China's Corporate Debt: Analyzed and Illustrated

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Background

China is currently the second largest economy in the world, and could easily surpass the United States as the largest within the next twenty years. China's economic growth has been described as "miraculous" and "recession-proof", as China had been able to maintain around double-digit economic growth prior to the global financial crisis, and ~7% afterward. In 2015, China accounted for over half of the world's total economic growth. That China was able to not only survive the financial crisis, but veritably thrive, is remarkable, and begs the question of what made China's approach different. How China arrived at its current position has major implications for the economic and financial policies of all emerging markets. Where China goes from here, however, has serious implications for the entire global economy.

Thesis

This project posits that a significant contributing factor to China's economic growth has been the rapid rise in Chinese private non-financial sector debt--particularly corporate debt. We hypothesize that this rise in corporate debt would compare unfavorably to historical comparisons and that these comparisons would indicate that China may indeed be headed for a debt crisis. We analyze data from two sources: the China Central Depository and Clearing Corporation, and the Bank of International Settlements, in an effort to illustrate the evolution and extent of China's corporate debt issue.

Disclaimer:

Before we fully delve into the project, we must make you aware of a few things. **Firstly**, the PDF version of this file has commented out (by putting a # before) the `!pip install` portions of downloading the python libraries and packages, this has been done for viewing purposes, to avoid multiple pages of downloading messages. The Jupyter notebook version of this project leaves the install packages active, so that readers who have not previously downloaded the package may still run the notebook. **Secondly**, the Chinese bond data frame that we created takes a bit of time to download and merge. If you're viewing this project as a Jupyter Notebook, you may want to allow 5 minutes or so to allow for this data frame to be created. **Lastly**, one of the graphs in this presentation is a Plotly interactive graphing module. In order to gain access to this graphing mechanism, you have to run the program that we use to create the graph, as Plotly requires a sign-in that we have provided. If you are viewing the project as a PDF or a Jupyter Notebook that did not run the program, then the graph will unfortunately not appear, and Plotly will send a "Plot twist" error message. This does not affect the other key points of the presentation or detract from the takeaways of the presentation, but for the full experience of the presentation, it is best to view it as a fully-run Jupyter Notebook so that you can interact with the graphs.

Some Key Terms:

Credit to Non-Financial Corporations

This is the key point of our paper--the credit to private, non-financial (meaning not banks) corporations. When we talk about corporate debt in this paper, this is what we will be referring to. A ballooning level of credit to non-financial corporations has often preceded crisis, as it did in both Japan and the countries impacted by the Asian Financial crisis. Disproportionately rapid growth in Credit to non-financial corporations has also been potentially shown to have links to risks of currency and financial crises (https://www.hks.harvard.edu/sites/default/files/centers/mrcbg/files/Pongmanavuth_final.pdf).

Credit to the Private Non-Financial Sector

This is a term we'll bring up a lot, and it is important to distinguish it from corporate debt. Credit to the private non-financial sector includes corporate debt, and also credit to households and non-corporate, private entities. Countries with high credit to corporations typically have high rates of credit to the private non-financial sector. Where credit to the private non-financial sector is less indicative of what we are trying to achieve, however, is in discerning the potential imbalances of credit allocation within a country. Often, macroeconomic imbalances are intertwined with credit imbalance (http://www.europarl.europa.eu/document/activities/cont/201204/20120419ATT43526/20120419ATT43526EN.pdf), and the rebalancing period can be painful.

Packages, Libraries, and Plotly

Below is a list of the packages and libraries we used for this project.

For Reading in Data

- `lxml`
    - `etree`
- `xlrd`

For Analyzing Data

- `pandas`
- `numpy`
- `datetime`
- `math`
    - `pi`

For Graphing Data

- `geopandas` (for maps)
    - `fiona`
- `shapely.geometry` (for maps)
    - `Point`
    - `Polygon`
- `seaborn` (for graphic designs)
- `matplotlib.pyplot`
- `plotly` (for interactive graphs)
    - `plotly.plotly`
    - `plotly.graph_objs`
- `warnings.filterwarnings('ignore')` (to avoid unnecessary warnings)

In [110]:
```
#!pip install lxml #needed to help read in HTML and EXCEL files from online
#!pip install xlrd
#!pip install geopandas
#!pip install plotly
import seaborn as sns     #Graphics tool we need for heatmap
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import lxml
import datetime as dt
import xlrd
from lxml import etree
from datetime import datetime
from math import pi
import fiona # Needed for geopandas to run
import geopandas as gpd # this is the main geopandas
import plotly.plotly as py          #needed for the interactive graph
import plotly.graph_objs as go      #also needed for the interactive graph

import numpy as np
from shapely.geometry import Point, Polygon # also needed
import warnings
warnings.filterwarnings('ignore')

#import pandas, matplotlib, and libraries to read html files
```

The Chinese Bond Market

From the China Central Depository and Clearing Corporation (http://www.chinabond.com.cn/d2s/engindex.html)

The China Central Depository and Clearing Corporation publish monthly data regarding the changes in the outstanding values of the Chinese bond markets. Unfortunately, this data isn't aggregated on anything more than a monthly basis, and aren't fully standardized (some are HTML files, some are excel files). This makes it difficult to read them all in and combine them. Luckily, we only needed one column from each of the datasets (the second column, which tracked outstanding values of each type of bond in 100's of millions of RMB), and we were able to merge each month successfully and track them by their month and year.

The Chinese Bond Market: Reading in the Data

Below we go through the process of reading in each month's data, formatting the column and row names, merging the data and then transposing it, and lastly setting the index as a datetime to make time series analysis much easier. The reason we have to go through this process is that the HTML/Excel files each only contain information about bond markets for a particular month, and they are indexed by the type of bond. By reading it in, merging it on the index of bond types, then transposing it and setting the index to the date, we are able to create a datetime-indexed dataframe out of ~200 individual, non-time-indexed files. ***Fair bit of warning, this merging process takes some time***.

In [89]:
```
l = []                     #create an empty list for URLs

exc_data = pd.DataFrame()  #create an empty dataframe for excel files
html_data = pd.DataFrame() #create and empty dataframe for html files

#In this loop we bring in data files from the website chinabond.com. Each data
 file is on a separate page (different URL adress) so
#we create a loop to bring in data for each month since 2001 to 2017.

for a in range(2001,2018):    #range of years
  for b in range(1,13):       #range of months
    if b <= 9:                #if the month is a singular digit
      url = 'http://www.chinabond.com.cn/DownLoadxlsx?sId=0300&sBbly=' + str(a
) +'0'+ str(b) + '&sMimeType=1&sc=EN'
      l.append(url)
    else:                     #if the month is two digits
      url = 'http://www.chinabond.com.cn/DownLoadxlsx?sId=0300&sBbly=' + str(a
) + str(b) + '&sMimeType=1&sc=EN'
      l.append(url)

counter = 0                   #create a counter to keep track the number of mo
nths
for i in l:                   #for each item in the list of urls
  counter += 1
  try:                        #try reading the data as a html file. If there i
s an exceprion, got to the excpet statement
    data = pd.read_html(i, skiprows=1)
    data = data[1].iloc[:, :2].set_index(0)

    if counter / 12 > 9:                                     #For years after 2009
      if counter%12 == 0:                                              #For Decemb
er
        D = '20' + str(counter//12) + '/' + str(12)
      else:
        D = '20' + str(counter//12+1) + '/' + str(counter%12)
    else:                                                  #For years between 2001 to 20
09
      if counter%12 == 0:
        D = '200' + str(counter//12) + '/' + str(12)
      else:
        D = '200' + str(counter//12+1) + '/' + str(counter%12)
    new_header = [D]
    data = data[1:]
    data.columns = new_header                                    #change column nam
es
    html_data = pd.concat([html_data, data],axis=1)
  except:                                                  # if the file is not a html fi
le, read it as an excel file.
    data = pd.read_excel(i, skiprows=1).iloc[:, :2]
    if counter / 12 > 9:
      if counter%12 == 0:
        D = '20' + str(counter//12) + '/' + str(12)
      else:
        D = '20' + str(counter//12+1) + '/' + str(counter%12)
    else:
      if counter%12 == 0:
```

```
            D = '200' + str(counter//12) + '/' + str(12)
          else:
            D = '200' + str(counter//12+1) + '/' + str(counter%12)
        new_header = [0,D]
        data = data[1:]
        data.columns = new_header                            #change column names
 to match
        data = data.set_index(0)                             #set bond/debt catego
ry as index
        exc_data = pd.concat([exc_data, data],axis=1)
```

In [90]:
```
exc_data = exc_data.iloc[:,:-4]
data1 = pd.concat([html_data, exc_data], axis = 1).dropna()
bonddata =data1.T
```

Prepping for Time Series and More Graphing

Now we've almost got our full bond dataset. We need to make sure the index and the data are optimized for time series graphing,

In [91]:
```
bonddata.index = pd.to_datetime(bonddata.index,format = "%y%m", infer_datetime
_format= True) #converting the bond dataset's index to datetime
bonddata.dtypes  #Checking the dtypes of the bonddata entries
```

Out[91]:
```
Agricultural Development Bank of China                  object
Asset-backed Securities/Mortgage-backed Securities    object
Central Bank Bonds                                    object
China Development Bank                                object
Commerial Bank Bonds                                  object
Corporate Bonds                                       object
Export-Import Bank of China                           object
Government Bonds                                      object
Local Corporate Bonds                                 object
Others                                                object
Policy Bank Bonds                                     object
State-owned Corporate Bonds                           object
Treasury Bonds                                        object
dtype: object
```

We're nearly done formatting the bonddata, but we noticed something crucial: the data is in the `object` dtype. Now before we do any graphing of the bond data, we have to make sure that the data is in a graphable type. It's currently an `object` dtype, so we'll have to convert it to a `float`. In the next step, we do so, and also add a set of columns detailing the multiples of each of the five bond categories listed in `varlist`, (we'll have more on these in a bit) for later plotting.

