Predicting future environmental intensity (Time Series) and Collect Pilot Stocks Companies Descriptions

In this notebook, we will predict future environmental intensity for all the companies in the 'Excel data'. We will be using data from previous years to predict the future environmental intesity.

First, we will create the following columns:

1) Industry Indicator

- 1 if above the industry average in current year
- 0 if at industry average in current yeat
- (-1) if below the industry average in current year 2) Environmental Intensity Growth : ((Environmental Intensity in Current Year / Environmental Intensity Last Year) - 1) * 100

At the end, we collected, directly from Yahoo Finance website, each company description. For this, we use the pilot stocks which have the Ticker identifier.

In [1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import missingno as msno
import warnings
from sklearn import linear_model
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import requests
from bs4 import BeautifulSoup
warnings.filterwarnings('ignore')
```

In [2]:
```python
df = pd.read_csv('/Users/maralinetorres/Documents/GitHub/Predicting-Environmental-and-Social-Actions/Datasets/E
print(f'The dataset has {df.shape[0]} rows and {df.shape[1]} columns')
df.head(3)
```

```
The dataset has 14515 rows and 39 columns
```

Out[2]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	EnvironmentalIntensity(OpInc)	TotalEnviror
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.82%	
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.11%	
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.16%	

3 rows × 39 columns

Now, we are going to subset for the columns that we are interested in. As discussed in the notebook 'Environmental-Impact-Data Cleaning', we transformed the EnvironmentalIntensity(Sales) to decimals and removed spaces in columns CompanyName and Country.

In [3]:
```python
df = df.loc[:,['ISIN','Year','CompanyName','Country','Industry(Exiobase)','EnvironmentalIntensity(Sales)','Env_
df.head()
```

Out[3]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.0007
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.0012
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.0016
3	GB00B1YW4409	2012	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.15%	-0.0015
4	US88579Y1010	2010	3M COMPANY	United States	Activities of membership organisation n.e.c. (91)	-7.90%	-0.0790

Creating industry indicator

In [4]:
```python
industry_avg = df.groupby('Industry(Exiobase)')[['Env_intensity']].mean().reset_index()
df['industry_avg'] = df['Env_intensity'].groupby(df['Industry(Exiobase)']).transform('mean')
```

In [5]:
```python
def create_ind(df):
    if(df['Env_intensity'] > df['industry_avg']):
        return 1
    elif (df['Env_intensity'] == df['industry_avg']):
        return 0
    elif (df['Env_intensity'] < df['industry_avg']):
        return -1

df['Industry_indicator'] = df.apply(create_ind, axis = 1)
df.head()
```

Out[5]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity	industry_avg	Industry_indica
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.0007	-0.020506	
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.0012	-0.028537	
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.0016	-0.028537	
3	GB00B1YW4409	2012	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.15%	-0.0015	-0.028537	
4	US88579Y1010	2010	3M COMPANY	United States	Activities of membership organisation n.e.c. (91)	-7.90%	-0.0790	-0.175838	

In [6]:
```python
def create_ind_year(df):
    if(df['Env_intensity'] > df['industry_avg_year']):
        return 1
    elif (df['Env_intensity'] == df['industry_avg_year']):
        return 0
    elif (df['Env_intensity'] < df['industry_avg_year']):
        return -1

df['industry_avg_year'] = df.groupby(['Industry(Exiobase)','Year']).transform('mean')[['Env_intensity']]

df['Industry_indicator_year'] = df.apply(create_ind_year, axis = 1)
df.head()
```

Out[6]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity	industry_avg	Industry_indica
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.0007	-0.020506	
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.0012	-0.028537	
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.0016	-0.028537	
3	GB00B1YW4409	2012	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.15%	-0.0015	-0.028537	
4	US88579Y1010	2010	3M COMPANY	United States	Activities of membership organisation n.e.c. (91)	-7.90%	-0.0790	-0.175838	

In [7]:
```python
df.loc[(df['Industry(Exiobase)'] == 'Activities auxiliary to financial intermediation (67)'),:].sort_values(by=
```

Out[7]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity	industry_avg	Industry_
190	CH0012138605	2010	ADECCO GROUP AG	Switzerland	Activities auxiliary to financial intermediati...	-0.14%	-0.0014	-0.00491	
2052	GB00B23K0M20	2010	CAPITA PLC	United Kingdom	Activities auxiliary to financial intermediati...	-0.40%	-0.0040	-0.00491	
1919	FR0006174348	2010	BUREAU VERITAS SA	France	Activities auxiliary to financial intermediati...	-0.52%	-0.0052	-0.00491	
3524	DE0005810055	2010	DEUTSCHE BOERSE AG	Germany	Activities auxiliary to financial intermediati...	-0.28%	-0.0028	-0.00491	
1718	ES0115056139	2010	BOLSAS Y MERCADOS ESPANOLES SHMSF SA	Spain	Activities auxiliary to financial intermediati...	-0.26%	-0.0026	-0.00491	
...	...	...	...	...	...	...	...	...	...
4428	GB00B19NLV48	2019	EXPERIAN PLC	United Kingdom	Activities auxiliary to financial intermediati...	-0.20%	-0.0020	-0.00491	
979	FR0000074148	2019	ASSYSTEM SA	France	Activities auxiliary to financial intermediati...	-0.31%	-0.0031	-0.00491	
3529	DE0005810055	2019	DEUTSCHE BOERSE AG	Germany	Activities auxiliary to financial intermediati...	1.88%	0.0188	-0.00491	
9793	GB0030232317	2019	PAGEGROUP PLC	United Kingdom	Activities auxiliary to financial intermediati...	-0.08%	-0.0008	-0.00491	
1925	FR0006174348	2019	BUREAU VERITAS SA	France	Activities auxiliary to financial intermediati...	-0.70%	-0.0070	-0.00491	

263 rows × 11 columns

Creating Environmental growth

Environmental Intensity Growth : ((Environmental Intensity in Current Year / Environmental Intensity Last Year) - 1) * 100

In [8]:
```python
df = df.sort_values(by=['CompanyName','Year'], ascending = True)
df.head()
```

Out[8]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity	industry_avg	Industry_indica
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.0007	-0.020506	
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.0012	-0.028537	
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.0016	-0.028537	
3	GB00B1YW4409	2012	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.15%	-0.0015	-0.028537	
4	US88579Y1010	2010	3M COMPANY	United States	Activities of membership organisation n.e.c. (91)	-7.90%	-0.0790	-0.175838	

In [9]:
```python
df['Environmental_Growth'] = df.groupby(['CompanyName'])['Env_intensity'].apply(lambda x: x.pct_change()).to_nu
df.head()
```

Out[9]:

	ISIN	Year	CompanyName	Country	Industry(Exiobase)	EnvironmentalIntensity(Sales)	Env_intensity	industry_avg	Industry_indica
0	DE0005545503	2016	1&1 DRILLISCH AG	Germany	Post and telecommunications (64)	-0.07%	-0.0007	-0.020506	
1	GB00B1YW4409	2010	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.12%	-0.0012	-0.028537	
2	GB00B1YW4409	2011	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.16%	-0.0016	-0.028537	
3	GB00B1YW4409	2012	3I GROUP PLC	United Kingdom	Financial intermediation, except insurance and...	-0.15%	-0.0015	-0.028537	
4	US88579Y1010	2010	3M COMPANY	United States	Activities of membership organisation n.e.c. (91)	-7.90%	-0.0790	-0.175838	

Model 1 - Past years Environmental Intensity

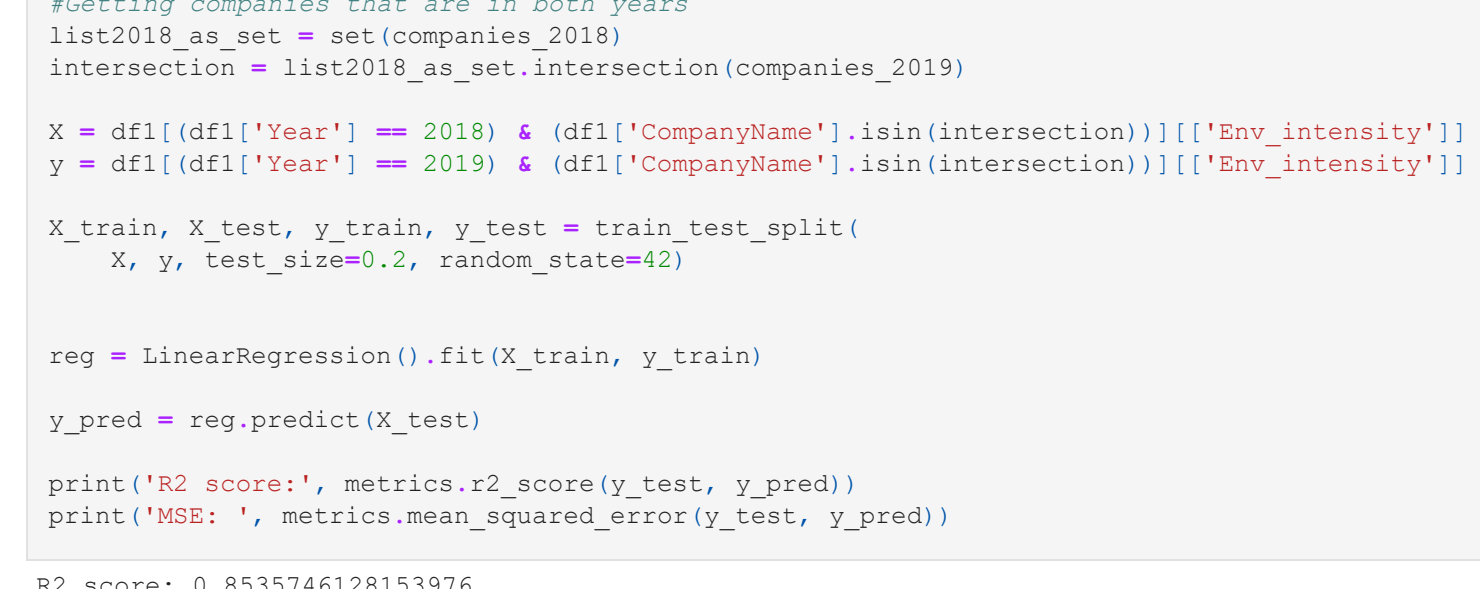
In [10]:
```python
df1 = df.copy()
```

In [11]:
```python
def p2f(x):
    return float(x.strip('%'))/100
df1['EnvironmentalIntensity(Sales)'] = df1['EnvironmentalIntensity(Sales)'].apply(p2f)
```

In [12]:
```python
companies_2018 = list(df1[df1['Year'] == 2018]['CompanyName'])
companies_2019 = list(df1[(df1['Year'] == 2019) & (df1['CompanyName'].isin(companies_2018))]['CompanyName'])

