Causal Effect of Amazon Warehouses on Employment and Wage

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Summary and Background:
The aim of this project will be to estimate the causal effect of amazon facilities on unemployment and wage. The inspiration for this project came from The Economist article (https://www.economist.com/news/united-states/21735020-worlds-largest-online-retailer-underpaying-its-employees-what-amazon-does-wages) that we read in class during this semester. This article detailed how once Amazon opened up a warehousing facility in Lexington County, South Carolina, total employment in the warehousing and storage industry increased sharply while wage unexpectedly dropped. While the infographic paints an interesting tale, a lot of variables weren't mentioned and thus left me with many questions. Did the total employment increase because Amazon brought with it employers from other states? Or did it increase because employees from other industries, or even similar industries, joined Amazon's warehouse? If it were either of these reasons, the benefit of Amazon's job creation seems to be a surface level effect. Perhaps unrelated to these reasons though, the boost in employment could have simply been a result from a general rising trend in employment throughout the state.

While I don't have the resources to answer all of these questions, my research project hopes to answer these types of questions. It will first focus on identifying a similar effect for all of the counties that have been exposed to new Amazon warehouses. It is very possible that the type of trend we saw in Lexington County was specific only to Lexington County. Before I answer any of these harder questions mentioned before, this is one I plan to address first.

Afterwards, I plan to construct a panel data set that would allows me to construct a fixed effects regressions. I believe this is necessary because I highly doubt Amazon's choice in the location for their warehouses was random. What this type of regression would allow me to do is to filter out any state or county specific trends in the data, so that I may see the causal economic impact of Amazon's facilities.

Data:
The data that I will use in this project comes from three main sources:

1) **Bureau of Economic Analysis (https://www.bea.gov/API/bea_web_service_api_user_guide.htm):** The data from the Bureau of Economic Analysis will be the foundation for this project. With it, I am able to access the total employment and compensation of workers across counties and years from 2001 to 2014 within the transportation and warehousing industry.

The two TableNames and their respective keys that I've used in this project are listed below.

- CA25N - Total Full-Time and Part-Time Employment by NAICS Industry
- CA6N - Compensation of Employees by NAICS Industry
- Key 800 - Private nonfarm employment: Transportation and warehousing (NAICS:48-49)

2) **MWPVL International (http://www.mwpvl.com/html/amazon_com.html):** MWPVL International is a specialized supply chain, logistics, and distribution firm that has compiled a data set on Amazon's warehouses. This data set details the size, location, type, and the year opened of all the warehouses. With this data, I'm able to locate which counties were treated with Amazon warehouses in which year, and thus am able to identify the

before and after effects of these facilities across all affected counties. However, the website is protected and will not allow me to copy the data. Because of this consideration, I have decided to use only the data on *The Amazon Fulfillment Center and Distribution Center Network in the United States* within this project.

3) **Bureau of Labor Statistics (https://www.bls.gov/data/):** The data from the Bureau of Labor Statistics shares similar attributes to the data from the Bureau of Economic Analysis. With it, I am able to access the total employment and compensation of workers across counties and years until as recently as 2016. However, due to the manual labour this method of data extraction requires, I will use this data set only to replicate the figure seen in The Economist article.

The keys and specifications for the manipulation of these data sets are listed below.

- ENU45063105493 - Quarterly Census of Employment and Wages --> 493 NAICS 493 Warehousing and storage --> 45063 Lexington County, South Carolina --> Private --> All Employees --> All establishment sizes
- ENU45063405493 - Quarterly Census of Employment and Wages --> 493 NAICS 493 Warehousing and storage --> 45063 Lexington County, South Carolina --> Private --> Average Weekly Wage --> All

---

Import packages that are necessary for the project:

In [1]:
```
import pandas as pd               # to create and manipulate DataFrames
import numpy as np                # to better handle numbers
import requests                   # to extract data from APIs
import matplotlib.pyplot as plt   # to plot visually appealing graphs
import matplotlib as mpl
import weightedcalcs as wc        # to better run statistical processes
```

Bureau of Labor Statistics

I want to start this project by trying to mimic The Economist's figure in the aforementioned article. To perfectly replicate this, and to ensure that my process is right, I've used data from the Bureau of Labor Statistics.

Read in Lexington County data:

In [2]:
```
lexington_wage = pd.read_csv("https://raw.githubusercontent.com/scottjmkim/Data_Bootcamp_Final_Project/master/data/ENU45063405493.csv")
lexington_employment = pd.read_csv("https://raw.githubusercontent.com/scottjmkim/Data_Bootcamp_Final_Project/master/data/ENU45063105493.csv")
```

Contextualize and clean the data:

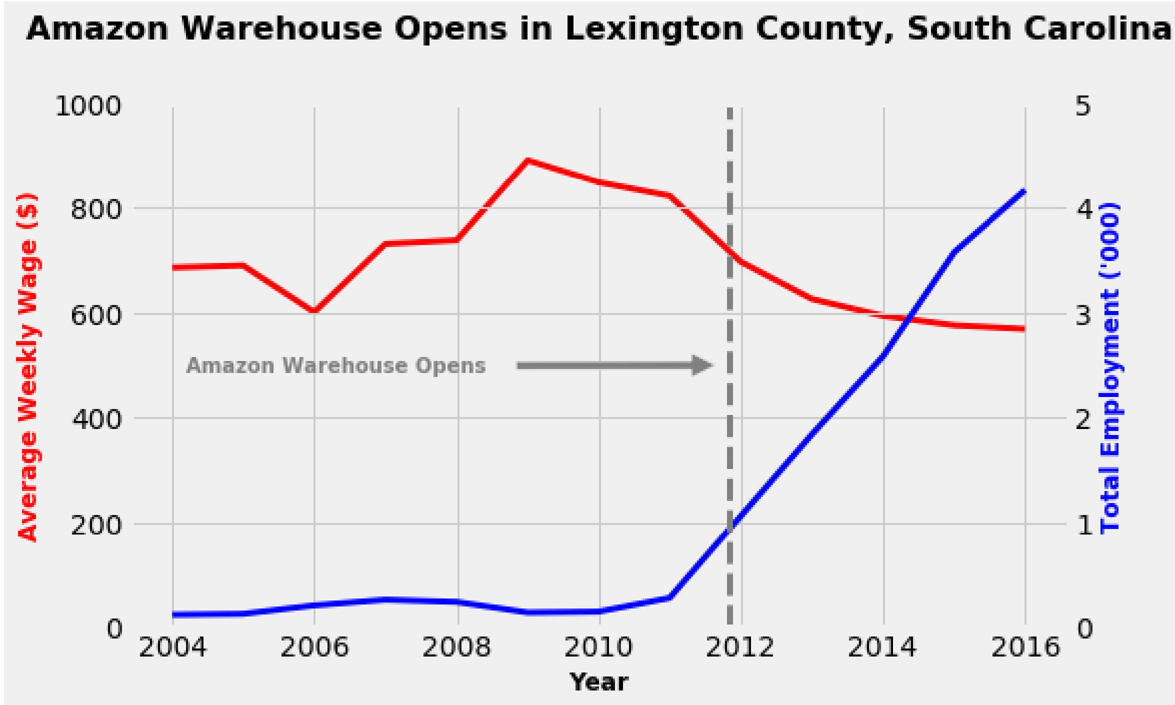
In [3]:
```
lexington_wage.rename(columns = {"Annual": "Weekly Wage"}, inplace = True)
lexington_employment.rename(columns = {"Annual": "Total Employment"}, inplace
= True)

sc_lexington = pd.merge(lexington_wage, lexington_employment,on = "Year")

sc_lexington["Total Employment"] = sc_lexington["Total Employment"] / 1000
sc_lexington["Weekly Wage"] = sc_lexington["Weekly Wage"]

sc_lexington.set_index("Year", inplace = True)

sc_lexington
```