In [92]:
```
bonddata = bonddata.astype(float) #converting bonddata entries into floats f
or graphing

varlist = ["Corporate Bonds", "Government Bonds","Policy Bank Bonds", "State
-owned Corporate Bonds", "Treasury Bonds"]
for var in varlist:
    new_name = var + " Growth"
    bonddata[new_name] = bonddata[var]/ bonddata[var].loc["2001-01-01"]
display(bonddata.tail(5))
```

	Agricultural Development Bank of China	Asset-backed Securities/Mortgage-backed Securities	Central Bank Bonds	China Development Bank	Commerial Bank Bonds	Corpora Bon
2017-04-01	32548.6	5485.502777	0.0	71993.72	16471.65	35403.2177
2017-05-01	32996.7	6046.269982	0.0	71590.62	16709.65	35292.2057
2017-06-01	33548.0	6168.667062	0.0	71834.32	16602.65	35166.8892
2017-07-01	33207.6	5702.526809	0.0	72039.22	17049.15	35537.7592
2017-08-01	33872.0	6294.784788	0.0	72627.22	17225.15	36193.0132

The Chinese Bond Market: Plotting the Data

Spider Graphs

Now that we've got the time series graph above, let's compare the growth in the Chinese corporate bonds with that in four other key bond markets: Treasury Bonds, Government bonds (closely tied to Treasury Bonds), state-owned corporate bonds, and policy bank bonds (bonds issued by any of the China Development Bank, China Agricultural Bank, and the China Export/Import Bank). For this, we're going to examine 4 different time periods to see how the outstanding values in each bond market change over time. For a rationale of why each bond type was selected, see below.

Corporate Bonds

We're plotting these because this is the purpose of the presentation. We aim to see how the outstanding value of this bond market has changed over time.

State-owned Corporate Bonds

These are included in the total `corporate bond` section, but it is important to view how these have changed over time to see how the role of state-owned enterprises (SOEs) in China's debt markets has evolved. At the outset (in 2001), all outstanding corporate bonds were from SOEs.

Treasury Bonds

Treasury Bonds were the traditional method that the Chinese government used to borrow money. In 2001, all outstanding Chinese government bonds were treasury bonds.

Government Bonds

We're plotting these to see if the state in 2001 (where all government bonds were treasury bonds) continues over time or if the Chinese government relies on other sources of debt financing.

Policy Bank Bonds

Lastly, China's Policy Bank Bonds are bonds issued by one of its three policy banks: The China Development Bank, The Agricultural Development Bank of China, and the Export-Import Bank of China. If there is a government-led economic policy driving China's rising debt, then it could potentially show up as a significant increase in outstanding policy bank bonds over time.

In [93]:
```
d = ['2001-01-01', '2006-01-01', '2011-01-01', '2017-01-01']     # a list of
 the 4 dates we want to chart
t = ['Corporate Bonds', 'Government Bonds', 'Treasury Bonds', 'State-owned C
orporate Bonds', 'Policy Bank Bonds']   #The types of bond data that we want
 to chart
def achieve_d(data,date,time):          #creating a function to facilitate ma
king the dataframe we'll use
  rslt = pd.DataFrame()                 #Result will be a dataframe
  for item in time:                     #Start of the for-loop
    i = item[:-5]
    l = []
    for d in date:
      l.append(data[item].loc[d])                   #adds the dates to the
 dataframe
    rslt = pd.concat([pd.DataFrame({i: l}), rslt], axis = 1)       #concaten
ates
  return rslt                                                      #returns t
he results

pendata = pd.concat([pd.DataFrame({'Time': d}),achieve_d(bonddata, d, t)], a
xis = 1)    #Creates the pentagon diagram dataframe "pendata"
display(pendata)                    #taking a look at pendata
```

	Time	Policy Bank	State-owned Corporate	Treasury	Government	Corporate
0	2001-01-01	7331.44890	288.57560	9160.658940	9160.658940	288.575600
1	2006-01-01	17998.25001	1791.50000	26702.568850	27073.743770	1896.500000
2	2011-01-01	52657.34286	8795.93980	59409.745875	66407.531919	14813.999800
3	2017-01-01	124109.42000	5440.44908	108653.145875	221713.428487	35362.485178

This dataset gives us a strong look at the outstanding value of the five bond markets every ~5 years from 2001 until 2017. There are a few interesting takeaways here:

1. Change in the prominence of state-owned corporate bonds

Back in 2001, all outstanding corporate bonds were issued by state-owned corporations. 2006 was a similar story. This trend changed by 2011, where less than 60% of outstanding corporate bonds were issued by state-owned enterprises. By January 2017 state-owned corporate bonds were around 1/7th of the total market for corporate bonds, meaning that the increase in corporate debt in China has been driven largely by private sector companies.

2. Separation of Treasury Bonds from Government Bonds

In 2001, the total amount of government bonds outstanding was simply the amount of Treasury Bonds. The Chinese government, then, did not tap bond markets outside of their Treasury Bond market. By 2017, however, Treasury Bonds comprised less than half of the total government bonds issued by value. As we've shown above, State-owned corporate bonds are also *not* driving this separation, as the importance of these bonds has decreased over time.

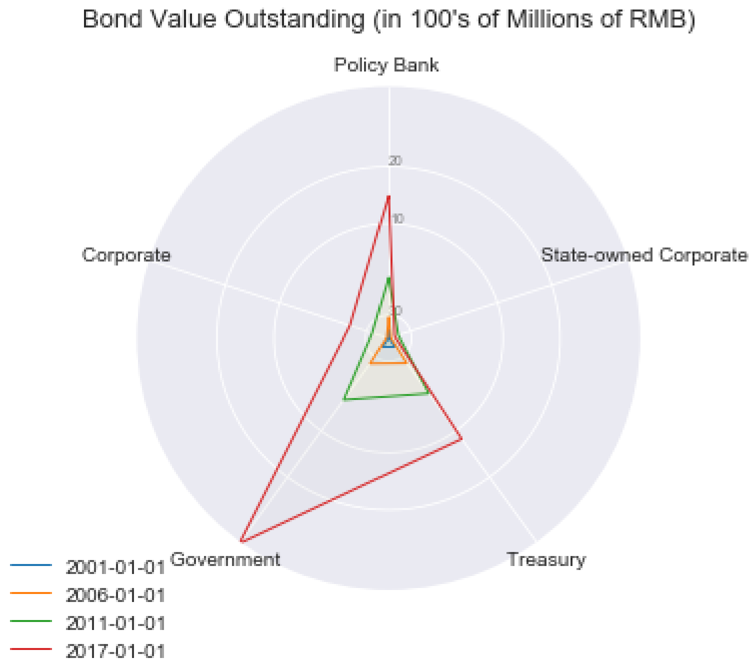
Plotting the Spider Graphs

We create 4 "spider" graphs that illustrate and plot the change in the value of the five bond markets we've selected. The five bond markets we have selected are, as mentioned above: Government Bonds, Policy Bank Bonds, Coporate Bonds, State-owned Corporate Bonds, and Treasury Bonds.

In [94]:
```
# we got the inspiration for this graph from this website: https://python-grap
h-gallery.com/radar-chart/
#create spider graphs to compare the distribution and growth of the following:

#corporate, government, treasury, state-owned corporate, policy bank
#the more one category stretches out to a vertex the higher its number is.

df = pendata


#function to create a spider graph
def make_spider(row, title, color):

  categories=list(df)[1:]
  N = len(categories)

 # Angle of each axis plot
  angles = [n / float(N) * 2 * pi for n in range(N)]
  angles += angles[:1]

  ax = plt.subplot(2,2,row+1, polar=True, )

 # Set axis on top
  ax.set_theta_offset(pi / 2)
  ax.set_theta_direction(-1)

  plt.xticks(angles[:-1], categories, color='grey', size=8)

 # Draw labels inside the graph
  ax.set_rlabel_position(0)
  plt.yticks([50000,100000,150000], ["50000","100000","150000"], color="grey",
 size=7)
  plt.ylim(0,220000)

  values=df.loc[row].drop('Time').values.flatten().tolist()
  values += values[:1]
  ax.plot(angles, values, color=color, linewidth=2, linestyle='solid')
  ax.fill(angles, values, color=color, alpha=0.4)

  plt.title(title, size=11, color=color, y=1.1)


 # initialize the figure
my_dpi=96
plt.figure(figsize=(1000/my_dpi, 1000/my_dpi), dpi=my_dpi)

 # Create a color palette:
my_palette = plt.cm.get_cmap("Set2", len(df.index))

 # Plot with a loop
for row in range(0, len(df.index)):
  make_spider( row=row, title=df['Time'][row], color=my_palette(row))
plt.suptitle("Bond Value Outstanding\n (in 100's of Millions of RMB)", fontsiz
e = 16, y = 1)

plt.tight_layout()
```

Through these graphs we can see clearly that four of the five bond markets have grown substantially since 2001 (the exception being `State-owned Corporate bonds`). The increase in `Government Bonds` seems particularly drastic. Furthermore, these graphs can be aggregated together onto one plane to further illustrate these changes. That aggregation is done below.