#Getting companies that are in both years
list2018_as_set = set(companies_2018)
intersection = list2018_as_set.intersection(companies_2019)

X = df1[(df1['Year'] == 2018) & (df1['CompanyName'].isin(intersection))][['Env_intensity']]
y = df1[(df1['Year'] == 2019) & (df1['CompanyName'].isin(intersection))][['Env_intensity']]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)


reg = LinearRegression().fit(X_train, y_train)

y_pred = reg.predict(X_test)

print('R2 score:', metrics.r2_score(y_test, y_pred))
print('MSE: ', metrics.mean_squared_error(y_test, y_pred))
```

```
R2 score: 0.8535746128153976
MSE:  0.015251450150102281
```

In [13]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2018');
```



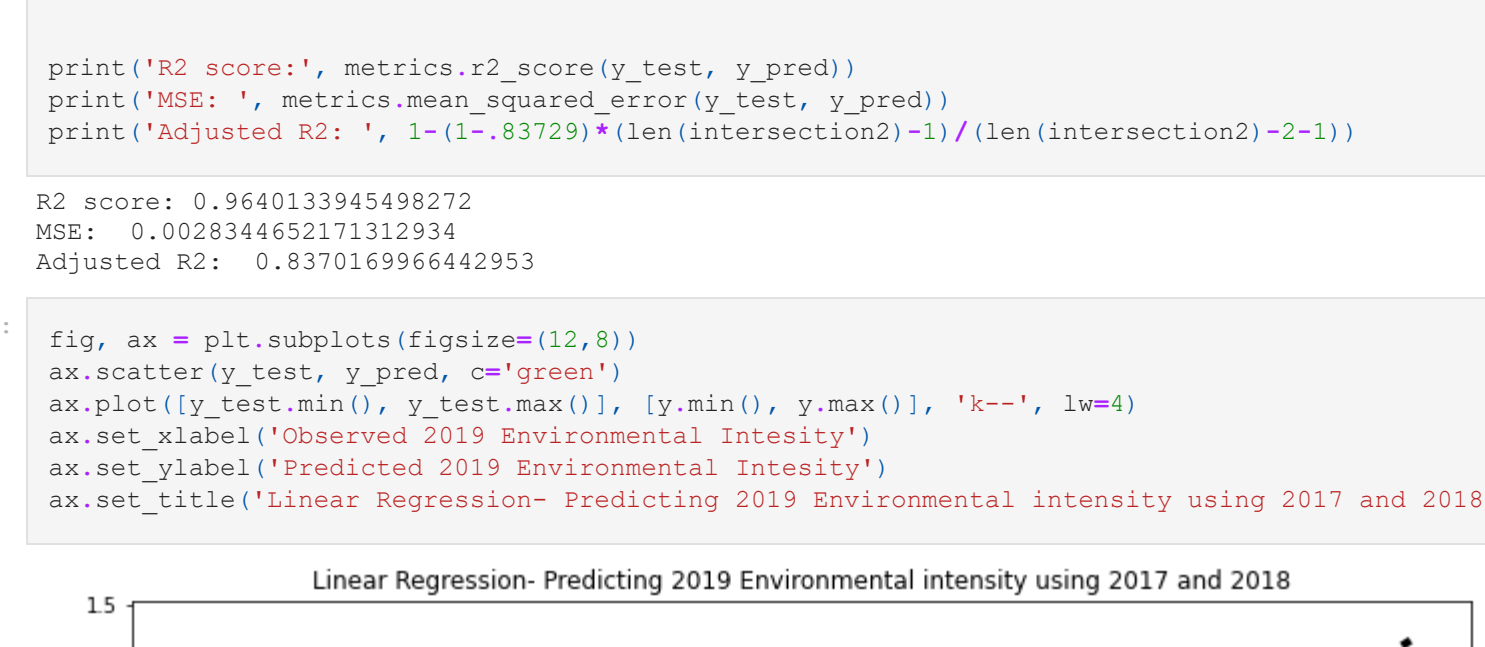
Including Multiple Years

Starting with 2017 & 2018 to predict values in 2019

In [14]:
```python
companies_2017 = list(df1[df1['Year'] == 2017]['CompanyName'])
list2017_as_set = set(companies_2017)
intersection2= list2017_as_set.intersection(intersection)

X = df1[(df1['Year'].isin([2017, 2018])) & (df1['CompanyName'].isin(intersection2))][['CompanyName','Environmer
X = X.groupby('CompanyName').mean()[['EnvironmentalIntensity(Sales)']]

y = df1[(df1['Year'] == 2019) & (df1['CompanyName'].isin(intersection2))][['EnvironmentalIntensity(Sales)']]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)


reg = LinearRegression().fit(X_train, y_train)

y_pred = reg.predict(X_test)


print('R2 score:', metrics.r2_score(y_test, y_pred))
print('MSE: ', metrics.mean_squared_error(y_test, y_pred))
print('Adjusted R2: ', 1-(1-.83729)*(len(intersection2)-1)/(len(intersection2)-2-1))
```

```
R2 score: 0.9640133945498272
MSE:  0.0028344652171312934
Adjusted R2:  0.8370169966442953
```

In [15]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2017 and 2018');
```



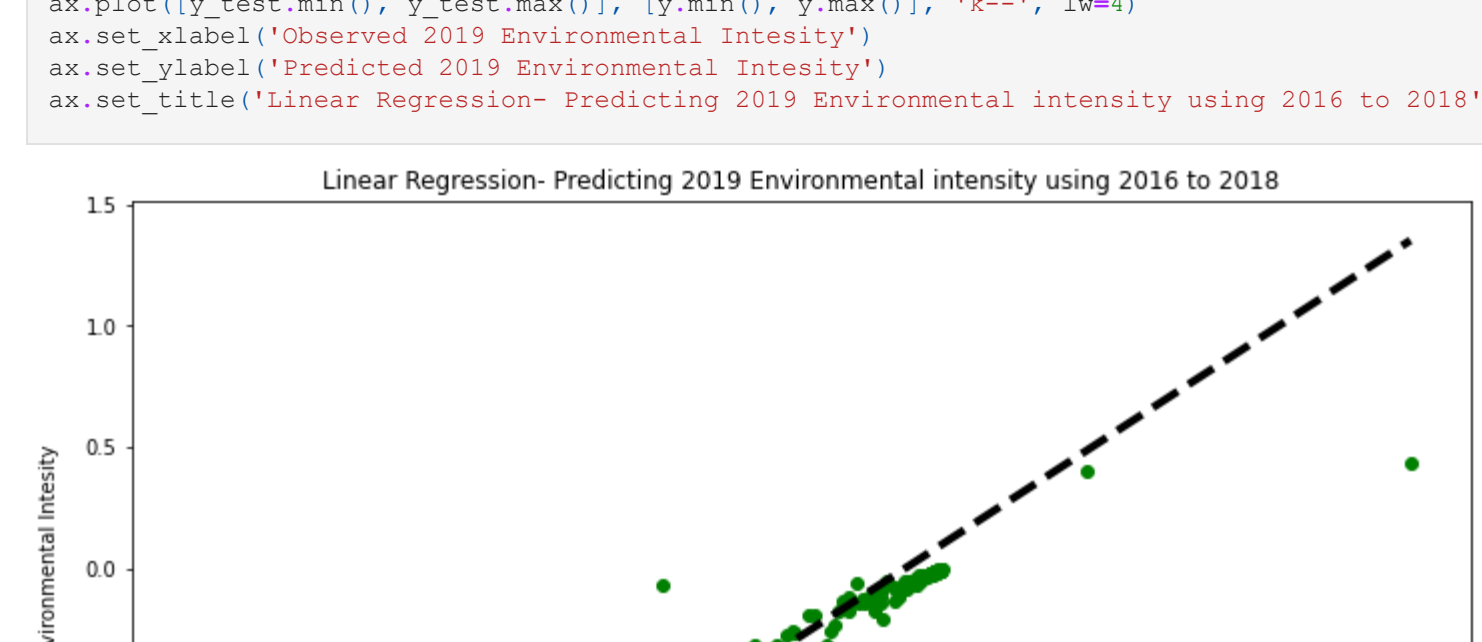
We see that the results of this model are worse than our first model which predicted 2019 numbers with 2018. We go on to include 2017.

In [16]:
```python
companies_2016 = list(df1[df1['Year'] == 2016]['CompanyName'])
list2016_as_set = set(companies_2016)
intersection3= list2016_as_set.intersection(intersection2)

X = df1[(df1['Year'].isin([2016, 2017, 2018])) & (df1['CompanyName'].isin(intersection3))][['CompanyName','Envi
X = X.groupby('CompanyName').mean()[['EnvironmentalIntensity(Sales)']]

y = df1[(df1['Year'] == 2019) & (df1['CompanyName'].isin(intersection3))][['EnvironmentalIntensity(Sales)']]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)


reg = LinearRegression().fit(X_train, y_train)

y_pred = reg.predict(X_test)

print('R2 score:', metrics.r2_score(y_test, y_pred))
print('MSE: ', metrics.mean_squared_error(y_test, y_pred))
print('Adjusted R2: ', 1-(1-.92741)*(len(intersection3)-1)/(len(intersection3)-3-1))
```

```
R2 score: 0.916454447105587
MSE:  0.00421395537780839
Adjusted R2:  0.9272047502356268
```

When we include 2016 both our R score and MSE improved.

In [17]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2016 to 2018');
```



Model 2 - Past years average environmental intensity

In this section, we will use the average environmental intensity of 2016-2018 to predict 2019 environmental intensity

In [18]:
```python
df2 = df.copy()
EI_2016 = df2[df2['Year'] == 2016]
EI_2017 = df2[df2['Year'] == 2017]
EI_2018 = df2[df2['Year'] == 2018]
EI_2019 = df2[df2['Year'] == 2019]
```

In [19]:
```python
df_mod2 = EI_2016.merge(EI_2017, how='inner', on='CompanyName', suffixes=('_2016', '_2017'))
df_mod2 = df_mod2.merge(EI_2018, how='inner', on='CompanyName')
df_mod2 = df_mod2.merge(EI_2019, how='inner', on='CompanyName', suffixes=('_2018', '_2019'))
```

