99,2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,
2015,2016]
prices=[ 96.2167, 96.675, 102.208, 131.117, 132.325, 124.025, 117.042, 113.858
, 108.258, 126.508, 137.575, 134.35, 131.667, 114.4, 98.4833, 99.9917, 96.375,
97.3167, 104.858, 125.783, 140.392, 182.825, 206.525, 256.033, 212.742, 256.04
2, 302.0, 276.783, 258.183, 242.508, 201.575, 200.083]
SovereignRisk=[ 25.0, 23.76, 24.28, 26.08, 27.45, 29.4, 32.38, 36.46, 37.83, 3
8.13, 38.0, 38.71, 37.59, 34.79, 35.45, 35.88, 36.36, 36.55, 37.32, 38.69, 39.
36, 40.31, 40.38, 39.49, 38.74, 40.73, 40.79, 40.56, 40.65, 40.08, 38.79, 39.0
4]
PoliticalRisk=[ 54.61, 53.25, 53.35, 53.61, 54.13, 55.37, 56.62, 60.37, 63.31,
66.68, 67.05, 68.0, 70.12, 68.56, 65.19, 64.43, 66.72, 65.84, 66.74, 67.77, 6
7.67, 67.69, 67.25, 66.6, 66.45, 65.86, 64.73, 63.87, 63.51, 63.17, 63.03, 63.
67]
CountryRisk=[ 41.81, 40.98, 41.29, 41.6, 41.82, 42.73, 43.96, 46.59, 48.84, 5
1.15, 51.37, 52.23, 53.15, 51.06, 48.8, 50.46, 51.62, 50.91, 51.85, 53.08, 53.
08, 53.36, 53.4, 52.61, 50.27, 51.08, 50.96, 50.43, 50.36, 50.04, 49.74, 49.62
]
ExportsEM=[ 94.05, 90.76, 91.12, 90.37, 90.79, 91.38, 90.2, 89.55, 89.02, 89.2
, 89.65, 90.02, 89.98, 88.16, 88.97, 91.41, 90.75, 90.91, 92.02, 93.63, 95.73,
97.47, 98.23, 100.32, 96.56, 98.76, 100.78, 100.0, 100.13, 99.54, 95.25, 94.62
]
ImportsIE=[ 96.56, 94.15, 94.53, 93.76, 94.16, 94.76, 93.87, 93.43, 93.04, 93.
05, 93.22, 93.61, 93.58, 92.2, 92.7, 94.53, 94.09, 94.24, 94.88, 95.91, 97.3,
98.36, 98.81, 100.08, 97.79, 99.25, 100.51, 100.0, 100.14, 99.78, 96.91, 96.53
]
ImportsEM=[63.21, 50.17, 51.17, 50.21, 51.4, 52.15, 46.5, 45.04, 42.92, 45.24,
47.52, 47.57, 47.77, 41.05, 41.74, 49.11, 46.65, 47.37, 51.51, 59.23, 68.47, 8
0.36, 85.77, 100.88, 77.56, 94.3, 109.65, 100.0, 101.39, 96.84, 71.62, 70.38]


PriceRiskIMEX=pd.DataFrame({'Commodity Prices':prices,'Sovereign Risk':Soverei
gnRisk,'Political Risk':PoliticalRisk,'Country Risk':CountryRisk,'ImportsIE':I
mportsIE,'ExportsEM':ExportsEM,'ImportsEM':ImportsEM},index=year)
PriceRiskIMEX
```

Out[164]:

| | Commodity Prices | Sovereign Risk | Political Risk | Country Risk | ImportsIE | ExportsEM | ImportsEM |
|---|---|---|---|---|---|---|---|
| **1985** | 96.2167 | 25.00 | 54.61 | 41.81 | 96.56 | 94.05 | 63.21 |
| **1986** | 96.6750 | 23.76 | 53.25 | 40.98 | 94.15 | 90.76 | 50.17 |
| **1987** | 102.2080 | 24.28 | 53.35 | 41.29 | 94.53 | 91.12 | 51.17 |
| **1988** | 131.1170 | 26.08 | 53.61 | 41.60 | 93.76 | 90.37 | 50.21 |
| **1989** | 132.3250 | 27.45 | 54.13 | 41.82 | 94.16 | 90.79 | 51.40 |
| **1990** | 124.0250 | 29.40 | 55.37 | 42.73 | 94.76 | 91.38 | 52.15 |
| **1991** | 117.0420 | 32.38 | 56.62 | 43.96 | 93.87 | 90.20 | 46.50 |
| **1992** | 113.8580 | 36.46 | 60.37 | 46.59 | 93.43 | 89.55 | 45.04 |
| **1993** | 108.2580 | 37.83 | 63.31 | 48.84 | 93.04 | 89.02 | 42.92 |
| **1994** | 126.5080 | 38.13 | 66.68 | 51.15 | 93.05 | 89.20 | 45.24 |
| **1995** | 137.5750 | 38.00 | 67.05 | 51.37 | 93.22 | 89.65 | 47.52 |
| **1996** | 134.3500 | 38.71 | 68.00 | 52.23 | 93.61 | 90.02 | 47.57 |
| **1997** | 131.6670 | 37.59 | 70.12 | 53.15 | 93.58 | 89.98 | 47.77 |
| **1998** | 114.4000 | 34.79 | 68.56 | 51.06 | 92.20 | 88.16 | 41.05 |
| **1999** | 98.4833 | 35.45 | 65.19 | 48.80 | 92.70 | 88.97 | 41.74 |
| **2000** | 99.9917 | 35.88 | 64.43 | 50.46 | 94.53 | 91.41 | 49.11 |
| **2001** | 96.3750 | 36.36 | 66.72 | 51.62 | 94.09 | 90.75 | 46.65 |
| **2002** | 97.3167 | 36.55 | 65.84 | 50.91 | 94.24 | 90.91 | 47.37 |
| **2003** | 104.8580 | 37.32 | 66.74 | 51.85 | 94.88 | 92.02 | 51.51 |
| **2004** | 125.7830 | 38.69 | 67.77 | 53.08 | 95.91 | 93.63 | 59.23 |
| **2005** | 140.3920 | 39.36 | 67.67 | 53.08 | 97.30 | 95.73 | 68.47 |
| **2006** | 182.8250 | 40.31 | 67.69 | 53.36 | 98.36 | 97.47 | 80.36 |
| **2007** | 206.5250 | 40.38 | 67.25 | 53.40 | 98.81 | 98.23 | 85.77 |
| **2008** | 256.0330 | 39.49 | 66.60 | 52.61 | 100.08 | 100.32 | 100.88 |
| **2009** | 212.7420 | 38.74 | 66.45 | 50.27 | 97.79 | 96.56 | 77.56 |
| **2010** | 256.0420 | 40.73 | 65.86 | 51.08 | 99.25 | 98.76 | 94.30 |
| **2011** | 302.0000 | 40.79 | 64.73 | 50.96 | 100.51 | 100.78 | 109.65 |
| **2012** | 276.7830 | 40.56 | 63.87 | 50.43 | 100.00 | 100.00 | 100.00 |
| **2013** | 258.1830 | 40.65 | 63.51 | 50.36 | 100.14 | 100.13 | 101.39 |
| **2014** | 242.5080 | 40.08 | 63.17 | 50.04 | 99.78 | 99.54 | 96.84 |
| **2015** | 201.5750 | 38.79 | 63.03 | 49.74 | 96.91 | 95.25 | 71.62 |
| **2016** | 200.0830 | 39.04 | 63.67 | 49.62 | 96.53 | 94.62 | 70.38 |

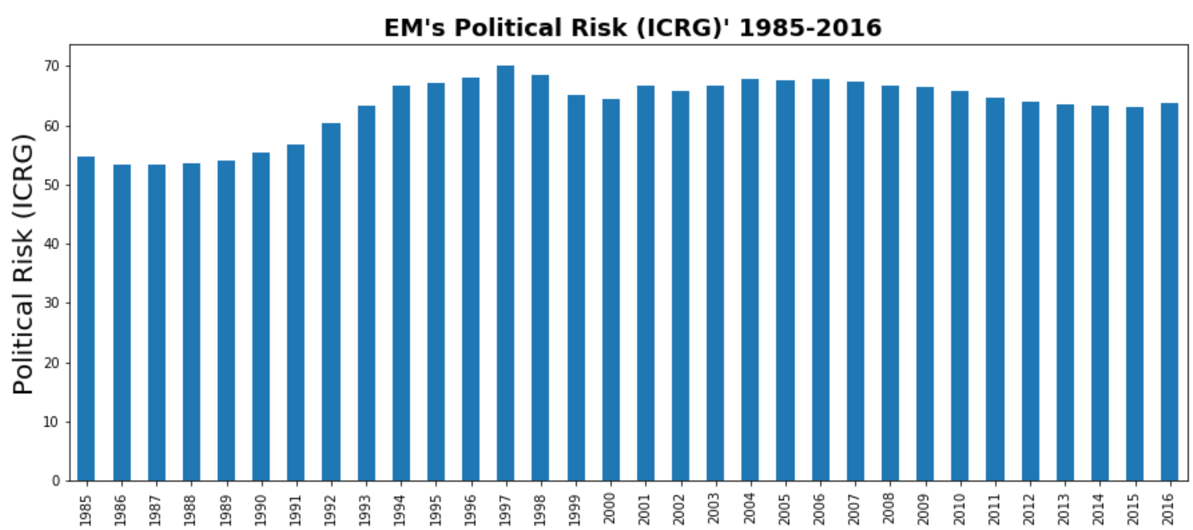
In [165]:
```
import numpy as np
import matplotlib.pyplot as plt
from pylab  import figure