In [95]:
```
categories=list(df)[1:]
N = len(categories)

#create one spider plot with data for all four years
# repeat a similar process as above

angles = [n / float(N) * 2 * pi for n in range(N)]
angles += angles[:1]

# Initialize plot
ax = plt.subplot(111, polar=True)

ax.set_theta_offset(pi / 2)
ax.set_theta_direction(-1)

plt.xticks(angles[:-1], categories)


ax.set_rlabel_position(0)
plt.yticks([100000,150000,20000], ["10","20","30"], color="grey", size=7)
plt.ylim(0,220000)



#plot data for 2001
values=df.loc[0].drop('Time').values.flatten().tolist()
values += values[:1]
ax.plot(angles, values, linewidth=1, linestyle='solid', label="2001-01-01")
ax.fill(angles, values, color='#0faf15', alpha=0.1)
#2006
values=df.loc[1].drop('Time').values.flatten().tolist()
values += values[:1]
ax.plot(angles, values, linewidth=1, linestyle='solid', label="2006-01-01")
ax.fill(angles, values, color='#4286f4', alpha=0.1)
#2011
values=df.loc[2].drop('Time').values.flatten().tolist()
values += values[:1]
ax.plot(angles, values, linewidth=1, linestyle='solid', label="2011-01-01")
ax.fill(angles, values, color='#fffa72', alpha=0.1)
#2017
values=df.loc[3].drop('Time').values.flatten().tolist()
values += values[:1]
ax.plot(angles, values, linewidth=1, linestyle='solid', label="2017-01-01")
ax.fill(angles, values, color='#c1c1c1', alpha=0.1)

plt.suptitle("Bond Value Outstanding (in 100's of Millions of RMB)", fontsiz
e = 13, y = 1.05)
# Add legend
plt.legend(loc='upper right', bbox_to_anchor=(0.1, 0.1))
plt.tight_layout()
```

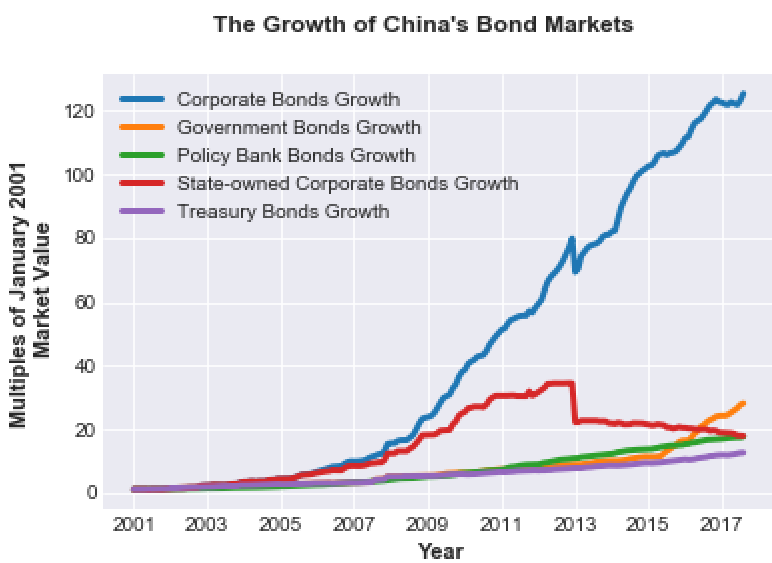


Spider Plots: Takeaways

These spider plots were informative, and showed the growth of each of the major bond markets in China. These plots seem to indicate, however, that the corporate bond market's growth has not been excessively high. We decided to take a closer look at this growth element, and will use a list of column names that we had created earlier to examine the actual growth over time of these five Chinese bond markets.

Time Series plot of Chinese Corporate Debt

In [96]:
```
#here we plot how much each category has grown compared to their base year
#the numbers represent how many times larger they are compared to the
#first year

trlist = []
for var in varlist:
  newname = var + " Growth"
  trlist.append(newname)

fig, ax = plt.subplots()
for var in trlist:
  plt.plot(bonddata[var], lw = 3)
plt.suptitle("The Growth of China's Bond Markets ", fontsize = 12, fontweight
= "bold")
sns.set_style("whitegrid")
plt.rcParams['figure.facecolor'] = 'white'
ax.set_ylabel("Multiples of January 2001\n Market Value", fontweight = "bold",
 fontsize = 11)
ax.set_xlabel("Year",fontweight = "bold", fontsize = 11)
plt.legend()
plt.show()
```



This graph is particularly revealing. We can take away several noticeable trends. Firstly, this graph makes it apparent when China's corporate bonds began to no longer be dominated by State-owned Enterprises. 2009 was a key point when they began to diverge, and private corporations began to control the Chinese corporate debt markets by 2011 and became the substantial majority of the corporate bond market by 2013. Secondly, this graph demonstrates much more clearly than the spider graphs that the sector of Chinese bonds that has experienced the most drastic growth over the past 17 years has most certainly been corporate bonds. While the market for Chinese government bonds has increased nearly 30-fold in the past two decades, the market value of China's corporate bonds has increased by over 125-fold. This demonstrates that China's corporate debt is on a significant upward trajectory, but it is not enough to sound the alarm bells. We need to contextualize this growth in corporate debt before we can determine whether it should be considered worrisome.

The Chinese Bond Market: In Summary

Though informative about the growth of China's corporate debt, this examination of China's Bond Markets hasn't fully given us the understanding of the global significance of this growth. After all, China's economy does not operate in a vacuum. The world's economy changes as well. In This brings us to our second dataset, the one that will form the bulk of our analysis of the extent of China's Corporate debt.

China's Corporate Debt Vs. The World

Data from the Bank of International Settlements (BIS) (http://www.bis.org/statistics/totcredit/totcredit.xlsx)

Now that we've taken a look at China's bond market over the past 17 years, it helps to provide context to truly understand the extent of China's corporate debt issue. For this section, we'll import a large dataset from the Bank of International Settlements that contains quarterly key debt indicators from a wide swath of countries dating back to 1950. The objective of using this data set will be to look specifically at certain debt to GDP ratios around the globe and over time to determine how China's current corporate debt stacks up against the rest of the world both currently and historically. We'll begin by reading in the data and formatting it properly, before going on to plot some time series graphs of corporate debt ratios around the globe.

Two Important Points of Comparison

Two countries, in particular, are important case studies in examining the implications of the rapid rise of China's corporate debt: Thailand and Japan. Both countries underwent significant run-ups of corporate debt relative to their GDP, and both countries experienced significant and painful "rebalancing" periods, where credit becomes tighter for corporations relative to households and the central government, and national leverage decreases significantly. That decrease in credit leads to lower spending and thus lower GDP growth. This is one particularly alarming aspect of China's corporate debt: *we've already demonstrated that China's corporate bonds have grown at a pace that has far outstripped that of its other bonds*--if we can show how China's corporate debt relates to these two historical cases, we can make more informed claims about the potential severity of this issue.

Japan and the "Lost Decade"

In the 1980's, Japan was a global economic powerhouse. As it turned out, it was also in the midst of a massive asset pricing bubble, fueled by easy credit available to corporations and financial institutions. The Bank of Japan facilitated this easy credit by adhering to a policy of "window guidance" (https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1465-7287.1999.tb00672.x). When the asset pricing bubble collapsed in 1991, and credit conditions worsened significantly, Japan's economy suffered for the next 10 years. This period of economic stagnation in what was once a prosperous economic powerhouse became known as Japan's "Lost Decade".

Thailand and the Asian Financial Crisis

Right around the peak of Japan's asset pricing bubble, the country of Thailand was also experiencing an economic boom. While much of Thailand's Financial Crisis in 1997-1998 was linked to the massive inflow of foreign "hot money", which could easily leave the country should the strong economic growth begin to reverse, it was also worsened by significant amounts of "risky lending practices", according to a speech by Janet Yellen in 2007 (https://www.frbsf.org/our-district/press/presidents-speeches/yellen-speeches/2007/february/the-asian-financial-crisis-ten-years-later-assessing-the-past-and-looking-to-the-future/).

Reading in and Formatting the Data

Now that we've provided an introduction to this section of the project, we can begin to read in and format the data required for this portion. We'll begin by reading in the data from this URL: http://www.bis.org/statistics/totcredit/totcredit.xlsx (http://www.bis.org/statistics/totcredit/totcredit.xlsx)

We'll format the data by weeding out the initial 90+ entries (almost entirely NAs) and setting the index to be the date of the information.