In [20]:
```python
df_mod2 = df_mod2[['CompanyName','Year_2016','Env_intensity_2016','Year_2017','Env_intensity_2017','Year_2018',
```

In [21]:
```python
df_mod2.head()
```

Out[21]:

	CompanyName	Year_2016	Env_intensity_2016	Year_2017	Env_intensity_2017	Year_2018	Env_intensity_2018	Year_2019	Env_intensity_2019
0	3M COMPANY	2016	-0.0705	2017	-0.0660	2018	-0.0710	2019	-0.0641
1	A.G.V. PRODUCTS CORP	2016	-0.0170	2017	-0.0190	2018	-0.0140	2019	-0.0172
2	AA PLC	2016	-0.0130	2017	-0.0124	2018	-0.0117	2019	-0.0070
3	AAC TECHNOLOGIES HOLDINGS INCORPORATION	2016	-0.0389	2017	-0.0591	2018	-0.0802	2019	-0.1080
4	AAREAL BANK AG	2016	-0.0024	2017	-0.0021	2018	-0.0019	2019	-0.0015

In [22]:
```python
df_melt2 = pd.melt(df_mod2, id_vars=['CompanyName'], value_vars=['Env_intensity_2016','Env_intensity_2016','Env
        var_name='myVarname', value_name='Environmental_intenrsity')
```

In [23]:
```python
df_melt2.head()
```

Out[23]:

	CompanyName	myVarname	Environmental_intenrsity
0	3M COMPANY	Env_intensity_2016	-0.0705
1	A.G.V. PRODUCTS CORP	Env_intensity_2016	-0.0170
2	AA PLC	Env_intensity_2016	-0.0130
3	AAC TECHNOLOGIES HOLDINGS INCORPORATION	Env_intensity_2016	-0.0389
4	AAREAL BANK AG	Env_intensity_2016	-0.0024

In [24]:
```python
ei_avg = df_melt2.groupby('CompanyName').mean().reset_index()
X = ei_avg[['Environmental_intenrsity']]
y = df_mod2[['Env_intensity_2019']]

print(X.shape)
print(y.shape)
```

```
(1065, 1)
(1065, 1)
```

In [25]:
```python
x_train, x_test, y_train, y_test = train_test_split(X ,y, test_size = 0.2, random_state = 42)
# train Linear Regression
LRtrainer = LinearRegression()
LRtrainer.fit(x_train,y_train)

# mse for linear regression
y_pred_lr = LRtrainer.predict(x_test)
print(metrics.mean_squared_error(y_pred_lr, y_test))
```

```
0.006269966737857914
```

In [26]:
```python
# display the parameters
print('Model intercept: ', LRtrainer.intercept_)
print('Model coefficients: ', LRtrainer.coef_)
```

```
Model intercept:  [-0.0051724]
Model coefficients:  [[0.80432622]]
```

In [27]:
```python
print('R2 score:', metrics.r2_score(y_test, y_pred_lr))
```

```
R2 score: 0.8756921251462437
```

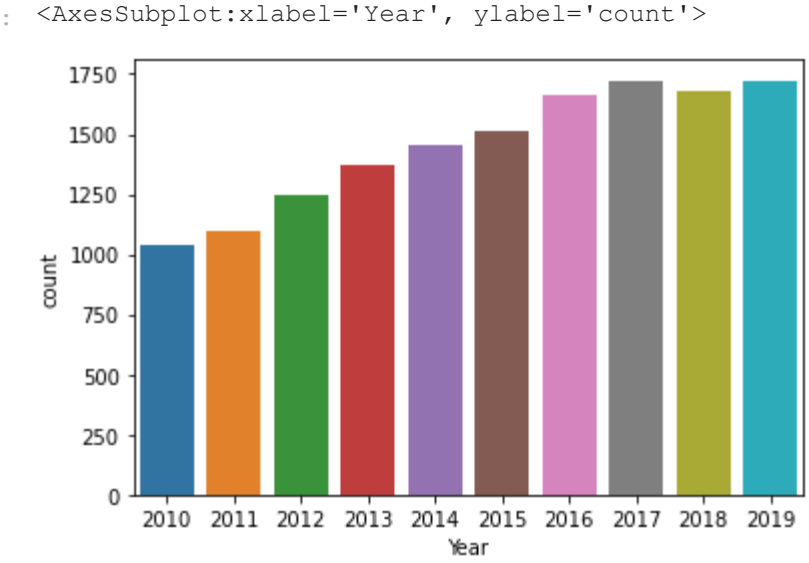
In [28]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred_lr, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using the companies average environmen
```

Model 3 - Yearly Industry Average

For this model, the predictor will be the industry average for the respective year. There is no data for 2020, so we plan to predict 2019 environmental intensity. Accordingly, we used 2018 and 2017 Industry data (past data) to predict 2019 evronmental intensity.

In [29]:
```python
sns.countplot(x='Year', data = df)
```

Out[29]:
```
<AxesSubplot:xlabel='Year', ylabel='count'>
```



The dataset does not contain consistent records throught out the years. Therefore, it could be possible we have data for one company in 2019 but not data from that company in 2018, 2017, etc.

We will start by only using 2018 industry average as a feature to predict 2019 environmental intensity. First, we will subset the companies that we have 2018 data and get their 2019 environmental intensity. Also, we will keep the industries that have more than 3 companies assigned to them.

In [30]:
```python
df_industry = df.groupby('Industry(Exiobase)').count()['CompanyName'].reset_index()

industries = df_industry[df_industry['CompanyName'] > 3]['Industry(Exiobase)']
```

In [31]:
```python
df_industry_count4 = df[df['Industry(Exiobase)'].isin(industries)]


df_2018 = df_industry_count4.loc[df.Year == 2018, ]
df_2019 = df_industry_count4.loc[df.Year == 2019, ]
df_mod3 = pd.merge(df_2018, df_2019, on='CompanyName',how='inner')
df_mod3 = df_mod3[['Year_x','CompanyName','industry_avg_year_x','Year_y','Env_intensity_y']]
df_mod3.head()
```

Out[31]:

	Year_x	CompanyName	industry_avg_year_x	Year_y	Env_intensity_y
0	2018	3M COMPANY	-0.229308	2019	-0.0641
1	2018	3SBIO INC	-0.027793	2019	-0.0340
2	2018	A.G.V. PRODUCTS CORP	-0.072254	2019	-0.0172
3	2018	AA PLC	-0.073777	2019	-0.0070
4	2018	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-0.023555	2019	-0.1080

In [32]:
```python
X = df_mod3[['industry_avg_year_x']]
y = df_mod3.iloc[:,4]
print(X.shape)
print(y.shape)
```

```
(1336, 1)
(1336,)
```

In [33]:
```python
x_train, x_test, y_train, y_test = train_test_split(X ,y, test_size = 0.2, random_state = 42)
# train Linear Regression
LRtrainer = LinearRegression()
LRtrainer.fit(x_train,y_train)

# mse for linear regression
y_pred_lr = LRtrainer.predict(x_test)
print(metrics.mean_squared_error(y_pred_lr, y_test))
```

```
0.06598743409385226
```

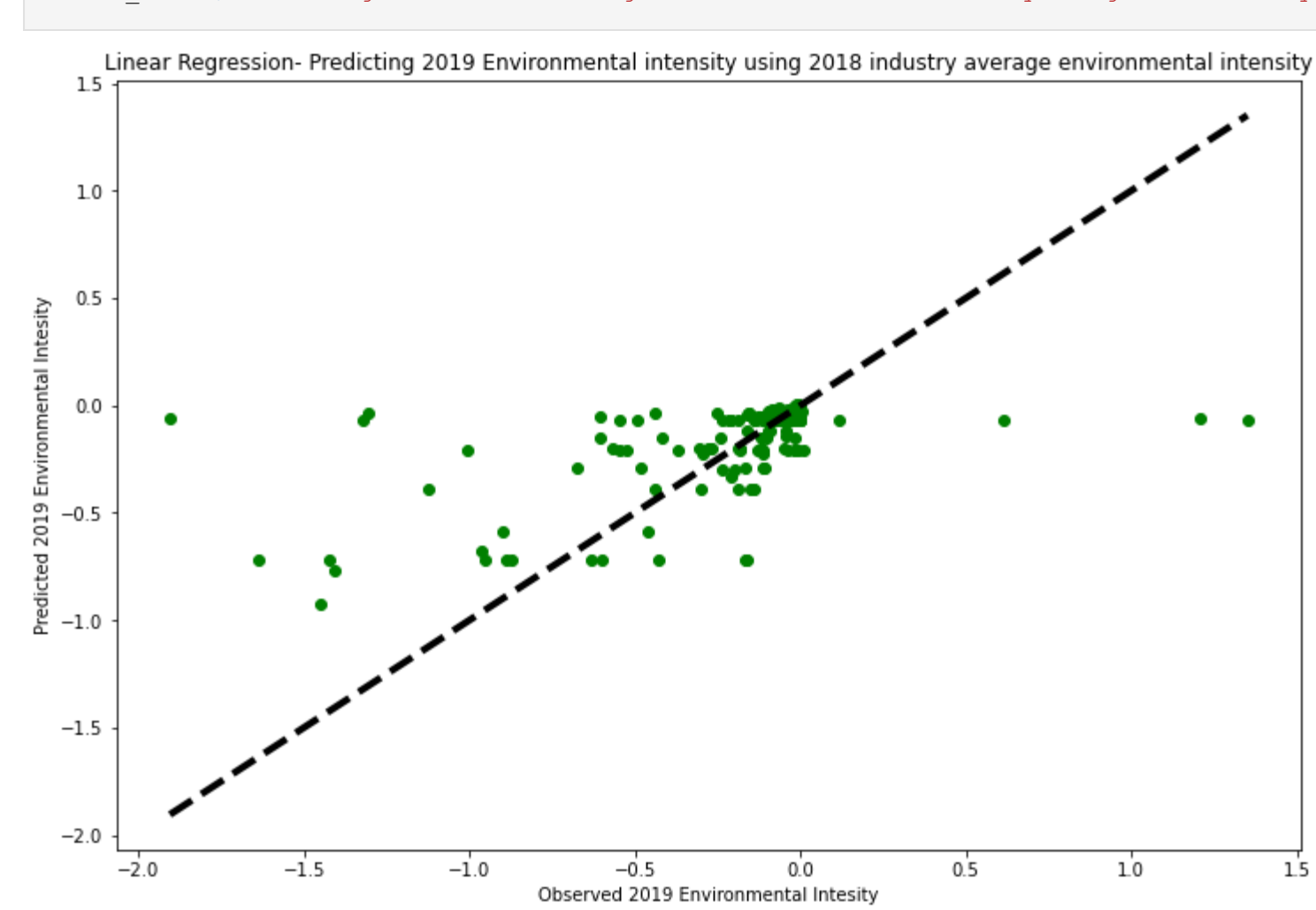
In [34]:
```python
# display the parameters
print('Model intercept: ', LRtrainer.intercept_)
print('Model coefficients: ', LRtrainer.coef_)
```