Out[3]:

	Weekly Wage	Total Employment
Year		
2004	686	0.118
2005	690	0.126
2006	601	0.207
2007	731	0.261
2008	738	0.240
2009	891	0.139
2010	849	0.147
2011	823	0.278
2012	697	1.062
2013	626	1.842
2014	594	2.586
2015	576	3.577
2016	569	4.169

Plot the data as shown by The Economist:

In [5]:
```
fig, ax1 = plt.subplots(figsize = (7.5, 4.5))

ax2 = ax1.twinx()

sc_lexington["Weekly Wage"].plot(ax = ax1, color = "r", linewidth = 3.0, lab
el = "Average Weekly Wage")
sc_lexington["Total Employment"].plot(ax = ax2, color = "b", linewidth = 3.0
, label = "Total Employment")

ax1.set_title("Amazon Warehouse Opens in Lexington County, South Carolina",
fontsize = 16, fontweight = "bold")
ax1.title.set_position([.5, 1.1])

ax1.set_xlabel("Year", fontsize = 12, fontweight = "bold")
ax1.set_ylabel("Average Weekly Wage ($)", color = "r", fontsize = 12, fontwe
ight = "bold")
ax2.set_ylabel("Total Employment ('000)", color = "b", fontsize = 12, fontwe
ight = "bold")

ax1.set_ylim(0, 1000)
ax2.set_ylim(0, 5)

plt.axvline(x = 2011.83, color = "gray", linewidth = 3.0, linestyle = "--")

ax1.annotate("Amazon Warehouse Opens",
             xy=(2012, 500),
             xytext=(2004.2, 488),
             fontsize = 10,
             fontweight = "bold",
             color = "gray",
             arrowprops = dict(facecolor = "gray", shrink = 0.10))

plt.style.use("fivethirtyeight")

# mpl.rcParams.update(mpl.rcParamsDefault)
# %matplotlib inline

plt.show()
```



Here we see that the figure is almost identical to the one we saw in The Economist article. We see the recurring trend of employment and wage increasing and decreasing respectively upon an Amazon warehouse appearing.

Unfortunately, as mentioned before I do not currently have a wage of retrieving the data for all counties simultaneously from the BLS. Therefore, moving forward I will be using data from the Bureau of Economic Analysis. This data does not contain data that is as specific to the industry *493 NAICS 493 Warehousing and storage*. Instead, it contains data on the broader category *Transportation and warehousing (NAICS:48-49)*. However, as we will find out later on, this allows us to further ascertain the nature of the shift of employment in the figure above.

Bureau of Economic Analysis

Fortunately, the Bureau of Economic Analysis allows for the easy aggregation of data on the county and industry level. Going forward in the project, the data from the BEA will be used instead of the BLS data as it allows for more efficient analyses with more data entries, resulting in a higher accuracy as well.

Set up variables required to access the Bureau of Economic Analysis's API. Once that is done, look for the key for the warehousing industry:

In [6]:
```
BEA_ID = "72DF5D45-977D-49AC-B6D8-9D485484C815"

my_key = "https://bea.gov/api/data?&UserID=" + BEA_ID + "&"

data_set = "datasetname=RegionalIncome&"

method = "method=GetParameterValuesFiltered&"

dataset = "datasetname=RegionalIncome&"

linecode = "TargetParameter=LineCode&"

tablename = "TableName=CA25N&"

location = "GeoFips=COUNTY&"

form = "ResultFormat=json"

API_URL = my_key + method + dataset + linecode + tablename + form

r = requests.get(API_URL)

r.json()["BEAAPI"]["Results"]
```

```
Out[6]: {'ParamValue': [{'Desc': '[CA25N] Total employment', 'Key': '10'},
          {'Desc': '[CA25N] Private nonfarm employment: Forestry, fishing, and rela
        ted activities (NAICS:113-115)',
           'Key': '100'},
          {'Desc': '[CA25N] Private nonfarm employment: Finance and insurance (NAIC
        S:52)',
           'Key': '1000'},
          {'Desc': '[CA25N] Private nonfarm employment: Real estate and rental and
        leasing (NAICS:53)',
           'Key': '1100'},
          {'Desc': '[CA25N] Private nonfarm employment: Professional, scientific, a
        nd technical services (NAICS:54)',
           'Key': '1200'},
          {'Desc': '[CA25N] Private nonfarm employment: Management of companies and
        enterprises (NAICS:55)',
           'Key': '1300'},
          {'Desc': '[CA25N] Private nonfarm employment: Administrative and support
        and waste management and remediation services (NAICS:56)',
           'Key': '1400'},
          {'Desc': '[CA25N] Private nonfarm employment: Educational services (NAIC
        S:61)',
           'Key': '1500'},
          {'Desc': '[CA25N] Private nonfarm employment: Health care and social assi
        stance (NAICS:62)',
           'Key': '1600'},
          {'Desc': '[CA25N] Private nonfarm employment: Arts, entertainment, and re
        creation (NAICS:71)',
           'Key': '1700'},
          {'Desc': '[CA25N] Private nonfarm employment: Accommodation and food serv
        ices (NAICS:72)',
           'Key': '1800'},
          {'Desc': '[CA25N] Private nonfarm employment: Other services (except gove
        rnment and government enterprises) (NAICS:81)',
           'Key': '1900'},
          {'Desc': '[CA25N] Wage and salary employment', 'Key': '20'},
          {'Desc': '[CA25N] Private nonfarm employment: Mining, quarrying, and oil
        and gas extraction (NAICS:21)',
           'Key': '200'},
          {'Desc': '[CA25N] Employment: Government and government enterprises',
           'Key': '2000'},
          {'Desc': '[CA25N] Govt. and govt. enterprises employment: Federal civilia
        n',
           'Key': '2001'},
          {'Desc': '[CA25N] Govt. and govt. enterprises employment: Military',
           'Key': '2002'},
          {'Desc': '[CA25N] Govt. and govt. enterprises employment: State and loca
        l',
           'Key': '2010'},
          {'Desc': '[CA25N] Govt. and govt. enterprises employment: State governmen
        t',
           'Key': '2011'},
          {'Desc': '[CA25N] Govt. and govt. enterprises employment: Local governmen
        t',
           'Key': '2012'},
          {'Desc': '[CA25N] Private nonfarm employment: Utilities (NAICS:22)',
           'Key': '300'},
          {'Desc': '[CA25N] Proprietors employment', 'Key': '40'},
```

```
  {'Desc': '[CA25N] Private nonfarm employment: Construction (NAICS:23)',
   'Key': '400'},
  {'Desc': '[CA25N] Farm proprietors employment', 'Key': '50'},
  {'Desc': '[CA25N] Private nonfarm employment: Manufacturing (NAICS:31-3
3)',
   'Key': '500'},
  {'Desc': '[CA25N] Nonfarm proprietors employment', 'Key': '60'},
  {'Desc': '[CA25N] Private nonfarm employment: Wholesale trade (NAICS:4
2)',
   'Key': '600'},
  {'Desc': '[CA25N] Farm employment (NAICS:111-112)', 'Key': '70'},
  {'Desc': '[CA25N] Private nonfarm employment: Retail trade (NAICS:44-4
5)',
   'Key': '700'},
  {'Desc': '[CA25N] Nonfarm employment', 'Key': '80'},
  {'Desc': '[CA25N] Private nonfarm employment: Transportation and warehous
ing (NAICS:48-49)',
   'Key': '800'},
  {'Desc': '[CA25N] Private nonfarm employment', 'Key': '90'},
  {'Desc': '[CA25N] Private nonfarm employment: Information (NAICS:51)',
   'Key': '900'}]}
```