In [97]:
```
#grab the BIS data from the website
urlbis = "http://www.bis.org/statistics/totcredit/totcredit.xlsx"
bisdata = pd.read_excel(urlbis, sheet_name = "Quarterly Series").iloc[90:]
bisdata.rename(columns = {"Back to menu":"date"}, inplace = True)
bisdata.set_index("date", inplace =True)
display(bisdata.tail(5))
```

	Emerging markets (aggregate) - Credit to Non financial sector from All sectors at Market value - Percentage of GDP - Adjusted for breaks	Emerging markets (aggregate) - Credit to Non financial sector from All sectors at Market value - Percentage of GDP (using PPP exchange rates) - Adjusted for breaks	Emerging markets (aggregate) - Credit to Non financial sector from All sectors at Market value - USD - US Dollar - Adjusted for breaks	Emerging markets (aggregate) - Credit to General government from All sectors at Nominal value - Percentage of GDP - Adjusted for breaks	Emerging markets (aggregate) - Credit to General government from All sectors at Nominal value - Percentage of GDP (using PPP exchange rates) - Adjusted for breaks	Emerging markets (aggregate) - Credit to General government from All sectors at Nominal value - USD - US Dollar - Adjusted for breaks	E (ag - (Hou and se Per (A fo
date							
2016-09-30	188.1	173.9	46824.6	46.4	45.8	11564.4	36.4
2016-12-31	183.1	174.9	46134.9	45.6	46.3	11493	35.6
2017-03-31	187.5	174.2	48372.4	47.2	46.1	12189.4	37
2017-06-30	189.4	174.8	49843.4	47.9	46.6	12604.1	37.9
2017-09-30	191.9	176	51793.9	48.5	47.1	13093.3	38.9

5 rows × 1130 columns

Comparing China's Corporate Debt to Emerging and Advanced Economies

Here, we aim to get a sense of how China's debt "behaves": that is to say, does China's debt levels more closely mirror that of a traditional emerging market, or a developed country. While we know China is an emerging market, we also know that its corporate debt is high.

It would make sense somewhat intuitively that *developed economies* would have a higher corporate debt to GDP ratios: companies from more established, developed nations may be seen as more trustworthy and thus be able to take on higher debt loads comfortably. Perhaps China does not, in fact, behave like its fellow emerging markets. Though China is an emerging market, it is also one of the most important economies in the world. For it to behave like a developed economy would not seem to be completely out of the question. Perhaps China's rise in debt is not anomalous, and actually mirrors that of developed economies? To figure this out, we start by working with a much smaller dataframe `bis_corp`, that only looks at corporate debt data per country. Then we graph the data.

In [98]:
```
#grab columns that have the word 'corporations'
bis_corp = bisdata.filter(like = 'corporations')
bis_corp.tail(5)
```

Out[98]:

	Emerging markets (aggregate) - Credit to Non-financial corporations from All sectors at Market value - Percentage of GDP - Adjusted for breaks	Emerging markets (aggregate) - Credit to Non-financial corporations from All sectors at Market value - Percentage of GDP (using PPP exchange rates) - Adjusted for breaks	Emerging markets (aggregate) - Credit to Non-financial corporations from All sectors at Market value - USD - US Dollar - Adjusted for breaks	All reporting countries (aggregate) - Credit to Non-financial corporations from All sectors at Market value - Percentage of GDP - Adjusted for breaks	All reporting countries (aggregate) - Credit to Non-financial corporations from All sectors at Market value - Percentage of GDP (using PPP exchange rates) - Adjusted for breaks	All reportin countrie (aggregate) Credit t Non financia corporation from A sectors a Market valu - USD - U Dollar Adjusted fo break
date						
2016-09-30	104.9	95.5	26130	95.7	93.1	64736.8
2016-12-31	101.6	95.5	25608.1	91.9	93	62656.8
2017-03-31	103	94.8	26584.5	93.7	92.9	64637.5
2017-06-30	103.4	94.3	27219.7	95.5	92.4	66575.1
2017-09-30	104.3	94.4	28153.5	96.5	92.3	68411.9

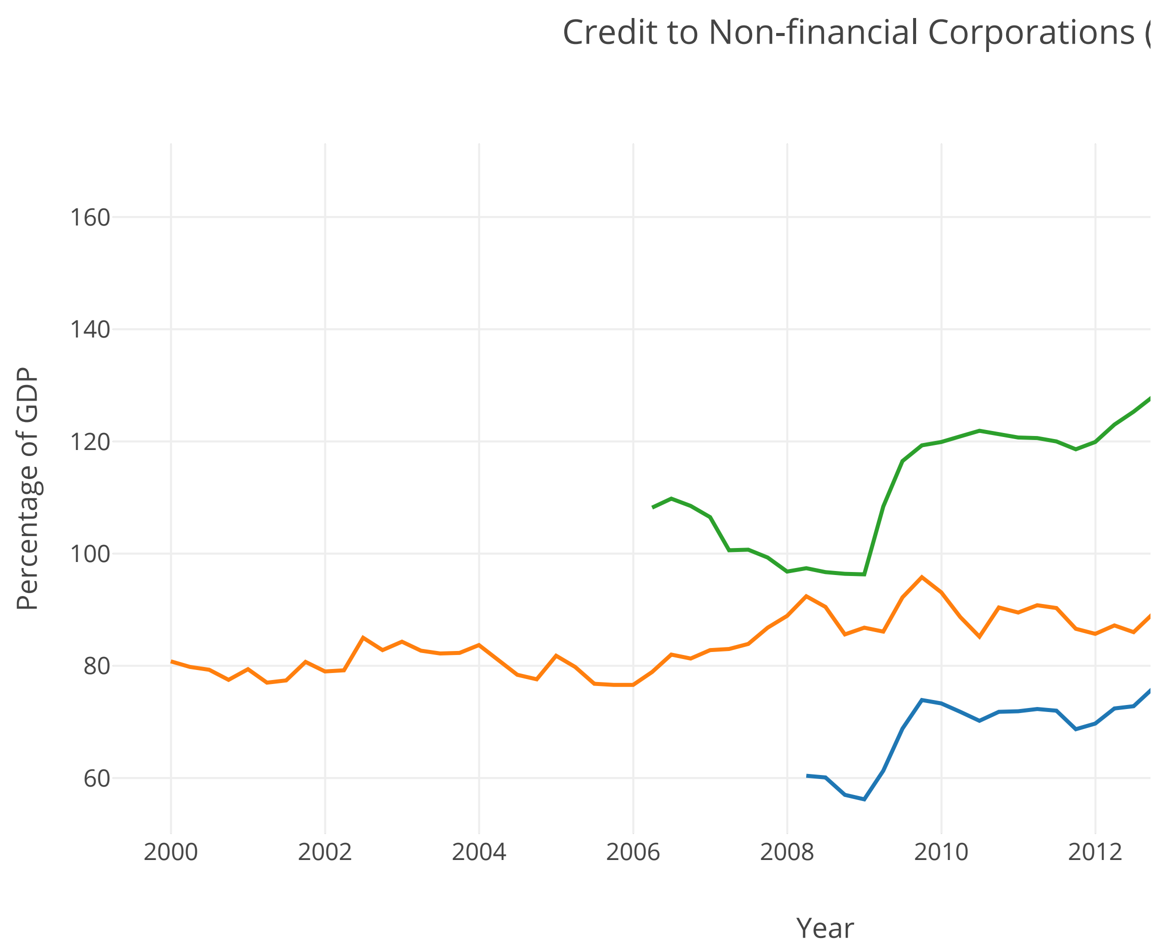
5 rows × 188 columns

China Vs. Emerging and Advanced Economies: Interactive Graph

Below, we plot China's quarterly corporate debt to GDP ratios, as compared to those of both emerging markets and developed economies, to see which it more closely mirrors. We use a `plotly` interactive graph. In order to interact with the graph, readers may need to sign in. Luckily, the sign-in username and passkey are provided within the code cell, under the line `py.sign_in`.

In [99]:
```
#create a plotly line graph to depict differences in credit
#to non-financial corporations between developing and advanced economies

N = 500
x = np.linspace(0, 1, N)
y = np.random.randn(N)
df = bis_corp.tail(75)

data = [
    go.Scatter(
      x=df.index, # assign x as the dataframe column 'x'
      y=df["Emerging markets (aggregate) - Credit to Non-financial corporation
s from All sectors at Market value - Percentage of GDP - Adjusted for breaks"
],
      name = "Emerging Markets")
      ,
    go.Scatter(
      x=df.index, # assign x as the dataframe column 'x'
      y=
      df["Advanced economies (aggregate) - Credit to Non-financial corporation
s from All sectors at Market value - Percentage of GDP - Adjusted for breaks"
],
      name = "Advanced Economies")
      ,
    go.Scatter(
      x=df.index, # assign x as the dataframe column 'x'
      y=df["China - Credit to Non-financial corporations from All sectors at M
arket value - Percentage of GDP - Adjusted for breaks"],
      name = "China")
]
layout = go.Layout(
    title= 'Credit to Non-financial Corporations (% of GDP)',
    yaxis=dict(title='Percentage of GDP'),
    xaxis=dict(title='Year')
)

#required to use plotly
#if this does not work, you can try using your own id
py.sign_in('hygj10', 'cnxpCxqE4WgfZ4jLYkTf')

py.iplot(go.Figure(data = data, layout=layout))

#plotly graphs are interactive. You can
#hover around with your mouse to see specific data points,
#zoom in, select to see specific line graphs, etc.
```

Out[99]:



Plotly Graph: Takeaways

As this interactive graph shows, China's corporate leverage ratio (in green) is not only abnormally high for emerging markets(in blue), but is even above that of advanced economies(in orange). An interesting trend arises in this graph, which is that corporations in emerging markets seemed to be substantially less leveraged compared to their counterparts in advanced economies. China appears to be the exception to the rule. But following the financial crisis, as corporate leverage in advanced economies remained relatively stagnant, corporate debt in emerging markets (China chief amongst them) rose substantially. As China is included in the values of emerging markets, when china's debt begins its significant rise, it also significantly pushes the aggregate Emerging Markets' values upwards. It would make sense for China's corporate debt, then, to be highly correlated with the corporate debt of aggregate emerging markets. But what else correlates strongly with the rise in China's corporate debt? And is the correlatory relationship causal?