```
Model intercept:  0.0002669631900767966
Model coefficients:  [0.91303819]
```

In [35]:
```python
print('R2 score:', metrics.r2_score(y_test, y_pred_lr))
```

```
R2 score: 0.36647102462935643
```

In [36]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred_lr, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2018 industry average environmen
```



Now, we are going to consider 2017 - 2018 to predict 2019

In [37]:
```python
df_2019=df_industry_count4[df_industry_count4['Year'] == 2019]
df_2018=df_industry_count4[df_industry_count4['Year'] == 2018]
df_2017=df_industry_count4[df_industry_count4['Year'] == 2017]
```

In [38]:
```python
df2019=df_2019[['Year','CompanyName','Env_intensity']]
df2019.rename(columns={'Env_intensity': 'Env_intensity2019'}, inplace=True)
df2018=df_2018[['CompanyName','industry_avg_year']]
df2018.rename(columns={'industry_avg_year': 'Ind_Yearavg2018'}, inplace=True)
df2017=df_2017[['CompanyName','industry_avg_year']]
df2017.rename(columns={'industry_avg_year': 'Ind_Yearavg2017'}, inplace=True)
mdl = pd.merge(df2019, df2018, on=["CompanyName"])
mdl1= pd.merge(mdl, df2017, on=["CompanyName"])
mdl1
```

Out[38]:

	Year	CompanyName	Env_intensity2019	Ind_Yearavg2018	Ind_Yearavg2017
0	2019	3M COMPANY	-0.0641	-0.229308	-0.225496
1	2019	3SBIO INC	-0.0340	-0.027793	-0.031771
2	2019	A.G.V. PRODUCTS CORP	-0.0172	-0.072254	-0.063618
3	2019	AA PLC	-0.0070	-0.073777	-0.096157
4	2019	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-0.1080	-0.023555	-0.027254
...	...	...	...	...	...
1190	2019	ZEON CORPORATION	-0.0730	-0.218707	-0.275385
1191	2019	ZHEN DING TECHNOLOGY HOLDING LIMITED	-0.0602	-0.076812	-0.068294
1192	2019	ZIG SHENG INDUSTRIAL COMPANY LIMITED	-0.1615	-0.124750	-0.117456
1193	2019	ZORLU ENERJI AS	-0.3430	-1.012140	-0.578986
1194	2019	ZUMTOBEL AG	-0.0051	-0.020683	-0.036006

1195 rows × 5 columns

In [39]:
```python
X=mdl1[['Ind_Yearavg2018','Ind_Yearavg2017']]
y=mdl1['Env_intensity2019']
print(X.shape)
print(y.shape)
```

```
(1195, 2)
(1195,)
```

In [40]:
```python
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = np.exp(regr.predict(X_train))
y_pred = np.exp(regr.predict(X_test))
y_test = np.exp(y_test)
```

In [41]:
```python
print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 1.064, test: 0.038
```

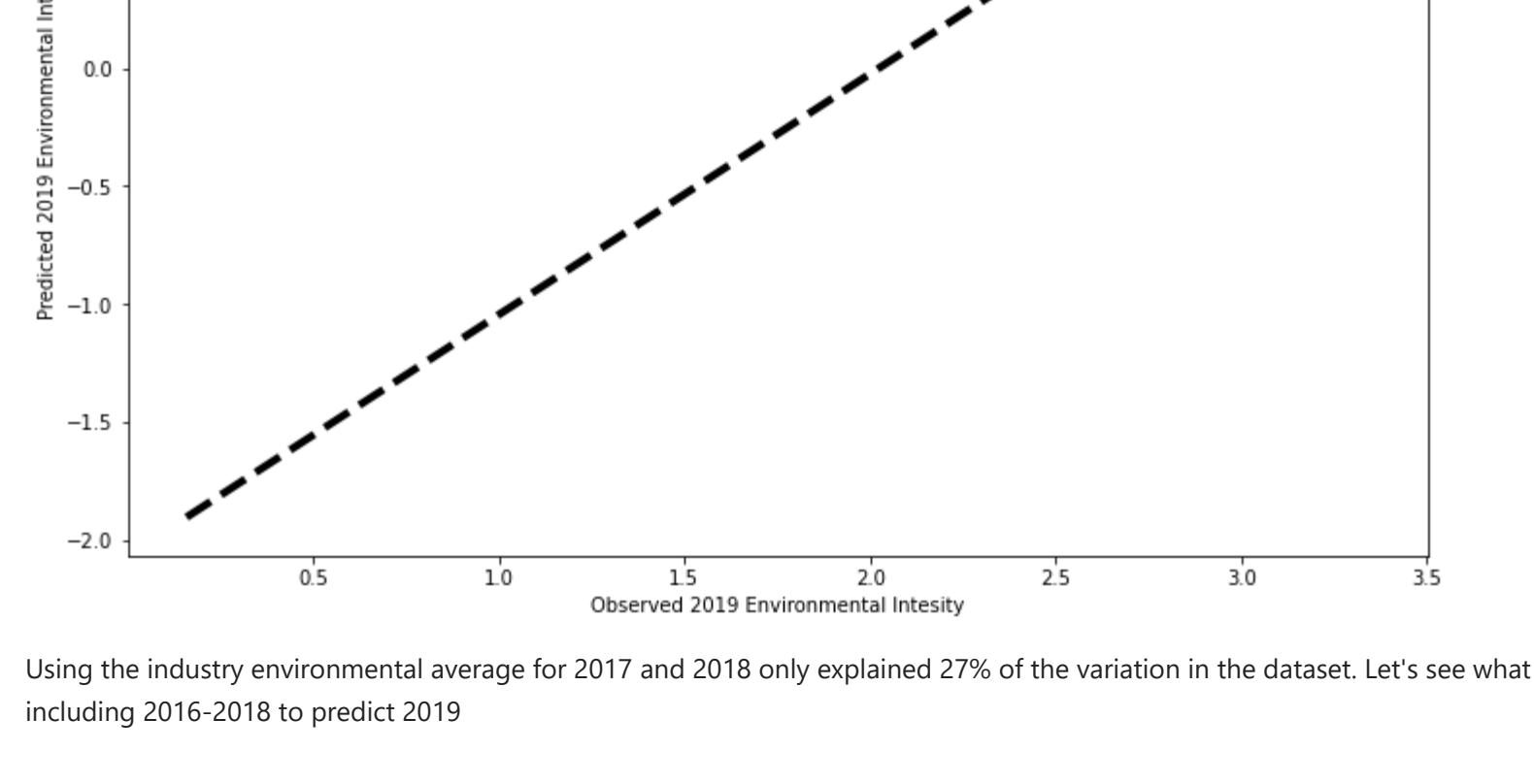
In [42]:
```python
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  0.0005763983280114432
Model coefficients:  [ 0.94555899 -0.06948928]
```

In [43]:
```python
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: 0.26873239153605133
```

In [44]:
```python
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2017- 2018 industry average envi
```



Using the industry environmental average for 2017 and 2018 only explained 27% of the variation in the dataset. Let's see what happens including 2016-2018 to predict 2019

```
In [45]:
df_2016 = df_industry_count4.loc[df_industry_count4.Year == 2016, ]
df_2017 = df_industry_count4.loc[df_industry_count4.Year == 2017, ]
df1 = df_2016.merge(df_2017, how='inner', on='CompanyName', suffixes=('_2016', '_2017'))
df1 = df1.merge(df_2018, how='inner', on='CompanyName')
df1 = df1.merge(df_2019, how='inner', on='CompanyName', suffixes=('_2018', '_2019'))
df1 = df1[['Year_2016','industry_avg_year_2016','Year_2017','industry_avg_year_2017','Year_2018','industry_avg_
```

```
In [46]:
X = df1[['industry_avg_year_2016','industry_avg_year_2017','industry_avg_year_2018']]
y = df1.iloc[:,7]
print(X.shape)
print(y.shape)
```

```
(1065, 3)
(1065,)
```

```
In [47]:
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = regr.predict(X_train)
y_pred = regr.predict(X_test)
```

```
In [48]:
print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 0.033, test: 0.036
```