%matplotlib inline

fig,axe = plt.subplots()
PriceRiskIMEX['Sovereign Risk'].plot.bar(figsize =(15,6))
axe.set_ylabel('Sovereign Risk (ICRG)', fontsize=20)
axe.set_title(" EM's Sovereign Risk (ICRG)' 1985-2016", loc='center', fontsize
=18, fontweight = "bold" )
```

Out[165]: Text(0.5, 1.0, " EM's Sovereign Risk (ICRG)' 1985-2016")



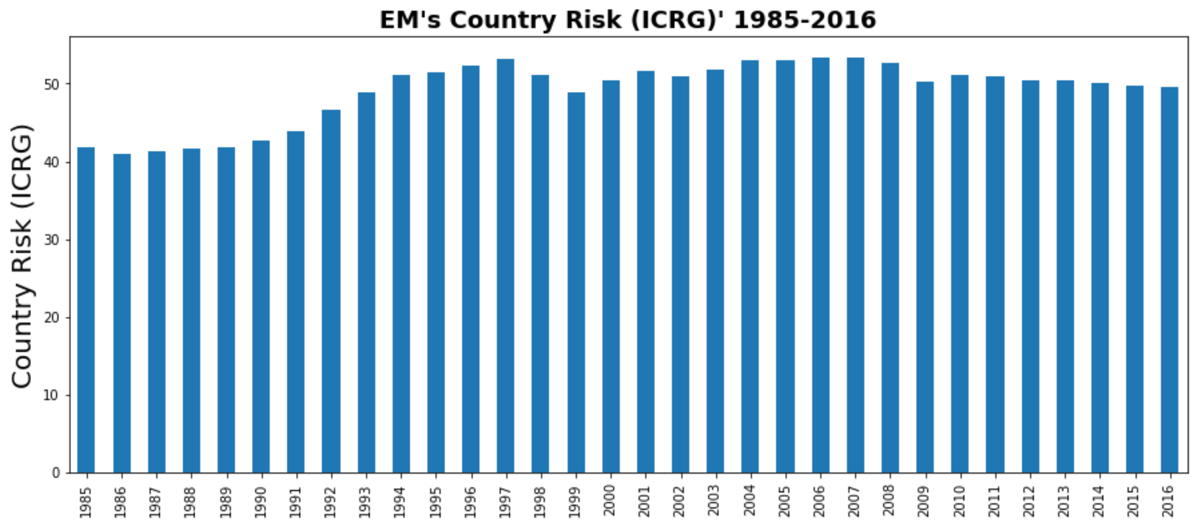

In [166]:
```
fig, axe = plt.subplots()
PriceRiskIMEX[ 'Political Risk'].plot.bar(figsize =(15,6))
axe.set_ylabel('Political Risk (ICRG)', fontsize=20)
axe.set_title(" EM's Political Risk (ICRG)' 1985-2016", loc='center', fontsize
=18, fontweight = "bold" )
```

Out[166]: Text(0.5, 1.0, " EM's Political Risk (ICRG)' 1985-2016")



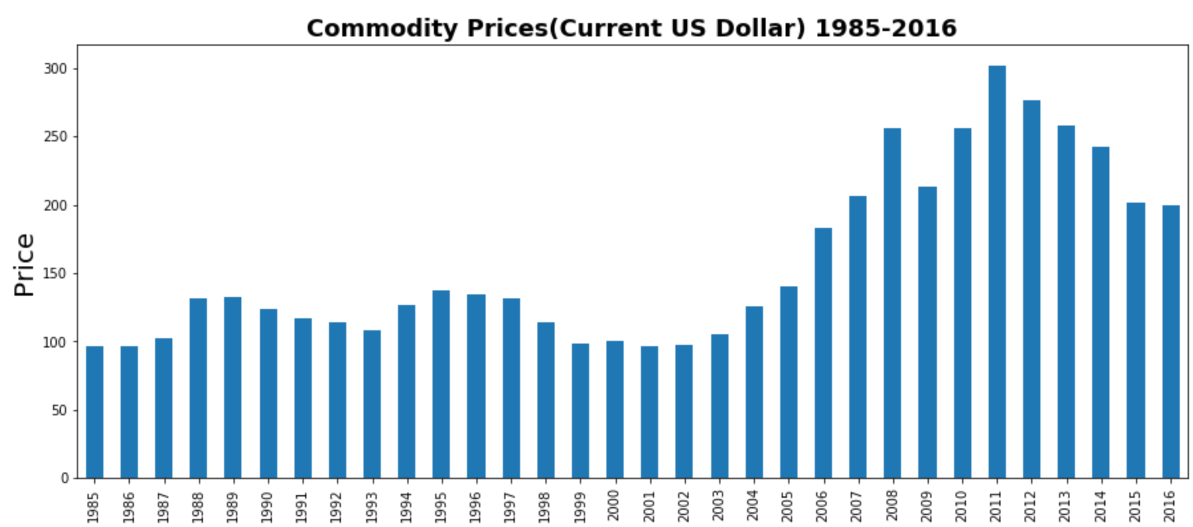
In [167]:
```
fig, axe = plt.subplots()
PriceRiskIMEX[ 'Country Risk'].plot.bar(figsize =(15,6))
axe.set_ylabel('Country Risk (ICRG)', fontsize=20)
axe.set_title("EM's Country Risk (ICRG)' 1985-2016", loc='center', fontsize=18
, fontweight = "bold" )
```

Out[167]:
```
Text(0.5, 1.0, "EM's Country Risk (ICRG)' 1985-2016")
```



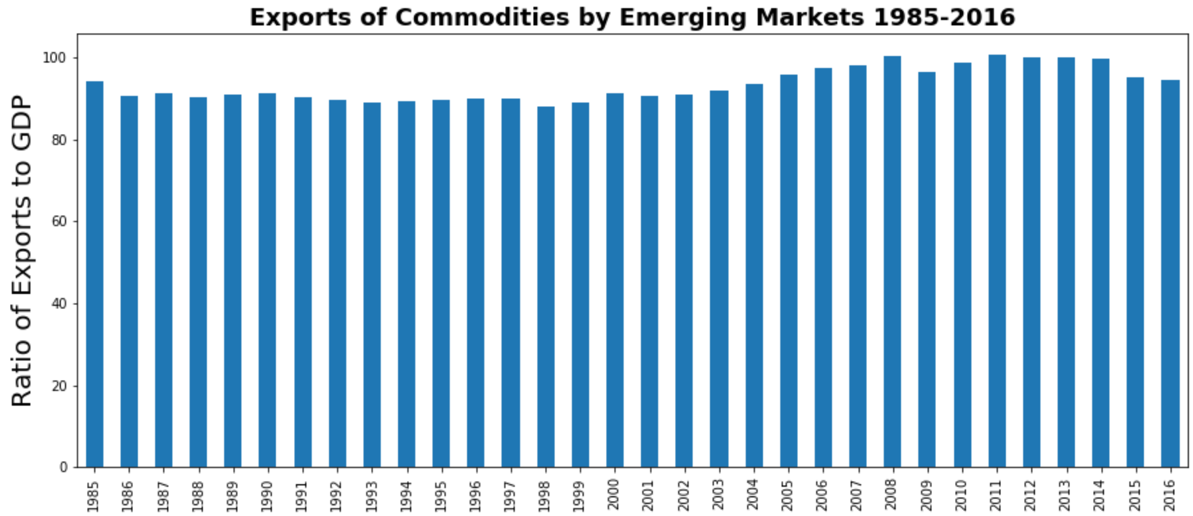

In [168]:
```
fig, axe = plt.subplots()
PriceRiskIMEX[ 'Commodity Prices'].plot.bar(figsize =(15,6))
axe.set_ylabel('Price', fontsize=20)
axe.set_title("Commodity Prices(Current US Dollar) 1985-2016", loc='center', f
ontsize=18, fontweight = "bold" )
```

Out[168]:
```
Text(0.5, 1.0, 'Commodity Prices(Current US Dollar) 1985-2016')
```



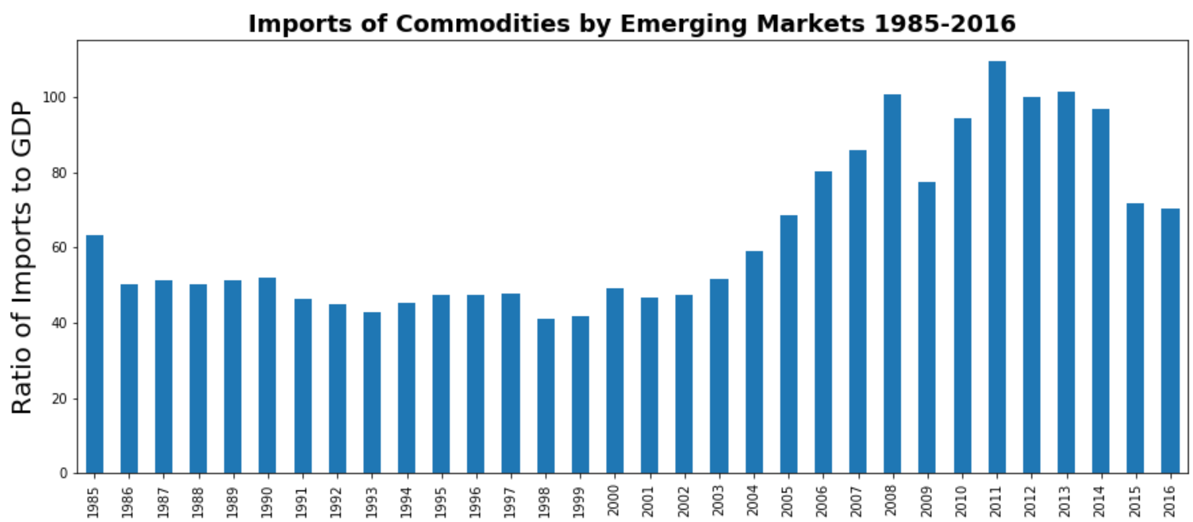
In [169]:
```
fig, axe = plt.subplots()
PriceRiskIMEX['ExportsEM'].plot.bar(figsize =(15,6))
axe.set_ylabel('Ratio of Exports to GDP', fontsize=20)
axe.set_title("Exports of Commodities by Emerging Markets 1985-2016", loc='center', fontsize=18, fontweight = "bold" )
```

Out[169]: Text(0.5, 1.0, 'Exports of Commodities by Emerging Markets 1985-2016')



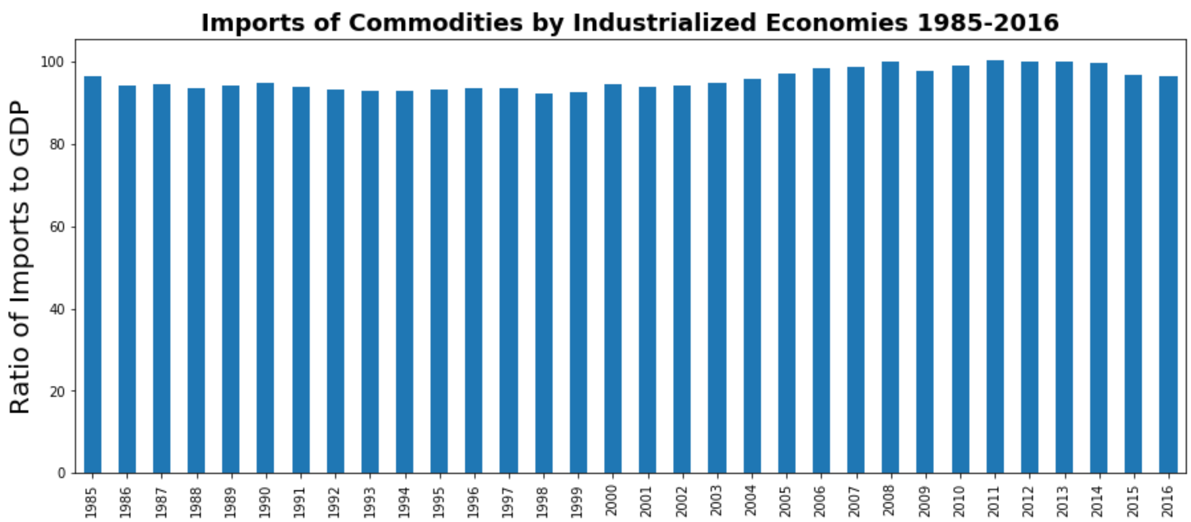

In [170]:
```
fig, axe = plt.subplots()
PriceRiskIMEX['ImportsEM'].plot.bar(figsize =(15,6))
axe.set_ylabel('Ratio of Imports to GDP', fontsize=20)
axe.set_title("Imports of Commodities by Emerging Markets 1985-2016", loc='center', fontsize=18, fontweight = "bold" )
```

Out[170]: Text(0.5, 1.0, 'Imports of Commodities by Emerging Markets 1985-2016')

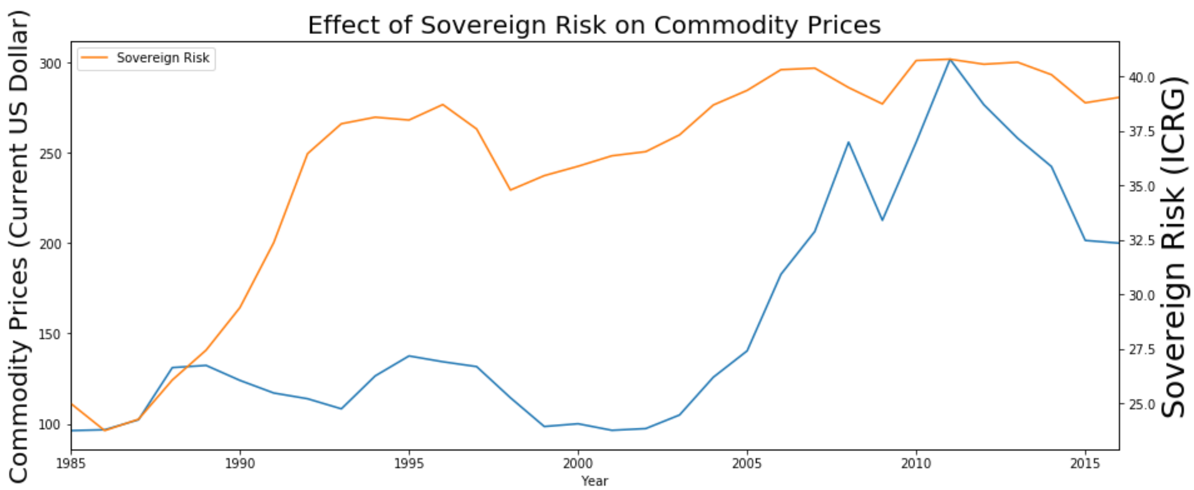


In [171]:
```
fig, axe = plt.subplots()
PriceRiskIMEX['ImportsIE'].plot.bar(figsize =(15,6))
axe.set_ylabel('Ratio of Imports to GDP', fontsize=20)
axe.set_title("Imports of Commodities by Industrialized Economies 1985-2016",
loc='center', fontsize=18, fontweight = "bold" )
```

Out[171]:
```
Text(0.5, 1.0, 'Imports of Commodities by Industrialized Economies 1985-201
6')
```

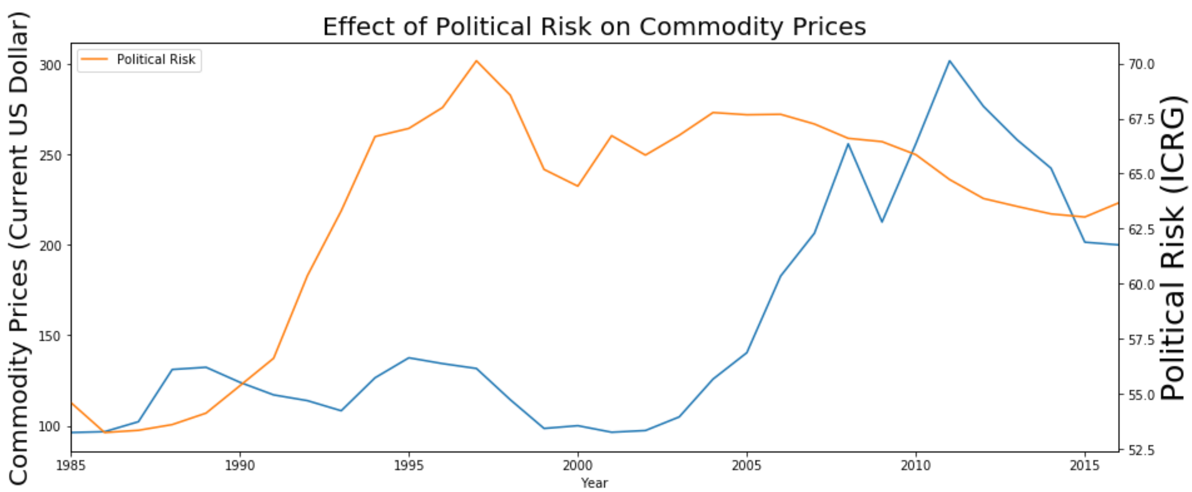


In [172]:
```
import matplotlib.pyplot as plt
from pylab import figure
%matplotlib inline