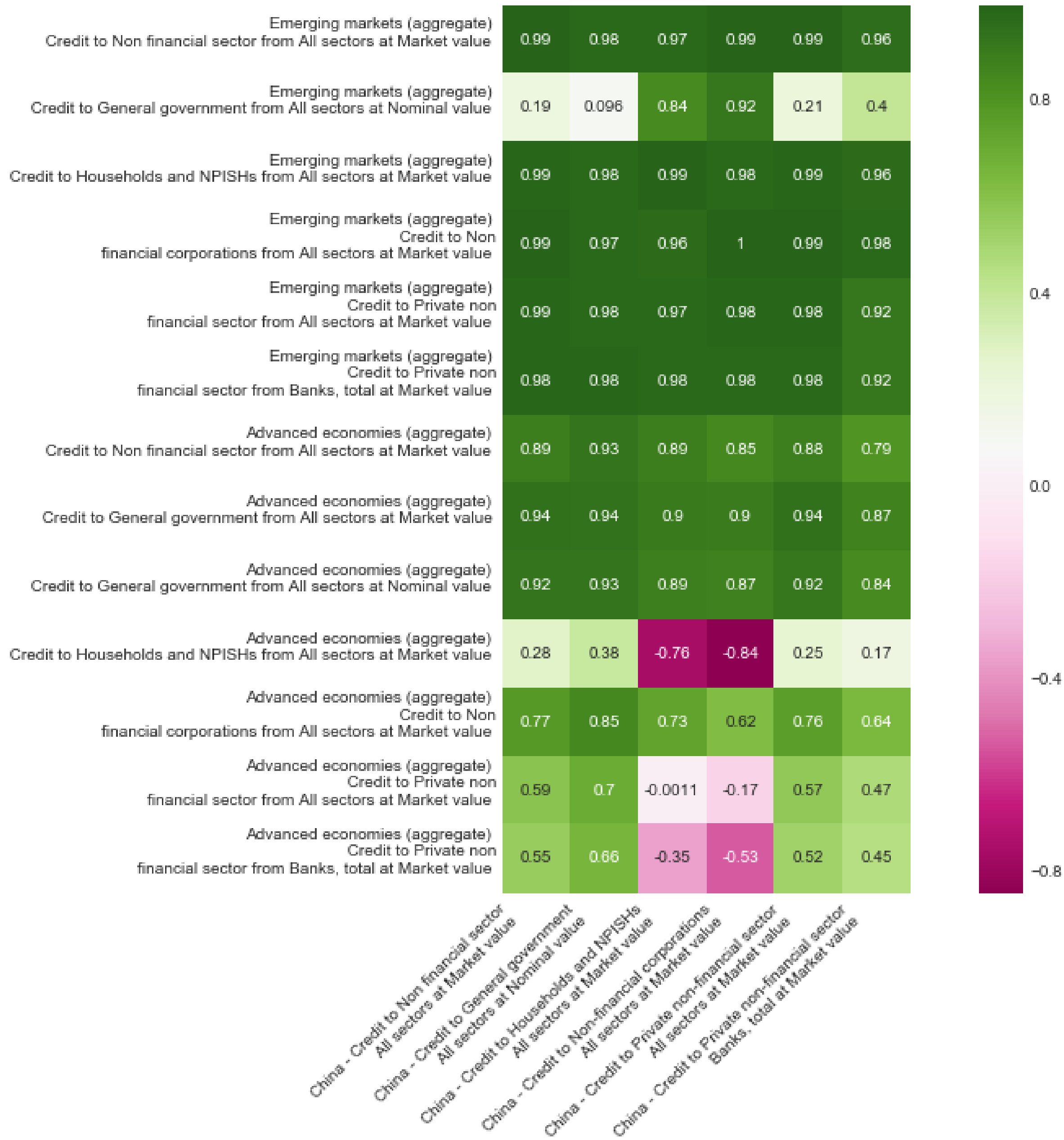
To further explore this, we can actually plot a correlation matrix to look at what might be driving/contributing to China's evolving debt. We'll create a correlation matrix comparing China to both emerging and advanced economies as shown above. After converting bisdata's values to floating point numbers so as to properly determine correlation, We did so below.

In [100]:
```
bisdata =bisdata.astype(float)    # in order to make a correlation matrix, w
e need the bisdata to be floats

bisdata1 = bisdata.filter(like = "Percentage of GDP", axis = 1)    #filterin
g by "Percentage of GDP", the standard unit we wish to use

corr_mat= bisdata1.corr()    #Creating the initial correlation Matrix

china_corr = corr_mat.filter(like = "China", axis = 1)   #filtering the colu
mns to make sure that we see China's correlation with other countries

emer = china_corr.filter(like = 'Emerging', axis = 0)    #filtering on "Emer
ging markets"
adva = china_corr.filter(like = 'Advanced', axis = 0)   #Filtering on "Advan
ced economies"
econs = emer.append(adva)                                #merging the two fro
m above

all_econs = econs.filter(like = '(using PPP exchange rates)', axis = 0) #Get
ting rid of some redundant entries, using PPP exchange rates
all_econs.shape      #Checking out what we've created
```

Out[100]: (13, 6)

We have all the data formatted in the way we need for a correlation heatmap. We've set it up to compare China's 6 key debt-to-GDP indicators to the indicators of both emerging markets and advanced economies. In order to make it more appealing visually, we also go throught the process of formatting the X- and Y- tick labels to remove significant redundancies. We concluded the last cell by checking the shape of the correlation matrix we're heatmapping, and we see that it compares 6 separate Chinese debt indicators with a corresponding 13 indicators from emerging markets and advanced economies. Below, we create the heatmap.

In [101]:
```
fig, ax =plt.subplots(figsize = (15,10))
hm = sns.heatmap(all_econs, mask=np.zeros_like(all_econs, dtype=np.bool), cmap
="PiYG",  #heatmapping all_econs
           annot = True, square=True, ax=ax)    #annot = True means the heatma
p will also show the correlations within the heatmap squares

xticklabels = []      #List for appending and formatting the X-ticks

#here we clean our x labels
#we split them and get rid of redundant parts using a for loop
for item in hm.get_xticklabels():     #
    part_1 = item.get_text().split('from')[0]
    part_2 = item.get_text().split('from')[1].split('-')[0]
    item.set_text(part_1 + '\n' + part_2 + '\n')
    xticklabels += [item]

yticklabels = []
#we clean our y labels
for item in hm.get_yticklabels():
    part_1 = item.get_text().split('-')[0]
    part_2 = item.get_text().split('-')[1]
    part_3 = item.get_text().split('-')[2]
    if 'Percentage of GDP' in part_3:
      item.set_text(part_1 + '\n' + part_2 + '\n')
    else:
      item.set_text(part_1 + '\n' + part_2 + '\n' + part_3 + '\n')
    yticklabels += [item]

hm.set_xticklabels(xticklabels)
hm.set_yticklabels(yticklabels)

#give labels a 45 degree inclination and shift them to make them more readable
plt.xticks(rotation=45)
plt.setp(ax.xaxis.get_majorticklabels(), ha='right')

plt.show()
```


Emerging markets (aggregate) Credit to Non financial sector from All sectors at Market value
Emerging markets (aggregate) Credit to General government from All sectors at Nominal value
Emerging markets (aggregate) Credit to Households and NPISHs from All sectors at Market value
Emerging markets (aggregate) Credit to Non financial corporations from All sectors at Market value
Emerging markets (aggregate) Credit to Private non financial sector from All sectors at Market value
Emerging markets (aggregate) Credit to Private non financial sector from Banks, total at Market value
Advanced economies (aggregate) Credit to Non financial sector from All sectors at Market value
Advanced economies (aggregate) Credit to General government from All sectors at Market value
Advanced economies (aggregate) Credit to General government from All sectors at Nominal value
Advanced economies (aggregate) Credit to Households and NPISHs from All sectors at Market value
Advanced economies (aggregate) Credit to Non financial corporations from All sectors at Market value
Advanced economies (aggregate) Credit to Private non financial sector from All sectors at Market value
Advanced economies (aggregate) Credit to Private non financial sector from Banks, total at Market value
0.99 0.98 0.97 0.99 0.99 0.96
0.19 0.096 0.84 0.92 0.21 0.4
0.99 0.98 0.99 0.98 0.99 0.96
0.99 0.97 0.96 1 0.99 0.98
0.99 0.98 0.97 0.98 0.98 0.92
0.98 0.98 0.98 0.98 0.98 0.92
0.89 0.93 0.89 0.85 0.88 0.79
0.94 0.94 0.9 0.9 0.94 0.87
0.92 0.93 0.89 0.87 0.92 0.84
0.28 0.38 -0.76 -0.84 0.25 0.17
0.77 0.85 0.73 0.62 0.76 0.64
0.59 0.7 -0.0011 -0.17 0.57 0.47
0.55 0.66 -0.35 -0.53 0.52 0.45
China - Credit to Non financial sector All sectors at Market value
China - Credit to General government All sectors at Nominal value
China - Credit to Households and NPISHs All sectors at Market value
China - Credit to Non-financial corporations All sectors at Market value
China - Credit to Private non-financial sector All sectors at Market value
China - Credit to Private non-financial sector Banks, total at Market value
0.8
0.4
0.0
-0.4
-0.8

Above we are able to see that the most of the heatmap is colored green, which signifies that the data is positively correlated with corresponding Chinese credit data. It is also evident however that some of the credit data of advanced economies are not positively correlated with Chinese credit data. As a matter of fact, some are negatively correlated. We that this correlation matrix implies to us that the trend of credit & debt of China is much more similar to that of an emerging market than that of an advanced market. This can be somewhat seen in the earlier Plotly graph, where China and emerging markets show a similar slope. As we've mentioned, as China's data is included in the aggregation of emerging markets' data, we would certainly expect this. But if China were the sole driver of the debt growth in emerging markets, we would likely see a much stronger correlation between the credit provided to China's General government and the credit to the general government in other emerging markets, but this correlation is less than .1.