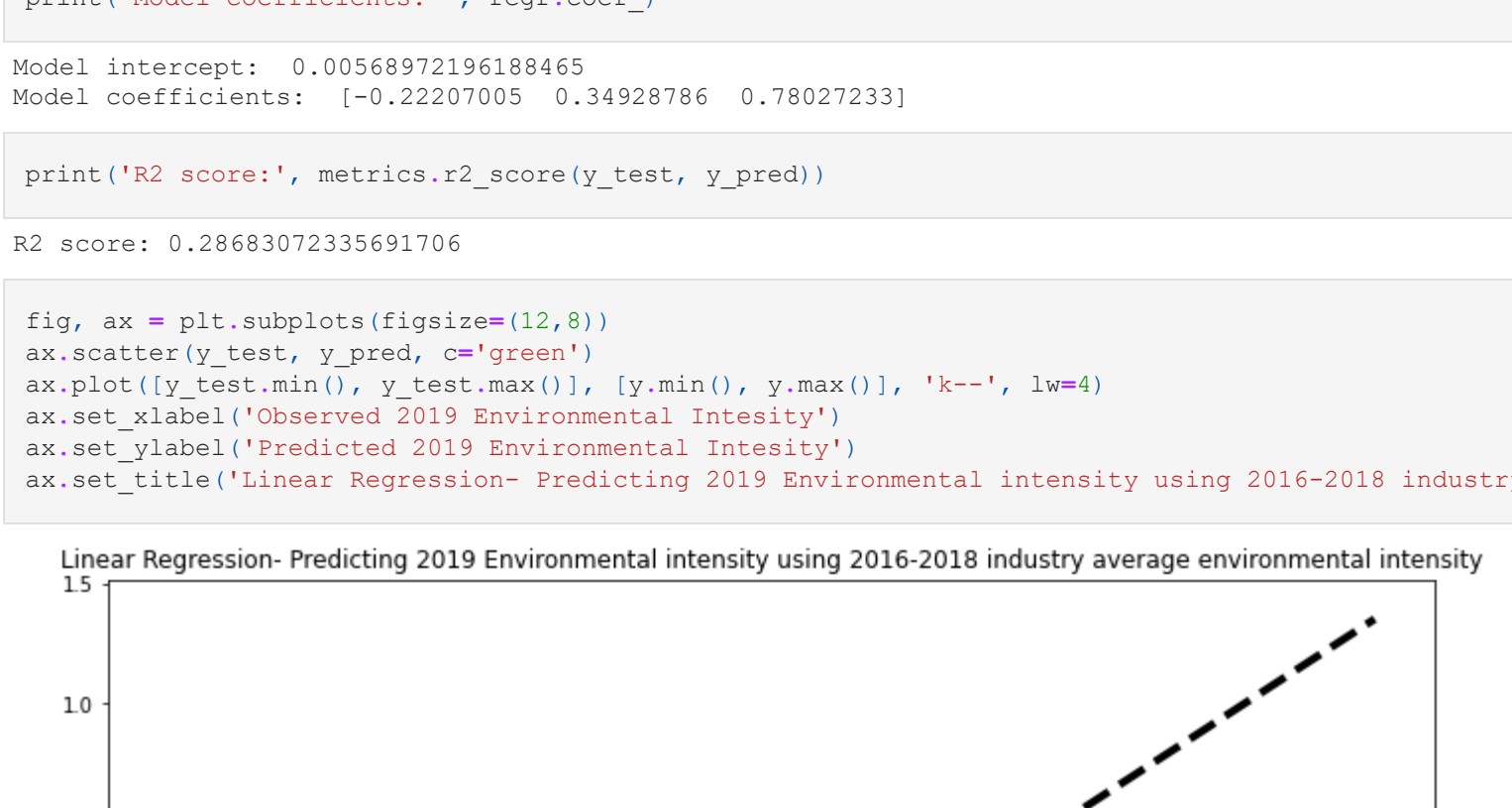
```
In [49]:
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  0.00568972196188465
Model coefficients:  [-0.22207005  0.34928786  0.78027233]
```

```
In [50]:
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: 0.28683072335691706
```

```
In [51]:
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2016-2018 industry average envi
```



Model 4 -Yearly Industry Indicator

For this model, we will consider the yearly industry indicator from past years to predict the company 2019 environmental intensity.

We are going to start from 2017-2018 to predict 2019.

```
In [52]:
df_2019=df_industry_count4[df_industry_count4['Year'] == 2019]
df_2018=df_industry_count4[df_industry_count4['Year'] == 2018]
df_2017=df_industry_count4[df_industry_count4['Year'] == 2017]

df2019=df_2019[['Year','CompanyName','Env_intensity']]
df2019.rename(columns={'Env_intensity': 'Env_intensity2019'}, inplace=True)
df2018=df_2018[['CompanyName','Industry_indicator_year']]
df2018.rename(columns={'Industry_indicator_year': 'Ind_Indicator_2018'}, inplace=True)
df2017=df_2017[['CompanyName','Industry_indicator_year']]
df2017.rename(columns={'Industry_indicator_year': 'Ind_Indicator_2017'}, inplace=True)
mdl4 = pd.merge(df2019, df2018, on=["CompanyName"])
mdl4= pd.merge(mdl4, df2017, on=["CompanyName"])
mdl4
```

Out[52]:

	Year	CompanyName	Env_intensity2019	Ind_Indicator_2018	Ind_Indicator_2017
0	2019	3M COMPANY	-0.0641	1	1
1	2019	3SBIO INC	-0.0340	-1	1
2	2019	A.G.V. PRODUCTS CORP	-0.0172	1	1
3	2019	AA PLC	-0.0070	1	1
4	2019	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-0.1080	-1	-1
...	...	...	...	...	...
1190	2019	ZEON CORPORATION	-0.0730	1	1
1191	2019	ZHEN DING TECHNOLOGY HOLDING LIMITED	-0.0602	1	1
1192	2019	ZIG SHENG INDUSTRIAL COMPANY LIMITED	-0.1615	-1	-1
1193	2019	ZORLU ENERJI AS	-0.3430	1	1
1194	2019	ZUMTOBEL AG	-0.0051	1	1

1195 rows × 5 columns

```
In [53]:
X=mdl4[['Ind_Indicator_2017','Ind_Indicator_2018']]
y=mdl4['Env_intensity2019']
print(X.shape)
print(y.shape)
```

```
(1195, 2)
(1195,)
```

```
In [54]:
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = regr.predict(X_train)
y_pred = regr.predict(X_test)
```

```
In [55]:
print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 0.048, test: 0.062
```

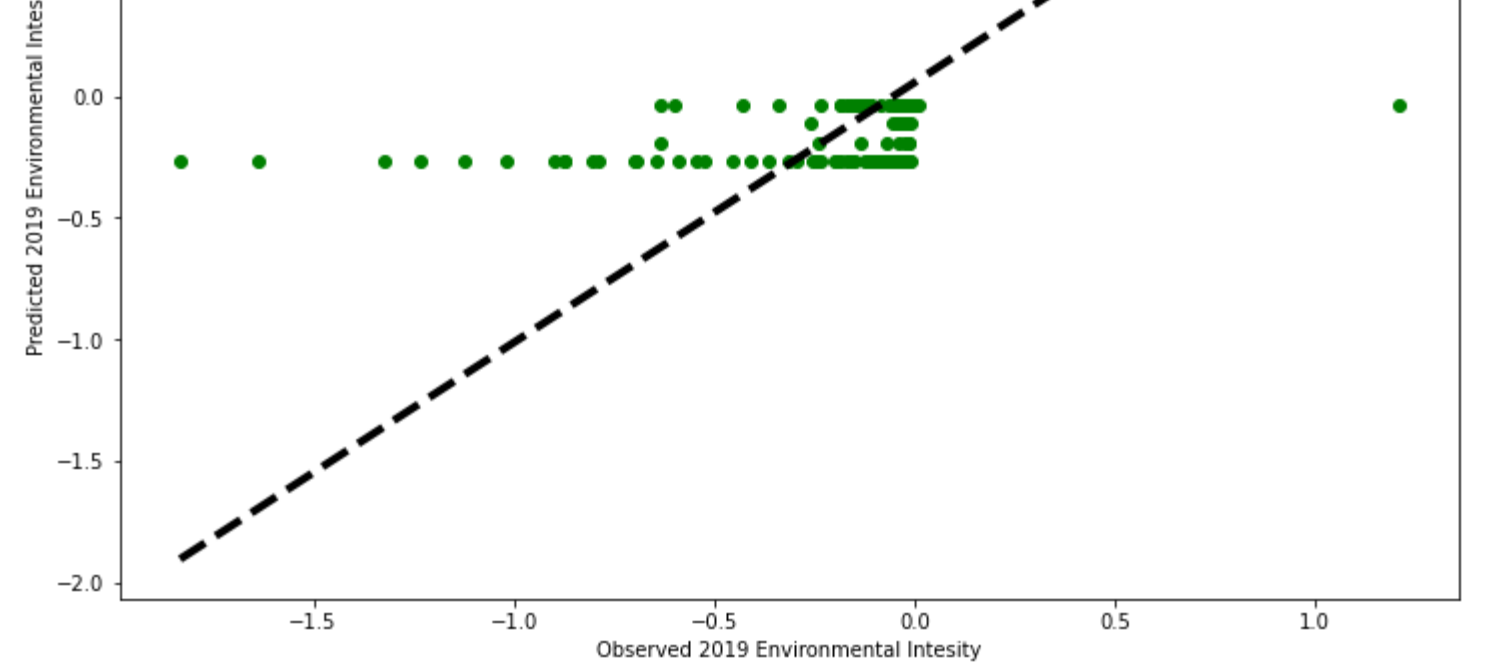
```
In [56]:
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  -0.15356410683376787
Model coefficients:  [0.03709691 0.07830873]
```

```
In [57]:
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: 0.21186363020947374
```

```
In [58]:
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2017- 2018 industry indicator');
```



The industry indicator isn't a good predictor for environmental intensity.

Let's try including 2016-2018 to predict 2019 environmental intensity.

```
In [59]:
df_2016=df_industry_count4[df_industry_count4['Year'] == 2016]
df2016=df_2016[['CompanyName','Industry_indicator_year']]
df2016.rename(columns={'Industry_indicator_year': 'Ind_Indicator_2016'}, inplace=True)

mdl4 = pd.merge(df2019, df2018, on=["CompanyName"])
mdl4= pd.merge(mdl4, df2017, on=["CompanyName"])
mdl4= pd.merge(mdl4, df2016, on=["CompanyName"])
mdl4.head()
```

Out[59]:

	Year	CompanyName	Env_intensity2019	Ind_Indicator_2018	Ind_Indicator_2017	Ind_Indicator_2016
0	2019	3M COMPANY	-0.0641	1	1	1
1	2019	A.G.V. PRODUCTS CORP	-0.0172	1	1	1
2	2019	AA PLC	-0.0070	1	1	1
3	2019	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-0.1080	-1	-1	-1
4	2019	AAREAL BANK AG	-0.0015	1	1	1

```
In [60]:
X = mdl4[['Ind_Indicator_2016','Ind_Indicator_2017','Ind_Indicator_2018']]
y = mdl4['Env_intensity2019']
print(X.shape)
print(y.shape)
```

```
(1065, 3)
(1065,)
```

```
In [61]:
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = regr.predict(X_train)
y_pred = regr.predict(X_test)

print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 0.047, test: 0.039
```