Adjust the variables to now extract the data into a Pandas DataFrame:

In [7]:
```
my_key = "https://bea.gov/api/data?&UserID=" + BEA_ID + "&method=GetData&"

table_and_line_employment = "TableName=CA25N&LineCode=800&"

API_URL = my_key + data_set + table_and_line_employment + location + form

r_total_employment = requests.get(API_URL)

df_total_employment = pd.DataFrame(r_total_employment.json()["BEAAPI"]["Result
s"]["Data"])

df_total_employment.head()
```

Out[7]:

	CL_UNIT	Code	DataValue	GeoFips	GeoName	NoteRef	TimePeriod	UNIT_MULT
0	number of jobs	CA25N-800	6020800	00000	United States	NaN	2013	0
1	number of jobs	CA25N-800	7169400	00000	United States	NaN	2016	0
2	number of jobs	CA25N-800	5872400	00000	United States	NaN	2012	0
3	number of jobs	CA25N-800	6291400	00000	United States	NaN	2014	0
4	number of jobs	CA25N-800	6939700	00000	United States	NaN	2015	0

Make the list of years applicable for the scope of this project (2001 to 2014):

In [8]:
```
years = range(2001, 2015)

years = list(years)

years = "".join(str(years))

years = years[1:-1]
```

Include the list of years as a variable when retrieving data:

In [9]:
```
year = "Year=" + years + "&"

API_URL = my_key + data_set + table_and_line_employment + year + location + fo
rm

r = requests.get(API_URL)

df_total_employment = pd.DataFrame(r.json()["BEAAPI"]["Results"]["Data"])

r_total_employment = requests.get(API_URL)

df_total_employment = pd.DataFrame(r_total_employment.json()["BEAAPI"]["Result
s"]["Data"])

df_total_employment.head()
```

Out[9]:

	CL_UNIT	Code	DataValue	GeoFips	GeoName	NoteRef	TimePeriod	UNIT_MULT
0	number of jobs	CA25N-800	6020800	00000	United States	NaN	2013	0
1	number of jobs	CA25N-800	5480000	00000	United States	NaN	2001	0
2	number of jobs	CA25N-800	5359300	00000	United States	NaN	2002	0
3	number of jobs	CA25N-800	6291400	00000	United States	NaN	2014	0
4	number of jobs	CA25N-800	5872400	00000	United States	NaN	2012	0

Clean the DataFrame by dropping and renaming some columns:

In [10]:
```
df_total_employment.drop(['CL_UNIT', 'Code',"NoteRef", "UNIT_MULT"], axis=1,
 inplace = True)

df_total_employment.rename(columns = {"DataValue":"TotalEmployment", "TimePe
riod": "Year"}, inplace = True)

df_total_employment.head()
```

Out[10]:

	TotalEmployment	GeoFips	GeoName	Year
0	6020800	00000	United States	2013
1	5480000	00000	United States	2001
2	5359300	00000	United States	2002
3	6291400	00000	United States	2014
4	5872400	00000	United States	2012

Now do the same for personal income:

In [11]:
```
table_and_line_income = "TableName=CA6N&LineCode=800&"

API_URL = my_key + data_set + table_and_line_income + year + location + form

r_income = requests.get(API_URL)

df_income = pd.DataFrame(r_income.json()["BEAAPI"]["Results"]["Data"])

df_income.drop(['CL_UNIT', 'Code',"NoteRef", "UNIT_MULT"], axis=1, inplace = T
rue)

df_income.rename(columns = {"DataValue":"Income", "TimePeriod": "Year"}, inpla
ce = True)

df_income.head()
```

Out[11]:

	Income	GeoFips	GeoName	Year
0	207975000	00000	United States	2001
1	206248000	00000	United States	2002
2	221951000	00000	United States	2004
3	241065000	00000	United States	2006
4	255476000	00000	United States	2008

Unfortunately, the BEA does not have data on the average income per worker for each industry. Since no data set exists, we must find the next best alternative. As we have the total amount of workers per county for each year, we can average it out using the two DataFrames later on.

Furthermore, the figures are listed in thousands of dollars. This is something we can remedy easily later on.

Now merge both DataFrames into one:

In [12]:
```
master = pd.merge(df_total_employment, df_income,
                  how = "inner",
                  on = ["GeoFips", "Year", "GeoName"],
                  indicator = True)
```

Clean the DataFrame of any invalid strings and set variables as floats:

In [13]:
```
master["TotalEmployment"].replace(["(NA)", "(D)", "(L)"], np.nan, inplace = Tr
ue)
master["TotalEmployment"] = master["TotalEmployment"].astype(float)

master["Income"].replace(["(NA)", "(D)", "(L)"], np.nan, inplace = True)
master["Income"] = master["Income"].astype(float)

# master["Year"] = pd.to_datetime(master["Year"], infer_datetime_format = Tru
e)
master["Year"] = master["Year"].astype(float)
```

Make a new column finding the average income:

In [14]:
```
master["AverageIncome"] = master["Income"] * 1000 / master["TotalEmployment"]

master.drop(["Income"], axis=1, inplace = True)
master.drop(["_merge"], axis = 1, inplace = True)

master.head()
```

Out[14]:

	TotalEmployment	GeoFips	GeoName	Year	AverageIncome
0	6020800.0	00000	United States	2013.0	46998.571618
1	5480000.0	00000	United States	2001.0	37951.642336
2	5359300.0	00000	United States	2002.0	38484.130390
3	6291400.0	00000	United States	2014.0	47060.431700
4	5872400.0	00000	United States	2012.0	46824.807574

We can now drop the *Income* column as we have the average income data.

Now Clean the data more and include new columns of CountyFips and Treated:

In [15]:
```
master["CountyFips"] = master["GeoFips"].str[2:]
master["Treated"] = 0
master["TreatedDate"] = 0

master = master[master["CountyFips"] != "000"]

master.head()
```

Out[15]:

	TotalEmployment	GeoFips	GeoName	Year	AverageIncome	CountyFips	Treated
28	356.0	01001	Autauga, AL	2013.0	21966.292135	001	0
29	349.0	01001	Autauga, AL	2001.0	23401.146132	001	0
30	331.0	01001	Autauga, AL	2002.0	24468.277946	001	0
31	350.0	01001	Autauga, AL	2014.0	20614.285714	001	0
32	352.0	01001	Autauga, AL	2012.0	23315.340909	001	0

We include CountyFips so that we can drop all unwanted entries of either all of the United States, or individual states themselves. We're also setting Treated = 0 for all entries now, which we will edit later to indicate which counties have been treated with an Amazon warehouse.