What was also perhaps unexpected was how negatively correlated China's private non-financial and corporate debt is with the household debt of advanced economies. This must mean that as China's private and corporate debt has risen, household and individuals in developed economies must have seen a decline in the credit provided to them. This also shows up in the very weak negative correlation between credit to China's private nonfinancial and to that of advanced economies.

China vs. the World: Mapping and Geopandas

Now, we'd like to further illustrate China's standing relative to the rest of the world. For this, we'll need to use a Geopandas map file. We pulled this world map file from [geopandas.org (http://geopandas.org/mapping.html)](http://geopandas.org/mapping.html). We aim to look at a map of the world in both 2007 and 2017 to visualize how global debt ratios have changed. Here, we'll begin the process of reading in the mapfile and merging relevant information into the worldmap file.

Reading in the World Map

In [102]:
```
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))    #geopan
das' preset dataframe for plotting world map
```

```
WARNING:Fiona:GDAL data files not located, GDAL_DATA not set
WARNING:Fiona:PROJ data files not located, PROJ_LIB not set
```

In [103]:
```
display(world.head(5))    #GeoDataframe that contains geometry information for
 every coutries in the world.
        # what we need to do is to merge the data we want to plot with this G
eoDataframe.
```

	pop_est	continent	name	iso_a3	gdp_md_est	geometry
0	28400000.0	Asia	Afghanistan	AFG	22270.0	POLYGON ((61.21081709172574 35.65007233330923,...
1	12799293.0	Africa	Angola	AGO	110300.0	(POLYGON ((16.32652835456705 -5.87747039146621...
2	3639453.0	Europe	Albania	ALB	21810.0	POLYGON ((20.59024743010491 41.85540416113361,...
3	4798491.0	Asia	United Arab Emirates	ARE	184300.0	POLYGON ((51.57951867046327 24.24549713795111,...
4	40913584.0	South America	Argentina	ARG	573900.0	(POLYGON ((-65.50000000000003 -55.199999999999...

Beginning the Merging Process

To begin merging, we'll create several functions. the first is the `bis()` function, which allows us to select the years we want data for and create separate yearly dataframes for easier merging.

In [104]:
```
def bis(year):
  # A function that grab certain year of data from the original BIS dataset
  data = pd.DataFrame(bisdata.loc[datetime.strptime(year +'-09-30', '%Y-%m-%d'
).date()])
  data.reset_index(inplace = True)
  foo = lambda data: pd.Series([i for i in (data.split('-', maxsplit = 1))])
  # Seperate original index into country/market column and debt_type column
  rev = data['index'].apply(foo)
  # replace the 'index' column by two seperated columns and use 'rev' to conta
in this new dataframe
  rslt = pd.concat([rev,(data[data.columns[1]])], axis=1)
  # Merge 'rev' with the number column from the original data to create datafr
ame we want
  rslt.columns = ["name", "debt_type", "total"]
  # Reset column names
  return rslt


#Pick 2007-09-30 and 2017-09-30 data
bis2007 = bis('2007')
bis2017 = bis('2017')
bis2007.tail(5)
```

Out[104]:

	name	debt_type	total
1125	South Africa	Credit to Private non-financial sector from A...	1735.327
1126	South Africa	Credit to Private non-financial sector from B...	72.000
1127	South Africa	Credit to Private non-financial sector from B...	213.338
1128	South Africa	Credit to Private non-financial sector from B...	1467.916
1129	South Africa	Credit to Private non-financial sector from B...	1669.685

Now that we have these dataframe, we define the `sep()` function, which separates different debt types into individual dataframes to further facilitate merging with the world map file.

In [105]:
```
def sep(data):             # Function that seperate different debt types' data
  priv = data[(data['debt_type']==
             " Credit to Private non-financial sector from All sectors at Mark
et value - Percentage of GDP - Adjusted for breaks")]
  priv["name"] = priv["name"].str.strip()
  priv.rename(columns = {'total': 'Credit to Private non-financial sector'}, i
nplace = True) # Find Private non-financial debt type, cut the name shorter, t
hen rename the column

  pcGDP = data[(data['debt_type'] ==
                ' Credit to General government from All sectors at Market valu
e - Percentage of GDP - Adjusted for breaks')]
  pcGDP["name"] = pcGDP["name"].str.strip()
  pcGDP.rename(columns = {'total': 'Credit to General government'}, inplace =
True)  # Find General government debt for all sector, do the same thing as the
 last one

  CorDe = data[(data['debt_type'] ==
                ' Credit to Non-financial corporations from All sectors at Mar
ket value - Percentage of GDP - Adjusted for breaks')]
  CorDe["name"] = CorDe["name"].str.strip()
  CorDe.rename(columns = {'total': 'Credit to Non-financial corporations'}, in
place = True) # Do the same thing for Non-Financial Corporations debt

  return priv, pcGDP, CorDe
```

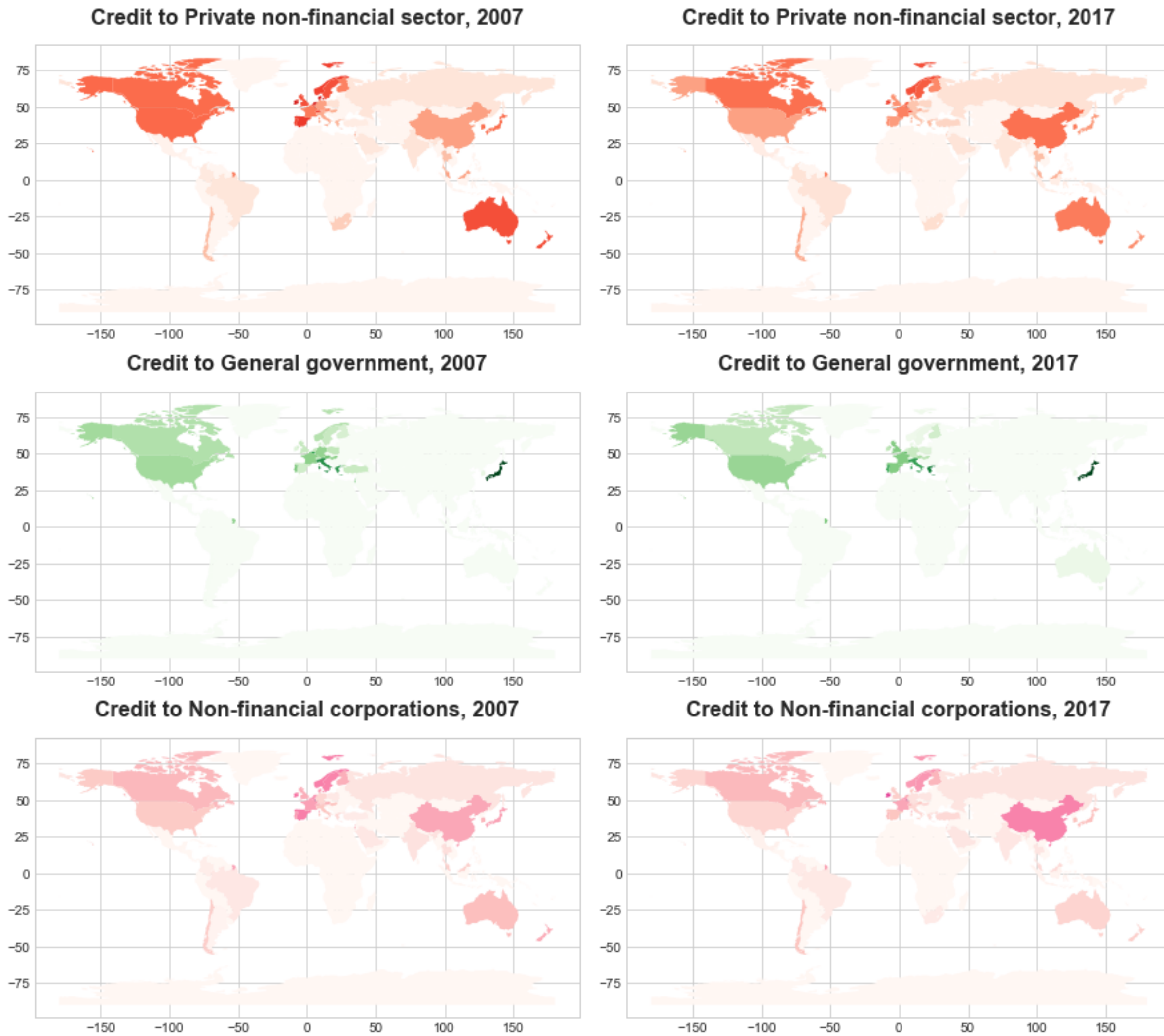
Lastly, now that we've formatted these dataframes to be properly merged, we'll define the `create_world()` as a function that will create the worldmap dataframes required to view both 2007 and 2017.