ax=PriceRiskIMEX['Commodity Prices'].plot(label='Prices',figsize=(15,6))
ax.set_ylabel('Commodity Prices (Current US Dollar)',fontsize=20)
ax.set_xlabel('Year')


ax2=PriceRiskIMEX['Sovereign Risk'].plot(secondary_y=True,label='Sovereign Ris
k')
ax2.set_ylabel('Sovereign Risk (ICRG)',fontsize=25)

plt.legend(loc='upper left')

plt.title('Effect of Sovereign Risk on Commodity Prices',fontsize=20)

plt.figure(figsize=(10,10))
plt.show()
```



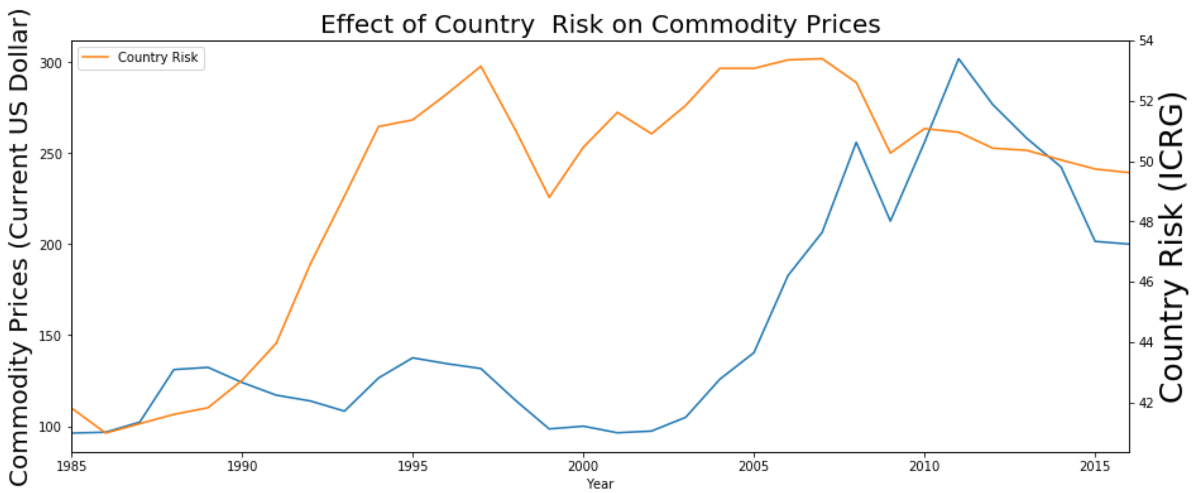

```
<Figure size 720x720 with 0 Axes>
```

In [173]:
```
ax=PriceRiskIMEX['Commodity Prices'].plot(label='Prices',figsize=(15,6))
ax.set_ylabel('Commodity Prices (Current US Dollar)',fontsize=20)
ax.set_xlabel('Year')


ax2=PriceRiskIMEX['Political Risk'].plot(secondary_y=True,label='Political Ris
k')
ax2.set_ylabel('Political Risk (ICRG)',fontsize=25)

plt.legend(loc='upper left')


plt.title('Effect of Political Risk on Commodity Prices',fontsize=20)

plt.figure(figsize=(10,10))
plt.show()
```



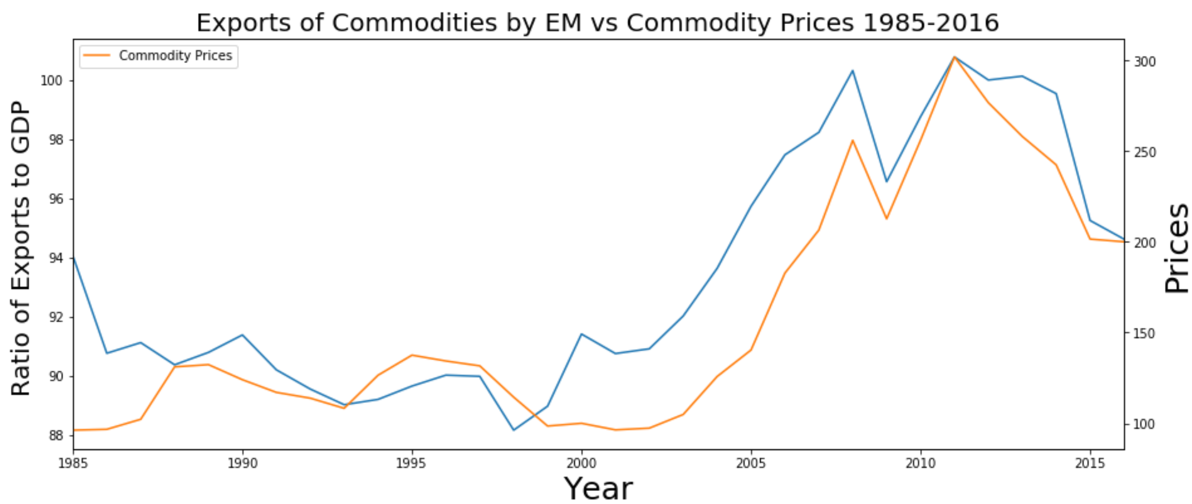

```
<Figure size 720x720 with 0 Axes>
```

In [174]:
```
ax=PriceRiskIMEX['Commodity Prices'].plot(label='Prices',figsize=(15,6))
ax.set_ylabel('Commodity Prices (Current US Dollar)',fontsize=20)
ax.set_xlabel('Year')


ax2=PriceRiskIMEX['Country Risk'].plot(secondary_y=True,label='Country Risk')
ax2.set_ylabel('Country Risk (ICRG)',fontsize=25)

plt.legend(loc='upper left')

plt.title('Effect of Country  Risk on Commodity Prices',fontsize=20)

plt.figure(figsize=(10,10))
plt.show()
```



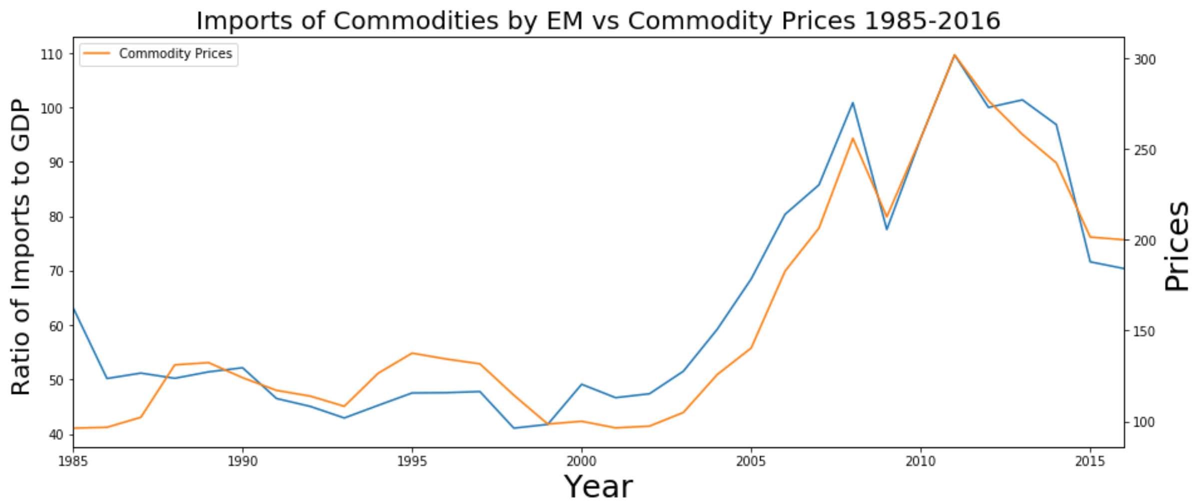