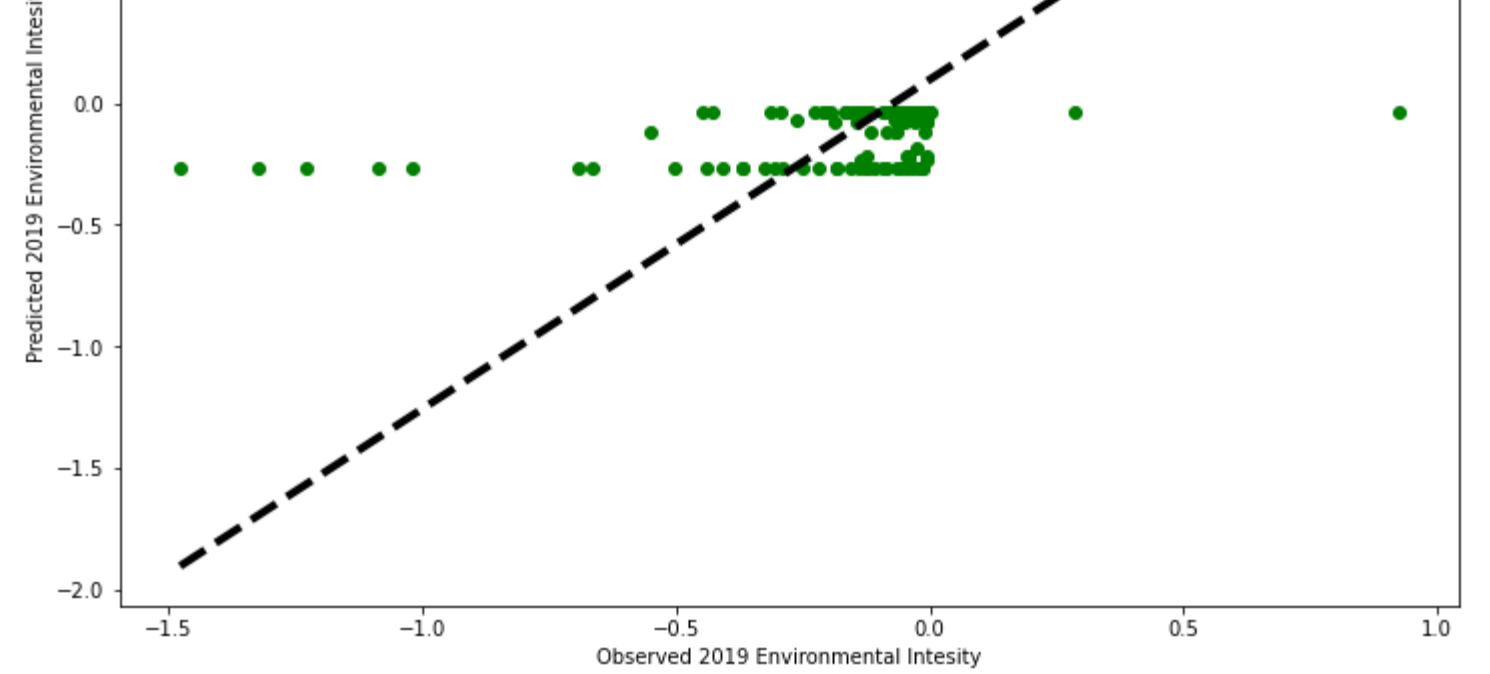
```
In [62]:
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  -0.14924959083044503
Model coefficients:  [0.02269159 0.01672383 0.07522696]
```

```
In [63]:
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: 0.22699240460633197
```

```
In [64]:
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2016- 2018 industry average envi
```



Model 5 -Growth Rate

For this model, we will consider the growth rate from past years to predict the company 2019 environmental intensity.

We are going to start from 2017-2018 to predict 2019.

```
In [65]:
df_2019=df[df['Year'] == 2019]
df_2018=df[df['Year'] == 2018]
df_2017=df[df['Year'] == 2017]

df2019=df_2019[['Year','CompanyName','Env_intensity']]
df2019.rename(columns={'Env_intensity': 'Env_intensity2019'}, inplace=True)
df2018=df_2018[['CompanyName','Environmental_Growth']]
df2018.rename(columns={'Environmental_Growth': 'Environmental_Growth_2018'}, inplace=True)
df2017=df_2017[['CompanyName','Environmental_Growth']]
df2017.rename(columns={'Environmental_Growth': 'Environmental_Growth_2017'}, inplace=True)
mdl5 = pd.merge(df2019, df2018, on=["CompanyName"])
mdl5= pd.merge(mdl5, df2017, on=["CompanyName"])
mdl5
```

Out[65]:

	Year	CompanyName	Env_intensity2019	Environmental_Growth_2018	Environmental_Growth_2017
0	2019	3M COMPANY	-0.0641	7.575758	-6.382979
1	2019	3SBIO INC	-0.0340	50.672646	NaN
2	2019	A.G.V. PRODUCTS CORP	-0.0172	-26.315789	11.764706
3	2019	AA PLC	-0.0070	-5.645161	-4.615385
4	2019	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-0.1080	35.702200	51.928021
...	...	...	...	...	...
1190	2019	ZEON CORPORATION	-0.0730	-1.272265	-10.273973
1191	2019	ZHEN DING TECHNOLOGY HOLDING LIMITED	-0.0602	1.990050	-30.927835
1192	2019	ZIG SHENG INDUSTRIAL COMPANY LIMITED	-0.1615	-4.232425	-20.251716
1193	2019	ZORLU ENERJI AS	-0.3430	48.046057	-81.144737
1194	2019	ZUMTOBEL AG	-0.0051	2.380952	-19.230769

1195 rows × 5 columns

```
In [66]:
mdl5.dropna(inplace = True)#delete rows with missing values
mdl5.shape
```

```
Out[66]: (1094, 5)
```

```
In [67]:
X=mdl5[['Environmental_Growth_2017','Environmental_Growth_2018']]
y=mdl5['Env_intensity2019']
print(X.shape)
print(y.shape)
```

```
(1094, 2)
(1094,)
```

```
In [68]:
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = regr.predict(X_train)
y_pred = regr.predict(X_test)
```

```
In [69]:
print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 0.053, test: 0.083
```

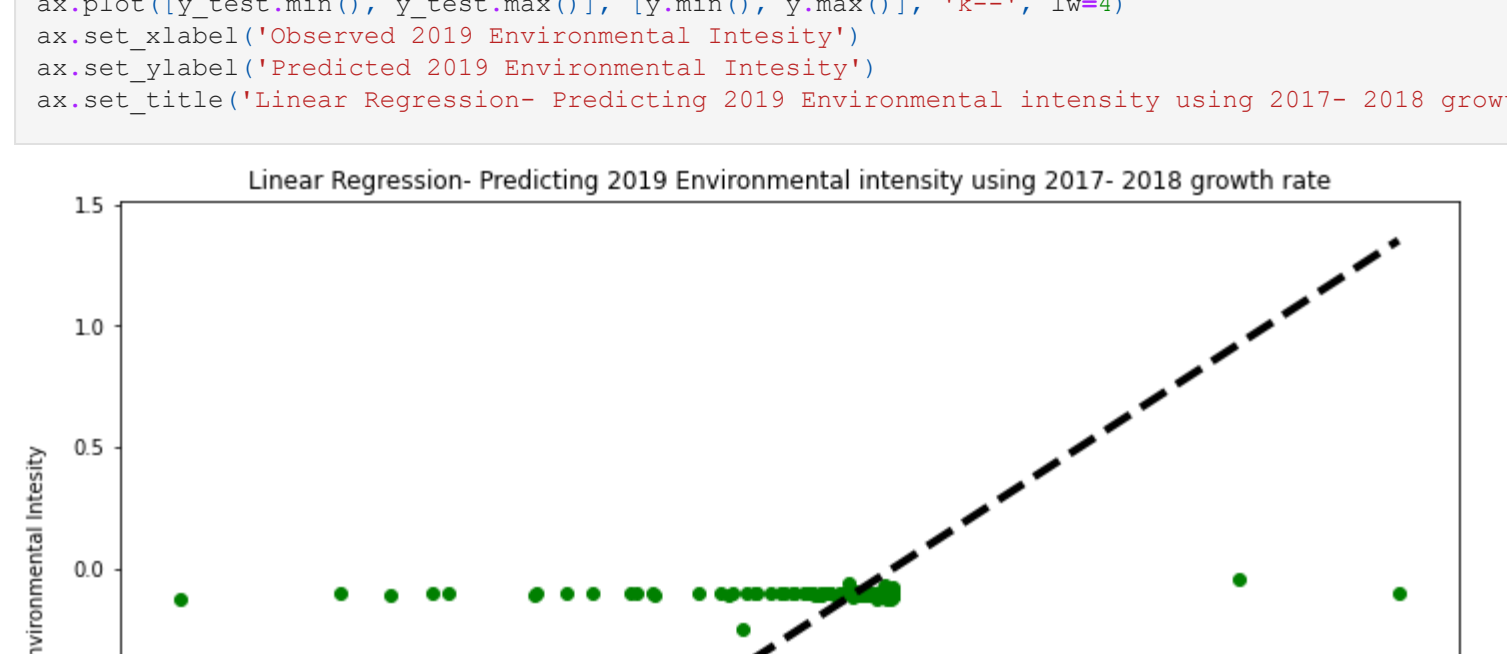
```
In [70]:
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  -0.10344845492642087
Model coefficients:  [-1.28035334e-04 -8.51885195e-05]
```

```
In [71]:
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: 0.015827756484296907
```

```
In [72]:
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2017- 2018 growth rate');
```



The growth rate isn't a good predictor for environmental intensity. Let's try including 2016-2018 to predict 2019 environmental intensity.

```
In [73]:
df_2016=df[df['Year'] == 2016]
df_2016.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1666 entries, 0 to 14505
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   ISIN                            1666 non-null   object
 1   Year                            1666 non-null   int64
 2   CompanyName                     1666 non-null   object
 3   Country                         1666 non-null   object
 4   Industry(Exiobase)              1666 non-null   object
 5   EnvironmentalIntensity(Sales)   1666 non-null   object
 6   Env_intensity                   1666 non-null   float64
 7   industry_avg                    1666 non-null   float64
 8   Industry_indicator              1666 non-null   int64
 9   industry_avg_year               1666 non-null   float64
 10  Industry_indicator_year         1666 non-null   int64
 11  Environmental_Growth            1534 non-null   float64
dtypes: float64(4), int64(3), object(5)
memory usage: 169.2+ KB
```

```
In [74]:
df_2016=df[df['Year'] == 2016]
df2016=df_2016[['CompanyName','Environmental_Growth']]
df2016.rename(columns={'Environmental_Growth': 'Environmental_Growth_2016'}, inplace=True)

mdl5 = pd.merge(df2016, df2017, on=["CompanyName"])
mdl5= pd.merge(mdl5, df2018, on=["CompanyName"])
mdl5= pd.merge(mdl5, df2019, on=["CompanyName"])
mdl5.dropna(inplace=True)
mdl5.head()
```