Set the index to each county and sort the DataFrame by time:

In [16]:
```
master.sort_values(by = "Year", inplace = True)

master.set_index(["GeoFips", "Year"], inplace = True)

master.sort_index(level = "GeoFips", inplace = True)

master.head(20)
```

Out[16]:

		TotalEmployment	GeoName	AverageIncome	CountyFips	Treated	Tre
GeoFips	**Year**						
01001	**2001.0**	349.0	Autauga, AL	23401.146132	001	0	0
	2002.0	331.0	Autauga, AL	24468.277946	001	0	0
	2003.0	342.0	Autauga, AL	24207.602339	001	0	0
	2004.0	313.0	Autauga, AL	27153.354633	001	0	0
	2005.0	359.0	Autauga, AL	25632.311978	001	0	0
	2006.0	390.0	Autauga, AL	27569.230769	001	0	0
	2007.0	391.0	Autauga, AL	26961.636829	001	0	0
	2008.0	318.0	Autauga, AL	21726.415094	001	0	0
	2009.0	295.0	Autauga, AL	22928.813559	001	0	0
	2010.0	297.0	Autauga, AL	23983.164983	001	0	0
	2011.0	363.0	Autauga, AL	22234.159780	001	0	0
	2012.0	352.0	Autauga, AL	23315.340909	001	0	0
	2013.0	356.0	Autauga, AL	21966.292135	001	0	0
	2014.0	350.0	Autauga, AL	20614.285714	001	0	0
01003	**2001.0**	1454.0	Baldwin, AL	21136.176066	003	0	0
	2002.0	1331.0	Baldwin, AL	21206.611570	003	0	0
	2003.0	1451.0	Baldwin, AL	22716.057891	003	0	0
	2004.0	1491.0	Baldwin, AL	23183.098592	003	0	0

		TotalEmployment	GeoName	AverageIncome	CountyFips	Treated	Tre
GeoFips	Year						
	2005.0	1493.0	Baldwin, AL	24325.519089	003	0	0
	2006.0	1475.0	Baldwin, AL	24399.322034	003	0	0

Make a separate DataFrame of just Lexington County, South Carolina:

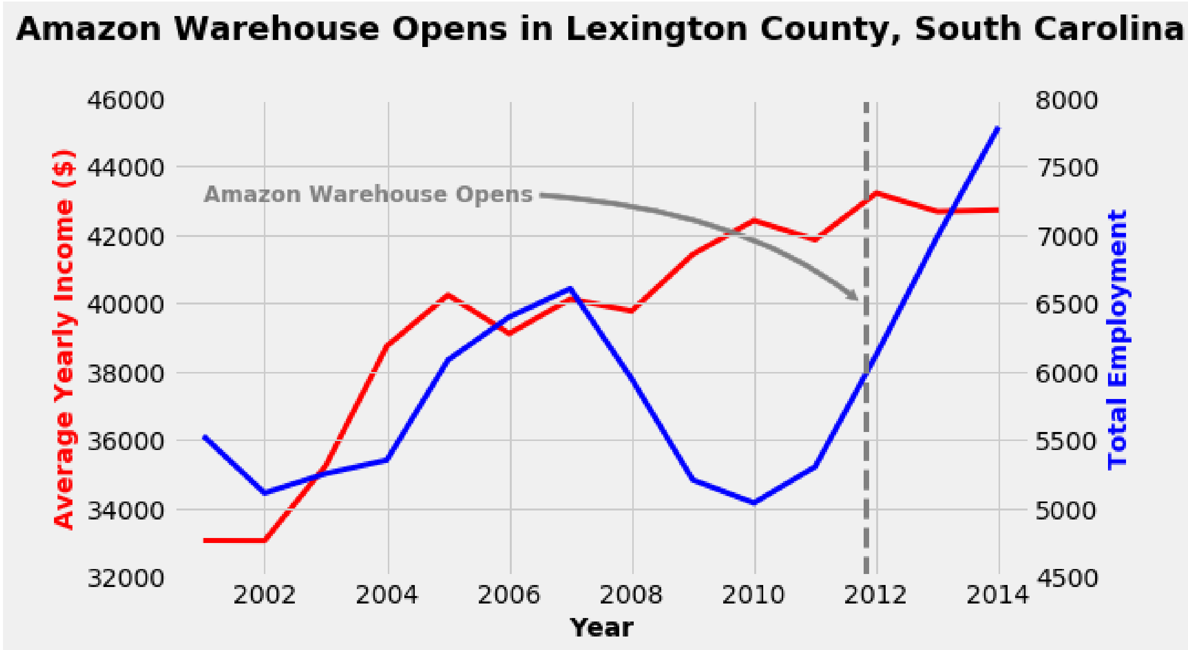
In [17]:
```
sc_lexington1 = master.loc["45063"]

sc_lexington1
```

Out[17]:

	TotalEmployment	GeoName	AverageIncome	CountyFips	Treated	TreatedDate
Year						
2001.0	5529.0	Lexington, SC	33056.429734	063	0	0
2002.0	5111.0	Lexington, SC	33051.457640	063	0	0
2003.0	5253.0	Lexington, SC	35240.434038	063	0	0
2004.0	5352.0	Lexington, SC	38742.339312	063	0	0
2005.0	6084.0	Lexington, SC	40236.686391	063	0	0
2006.0	6398.0	Lexington, SC	39107.846202	063	0	0
2007.0	6606.0	Lexington, SC	40119.588253	063	0	0
2008.0	5947.0	Lexington, SC	39767.277619	063	0	0
2009.0	5207.0	Lexington, SC	41424.620703	063	0	0
2010.0	5039.0	Lexington, SC	42415.161738	063	0	0
2011.0	5303.0	Lexington, SC	41853.856308	063	0	0
2012.0	6122.0	Lexington, SC	43215.779157	063	0	0
2013.0	6988.0	Lexington, SC	42678.878077	063	0	0
2014.0	7789.0	Lexington, SC	42721.016819	063	0	0

Now plot a similar figure to the one we assembled in the beginning where we used the BLS data:

In [18]:
```
fig, ax1 = plt.subplots(figsize = (7.5, 4.5))

ax2 = ax1.twinx()

sc_lexington1["AverageIncome"].plot(ax = ax1, color = "r", linewidth = 3.0, la
bel = "Average Income")
sc_lexington1["TotalEmployment"].plot(ax = ax2, color = "b", linewidth = 3.0,
label = "Total Employment")

ax1.set_title("Amazon Warehouse Opens in Lexington County, South Carolina", fo
ntsize = 18, fontweight = "bold")
ax1.title.set_position([.5, 1.1])

ax1.set_xlabel("Year", fontsize = 14, fontweight = "bold")
ax1.set_ylabel("Average Yearly Income ($)", color = "r", fontsize = 14, fontwe
ight = "bold")
ax2.set_ylabel("Total Employment", color = "b", fontsize = 14, fontweight = "b
old")

ax1.set_xlim(2000.5, 2014.5)
ax1.set_ylim(32000, 46000)
ax2.set_ylim(4500, 8000)

plt.axvline(x = 2011.83, color = "gray", linewidth = 3.0, linestyle = "--")

ax1.annotate("Amazon Warehouse Opens",
             xy = (2011.75, 40000),
             xytext = (2001, 43000),
             fontsize = 12,
             fontweight = "bold",
             color = "gray",
             arrowprops = {
                 "arrowstyle": "simple",
                 "connectionstyle": "angle3, angleA = 3, angleB = 140",
                 "color": "gray"})

plt.show()
```



Now that we have another version of the Lexington County graph, we can start to compare some details and draw further conclusions. This new graph is using data from not just the *493 NAICS 493 Warehousing and storage* industry, but also from every other industry in the broad category of *Transportation and warehousing (NAICS:48-49)* (as a consequence of the nature of the data sets available.

Thus, any change in employment will be a reflection of the entire related industry, and not just the specific industry of Warehousing and storage. Here we see from 2012 until 2014, there was roughly a 2800 increase in total employment in the *Transporation and warehousing* industry. From our previous graph, we see that there was just over a 3000 increase in total employment in just the *Warehousing and storage* industry alone. This is suggestive that there were very little employment coming into the *Warehousing and storage* industry from closely related industries, at least within Lexington County.

Time Series: Aggregate Change

Unfortunately, the previous graph as it is only depicts the scenario for Lexington County, South Carolina only. This could be a misrepresentation of data, as Lexington County could be the only county to show such results. To gain a more holistic understanding of the causal impact of Amazon warehouses, we aim to find the average change in total employment and wages from 2 years before and after an Amazon warehouse is introduced in all counties.

This will allow us to have a better idea of what the average impact of Amazon warehouses given a random county. We will add touches later on to make this proposed figure even more informative.