In [106]:
```
def create_world(data):       # Create world map GeoDataframe based on data we
 have

  priv, pcGDP, CorDe = sep(data)   # Seperate data as three types
  dfs = [priv, pcGDP, CorDe]
  rslt = world
  for item in dfs:
    rslt= pd.DataFrame.merge(rslt,item,on='name', how="outer")   # Merge three
 debt_type data into original World GeoDataframe
  rslt.drop(columns = ['debt_type_x', 'debt_type_y', 'debt_type'])   # Drop re
dundant columns generated from merging
  return rslt

world_2007 = create_world(bis2007)    # Create world dataframe for 2007
world_2017 = create_world(bis2017)    # Create world dataframe for 2017
```

World Map: Plotting the Data

Now that we have all of this formatted properly, let's take a look at 3 key debt-to-GDP Ratios from this timeframe (2017 Q3) These three maps will illustrate (via color shades) the severity or magnitude of each country's relevant debt-to-GDP ratio. The darker the colors, the higher the ratio.

In [107]:
```
title = ['Credit to Private non-financial sector','Credit to General governmen
t','Credit to Non-financial corporations'] # Type of debt we want to compare
color = ['Reds', 'Greens', 'RdPu']   # Color we want to use for our map
fig, ((ax1, ax2), (ax3, ax4), (ax5, ax6)) = plt.subplots(nrows=3, ncols=2, fig
size=(12.5,11))   # Create pyplot grid for six graphs in 2*3 format

world_2007.plot(ax = ax1, column = title[0], cmap = color[0])  # Plot first ty
pe of debt we want to analyse in ax1, using color1 in the 'color' list
ax1.set_title(title[0]+', 2007', fontsize = 16, y = 1.05, fontweight = "bold")
 # Set the subplot title

world_2017.plot(ax = ax2, column = title[0], cmap = color[0])
ax2.set_title(title[0]+', 2017', fontsize = 16, y = 1.05, fontweight = "bold")

world_2007.plot(ax = ax3, column = title[1], cmap = color[1])
ax3.set_title(title[1]+', 2007', fontsize = 16, y = 1.05, fontweight = "bold")

world_2017.plot(ax = ax4, column = title[1], cmap = color[1])
ax4.set_title(title[1]+', 2017', fontsize = 16, y = 1.05, fontweight = "bold")

world_2007.plot(ax = ax5, column = title[2], cmap = color[2])
ax5.set_title(title[2]+', 2007', fontsize = 16, y = 1.05, fontweight = "bold")

world_2017.plot(ax = ax6, column = title[2], cmap = color[2])
ax6.set_title(title[2]+', 2017', fontsize = 16, y = 1.05, fontweight = "bold")

plt.tight_layout()  # Polishing, prevent axis names from overlapping each othe
r
```



From these maps, it's clear that by Q3 of 2017, China's non-financial corporate and private sector debt is higher than the global average, but not necessarily unprecedented. There seem to be countries with at least similar non-financial private sector and non-financial corporate debt-to-GDP ratios. Notably, Canada and the several Scandinavian countries each appear with similar colors to China. Perhaps this is a structural result of these countries' economies, and these ratios have always been this high. When compared with 2007, however, we can see that the private sectors of many developed countries had higher leverage back then. This is true for the corporations and households of these developed economies, but by and large, the governments of developed economies have higher debt levels than 10 years ago, while it is unclear as to how much higher China's government debt is. Interestingly, countries in Europe and North America seem to have decreased their credit to the non-financial private sector and credit to non-financial corporations, while China increased their credit to non-financial private sector and credit to non-financial corporations and seem to have no notable change in their credit to the central government.

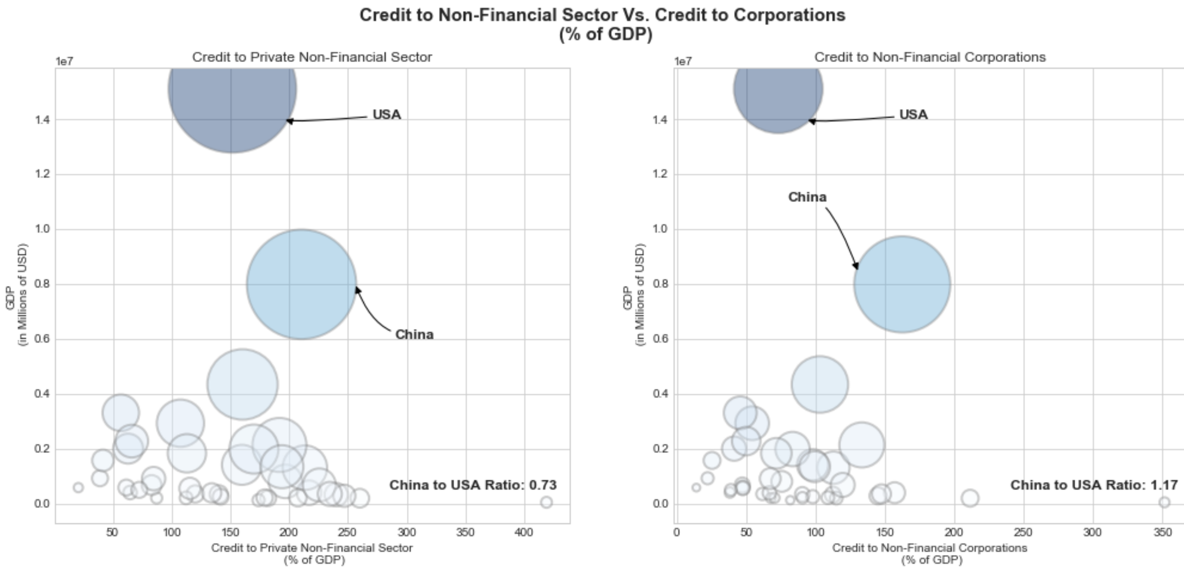
China Vs. The World: Scatterplot

The above graph brings up an interesting trend--that China's corporate debt and its broader, private non-financial debt are both high. Private, nonfinancial debt also includes Chinese households. We want to see whether China's issue is not only with its corporations, but with private non-financial sector debt generally. We know China is the second largest economy in the world, and we know that its characteristics differ significantly from that of the largest economy in the world, the United States. But how do their private and corporate debts compare? We aim to plot that below, with two side-by-side scatter plots comparing GDP (pulled from the imbedded worldmap file) with debt-to-GDP ratios. In the next cell, we go through the process of creating these plots.

In [108]:
```
#Here we implement our scatterplot

fig, (ax1, ax2) = plt.subplots(1, 2, sharex ="col", figsize = (17, 7))
plt.xlabel("the X axis")
plt.ylabel("the Y axis")
plt.suptitle("Credit to Non-Financial Sector Vs. Credit to Corporations\n (%
 of GDP)", fontsize = 15, fontweight = "bold")

wcg = np.float64(world_2017["Credit to General government"])
wf = np.float64(world_2017["Credit to Private non-financial sector"])
wnc = np.float64(world_2017["Credit to Non-financial corporations"])
wg = np.float64(world_2017["gdp_md_est"])

#We want the size of each bubble to represent the size of each country's
#gdp * debt
ax1.scatter(wf, wg, s=(wf * wg)/200000, c=wg, cmap="Blues", alpha=0.4, edgec
olors="grey", linewidth=2)
# Add titles (main and on axis)
ax1.set_title("Credit to Private Non-Financial Sector")
ax1.set_xlabel('Credit to Private Non-Financial Sector\n (% of GDP)')
ax1.set_ylabel('GDP\n (in Millions of USD)')

ax2.scatter(wnc, wg, s=(wnc * wg)/200000, c=wg, cmap="Blues", alpha=0.4, edg
ecolors="grey", linewidth=2)
ax2.set_title("Credit to Non-Financial Corporations")
ax2.set_xlabel('Credit to Non-Financial Corporations\n (% of GDP)')
ax2.set_ylabel('GDP\n (in Millions of USD)')

#below, we annotate the USA and China bubbles for both graphs

ax1.annotate(
    "USA",
    xy=(195, 14000000),
    xycoords="data",
    xytext=(270, 14000000),
    horizontalalignment="left", # The Text Alignment
    arrowprops={
        "arrowstyle": "-|>", # Style of arrow (we liked the ones you had in
 class)
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
    fontsize=12, fontweight = "bold"
)

ax1.annotate(
    "China",
    xy=(256, 8000000),
    xycoords="data",
    xytext=(290, 6000000),
    horizontalalignment="left",
    arrowprops={
        "arrowstyle": "-|>",
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
```

```
    fontsize=12, fontweight = "bold"
)
ax2.annotate(
    "USA",
    xy=(93, 14000000),
    xycoords="data",
    xytext=(160, 14000000),
    horizontalalignment="left",
    arrowprops={
        "arrowstyle": "-|>",
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
    fontsize=12, fontweight = "bold"
)

ax2.annotate(
    "China",
    xy=(131, 8400000),
    xycoords="data",
    xytext=(80, 11000000),
    horizontalalignment="left",
    arrowprops={
        "arrowstyle": "-|>",
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
    fontsize=12, fontweight = "bold"
)

#here we display the China to USA ratio for both graphs
message = "China to USA Ratio: "
ax1.annotate(message +
    str(np.around((world_2017.loc[30]["gdp_md_est"]*
    world_2017.loc[30]["Credit to Private non-financial sector"])/
    (world_2017.loc[168]["gdp_md_est"]*
    world_2017.loc[168]["Credit to Private non-financial sector"]), decimals
=2)),
    xy=(270, 500000), # This is where we point at...
    #xycoords="data", # Not exactly sure about this
    xytext=(285, 500000), # This is about where the text is
    horizontalalignment="left", # How the text is alined

    fontsize=12, fontweight = "bold"
)

message1 = "China to USA Ratio: "

ax2.annotate(message1 +
    str(np.around((world_2017.loc[30]["gdp_md_est"]*
    world_2017.loc[30]["Credit to Non-financial corporations"])/
    (world_2017.loc[168]["gdp_md_est"]*
    world_2017.loc[168]["Credit to Non-financial corporations"]), decimals=2
)),
    xy=(250, 500000),
    #xycoords="data",
    xytext=(240, 500000),
```

```
    horizontalalignment="left",
    fontsize = 12,
    fontweight = "bold"
            )

plt.show()
```