```
<Figure size 720x720 with 0 Axes>
```

In [175]:
```
ax=PriceRiskIMEX['ExportsEM'].plot(label='ExportsEM',figsize=(15,6))
ax.set_ylabel('Ratio of Exports to GDP ',fontsize=20)
ax.set_xlabel('Year',fontsize=25)
ax2=PriceRiskIMEX['Commodity Prices'].plot(secondary_y=True,label='Commodity P
rices')
ax2.set_ylabel('Prices',fontsize=25)

plt.legend(loc='upper left')
plt.title('Exports of Commodities by EM vs Commodity Prices 1985-2016',fontsiz
e=20)
plt.figure(figsize=(10,10))

plt.show()
```



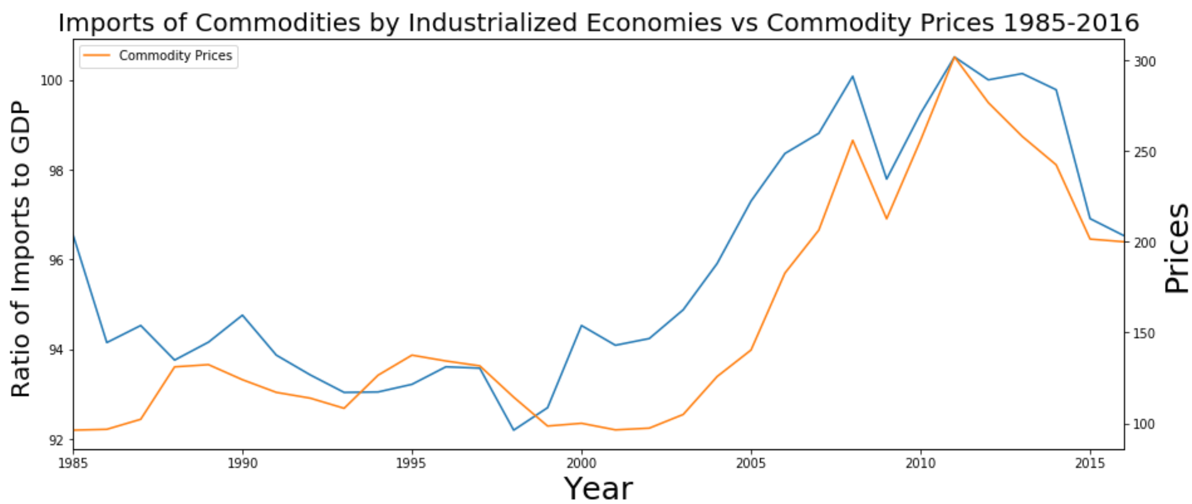

```
<Figure size 720x720 with 0 Axes>
```

In [176]:
```
ax=PriceRiskIMEX['ImportsEM'].plot(label='ExportsEM',figsize=(15,6))
ax.set_ylabel('Ratio of Imports to GDP ',fontsize=20)
ax.set_xlabel('Year',fontsize=25)
ax2=PriceRiskIMEX['Commodity Prices'].plot(secondary_y=True,label='Commodity P
rices')
ax2.set_ylabel('Prices',fontsize=25)

plt.legend(loc='upper left')
plt.title('Imports of Commodities by EM vs Commodity Prices 1985-2016',fontsiz
e=20)
plt.figure(figsize=(10,10))

plt.show()
```




```
<Figure size 720x720 with 0 Axes>
```

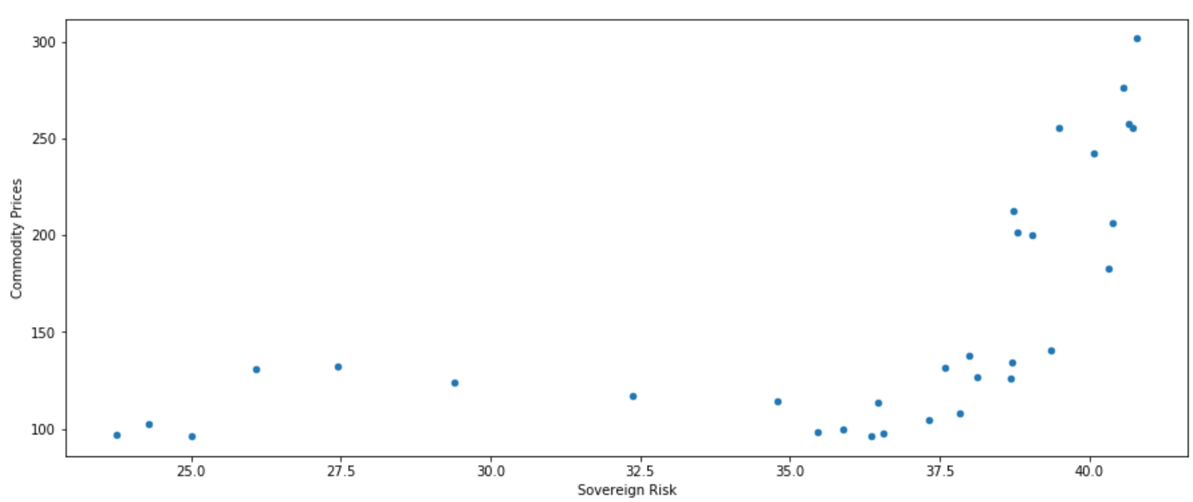
In [177]:
```
ax=PriceRiskIMEX['ImportsIE'].plot(label='ExportsEM',figsize=(15,6))
ax.set_ylabel('Ratio of Imports to GDP ',fontsize=20)
ax.set_xlabel('Year',fontsize=25)
ax2=PriceRiskIMEX['Commodity Prices'].plot(secondary_y=True,label='Commodity P
rices')
ax2.set_ylabel('Prices',fontsize=25)

plt.legend(loc='upper left')
plt.title('Imports of Commodities by Industrialized Economies vs Commodity Pri
ces 1985-2016',fontsize=20)
plt.figure(figsize=(10,10))

plt.show()
```




```
<Figure size 720x720 with 0 Axes>
```

In [178]:
```
PriceRiskIMEX.plot.scatter(x='Sovereign Risk',y='Commodity Prices',figsize=(15
,6))
PriceRiskIMEX['Sovereign Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[178]: 0.5831224067321231



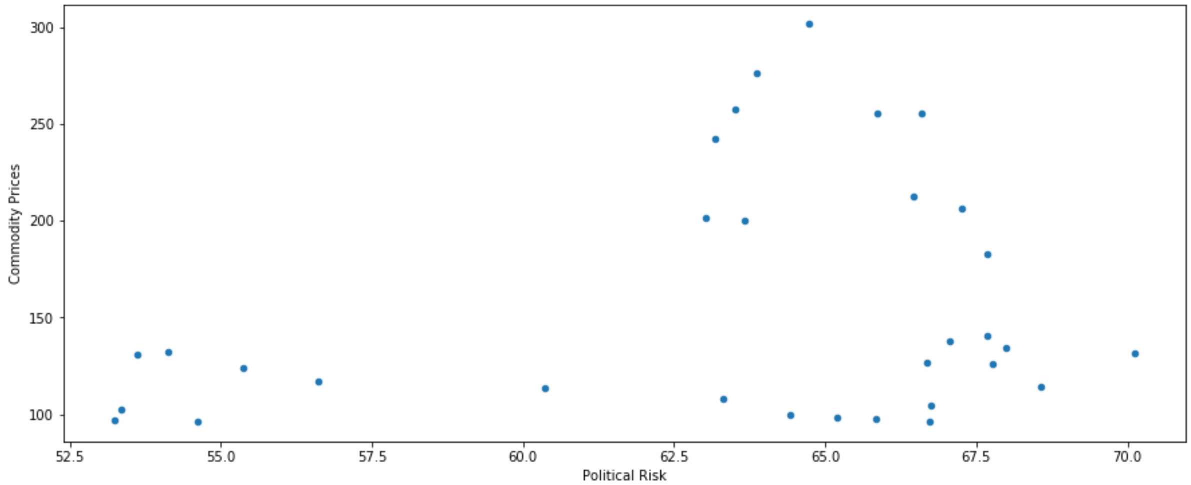
In [179]:
```
import statsmodels.formula.api as smf
import statsmodels.api as sm

x=PriceRiskIMEX['Sovereign Risk']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.34
0
Model:                            OLS   Adj. R-squared:                  0.31
8
Method:                 Least Squares   F-statistic:                     15.4
6
Date:                Wed, 06 Nov 2019   Prob (F-statistic):           0.00046
1
Time:                        01:52:17   Log-Likelihood:                -170.8
6
No. Observations:                  32   AIC:                             345.
7
Df Residuals:                      30   BIC:                             348.
7
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=====
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
const            -93.7816     64.454     -1.455      0.156    -225.415      3
7.852
Sovereign Risk     6.9848      1.777      3.932      0.000       3.356      1
0.613
==============================================================================
=
Omnibus:                        4.028   Durbin-Watson:                   0.19
1
Prob(Omnibus):                  0.133   Jarque-Bera (JB):                2.11
4
Skew:                           0.358   Prob(JB):                        0.34
8
Kurtosis:                       1.965   Cond. No.                         25
4.
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

```
C:\Users\ishaa\Anaconda3NEW1\lib\site-packages\numpy\core\fromnumeric.py:238
9: FutureWarning: Method .ptp is deprecated and will be removed in a future v
ersion. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

In [180]:
```
PriceRiskIMEX.plot.scatter(x='Political Risk',y='Commodity Prices',figsize=(15
,6))
PriceRiskIMEX['Political Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[180]: 0.25313536002492953

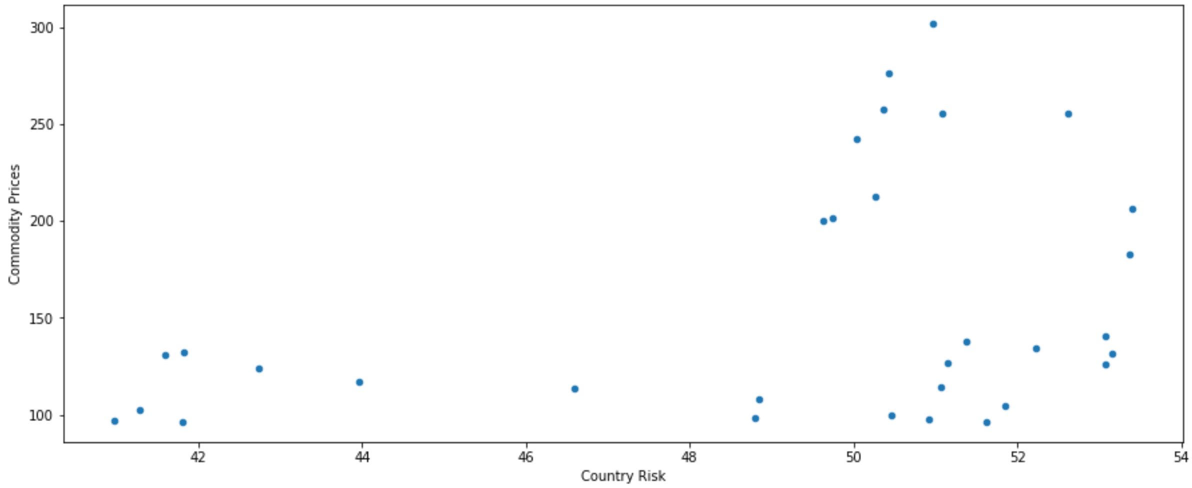


In [181]:
```
x=PriceRiskIMEX['Political Risk']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
=============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.06
4
Model:                            OLS   Adj. R-squared:                  0.03
3
Method:                 Least Squares   F-statistic:                     2.05
4
Date:                Wed, 06 Nov 2019   Prob (F-statistic):              0.16
2
Time:                        01:52:17   Log-Likelihood:                -176.4
5
No. Observations:                  32   AIC:                             356.
9
Df Residuals:                      30   BIC:                             359.
8
Df Model:                           1
Covariance Type:            nonrobust
=============================================================================
=====
                     coef    std err          t      P>|t|      [0.025
0.975]
-----------------------------------------------------------------------------
-----
const            -38.2247    136.676     -0.280      0.782    -317.355     24
0.906
Political Risk     3.0851      2.153      1.433      0.162      -1.311
7.481
=============================================================================
=
Omnibus:                        4.280   Durbin-Watson:                   0.14
5
Prob(Omnibus):                  0.118   Jarque-Bera (JB):                3.92
1
Skew:                           0.810   Prob(JB):                        0.14
1
Kurtosis:                       2.437   Cond. No.                         79
2.
=============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [182]:
```
PriceRiskIMEX.plot.scatter(x='Country Risk',y='Commodity Prices',figsize=(15,6
))
PriceRiskIMEX['Country Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[182]: 0.36031849863290183



In [183]:
```
x=PriceRiskIMEX['Country Risk']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