First, read in the csv. file constructed from the MWPVL data set:

In [19]:
```
mwpvl = pd.read_csv("https://raw.githubusercontent.com/scottjmkim/Data_Bootcam
p_Final_Project/master/data/MWPVL.csv")

mwpvl
```

Out[19]:

	GeoFips	County	State	Year Opened
0	4013	Maricopa	Arizona	2007
1	4013	Maricopa	Arizona	2008
2	4013	Maricopa	Arizona	2010
3	4013	Maricopa	Arizona	2011
4	6071	San Bernardino	California	2012
5	10003	New Castle	Delaware	2012
6	18011	White	Indiana	2008
7	18063	Hendricks	Indiana	2008
8	18097	Marion	Indiana	2011
9	18063	Hendricks	Indiana	2011
10	18019	Clark	Indiana	2012
11	21015	Boone	Kentucky	2005
12	21015	Boone	Kentucky	2005
13	21067	Fayette	Kentucky	2006
14	21111	Jefferson	Kentucky	2005
15	21029	Bullitt	Kentucky	2012
16	21029	Bullitt	Kentucky	2012
17	32003	Clark	Nevada	2008
18	32031	Washoe	Nevada	2010
19	33011	Hillsborough	New Hampshire	2007
20	42077	Lehigh	Pennsylvania	2010
21	42077	Lehigh	Pennsylvania	2011
22	42127	Wayne	Pennsylvania	2010
23	42041	Cumberland	Pennsylvania	2010
24	42133	York	Pennsylvania	2010
25	42041	Cumberland	Pennsylvania	2010
26	45063	Lexington	South Carolina	2011
27	45083	Spartanburg	South Carolina	2012
28	47149	Rutherford	Tennessee	2012
29	47065	Hamilton	Tennessee	2011
30	47011	Bradley	Tennessee	2011
31	51041	Chesterfield	Virginia	2012

	GeoFips	County	State	Year Opened
32	53053	Pierce	Washington	2011

Note all counties that were treated with Amazon facilities, and also in which year they were treated:

In [20]:
```
# Maricopa County, Arizona
master.loc["04013", "Treated"] = 1
master.loc["04013", "TreatedDate"] = 6

# San Bernardino County, California
master.loc["06071", "Treated"] = 1
master.loc["06071", "TreatedDate"] = 11

# New Castle County, Delaware
master.loc["10003", "Treated"] = 1
master.loc["10003", "TreatedDate"] = 11

# White County, Indiana
master.loc["18011", "Treated"] = 1
master.loc["18011", "TreatedDate"] = 8

# Hendricks County, Indiana
master.loc["18063", "Treated"] = 1
master.loc["18063", "TreatedDate"] = 8

# Marion County, Indiana
master.loc["18097", "Treated"] = 1
master.loc["18097", "TreatedDate"] = 10

# Clark County, Indiana
master.loc["18019", "Treated"] = 1
master.loc["18019", "TreatedDate"] = 11

# Boone County, Kentucky
master.loc["21015", "Treated"] = 1
master.loc["21015", "TreatedDate"] = 4

# Fayette County, Kentucky
master.loc["21067", "Treated"] = 1
master.loc["21067", "TreatedDate"] = 4

# Jefferson County, Kentucky
master.loc["21111", "Treated"] = 1
master.loc["21111", "TreatedDate"] = 4

# Bullitt County, Kentucky
master.loc["21029", "Treated"] = 1
master.loc["21029", "TreatedDate"] = 11

# Clark County, Nevada
master.loc["32003", "Treated"] = 1
master.loc["32003", "TreatedDate"] = 7

# Washoe County, Nevada
master.loc["32031", "Treated"] = 1
master.loc["32031", "TreatedDate"] = 9

# Hillsborough County, New Hampshire
master.loc["33011", "Treated"] = 1
master.loc["33011", "TreatedDate"] = 6
```

```
# Lehigh County, Pennsylvania
master.loc["42077", "Treated"] = 1
master.loc["42077", "TreatedDate"] = 9

# Wayne County, Pennsylvania
master.loc["42127", "Treated"] = 1
master.loc["42127", "TreatedDate"] = 9

# Cumberland County, Pennsylvania
master.loc["42041", "Treated"] = 1
master.loc["42041", "TreatedDate"] = 9

# Lexington County, South Carolina
master.loc["45063", "Treated"] = 1
master.loc["45063", "TreatedDate"] = 10

# Spartanburg County, South Carolina
master.loc["45083", "Treated"] = 1
master.loc["45083", "TreatedDate"] = 11

# Rutherford County, Tennessee
master.loc["47149", "Treated"] = 1
master.loc["47149", "TreatedDate"] = 11

# Hamilton County, Tennessee
master.loc["47065", "Treated"] = 1
master.loc["47065", "TreatedDate"] = 10

# Bradley County, Tennessee
master.loc["47011", "Treated"] = 1
master.loc["47011", "TreatedDate"] = 10

# Chesterfield County, Virginia
master.loc["51041", "Treated"] = 1
master.loc["51041", "TreatedDate"] = 11

# Pierce County, Washington
master.loc["53053", "Treated"] = 1
master.loc["53053", "TreatedDate"] = 10

master["TreatedDate"] = master["TreatedDate"].astype(int)
```

Note how the date I'm using is purely in integers. This is because later on when I define my function, I will be taking advantage of the fact that my years are all standardized from 2001 to 2014 to call their indexes appropriately.

Furthermore, there were more counties that were treated with Amazon warehouses, but they did not make it into this phase of the project either because the BEA did not have data on them, or the Amazon warehouses were too recent for an analysis to be made with a data set reaching up until only 2014.

Furthermore, it is also important to disclose that some counties received multiple warehouses either at the same time or at different times. For simplicity, I've counted the *TreatedDate* as the year in which the first Amazon warehouse opened.

Now make a new DataFrame that isolates only treated counties:

In [38]:
```
master_treated = master.groupby("Treated")

master_treated = master_treated.get_group(int(1))

master_treated.head(20)
```

Out[38]:

		TotalEmployment	GeoName	AverageIncome	CountyFips	Treated	Tr
GeoFips	**Year**						
04013	**2001.0**	60849.0	Maricopa, AZ	39703.659879	013	1	6
	2002.0	61247.0	Maricopa, AZ	40507.061570	013	1	6
	2003.0	61901.0	Maricopa, AZ	41482.076218	013	1	6
	2004.0	63818.0	Maricopa, AZ	43799.163245	013	1	6
	2005.0	66507.0	Maricopa, AZ	44254.499526	013	1	6
	2006.0	71086.0	Maricopa, AZ	45819.781673	013	1	6
	2007.0	72692.0	Maricopa, AZ	48055.150498	013	1	6
	2008.0	71337.0	Maricopa, AZ	47180.495395	013	1	6
	2009.0	67275.0	Maricopa, AZ	47162.749907	013	1	6
	2010.0	64454.0	Maricopa, AZ	49293.356502	013	1	6
	2011.0	68016.0	Maricopa, AZ	49834.891790	013	1	6
	2012.0	70921.0	Maricopa, AZ	49723.466956	013	1	6
	2013.0	72004.0	Maricopa, AZ	49374.812510	013	1	6
	2014.0	75484.0	Maricopa, AZ	48223.014149	013	1	6
06071	**2001.0**	38789.0	San Bernardino, CA	35691.974529	071	1	11
	2002.0	39558.0	San Bernardino, CA	36105.718186	071	1	11
	2003.0	41145.0	San Bernardino, CA	37714.764856	071	1	11

		TotalEmployment	GeoName	AverageIncome	CountyFips	Treated	Tr
GeoFips	**Year**						
	2004.0	48697.0	San Bernardino, CA	41795.552087	071	1	11
	2005.0	53013.0	San Bernardino, CA	41789.825137	071	1	11
	2006.0	54830.0	San Bernardino, CA	41827.484953	071	1	11