Out[74]:

	CompanyName	Environmental_Growth_2016	Environmental_Growth_2017	Environmental_Growth_2018	Year	Env_intensity2019
0	3M COMPANY	8.964451	-6.382979	7.575758	2019	-0.0641
1	A.G.V. PRODUCTS CORP	-13.265306	11.764706	-26.315789	2019	-0.0172
2	AA PLC	41.304348	-4.615385	-5.645161	2019	-0.0070
3	AAC TECHNOLOGIES HOLDINGS INCORPORATION	-7.159905	51.928021	35.702200	2019	-0.1080
4	AAREAL BANK AG	9.090909	-12.500000	-9.523810	2019	-0.0015

```
In [75]:
X=mdl5[['Environmental_Growth_2016','Environmental_Growth_2017','Environmental_Growth_2018']]
y=mdl5['Env_intensity2019']
print(X.shape)
print(y.shape)
```

```
(1010, 3)
(1010,)
```

```
In [76]:
regr = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
regr.fit(X_train, y_train)
y_train_pred = regr.predict(X_train)
y_pred = regr.predict(X_test)

print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE train: 0.050, test: 0.057
```

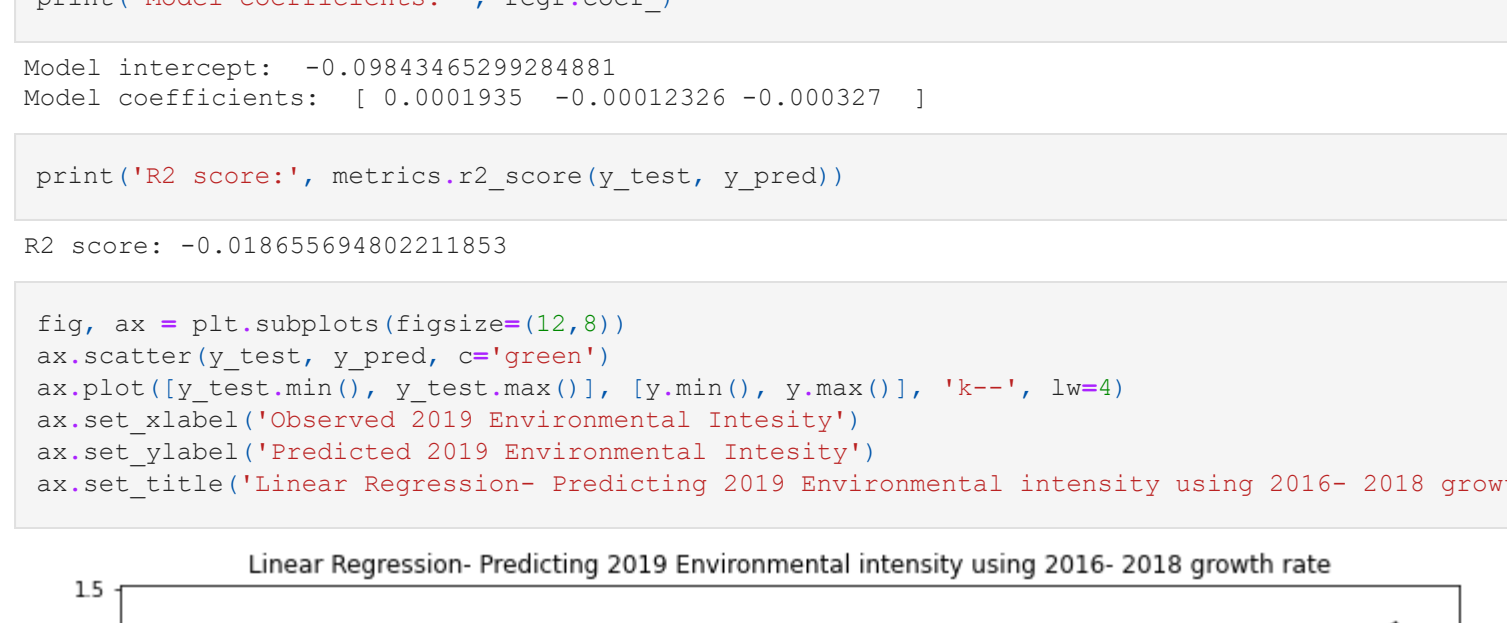
```
In [77]:
# display the parameters
print('Model intercept: ', regr.intercept_)
print('Model coefficients: ', regr.coef_)
```

```
Model intercept:  -0.09843465299284881
Model coefficients:  [ 0.0001935  -0.00012326 -0.000327  ]
```

```
In [78]:
print('R2 score:', metrics.r2_score(y_test, y_pred))
```

```
R2 score: -0.018655694802211853
```

```
In [79]:
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(y_test, y_pred, c='green')
ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
ax.set_xlabel('Observed 2019 Environmental Intesity')
ax.set_ylabel('Predicted 2019 Environmental Intesity')
ax.set_title('Linear Regression- Predicting 2019 Environmental intensity using 2016- 2018 growth rate');
```



Again, we see that each coefficient is negative which could be interpret that an increase in environmental growth decreases the environmental intensity for 2019. R1 score is also negative (is worse that a horizontal line) which mean we can discard this regression.

Individual model conclusions

As expected, using Environmental intensity from previous years had better accuracy to predict the next year Environmental intensity. We proved that in Model 1 and Model 2 were the regression was able to explain 88% of the variance.

When using the industry average for each year, the model was able to explain around 30-34% of the variance. Moreover, by running these regressions, we concluded that the envirionmental growth from previous years isn't a good predictor.

However, maybe the industry indicator and growth rate would help explain the future environmental intensity better if we combine this features with previous models. For example, predicting 2019 environmental intensity using last years environmental intensity, industry indicator, average industry and growth rate.

Let's see what happens!

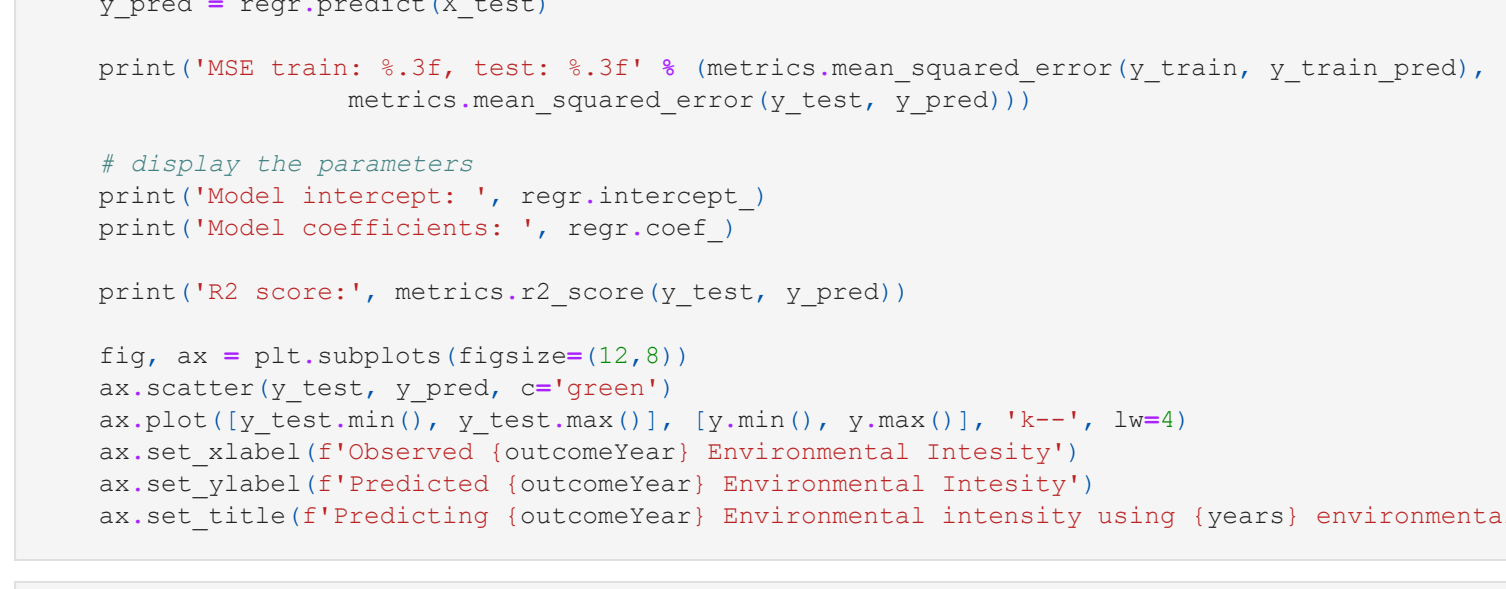
Building new predictive models by combinig features

In this section, we will create a function to calculate the desired future environmental intensity using different features.

```
In [80]:
years = [2016, 2017, 2018]
df_c = df_industry_count4.copy()
def predictiveModel(outcomeYear, pastYears, df_c):
    years.sort()
    for year in years:
        data = df_c[df_c['Year'] == year]
        data = data.loc[:,['CompanyName','Env_intensity','industry_avg_year']]
        data.rename(columns={'Env_intensity': f'Env_intensity_{year}','industry_avg_year':f'industry_avg_year_
        if(year == min(years)):
            data1 = pd.DataFrame(data)
        else:
            data2 = pd.merge(data1, data, on=["CompanyName"])
            data1 = data2.copy()
    data3 = df_c[df_c['Year'] == outcomeYear]
    data3 = data3[['CompanyName','Env_intensity','industry_avg_year']]
    data3.rename(columns={'Env_intensity': f'Env_intensity_{outcomeYear}','industry_avg_year':f'industry_avg_ye
    data3 = pd.merge(data3, data2, on=["CompanyName"])

    filter_col = [col for col in data3 if ((col.startswith('Env_intensity') and not(col.endswith(f'{outcomeYear
    outcome_col = [col for col in data3 if (col.startswith('Env_intensity') and col.endswith(f'{outcomeYear}'))
    X=data3[filter_col]
    y=data3[outcome_col]

    regr = linear_model.LinearRegression()
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
    regr.fit(X_train, y_train)
    y_train_pred = regr.predict(X_train)
    y_pred = regr.predict(X_test)

    print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))

    # display the parameters
    print('Model intercept: ', regr.intercept_)
    print('Model coefficients: ', regr.coef_)

    print('R2 score:', metrics.r2_score(y_test, y_pred))

    fig, ax = plt.subplots(figsize=(12,8))
    ax.scatter(y_test, y_pred, c='green')
    ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
    ax.set_xlabel(f'Observed {outcomeYear} Environmental Intesity')
    ax.set_ylabel(f'Predicted {outcomeYear} Environmental Intesity')
    ax.set_title(f'Predicting {outcomeYear} Environmental intensity using {years} environmental intensity and i
```

```
In [81]:
predictiveModel(2019, years, df_c)
```

```
MSE train: 0.007, test: 0.003
Model intercept:  [-0.00057703]
Model coefficients:  [[-0.01184595 -0.15828118 -0.1777978  -0.09734991  1.08688792  0.29898607]]
R2 score: 0.9458906332169734
```