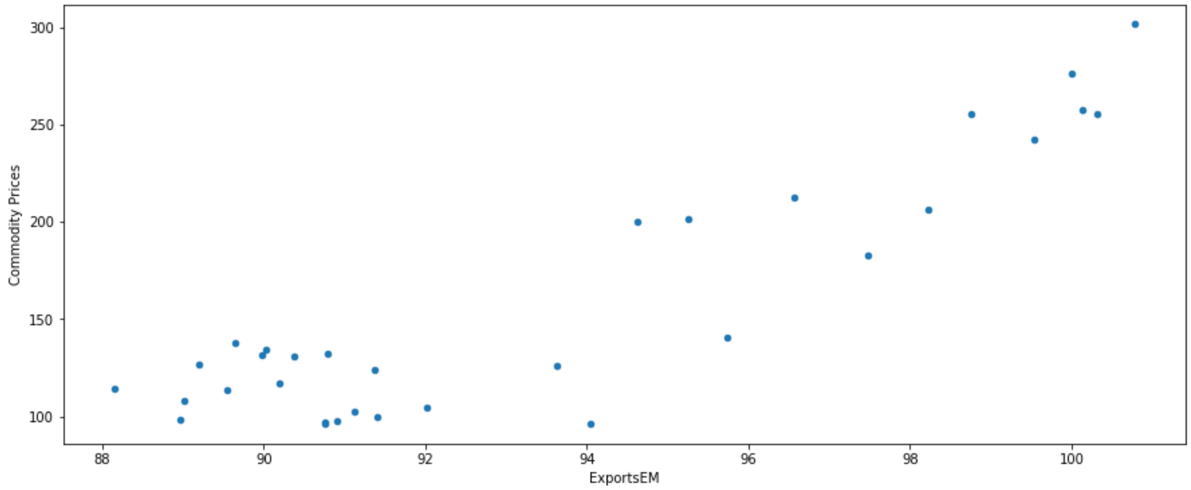
```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.13
0
Model:                            OLS   Adj. R-squared:                  0.10
1
Method:                 Least Squares   F-statistic:                     4.47
6
Date:                Wed, 06 Nov 2019   Prob (F-statistic):             0.042
8
Time:                        01:52:18   Log-Likelihood:                -175.2
9
No. Observations:                  32   AIC:                             354.
6
Df Residuals:                      30   BIC:                             357.
5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
===
                   coef    std err          t      P>|t|      [0.025      0.9
75]
------------------------------------------------------------------------------
---
const         -116.4289    129.683     -0.898      0.376    -381.277     148.
419
Country Risk     5.5726      2.634      2.116      0.043       0.193      10.
952
==============================================================================
=
Omnibus:                        3.435   Durbin-Watson:                   0.14
0
Prob(Omnibus):                  0.180   Jarque-Bera (JB):                3.07
3
Skew:                           0.693   Prob(JB):                        0.21
5
Kurtosis:                       2.381   Cond. No.                         60
4.
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [184]:
```
x=PriceRiskIMEX['ExportsEM']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.81
4
Model:                            OLS   Adj. R-squared:                  0.80
8
Method:                 Least Squares   F-statistic:                     131.
3
Date:                Wed, 06 Nov 2019   Prob (F-statistic):           1.75e-1
2
Time:                        01:52:18   Log-Likelihood:                -150.6
0
No. Observations:                  32   AIC:                             305.
2
Df Residuals:                      30   BIC:                             308.
1
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
const      -1146.1023    113.827    -10.069      0.000   -1378.567    -913.63
7
ExportsEM     13.9496      1.217     11.459      0.000      11.463      16.43
6
==============================================================================
=
Omnibus:                        2.504   Durbin-Watson:                   0.40
2
Prob(Omnibus):                  0.286   Jarque-Bera (JB):                2.22
1
Skew:                          -0.616   Prob(JB):                        0.32
9
Kurtosis:                       2.615   Cond. No.                     2.18e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 2.18e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [185]:
```
PriceRiskIMEX.plot.scatter(x='ExportsEM',y='Commodity Prices',figsize=(15,6))
PriceRiskIMEX['Country Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[185]: 0.36031849863290183

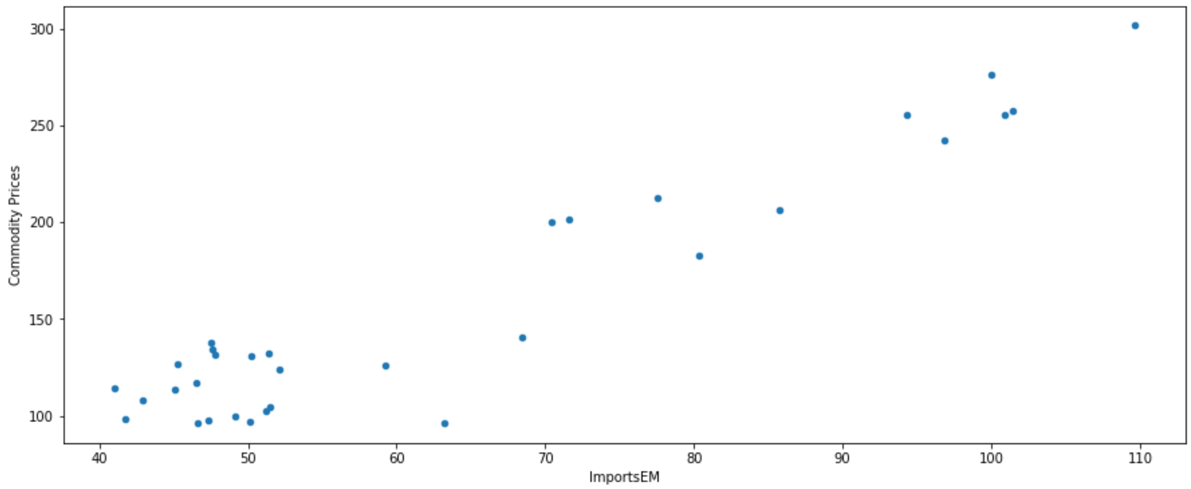


In [186]:
```
x=PriceRiskIMEX['ImportsEM']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.90
0
Model:                            OLS   Adj. R-squared:                  0.89
6
Method:                 Least Squares   F-statistic:                     269.
2
Date:                Wed, 06 Nov 2019   Prob (F-statistic):           1.58e-1
6
Time:                        01:52:19   Log-Likelihood:                -140.7
2
No. Observations:                  32   AIC:                             285.
4
Df Residuals:                      30   BIC:                             288.
4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
const        -20.1673     11.381     -1.772      0.087     -43.410       3.07
5
ImportsEM      2.7866      0.170     16.406      0.000       2.440       3.13
4
==============================================================================
=
Omnibus:                        5.349   Durbin-Watson:                   0.45
7
Prob(Omnibus):                  0.069   Jarque-Bera (JB):                3.91
2
Skew:                          -0.820   Prob(JB):                        0.14
1
Kurtosis:                       3.493   Cond. No.                         21
3.
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

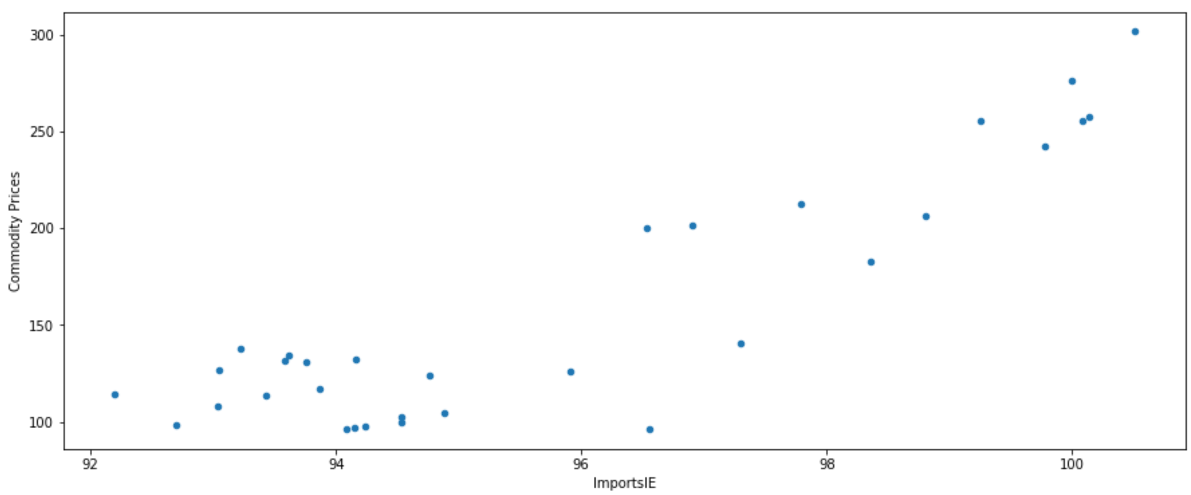
In [187]:
```
PriceRiskIMEX.plot.scatter(x='ImportsEM',y='Commodity Prices',figsize=(15,6))
PriceRiskIMEX['Country Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[187]: 0.36031849863290183




In [188]:
```
PriceRiskIMEX.plot.scatter(x='ImportsIE',y='Commodity Prices',figsize=(15,6))
PriceRiskIMEX['Country Risk'].corr(PriceRiskIMEX['Commodity Prices'])
```

Out[188]: 0.36031849863290183



In [189]:
```
x=PriceRiskIMEX['ImportsIE']
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.79
6
Model:                            OLS   Adj. R-squared:                  0.78
9
Method:                 Least Squares   F-statistic:                     116.
9
Date:                Wed, 06 Nov 2019   Prob (F-statistic):           7.20e-1
2
Time:                        01:52:20   Log-Likelihood:                -152.0
9
No. Observations:                  32   AIC:                             308.
2
Df Residuals:                      30   BIC:                             311.
1
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
const      -1901.8706    190.488     -9.984      0.000   -2290.899   -1512.84
2
ImportsIE     21.4907      1.988     10.812      0.000      17.431      25.55
0
==============================================================================
=
Omnibus:                        2.859   Durbin-Watson:                   0.45
5
Prob(Omnibus):                  0.239   Jarque-Bera (JB):                2.29
5
Skew:                          -0.652   Prob(JB):                        0.31
7
Kurtosis:                       2.866   Cond. No.                     3.57e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 3.57e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