Now define functions to return a new transposed DataFrame that shows the level change of employment and income for each county depending on when an Amazon warehouse was opened:

In [22]:
```
def employment_aggregate(df):

    data = [df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] - 2] - df["To
talEmployment"].iloc[df["TreatedDate"].iloc[0]],
            df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] - 1] - df["To
talEmployment"].iloc[df["TreatedDate"].iloc[0]],
            df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]] - df["TotalE
mployment"].iloc[df["TreatedDate"].iloc[0]],
            df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] + 1] - df["To
talEmployment"].iloc[df["TreatedDate"].iloc[0]],
            df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] + 2] - df["To
talEmployment"].iloc[df["TreatedDate"].iloc[0]]]

    data = pd.DataFrame(data).T

    data.columns = ["-2", "-1", "0", "1", "2"]

    return data
```

In [23]:
```
def income_aggregate(df):

    data = [df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] - 2] - df["Aver
ageIncome"].iloc[df["TreatedDate"].iloc[0]],
            df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] - 1] - df["Aver
ageIncome"].iloc[df["TreatedDate"].iloc[0]],
            df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]] - df["AverageI
ncome"].iloc[df["TreatedDate"].iloc[0]],
            df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] + 1] - df["Aver
ageIncome"].iloc[df["TreatedDate"].iloc[0]],
            df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] + 2] - df["Aver
ageIncome"].iloc[df["TreatedDate"].iloc[0]]]

    data = pd.DataFrame(data).T

    data.columns = ["-2", "-1", "0", "1", "2"]

    return data
```

Now apply these functions to each county in the DataFrame with only treated counties:

In [24]:
```
series = master_treated.groupby("GeoFips")

total_employment = series.apply(employment_aggregate)

total_employment = total_employment.reset_index().drop(["level_1"], axis = 1).
set_index("GeoFips")

total_employment.head(10)
```

Out[24]:

	-2	-1	0	1	2
GeoFips					
04013	-6185.0	-1606.0	0.0	-1355.0	-5417.0
06071	-4979.0	-2064.0	0.0	6226.0	12040.0
10003	-694.0	-384.0	0.0	1199.0	2382.0
18011	-242.0	43.0	0.0	-55.0	-111.0
18019	291.0	84.0	0.0	54.0	178.0
18063	-910.0	-521.0	0.0	225.0	134.0
18097	-1336.0	-1309.0	0.0	1087.0	4768.0
21015	-1421.0	555.0	0.0	-2994.0	-3213.0
21029	-2084.0	-1139.0	0.0	102.0	746.0
21067	-204.0	-620.0	0.0	-125.0	17.0

In [25]:
```
series = master_treated.groupby("GeoFips")

total_income = series.apply(income_aggregate)

total_income = total_income.reset_index().drop(["level_1"], axis = 1).set_inde
x("GeoFips")

total_income.head(10)
```

Out[25]:

	-2	-1	0	1	2
GeoFips					
04013	-3800.650972	-2235.368825	0.0	-874.655103	-892.400591
06071	-1707.469119	-235.473971	0.0	268.195062	-1084.941836
10003	-3025.546844	-1778.783554	0.0	-1126.578002	-1053.966223
18011	-4115.461128	-1623.740222	0.0	2234.319763	1744.673461
18019	-1673.278078	3256.261360	0.0	834.952838	1219.359809
18063	-1767.962436	-538.256046	0.0	1647.791500	2163.425859
18097	-1037.232935	305.960187	0.0	1697.415345	2189.418347
21015	5596.970016	4182.092509	0.0	-6697.424317	5130.724327
21029	1085.024429	-545.058655	0.0	-482.955374	-2093.097543
21067	-880.727951	1030.456745	0.0	261.419099	1802.071842

Now transpose both DataFrames and merge them together to see the results:

In [26]:
```
mean_agg_employment = pd.DataFrame(total_employment.mean())
mean_agg_income = pd.DataFrame(total_income.mean())

mean_agg_employment.columns = ["Total Employment"]
mean_agg_income.columns = ["Average Income"]

mean_agg_employment.index.name = "Delta Years"
mean_agg_income.index.name = "Delta Years"

mean_agg_employment.reset_index(inplace = True)
mean_agg_income.reset_index(inplace = True)

final_agg = pd.merge(mean_agg_employment, mean_agg_income,
                 how = "inner",
                 on = "Delta Years")

final_agg["Delta Years"] = final_agg["Delta Years"].astype(float)

final_agg.set_index("Delta Years", inplace = True)

final_agg
```

Out[26]:

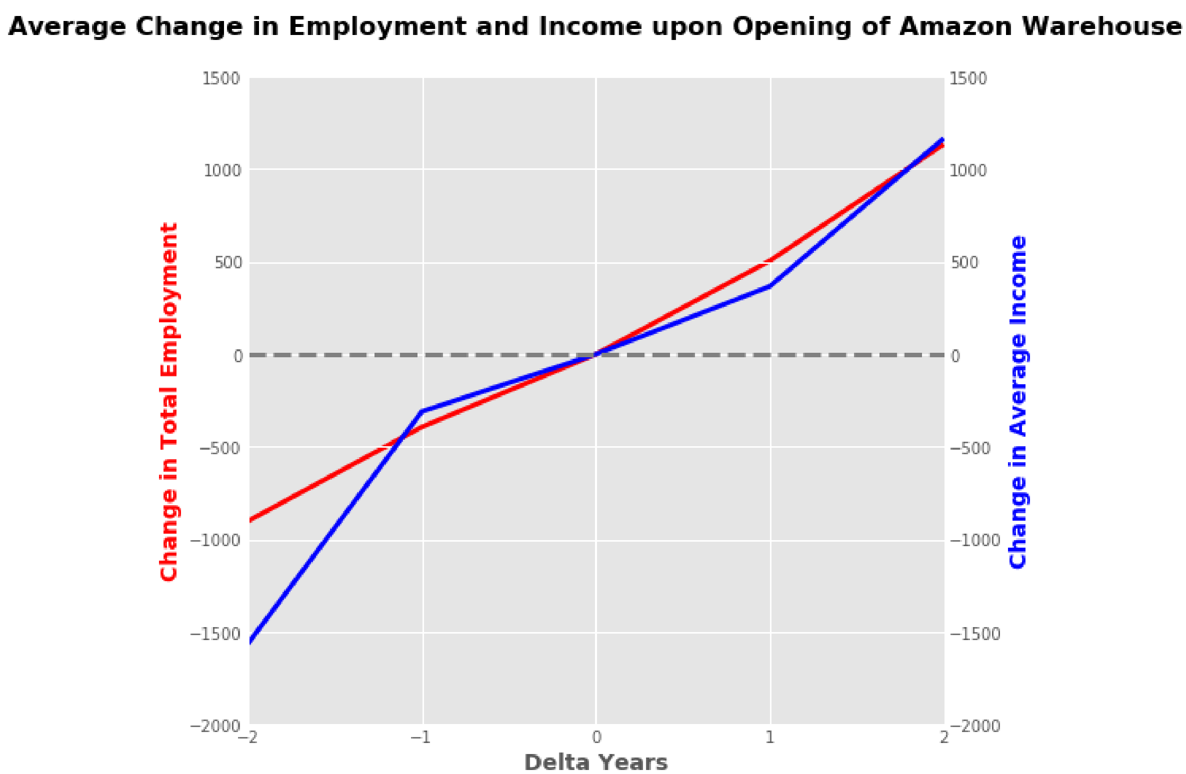
	Total Employment	Average Income
Delta Years		
-2.0	-901.541667	-1564.133524
-1.0	-392.833333	-309.600526
0.0	0.000000	0.000000
1.0	504.041667	366.384257
2.0	1133.916667	1165.558307

Now this is really interesting! Here we see that on average, after an Amazon warehouse entered a county their total employment went up by around 1134 and their average income by around $1166 after two years. Now it's important to note that this is in aggregate figures, and thus an average may not the best way to represent accurate figures, but nevertheless this is our first step towards seeing that Amazon warehouses indeed do have a positive impact on the employment of their respective counties.