Now, we are going to create another function that will create a predictive model using environmental intensity, industry average and industry indicator.

```
In [82]:
def predictiveModel1(outcomeYear, pastYears, df_c):
    years.sort()
    for year in years:
        data = df_c[df_c['Year'] == year]
        data = data.loc[:,['CompanyName','Env_intensity','industry_avg_year','Industry_indicator_year']]
        data.rename(columns={'Env_intensity': f'Env_intensity_{year}','industry_avg_year':f'industry_avg_year_
        if(year == min(years)):
            data1 = pd.DataFrame(data)
        else:
            data2 = pd.merge(data1, data, on=["CompanyName"])
            data1 = data2.copy()
    data3 = df_c[df_c['Year'] == outcomeYear]
    data3 = data3[['CompanyName','Env_intensity']]
    data3.rename(columns={'Env_intensity': f'Env_intensity_{outcomeYear}'}, inplace=True)
    data3 = pd.merge(data3, data2, on=["CompanyName"])

    filter_col = [col for col in data3 if ((col.startswith('Env_intensity') and not(col.endswith(f'{outcomeYear
    outcome_col = [col for col in data3 if (col.startswith('Env_intensity') and col.endswith(f'{outcomeYear}'))
    X=data3[filter_col]
    y=data3[outcome_col]

    regr = linear_model.LinearRegression()
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
    regr.fit(X_train, y_train)
    y_train_pred = regr.predict(X_train)
    y_pred = regr.predict(X_test)

    print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))

    # display the parameters
    print('Model intercept: ', regr.intercept_)
    print('Model coefficients: ', regr.coef_)

    print('R2 score:', metrics.r2_score(y_test, y_pred))

    fig, ax = plt.subplots(figsize=(12,8))
    ax.scatter(y_test, y_pred, c='red')
    ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
    ax.set_xlabel(f'Observed {outcomeYear} Environmental Intesity')
    ax.set_ylabel(f'Predicted {outcomeYear} Environmental Intesity')
    ax.set_title(f'Predicting {outcomeYear} Environmental intensity using {years} environmental intensity, indu
```

```
In [83]:
predictiveModel1(2019, years, df_c)
```

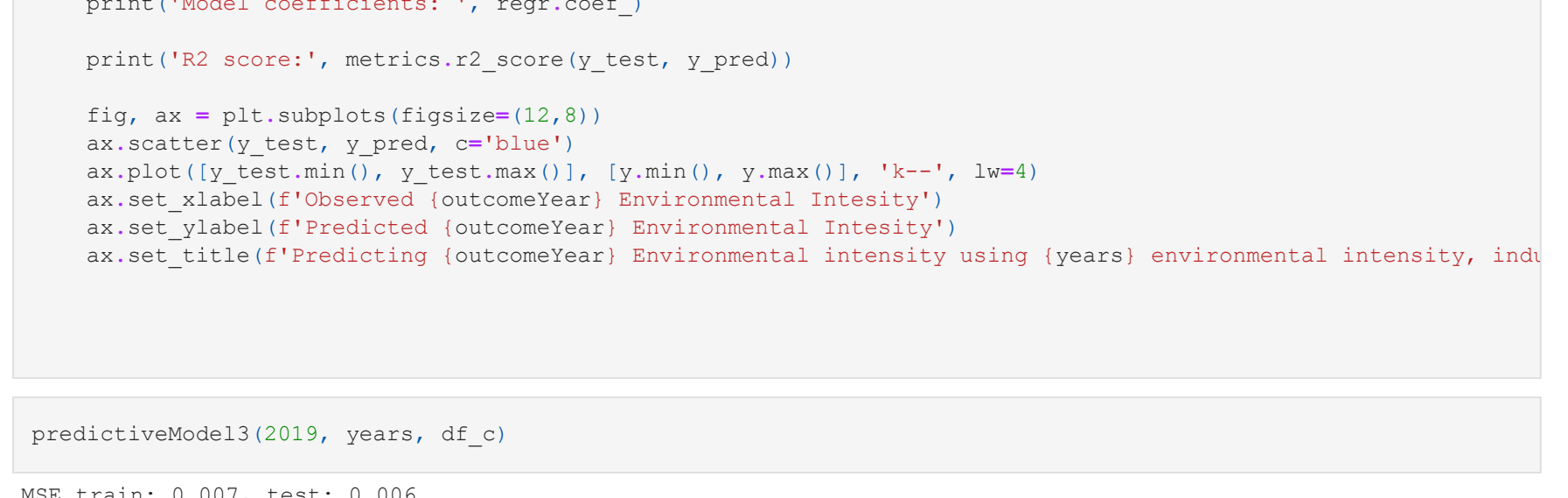
```
MSE train: 0.007, test: 0.003
Model intercept:  [-0.00054624]
Model coefficients:  [[-0.01778571 -0.14500433  0.00410858 -0.18026925 -0.09273773  0.00114723
   1.09366632  0.28265093 -0.00444881]]
R2 score: 0.9465508192299915
```

Now, we are going to create a third function that will create a predictive model using past years environmental intensity, industry average, industry indicator and environmental growth.

```
In [84]:
def predictiveModel3(outcomeYear, pastYears, df_c):
    years.sort()
    for year in years:
        data = df_c[df_c['Year'] == year]
        data = data.loc[:,['CompanyName','Env_intensity','industry_avg_year','Industry_indicator_year','Enviror
        data.rename(columns={'Env_intensity': f'Env_intensity_{year}','industry_avg_year':f'industry_avg_year_
        if(year == min(years)):
            data1 = pd.DataFrame(data)
        else:
            data2 = pd.merge(data1, data, on=["CompanyName"])
            data1 = data2.copy()
    data2.dropna(inplace=True)
    data3 = df_c[df_c['Year'] == outcomeYear]
    data3 = data3[['CompanyName','Env_intensity']]
    data3.rename(columns={'Env_intensity': f'Env_intensity_{outcomeYear}'}, inplace=True)
    data3 = pd.merge(data3, data2, on=["CompanyName"])

    filter_col = [col for col in data3 if ((col.startswith('Env_intensity') and not(col.endswith(f'{outcomeYear
    outcome_col = [col for col in data3 if (col.startswith('Env_intensity') and col.endswith(f'{outcomeYear}'))
    X=data3[filter_col]
    y=data3[outcome_col]

    regr = linear_model.LinearRegression()
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
    regr.fit(X_train, y_train)
    y_train_pred = regr.predict(X_train)
    y_pred = regr.predict(X_test)

    print('MSE train: %.3f, test: %.3f' % (metrics.mean_squared_error(y_train, y_train_pred),
                metrics.mean_squared_error(y_test, y_pred)))

    # display the parameters
    print('Model intercept: ', regr.intercept_)
    print('Model coefficients: ', regr.coef_)

    print('R2 score:', metrics.r2_score(y_test, y_pred))

    fig, ax = plt.subplots(figsize=(12,8))
    ax.scatter(y_test, y_pred, c='blue')
    ax.plot([y_test.min(), y_test.max()], [y.min(), y.max()], 'k--', lw=4)
    ax.set_xlabel(f'Observed {outcomeYear} Environmental Intesity')
    ax.set_ylabel(f'Predicted {outcomeYear} Environmental Intesity')
    ax.set_title(f'Predicting {outcomeYear} Environmental intensity using {years} environmental intensity, indu
```

```
In [85]:
predictiveModel3(2019, years, df_c)
```

```
MSE train: 0.007, test: 0.006
Model intercept:  [0.00042707]
Model coefficients:  [[-3.57050028e-02 -3.78767304e-01  7.82484846e-03  2.45351332e-04
  -3.35314980e-01  1.42406825e-01  5.22876608e-03 -1.84557134e-05
   1.22949797e+00  3.53350072e-01 -8.44622269e-03  1.62779214e-04]]
R2 score: 0.8928299824780621
```



Conclusion - Predictive models

Awesome results! By combining the predictors from the individual models, we were able to yield a lowers MSE and a higher R2 Score. When using past years environmental intensity and indsutry average, the linear model is able to explain 94.5% of the variance in the dataset. By including the industry indicator, it explains 94.6% and lastly, by including all four, it explains 90% of the variance. Even the lowest R2 Score (90%) was able to explain more than when considering the models with only one predictor.

Collect the Company Description

In this section, we will grab the company description directly from the Yahoo Finance website. We started with the pilot stocks but plan to see the possibility of mapping the ISIN with their corresponding ticker and be able to grab the company description

```
In [86]:
tickers_df = pd.read_csv('/Users/maralinetorres/Documents/GitHub/Predicting-Environmental-and-Social-Actions/Da
```

```
In [87]:
tickers = tickers_df.Ticker
```

```
In [88]:
# Create a loop to store URLs of all stocks' description page
URL = []
DES = []
comp_desc = {}
for i in tickers:
  url ='https://finance.yahoo.com/quote/'+i+'/profile'
  URL.append(url)
  page = requests.get(url) # visits the URL
  htmldata = BeautifulSoup(page.content, 'html.parser')
  Business_Description = htmldata.find('p',{'class':'Mt(15px) Lh(1.6)'}) # finds the business description part
  DES.append(Business_Description)
  comp_desc[i] = [Business_Description]
```

```
In [89]:
df_comp_desc = pd.DataFrame.from_dict(comp_desc, orient='index', columns = ['Description'])
df_comp_desc.reset_index(inplace = True)
df_comp_desc.rename(columns = {'index':'Ticker'}, inplace=True)
df_comp_desc.head()
```

Out[89]:

	Ticker	Description
0	AEE	None
1	AEP	None
2	AES	None
3	APA	None
4	ATO	None

```
In [90]:
df_comp_desc.to_csv('52ticker_companydescription.csv',index=False)
```

We will continue our analysis in 'IndustriesPredictingTimeSeries' notebook.