# Multivariate Regression Analysis

In [190]:
```
x=PriceRiskIMEX[['Sovereign Risk', 'Political Risk', 'Country Risk','ExportsE
M','ImportsIE','ImportsEM']]
y=PriceRiskIMEX['Commodity Prices']

x=sm.add_constant(x)
est= sm.OLS(y,x).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:       Commodity Prices   R-squared:                       0.97
6
Model:                            OLS   Adj. R-squared:                  0.97
1
Method:                 Least Squares   F-statistic:                     172.
2
Date:                Wed, 06 Nov 2019   Prob (F-statistic):           4.35e-1
9
Time:                        01:52:20   Log-Likelihood:                -117.5
8
No. Observations:                  32   AIC:                             249.
2
Df Residuals:                      25   BIC:                             259.
4
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
=====
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
const           3076.5670    749.263      4.106      0.000    1533.430    461
9.704
Sovereign Risk     4.6799      1.191      3.929      0.001       2.227
7.133
Political Risk     1.4478      2.860      0.506      0.617      -4.443
7.338
Country Risk      -6.4453      4.330     -1.488      0.149     -15.364
2.473
ExportsEM         17.0502     16.387      1.040      0.308     -16.699      5
0.799
ImportsIE        -50.0595     22.239     -2.251      0.033     -95.862      -
4.257
ImportsEM          5.3500      0.762      7.020      0.000       3.781
6.920
==============================================================================
=
Omnibus:                        0.181   Durbin-Watson:                   1.42
6
Prob(Omnibus):                  0.913   Jarque-Bera (JB):                0.24
9
Skew:                          -0.158   Prob(JB):                        0.88
3
Kurtosis:                       2.706   Cond. No.                     6.79e+0
4
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 6.79e+04. This might indicate that there a
```

```
re
strong multicollinearity or other numerical problems.
```

**-As seen with the completed correleations and the regression analysis with all of the variables combined, Sovereign Risk is the leading risk factor in this model that has a high enough impact on Commodity Prices.**

# Machine Learning Classification: How Country, Political, and Sovereign Risk will impact Commodity Prices

In [191]:
```
EMCPRML=pd.read_excel (r"C:\New folder\RiskCPData.xlsx")
EMCPRML
```

Out[191]:

| | Year | Category of Political Risk according to ICRG | Political Risk | Category of SovereignRisk according to ICRG | Sovereign Risk | Category of Country Risk according to ICRG | Country Risk | Commodity Prices | In |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1985 | Very High Risk | 54.311404 | Very High Risk | 24.956140 | Very Low Risk | 41.607493 | 96.2167 | |
| **1** | 1986 | Very High Risk | 52.978070 | Very High Risk | 23.640351 | Very Low Risk | 40.832237 | 96.6750 | |
| **2** | 1987 | High Risk | 53.026316 | High Risk | 24.131579 | Very Low Risk | 41.107456 | 102.2080 | |
| **3** | 1988 | High Risk | 53.065789 | High Risk | 25.846491 | Very Low Risk | 41.325658 | 131.1170 | |
| **4** | 1989 | High Risk | 53.741228 | High Risk | 27.311404 | Very Low Risk | 41.560307 | 132.3250 | |
| **5** | 1990 | High Risk | 55.100877 | High Risk | 29.333333 | Very Low Risk | 42.598684 | 124.0250 | |
| **6** | 1991 | Moderate Risk | 56.228070 | Moderate Risk | 32.399123 | Very Low Risk | 43.816886 | 117.0420 | |
| **7** | 1992 | Low Risk | 60.134722 | Low Risk | 36.590278 | Very Low Risk | 46.523264 | 113.8580 | |
| **8** | 1993 | Low Risk | 63.200000 | Low Risk | 37.912500 | Very Low Risk | 48.798958 | 108.2580 | |
| **9** | 1994 | Low Risk | 66.479167 | Low Risk | 38.233333 | Very Low Risk | 51.075000 | 126.5080 | |
| **10** | 1995 | Low Risk | 66.683333 | Low Risk | 38.066667 | Very Low Risk | 51.177083 | 137.5750 | |
| **11** | 1996 | Low Risk | 67.495833 | Low Risk | 38.729167 | Very Low Risk | 51.990625 | 134.3500 | |
| **12** | 1997 | Low Risk | 69.587500 | Low Risk | 37.633333 | Very Low Risk | 52.894792 | 131.6670 | |
| **13** | 1998 | Low Risk | 67.825000 | Low Risk | 34.797917 | Very Low Risk | 50.618750 | 114.4000 | |
| **14** | 1999 | Low Risk | 64.558333 | Low Risk | 35.470833 | Very Low Risk | 48.350792 | 98.4833 | |
| **15** | 2000 | Low Risk | 63.683333 | Low Risk | 36.064583 | Very Low Risk | 50.022917 | 99.9917 | |
| **16** | 2001 | Low Risk | 66.133333 | Low Risk | 36.518750 | Very Low Risk | 51.238542 | 96.3750 | |
| **17** | 2002 | Low Risk | 65.300000 | Low Risk | 36.704167 | Very Low Risk | 50.562500 | 97.3167 | |
| **18** | 2003 | Low Risk | 66.183333 | Low Risk | 37.404167 | Very Low Risk | 51.552083 | 104.8580 | |
| **19** | 2004 | Low Risk | 67.306250 | Low Risk | 38.854167 | Very Low Risk | 52.873958 | 125.7830 | |
| **20** | 2005 | Low Risk | 67.189583 | Low Risk | 39.608333 | Very Low Risk | 52.891667 | 140.3920 | |

| | Year | Category of Political Risk according to ICRG | Political Risk | Category of SovereignRisk according to ICRG | Sovereign Risk | Category of Country Risk according to ICRG | Country Risk | Commodity Prices | Im |
|---|---|---|---|---|---|---|---|---|---|
| **21** | 2006 | Very Low Risk | 67.225000 | Very Low Risk | 40.583333 | Very Low Risk | 53.188542 | 182.8250 | |
| **22** | 2007 | Very Low Risk | 66.777083 | Very Low Risk | 40.716667 | Very Low Risk | 53.243750 | 206.5250 | |
| **23** | 2008 | Very Low Risk | 66.199583 | Very Low Risk | 39.827083 | Very Low Risk | 52.481042 | 256.0330 | |
| **24** | 2009 | Low Risk | 66.125000 | Low Risk | 39.002083 | Very Low Risk | 50.180208 | 212.7420 | |
| **25** | 2010 | Very Low Risk | 65.666667 | Very Low Risk | 41.262500 | Very Low Risk | 51.211458 | 256.0420 | |
| **26** | 2011 | Very Low Risk | 64.593750 | Very Low Risk | 41.337500 | Very Low Risk | 51.157292 | 302.0000 | |
| **27** | 2012 | Very Low Risk | 63.718750 | Very Low Risk | 41.083333 | Very Low Risk | 50.612500 | 276.7830 | |
| **28** | 2013 | Very Low Risk | 63.427083 | Very Low Risk | 41.072917 | Very Low Risk | 50.480208 | 258.1830 | |
| **29** | 2014 | Very Low Risk | 63.027083 | Very Low Risk | 40.608333 | Very Low Risk | 50.048958 | 242.5080 | |
| **30** | 2015 | Low Risk | 62.668750 | Low Risk | 39.339583 | Very Low Risk | 49.544792 | 201.5750 | |
| **31** | 2016 | Low Risk | 63.327083 | Low Risk | 39.550000 | Very Low Risk | 49.477083 | 200.0830 | |

In [192]:
```
EMCPRML.dtypes
```

Out[192]:
```
Year                                              int64
Category of Political Risk according to ICRG     object
Political Risk                                  float64
Category of SovereignRisk according to ICRG      object
Sovereign Risk                                  float64
Category of Country  Risk according to ICRG      object
Country Risk                                    float64
Commodity Prices                                float64
 Impact                                          object
dtype: object
```

In [193]:
```
EMCPRML.columns
```

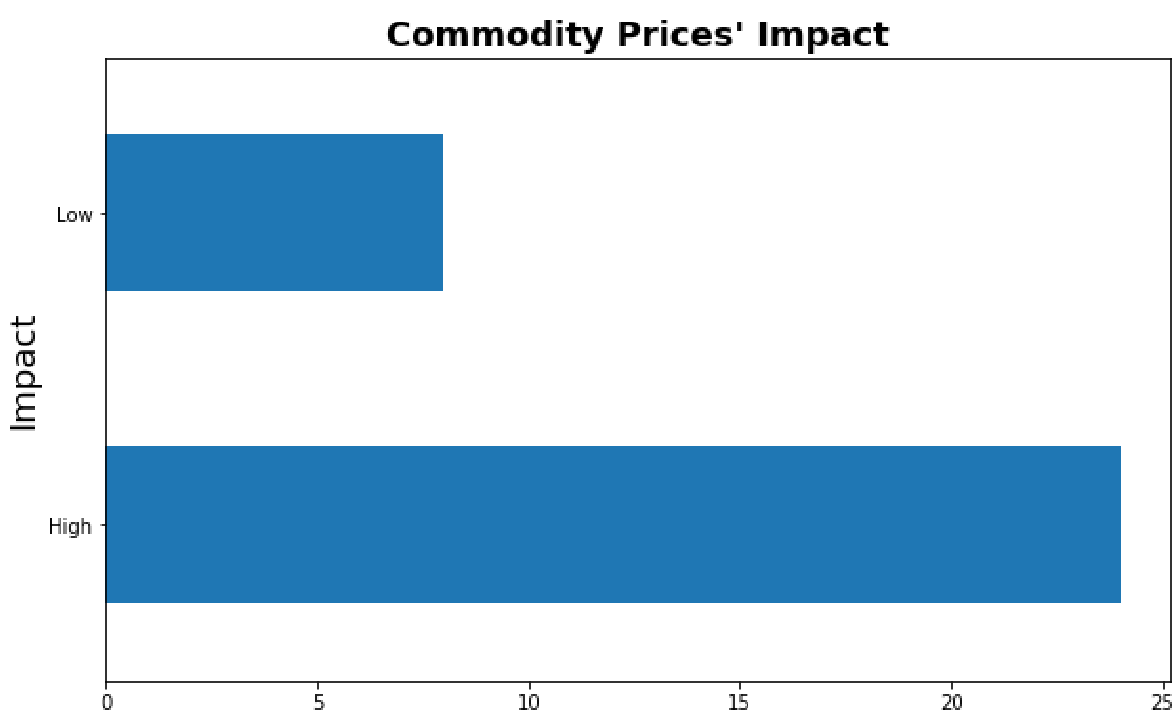
Out[193]:
```
Index(['Year', 'Category of Political Risk according to ICRG ',
       'Political Risk', 'Category of SovereignRisk according to ICRG ',
       'Sovereign Risk', 'Category of Country  Risk according to ICRG ',
       'Country Risk', 'Commodity Prices ', ' Impact '],
      dtype='object')
```

In [194]:
```
EMCPRML['Category of Political Risk according to ICRG ']=EMCPRML['Category of
 Political Risk according to ICRG '].astype('category')
EMCPRML['Category of SovereignRisk according to ICRG ']=EMCPRML['Category of S
overeignRisk according to ICRG '].astype('category')
EMCPRML['Category of Country  Risk according to ICRG ']=EMCPRML['Category of C
ountry  Risk according to ICRG '].astype('category')

EMCPRML.dtypes
```

Out[194]:
```
Year                                              int64
Category of Political Risk according to ICRG     category
Political Risk                                  float64
Category of SovereignRisk according to ICRG     category
Sovereign Risk                                  float64
Category of Country  Risk according to ICRG     category
Country Risk                                    float64
Commodity Prices                                float64
 Impact                                          object
dtype: object
```