It's also important to note that contrary to what we saw in our previous findings in Lexington County, Amazon warehouses, on average, also seem to have a similar positive effect on average wages too.

Now plot it!

In [28]:
```
fig, ax1 = plt.subplots(figsize = (7, 7))

ax2 = ax1.twinx()

final_agg["Total Employment"].plot(ax = ax1, color = "r", linewidth = 3.0, lab
el = "Total Employment", xticks = [-2, -1, 0, 1, 2])
final_agg["Average Income"].plot(ax = ax2, color = "b", linewidth = 3.0, label
 = "Average Income")

ax1.set_title("Average Change in Employment and Income upon Opening of Amazon
 Warehouse", fontsize = 16, fontweight = "bold")
ax1.title.set_position([.5, 1.05])

ax1.set_xlabel("Delta Years", fontsize = 14, fontweight = "bold")
ax1.set_ylabel("Change in Total Employment", color = "r", fontsize = 14, fontw
eight = "bold")
ax2.set_ylabel("Change in Average Income", color = "b", fontsize = 14, fontwei
ght = "bold")

ax1.set_xlim(-2, 2)
ax1.set_ylim(-2000, 1500)
ax2.set_ylim(-2000, 1500)

plt.axhline(y = 0, color = "gray", linewidth = 3.0, linestyle = "--")

plt.style.use("ggplot")

plt.show()
```



Here we have a nice graphical representation of our initial findings. While it's visually nice, we see that the aggregate increases for both employment and wage seem very close to each other.

However, does this mean the same thing? Upon some thought, the answer would be no. We already mentioned before that an average would likely not be the best measure of pinpointing the extent of the effect of Amazon warehouses. Instead it does a good job of showing the direction of the causal effect. This gives us some ideas now to better represent the data:

- The first is that while the average change for employment and average income seem to be similar, perhaps their median is not. Perhaps plotting their median and interquartile range will show some differentiation.
- The second is that while both variables seemed to experience just above an aggregate change of 1000 after 2 years, the scale of their initial values were very different. This means that an aggregate change of 1000 could mean a lot for one variable, but not as much for the other. To identify this, we could use growth rate instead of aggregate change.

Now we will begin to work on representing these changes, beginning with showing the interquartile range.

Retrive the interquartile range statistics of the change in employment and average income:

In [29]:
```
employment_quartile = total_employment.describe().T.reset_index()

employment_quartile["Delta Years"] = employment_quartile["Delta Years"].astype
(float)

employment_quartile = employment_quartile.drop(["count", "mean", "std", "min",
 "max"], axis = 1).set_index("Delta Years")

employment_quartile
```

Out[29]:

	25%	50%	75%
Delta Years			
-2.0	-1339.50	-417.0	96.5
-1.0	-705.75	-208.5	41.5
0.0	0.00	0.0	0.0
1.0	-1.75	206.5	1115.0
2.0	29.75	695.0	1921.0

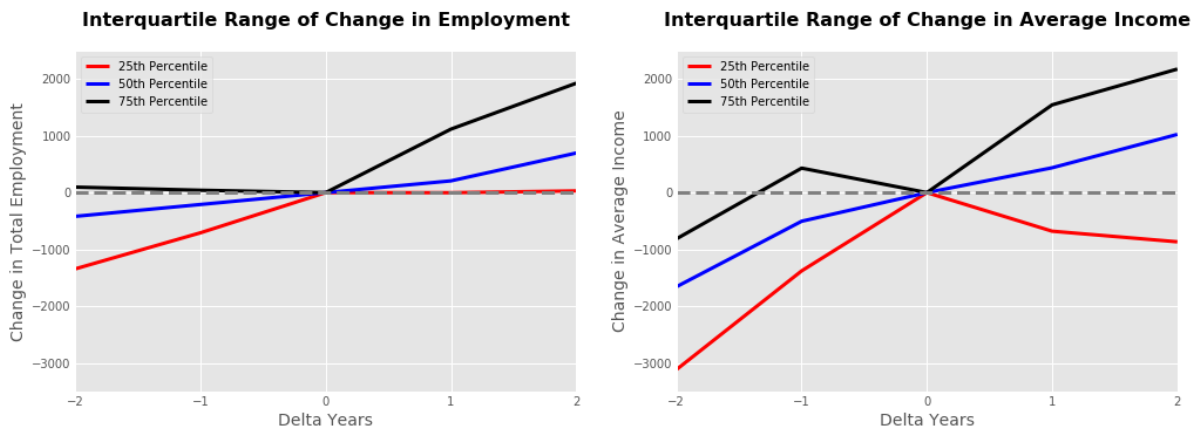
In [30]:
```
income_quartile = total_income.describe().T.reset_index()

income_quartile["Delta Years"] = income_quartile["Delta Years"].astype(float)

income_quartile = income_quartile.drop(["count", "mean", "std", "min", "max"],
 axis = 1).set_index("Delta Years")

income_quartile
```

Out[30]:

	25%	50%	75%
Delta Years			
-2.0	-3108.628768	-1653.686529	-812.525788
-1.0	-1374.663192	-502.838364	430.110930
0.0	0.000000	0.000000	0.000000
1.0	-677.452368	436.300206	1541.167208
2.0	-863.967850	1022.190789	2169.923981

Now plot them!

In [31]:
```
fig, ax = plt.subplots(1, 2, figsize = (15, 5))

employment_quartile["25%"].plot(ax = ax[0], lw = 3, color = "r", label = "25th
 Percentile", xticks = [-2, -1, 0, 1, 2])
employment_quartile["50%"].plot(ax = ax[0], lw = 3, color = "b", label = "50th
 Percentile")
employment_quartile["75%"].plot(ax = ax[0], lw = 3, color = "black", label =
"75th Percentile")

income_quartile["25%"].plot(ax = ax[1], lw = 3, color = "r", label = "25th Per
centile", xticks = [-2, -1, 0, 1, 2])
income_quartile["50%"].plot(ax = ax[1], lw = 3, color = "b", label = "50th Per
centile")
income_quartile["75%"].plot(ax = ax[1], lw = 3, color = "black", label = "75th
 Percentile")

ax[0].title.set_position([.5, 1.05])
ax[1].title.set_position([.5, 1.05])

ax[0].set_xlim(-2, 2)
ax[1].set_xlim(-2, 2)

ax[0].set_ylim(-3500, 2500)
ax[1].set_ylim(-3500, 2500)

ax[0].set_xticks([-2, -1, 0, 1, 2])
ax[1].set_xticks([-2, -1, 0, 1, 2])

ax[0].set_xlabel("Delta Years", fontsize = 14)
ax[1].set_xlabel("Delta Years", fontsize = 14)

ax[0].set_ylabel("Change in Total Employment", fontsize = 14)
ax[1].set_ylabel("Change in Average Income", fontsize = 14)

ax[0].set_title("Interquartile Range of Change in Employment", fontsize = 16,
fontweight = "bold")
ax[1].set_title("Interquartile Range of Change in Average Income", fontsize =
16, fontweight = "bold")

ax[0].axhline(y = 0, color = "gray", linewidth = 3.0, linestyle = "--")
ax[1].axhline(y = 0, color = "gray", linewidth = 3.0, linestyle = "--")

ax[0].legend()
ax[1].legend()

plt.show()
```



So now we're finally beginning to notice some variation between average income and total employment! Here we see that in terms of aggregate numbers, employment overall seems to vary less from the mean than average income. This is especially observable when we see the figures past 0 delta years, which is understandable as we would expect Amazon warehouses to have some impact on these economic variables.

It may also be important to note that the increased variation of average income may be derived from the fact that it usually is larger than total employment in aggregate form.

Now we will move on to display this information in terms of growth rate.

Time Series: Growth Rate Change

We will begin to work on observing the growth rate change in the variables average income and total employment in counties upon an Amazon warehouse entering. As mentioned before, the benefit of this approach is that it will show the change relative to the magnitude of the value of the variable. For example, the numbers for average income tend to be higher than total employment, and thus similar numbers in aggregate change may signify different degrees of change.

Now begin working on showing the growth rate change for both employment and average income. To do this, we will have to create similar but different functions to the previous ones we were working with:

In [32]:
```
def employment_rate(df):

    data = [100*(df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] - 2] - df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]) / df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] - 1] - df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]) / df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]] - df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]) / df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] + 1] - df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]) / df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0] + 2] - df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]) / df["TotalEmployment"].iloc[df["TreatedDate"].iloc[0]]]

    data = pd.DataFrame(data).T

    data.columns = ["-2", "-1", "0", "1", "2"]

    return data
```

In [33]:
```
def income_rate(df):

    data = [100*(df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] - 2] - df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]) / df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] - 1] - df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]) / df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]] - df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]) / df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] + 1] - df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]) / df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]],
            100*(df["AverageIncome"].iloc[df["TreatedDate"].iloc[0] + 2] - df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]) / df["AverageIncome"].iloc[df["TreatedDate"].iloc[0]]]

    data = pd.DataFrame(data).T

    data.columns = ["-2", "-1", "0", "1", "2"]

    return data
```

Now apply these functions to each county in the DataFrame with only treated counties:

In [34]:
```
rate_employment = series.apply(employment_rate)

rate_employment = rate_employment.reset_index().drop(["level_1"], axis = 1).
set_index("GeoFips")

rate_employment.head(10)
```

Out[34]:

	-2	-1	0	1	2
GeoFips					
04013	-8.508502	-2.209322	0.0	-1.864029	-7.451989
06071	-8.321773	-3.449717	0.0	10.405977	20.123347
10003	-8.108424	-4.486505	0.0	14.008646	27.830354
18011	-12.656904	2.248954	0.0	-2.876569	-5.805439
18019	6.196763	1.788756	0.0	1.149915	3.790460
18063	-12.532709	-7.175320	0.0	3.098747	1.845476
18097	-3.457289	-3.387418	0.0	2.812929	12.338587
21015	-8.810764	3.441220	0.0	-18.563988	-19.921875
21029	-46.979261	-25.676285	0.0	2.299369	16.816952
21067	-3.366892	-10.232712	0.0	-2.063047	0.280574

In [35]:
```
rate_income = series.apply(income_rate)

rate_income = rate_income.reset_index().drop(["level_1"], axis = 1).set_index(
"GeoFips")

rate_income.head(10)
```

Out[35]:

	-2	-1	0	1	2
GeoFips					
04013	-7.908936	-4.651674	0.0	-1.820107	-1.857034
06071	-3.767991	-0.519637	0.0	0.591845	-2.394217
10003	-5.736641	-3.372694	0.0	-2.136068	-1.998391
18011	-10.316170	-4.070207	0.0	5.600739	4.373349
18019	-2.916649	5.675907	0.0	1.455385	2.125435
18063	-4.025972	-1.225707	0.0	3.752321	4.926515
18097	-2.245393	0.662340	0.0	3.674550	4.739634
21015	9.136190	6.826621	0.0	-10.932512	8.375116
21029	3.355083	-1.685415	0.0	-1.493381	-6.472219
21067	-2.239324	2.620021	0.0	0.664680	4.581917

Now transpose both DataFrames and merge them together to see the results:

In [36]:
```
mean_rate_employment = pd.DataFrame(rate_employment.mean())
mean_rate_income = pd.DataFrame(rate_income.mean())

mean_rate_employment.columns = ["Total Employment"]
mean_rate_income.columns = ["Average Income"]

mean_rate_employment.index.name = "Delta Years"
mean_rate_income.index.name = "Delta Years"

mean_rate_employment.reset_index(inplace = True)
mean_rate_income.reset_index(inplace = True)

final_rate = pd.merge(mean_rate_employment, mean_rate_income,
                 how = "inner",
                 on = "Delta Years")

final_rate["Delta Years"] = final_rate["Delta Years"].astype(float)

final_rate.set_index("Delta Years", inplace = True)

final_rate
```

Out[36]:

	Total Employment	Average Income
Delta Years		
-2.0	-5.048194	-3.522987
-1.0	-2.646172	-0.996466
0.0	0.000000	0.000000
1.0	4.674093	0.982321
2.0	10.153036	2.404562

Plot it!

In [37]:

```
fig, ax1 = plt.subplots(figsize = (7, 7))

ax2 = ax1.twinx()

final_rate["Total Employment"].plot(ax = ax1, color = "r", linewidth = 3.0, la
bel = "Total Employment", xticks = [-2, -1, 0, 1, 2])
final_rate["Average Income"].plot(ax = ax2, color = "b", linewidth = 3.0, labe
l = "Average Income")

ax1.set_title("Average Growth Rate in Employment and Income upon Opening of Am
azon Warehouse", fontsize = 16, fontweight = "bold")
ax1.title.set_position([.5, 1.05])

ax1.set_xlabel("Delta Years", fontsize = 14, fontweight = "bold")
ax1.set_ylabel("% Change in Total Employment", color = "r", fontsize = 14, fon
tweight = "bold")
ax2.set_ylabel("% Change in Average Income", color = "b", fontsize = 14, fontw
eight = "bold")

ax1.set_xlim(-2, 2)
ax1.set_ylim(-10, 11)
ax2.set_ylim(-10, 11)

plt.axhline(y = 0, color = "gray", linewidth = 3.0, linestyle = "--")

plt.style.use("ggplot")

plt.show()
```

Now we see a lot of variation between the levels of change between average income and total employment! As expected, the change of just over 1000 in aggregate terms meant more for employment than average income, which is reflected by the roughly 10% increase in comparison to the 2.5% experienced by average income.

Another interesting thing to note is that the growth rate of average income seems to follow a rather constant trend upwards. When compared to the growth trend of total employment, which is noticeably higher after an Amazon warehouse enters, this becomes more evident.

In fact, the growth rate of average income seems to resemble something similar to general levels of inflation within the United States. In that case, perhaps this slight growth in average income could not be so much an effect of Amazon warehouses, but simply wages adjusting to levels of inflation. In this case, the effect of Amazon warehouses on average income could be even less than what is depicted in this graph!

Conclusion

So we've come a long way since the original graph of Lexington County, South Carolina. We were able to show that, on average, counties that were treated with Amazon warehouses exhibited positive levels of growth in total employment and average income.

We also showed that while the average aggregate levels for these changes were similar, in terms of growth rate total employment seemed to be more positively affected by Amazon warehouses than average income. In fact, we were also able to observe that there was a high chance the growth rate of average income may have been driven by inflation instead of Amazon warehouses.

Of course, this project is by no means a perfect analysis or proof that Amazon warehouses do indeed have a causal impact on economic variables such as employment and average income. To begin with, many Amazon warehouse data points could not be used due to the year restriction of until 2014 the BEA data set. There are also still biases that this analysis does not deal with. To deal with such omitted variable biases, more advanced econometric tools would be necessary.

Nevertheless, the data and approached used was the best available at this time, and the project displays a more holistic overview of what the causal impact of Amazon warehouses would look like than figure in The Economist article, which was the original goal of this project!