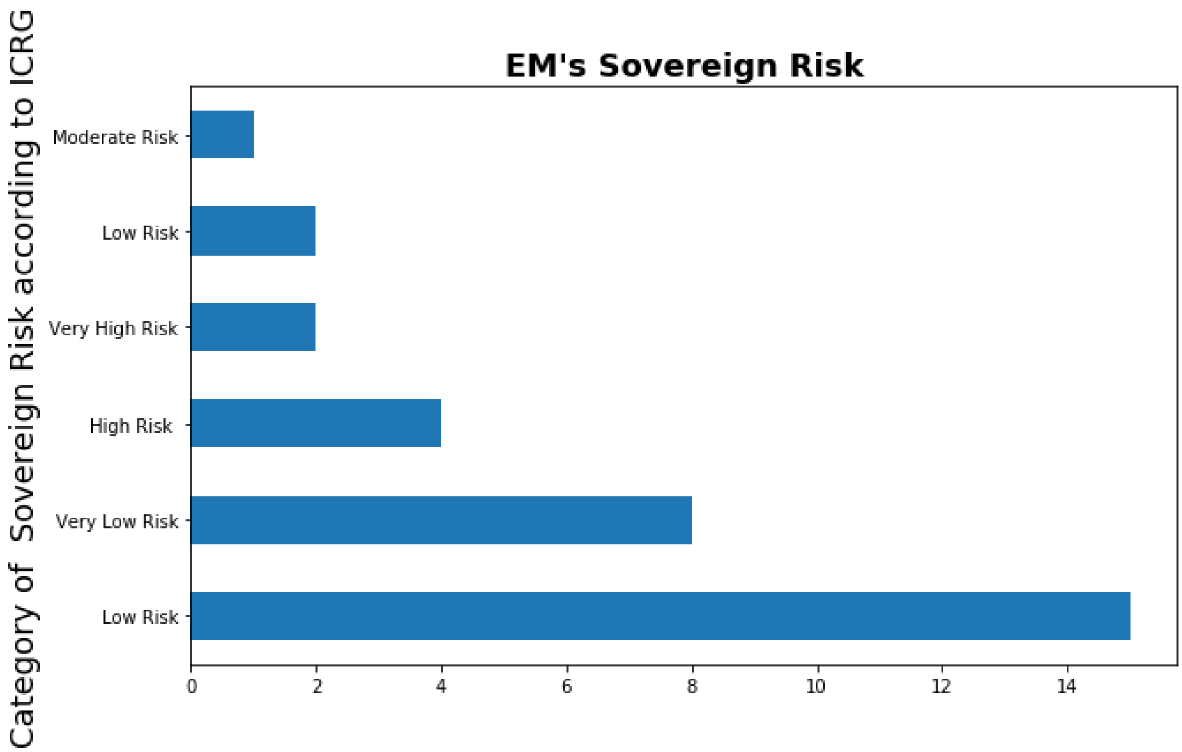
In [196]:
```
fig, axe = plt.subplots()
EMCPRML[' Impact '].value_counts().plot.barh(figsize =(10,6))
axe.set_ylabel("Impact", fontsize=18)
axe.set_title("Commodity Prices' Impact", loc='center', fontsize=18, fontweigh
t = "bold" )
```

Out[196]:
```
Text(0.5, 1.0, "Commodity Prices' Impact")
```



In [197]:
```
fig, axe = plt.subplots()
EMCPRML['Category of SovereignRisk according to ICRG '].value_counts().plot.ba
rh(figsize =(10,6))
axe.set_ylabel("Category of  Sovereign Risk according to ICRG", fontsize=18)
axe.set_title("EM's Sovereign Risk", loc='center', fontsize=18, fontweight =
"bold" )
```

Out[197]:
```
Text(0.5, 1.0, "EM's Sovereign Risk")
```

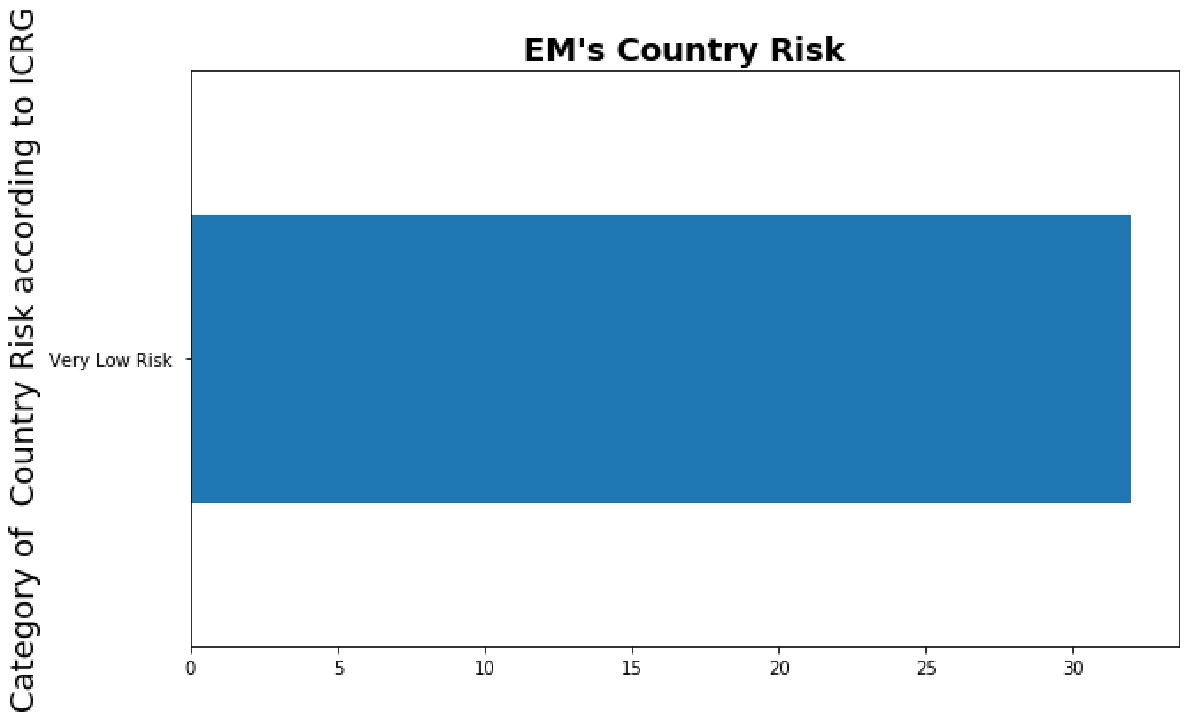


In [198]:

```
fig, axe = plt.subplots()
EMCPRML['Category of Country  Risk according to ICRG '].value_counts().plot.ba
rh(figsize =(10,6))
axe.set_ylabel("Category of  Country Risk according to ICRG", fontsize=18)
axe.set_title("EM's Country Risk", loc='center', fontsize=18, fontweight = "bo
ld" )
```

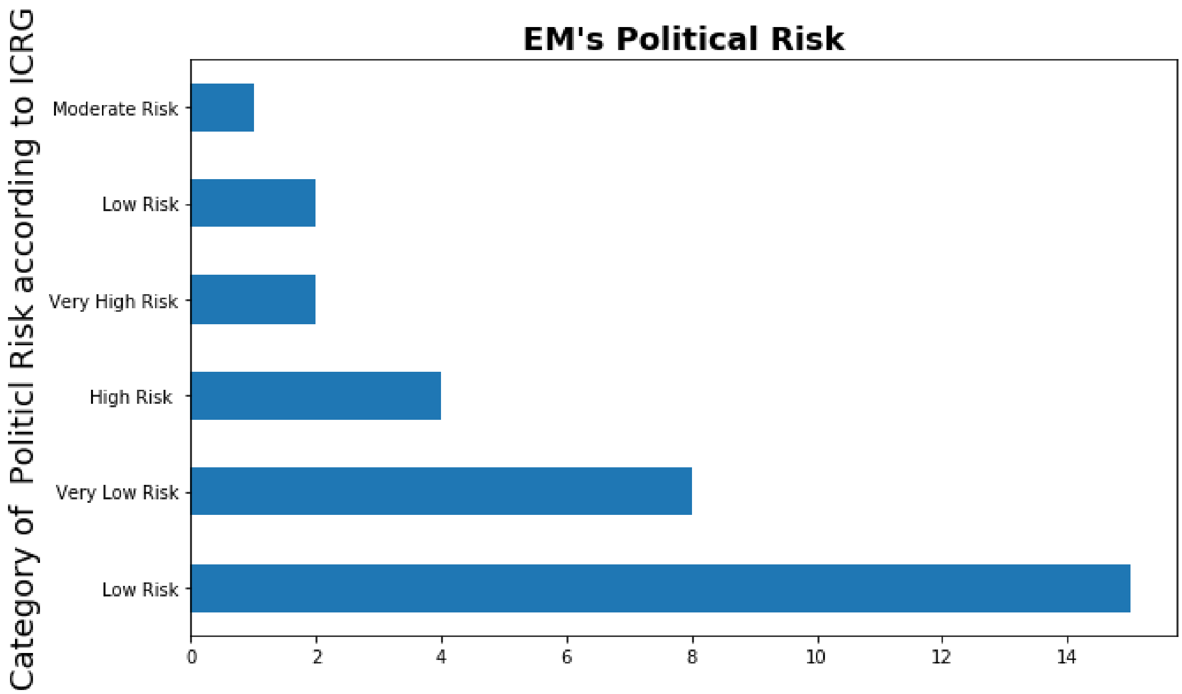
Out[198]:

```
Text(0.5, 1.0, "EM's Country Risk")
```



In [199]:
```
fig, axe = plt.subplots()
EMCPRML['Category of Political Risk according to ICRG '].value_counts().plot.b
arh(figsize =(10,6))
axe.set_ylabel("Category of  Politicl Risk according to ICRG", fontsize=18)
axe.set_title("EM's Political Risk", loc='center', fontsize=18, fontweight =
"bold" )
```

Out[199]:
```
Text(0.5, 1.0, "EM's Political Risk")
```




In [200]:
```
EMCPRML['Category of Political Risk according to ICRG ']=EMCPRML['Category of
 Political Risk according to ICRG '].cat.codes
EMCPRML['Category of SovereignRisk according to ICRG ']=EMCPRML['Category of S
overeignRisk according to ICRG '].cat.codes
EMCPRML['Category of Country  Risk according to ICRG ']=EMCPRML['Category of C
ountry  Risk according to ICRG '].cat.codes
```

In [201]:
```
EMCPRML=pd.get_dummies(EMCPRML, columns=[' Impact '])
```

In [202]:
```
EMCPRML
```

Out[202]:

| | Year | Category of Political Risk according to ICRG | Political Risk | Category of SovereignRisk according to ICRG | Sovereign Risk | Category of Country Risk according to ICRG | Country Risk | Commodity Prices | In _ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1985 | 4 | 54.311404 | 4 | 24.956140 | 0 | 41.607493 | 96.2167 | |
| **1** | 1986 | 4 | 52.978070 | 4 | 23.640351 | 0 | 40.832237 | 96.6750 | |
| **2** | 1987 | 1 | 53.026316 | 1 | 24.131579 | 0 | 41.107456 | 102.2080 | |
| **3** | 1988 | 1 | 53.065789 | 1 | 25.846491 | 0 | 41.325658 | 131.1170 | |
| **4** | 1989 | 1 | 53.741228 | 1 | 27.311404 | 0 | 41.560307 | 132.3250 | |
| **5** | 1990 | 1 | 55.100877 | 1 | 29.333333 | 0 | 42.598684 | 124.0250 | |
| **6** | 1991 | 3 | 56.228070 | 3 | 32.399123 | 0 | 43.816886 | 117.0420 | |
| **7** | 1992 | 2 | 60.134722 | 2 | 36.590278 | 0 | 46.523264 | 113.8580 | |
| **8** | 1993 | 2 | 63.200000 | 2 | 37.912500 | 0 | 48.798958 | 108.2580 | |
| **9** | 1994 | 2 | 66.479167 | 2 | 38.233333 | 0 | 51.075000 | 126.5080 | |
| **10** | 1995 | 2 | 66.683333 | 2 | 38.066667 | 0 | 51.177083 | 137.5750 | |
| **11** | 1996 | 2 | 67.495833 | 2 | 38.729167 | 0 | 51.990625 | 134.3500 | |
| **12** | 1997 | 2 | 69.587500 | 2 | 37.633333 | 0 | 52.894792 | 131.6670 | |
| **13** | 1998 | 2 | 67.825000 | 2 | 34.797917 | 0 | 50.618750 | 114.4000 | |
| **14** | 1999 | 2 | 64.558333 | 2 | 35.470833 | 0 | 48.350792 | 98.4833 | |
| **15** | 2000 | 2 | 63.683333 | 2 | 36.064583 | 0 | 50.022917 | 99.9917 | |
| **16** | 2001 | 2 | 66.133333 | 2 | 36.518750 | 0 | 51.238542 | 96.3750 | |
| **17** | 2002 | 2 | 65.300000 | 2 | 36.704167 | 0 | 50.562500 | 97.3167 | |
| **18** | 2003 | 2 | 66.183333 | 2 | 37.404167 | 0 | 51.552083 | 104.8580 | |
| **19** | 2004 | 2 | 67.306250 | 2 | 38.854167 | 0 | 52.873958 | 125.7830 | |
| **20** | 2005 | 2 | 67.189583 | 2 | 39.608333 | 0 | 52.891667 | 140.3920 | |
| **21** | 2006 | 5 | 67.225000 | 5 | 40.583333 | 0 | 53.188542 | 182.8250 | |
| **22** | 2007 | 5 | 66.777083 | 5 | 40.716667 | 0 | 53.243750 | 206.5250 | |
| **23** | 2008 | 5 | 66.199583 | 5 | 39.827083 | 0 | 52.481042 | 256.0330 | |
| **24** | 2009 | 0 | 66.125000 | 0 | 39.002083 | 0 | 50.180208 | 212.7420 | |
| **25** | 2010 | 5 | 65.666667 | 5 | 41.262500 | 0 | 51.211458 | 256.0420 | |
| **26** | 2011 | 5 | 64.593750 | 5 | 41.337500 | 0 | 51.157292 | 302.0000 | |
| **27** | 2012 | 5 | 63.718750 | 5 | 41.083333 | 0 | 50.612500 | 276.7830 | |
| **28** | 2013 | 5 | 63.427083 | 5 | 41.072917 | 0 | 50.480208 | 258.1830 | |
| **29** | 2014 | 5 | 63.027083 | 5 | 40.608333 | 0 | 50.048958 | 242.5080 | |
| **30** | 2015 | 0 | 62.668750 | 0 | 39.339583 | 0 | 49.544792 | 201.5750 | |
| **31** | 2016 | 2 | 63.327083 | 2 | 39.550000 | 0 | 49.477083 | 200.0830 | |

In [203]:
```
EMCPRML.columns
```

Out[203]:
```
Index(['Year', 'Category of Political Risk according to ICRG ',
       'Political Risk', 'Category of SovereignRisk according to ICRG ',
       'Sovereign Risk', 'Category of Country  Risk according to ICRG ',
       'Country Risk', 'Commodity Prices ', ' Impact _High', ' Impact _Low'],
      dtype='object')
```

In [212]:
```
EMCPRML=EMCPRML.rename(columns={' Impact _High':'Impact_High','Category of Political Risk according to ICRG ':'PoliticalRisk_CategoryICRG','Category of SovereignRisk according to ICRG ':'SovereignRisk_CategoryICRG','Category of Country  Risk according to ICRG ':'CountryRisk_CategoryICRG'})
```

In [211]:
```
EMCPRML.Impact_High.value_counts()
```

Out[211]:
```
1    24
0     8
Name: Impact_High, dtype: int64
```

# Political Risk and Commodity Prices Machine Learning

In [213]:
```
from patsy import dmatrices
y,X = dmatrices('Impact_High ~ PoliticalRisk_CategoryICRG',data=EMCPRML)
```

In [214]:
```
 y=np.ravel(y)
```

In [215]:
```
from sklearn.linear_model import LogisticRegression as logit
logit(solver='lbfgs').fit(X,y).score(X,y)
```

Out[215]:
```
array(0.75)
```

In [216]:
```
 from sklearn.model_selection import cross_val_score
cross_val_score(logit(solver='lbfgs'),X,y,cv=5,scoring='accuracy').mean()
```

Out[216]:
```
0.7152380952380952
```

In [217]:
```
 cross_val_score(logit(solver='lbfgs'),X,y,cv=3,scoring='roc_auc').mean()
```

Out[217]:
```
0.6319444444444445
```

In [218]:
```
from sklearn.neighbors import KNeighborsClassifier as knn
cross_val_score(knn(),X,y,cv=3,scoring='accuracy').mean()
```

Out[218]:
```
0.6606060606060606
```

In [220]:
```
from sklearn.ensemble import RandomForestClassifier as rf
cross_val_score(rf(n_estimators=100, max_depth=2,max_features=2),X,y,cv=2,scor
ing='accuracy').mean()
```

Out[220]:
```
0.5
```

In [221]:
```
for i in range(1,10):
        for j in range(1,3):
            print(i,j,cross_val_score(rf(n_estimators=100,max_depth=i,max_feat
ures =j),X,y,cv=3,scoring='accuracy').mean())
```

```
1 1 0.6848484848484849
1 2 0.7515151515151516
2 1 0.6848484848484849
2 2 0.7515151515151516
3 1 0.7515151515151516
3 2 0.6848484848484849
4 1 0.6848484848484849
4 2 0.6848484848484849
5 1 0.7515151515151516
5 2 0.7515151515151516
6 1 0.7515151515151516
6 2 0.7515151515151516
7 1 0.6848484848484849
7 2 0.6848484848484849
8 1 0.6848484848484849
8 2 0.7515151515151516
9 1 0.7515151515151516
9 2 0.6848484848484849
```

In [224]:
```
EMCPRML['high_impact_rf'] = rf(n_estimators=100, max_depth=2,max_features=2).f
it( X,y).predict(X)
EMCPRML.high_impact_rf.value_counts()
```

Out[224]:
```
1.0    32
Name: high_impact_rf, dtype: int64
```

**This model shows that from 2017-2023, Country Risk will have a 100% chance of highly impacting commodity prices.**

# Political Risk and Commodity Prices Machine Learning

In [225]:
```
from patsy import dmatrices
y,X = dmatrices('Impact_High ~ CountryRisk_CategoryICRG',data=EMCPRML)
```

In [226]:
```
 y=np.ravel(y)
```

In [227]:
```
from sklearn.linear_model import LogisticRegression as logit
logit(solver='lbfgs').fit(X,y).score(X,y)
```

Out[227]:
```
array(0.75)
```

In [228]:
```
 from sklearn.model_selection import cross_val_score
cross_val_score(logit(solver='lbfgs'),X,y,cv=5,scoring='accuracy').mean()
```

Out[228]:
```
0.7552380952380953
```

In [229]:
```
 cross_val_score(logit(solver='lbfgs'),X,y,cv=3,scoring='roc_auc').mean()
```

Out[229]:
```
0.5
```

In [230]:
```
from sklearn.neighbors import KNeighborsClassifier as knn
cross_val_score(knn(),X,y,cv=3,scoring='accuracy').mean()
```

Out[230]:
```
0.6
```

In [231]:
```
from sklearn.ensemble import RandomForestClassifier as rf
cross_val_score(rf(n_estimators=100, max_depth=2,max_features=2),X,y,cv=2,scor
ing='accuracy').mean()
```

Out[231]:
```
0.75
```

In [232]:
```
for i in range(1,10):
        for j in range(1,3):
            print(i,j,cross_val_score(rf(n_estimators=100,max_depth=i,max_feat
ures =j),X,y,cv=3,scoring='accuracy').mean())
```

```
1 1 0.7515151515151516
1 2 0.7515151515151516
2 1 0.7515151515151516
2 2 0.7515151515151516
3 1 0.7515151515151516
3 2 0.7515151515151516
4 1 0.7515151515151516
4 2 0.7515151515151516
5 1 0.7515151515151516
5 2 0.7515151515151516
6 1 0.7515151515151516
6 2 0.7515151515151516
7 1 0.7515151515151516
7 2 0.7515151515151516
8 1 0.7515151515151516
8 2 0.7515151515151516
9 1 0.7515151515151516
9 2 0.7515151515151516
```

In [234]:
```
from sklearn.linear_model import LogisticRegression as reg
from sklearn.model_selection import train_test_split
```

In [236]:
```
x=EMCPRML.drop(['Impact_High'],axis=1)
y=EMCPRML['Impact_High']
```

In [237]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=.2)
```

In [239]:
```
result = reg(solver='liblinear').fit(x_train,y_train).predict(x_test)
```

In [240]:
```
pd.Series(result).value_counts()
```

Out[240]:
```
1    6
0    1
dtype: int64
```

**This model shows that political risk will have a 85.7% chance of highly impacting commodity prices.**

# Sovereign Risk and Commodity Prices Machine Learning

In [241]:
```
from patsy import dmatrices
y,X = dmatrices('Impact_High ~ SovereignRisk_CategoryICRG',data=EMCPRML)
```

In [242]:
```
y=np.ravel(y)
```

In [243]:
```
from sklearn.linear_model import LogisticRegression as logit
logit(solver='lbfgs').fit(X,y).score(X,y)
```

Out[243]:
```
array(0.75)
```

In [244]:
```
 from sklearn.model_selection import cross_val_score
cross_val_score(logit(solver='lbfgs'),X,y,cv=5,scoring='accuracy').mean()
```

Out[244]:
```
0.7152380952380952
```

In [245]:
```
cross_val_score(logit(solver='lbfgs'),X,y,cv=3,scoring='roc_auc').mean()
```

Out[245]:
```
0.6319444444444445
```

In [246]:
```
from sklearn.neighbors import KNeighborsClassifier as knn
cross_val_score(knn(),X,y,cv=3,scoring='accuracy').mean()
```

Out[246]:
```
0.6606060606060606
```

In [247]:
```
from sklearn.ensemble import RandomForestClassifier as rf
cross_val_score(rf(n_estimators=100, max_depth=2,max_features=2),X,y,cv=2,scor
ing='accuracy').mean()
```

Out[247]:
```
0.6875
```

In [248]:
```
for i in range(1,10):
        for j in range(1,3):
            print(i,j,cross_val_score(rf(n_estimators=100,max_depth=i,max_feat
ures =j),X,y,cv=3,scoring='accuracy').mean())
```

```
1 1 0.7515151515151516
1 2 0.6848484848484849
2 1 0.6848484848484849
2 2 0.6848484848484849
3 1 0.7515151515151516
3 2 0.6848484848484849
4 1 0.6848484848484849
4 2 0.7515151515151516
5 1 0.7515151515151516
5 2 0.6848484848484849
6 1 0.6848484848484849
6 2 0.6848484848484849
7 1 0.7515151515151516
7 2 0.6848484848484849
8 1 0.6848484848484849
8 2 0.7515151515151516
9 1 0.7515151515151516
9 2 0.6848484848484849
```

In [249]:
```
EMCPRML['high_impact_rf'] = rf(n_estimators=100, max_depth=2,max_features=2).f
it( X,y).predict(X)
EMCPRML.high_impact_rf.value_counts()
```

Out[249]:
```
1.0    32
Name: high_impact_rf, dtype: int64
```

# This model shows that in the next 32 years, sovereign risk will have a high impact on commodity prices.

In [ ]:
```

```