China Vs. The World: Scatterplot Takeaways

In the maps plotted earlier, we have seen that credit to non-financial private sector and credit to non-financial corporations for China has increased more compared to other countries, so we decided to take a closer look. The scatterplots display the relationship between GDP and Credit for each country in the BIS dataset. China and the United States represent the highest level of (GDP) X (Credit as % of GDP).

In this first plot, we can see that the ratio between China and the US is approximatly 0.73, meaning that the GDP X Credit as % of GDP to Private Non-Financial Sector level of the US is considerably bigger. However, if we look at the second plot, we can see that the China to US GDP X Credit as % of GDP to Non-Financial Corporations ratio is 1.17, meaning that China exceeds the US by 17%. Taking in count that the US GDP is greater than China, the fact that China still exceeds in the GDP X Credit to Non-Financial Corporations as % of GDP tells us how large its credit to corporations is compared to the US. By looking at the x-axis of the graphs themselves, it can also be seen that the % of Credit to Corporations as a % of GDP for China is nearly twice that of the US.

China Vs The World: Thailand and Japan

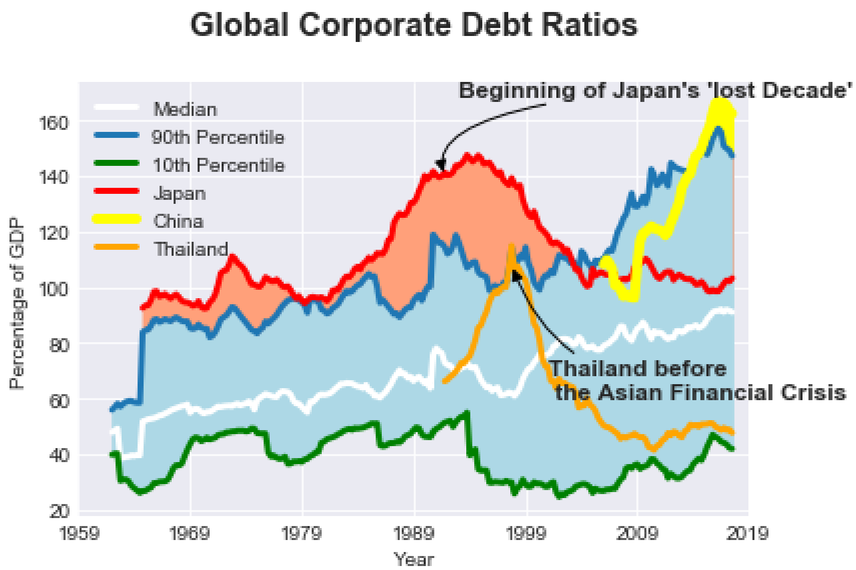
Now that we've examined the graphs above, we can more confidently say that China certainly does have an excessive amount of corporate leverage. But what does that imply about the outlook for Chinese companies and the global economy? Where is China likely to go from here?

For this, we turn to the two interesting comparison countries we mentioned at the outset of the project: Thailand and Japan. We know that we cannot reduce a country's debt crisis to a simple number, but if in the run-up to their crises these countries' corporate debt levels rose in a way consistent with how China's is currently, then that is a significant warning sign. To discern how each country's corporate debt evolved leading up to and after their crises, we plot their corporate debt to GDP ratios below, along with the global ratios at the median, 90th, and 10th percentiles. The reason for this is to provide context to the numbers we'll see. If China's corporate debt currently doubles Thailands in the 1990's, that fact becomes much less alarming if we see that global debt ratios have also doubled than if we see that global debt has remained flat while China's has soared. On the graph, we also shade between the lines of the 90th and 10th percentiles because we hope to show the change in variance between national corporate leverage over time. We also shade between the lines of Japan/China and the 90th percentile, in order to show how much of an outlier each country is/was during their periods of corporate debt growth. The same would have been done with Thailand, but it was not substantially above the 90th percentile for long enough.

With this all in mind, we create the graph below.

In [109]:
```
#we try to display the corporate debt of different countries that showed
#similar increases in corporate debt as China.
#We also add in the median, 10th, and 90th percentile values of
#corporate debt across time

sns.set_style("darkgrid")
corpdebt = bisdata.filter(
    like = "Credit to Non-financial corporations from All sectors at Market
 value - Percentage of GDP",axis = 1)
corpdebt = corpdebt.astype(float) #We need this to make sure that the values
 of corpdebt can be graphed

med = corpdebt.median(axis=1) # This will compute the median, across countri
es, within a year
q90 = corpdebt.quantile(0.90, axis=1) # This is going to compute the 90th pe
rcentile
q10 = corpdebt.quantile(0.10, axis=1) # This is going to compute teh 10th pe
rcentile


fig, ax  = plt.subplots()

med.plot(ax = ax, color ="white", lw = 3, label = 'Median')

q90.plot(ax = ax, lw = 3, label= '90th Percentile')

q10.plot(ax = ax, lw = 3, label = '10th Percentile', color = "green")

#we choose Japan and Thailand as comparable countries to China

corpdebt["""Japan - Credit to Non-financial corporations from All sectors \
at Market value - Percentage of GDP - Adjusted for breaks"""].plot(
    ax = ax, color = "red", lw = 3, label = 'Japan', )

corpdebt["""China - Credit to Non-financial corporations from All sectors at
 Market value \
- Percentage of GDP - Adjusted for breaks"""].plot(
    ax = ax, color = "yellow", lw = 5, label = "China")

corpdebt["""Thailand - Credit to Non-financial corporations from All sectors
 at Market value \
- Percentage of GDP - Adjusted for breaks"""].plot(
    ax = ax, color = "orange", lw = 3, label = "Thailand")

#we fill the spaces between the line grpahs to highlight the difference
#between countries

ax.fill_between(med.index, q10, q90, color = "#ADD8E6")

ax.fill_between(med.index, q90,
                corpdebt["""Japan - Credit to Non-financial corporations fro
m \
All sectors at Market value - Percentage of GDP - Adjusted for breaks"""],
                color = "#FFA07A" )

ax.fill_between(med.index,corpdebt["""Japan - Credit to Non-financial corpor
```

```
ations from \
All sectors at Market value - Percentage of GDP - Adjusted for breaks"""],
                q90,
where=corpdebt["""Japan - Credit to Non-financial corporations from All sect
ors at Market value \
- Percentage of GDP - Adjusted for breaks"""] <= q90,
                color = "#ADD8E6")

ax.fill_between(med.index,corpdebt["""China - Credit to Non-financial corpor
ations from All sectors at Market value \
- Percentage of GDP - Adjusted for breaks"""],
q90, where=corpdebt["""China - Credit to Non-financial corporations from All
 sectors at Market value \
- Percentage of GDP - Adjusted for breaks"""] >= q90,
                color = "yellow")


ax.set_title("Global Corporate Debt Ratios\n", fontweight = "bold", fontsize
 = 16)
ax.set_ylabel("Percentage of GDP")
ax.set_xlabel("Year")
plt.xlim(('1959-01-01', '2019-01-01'))
japyear = .5

#We annotate notes for Thailand and Japan

ax.annotate(
    "Beginning of Japan's 'lost Decade'",
    xy=("1991-12-31", 140), # This is where we point at...
    xycoords="data", # Not exactly sure about this
    xytext=("1993-03-31", 169), # This is about where the text is
    horizontalalignment="left", # How the text is alined
    arrowprops={
        "arrowstyle": "-|>", # This is stuff about the arrow
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
    fontsize=12, fontweight = "bold"
)
ax.annotate(
    "Thailand before \n the Asian Financial Crisis",
    xy=("1997-12-31", 108), # This is where we point at...
    xycoords="data", # Not exactly sure about this
    xytext=("2001-03-31", 60), # This is about where the text is
    horizontalalignment="left", # How the text is alined
    arrowprops={
        "arrowstyle": "-|>", # This is stuff about the arrow
        "connectionstyle": "angle3,angleA=5,angleB=110",
        "color": "black"
    },
    fontsize=12, fontweight = "bold"
)


plt.legend()
plt.show()
```



China Vs. The World: Key Takeaways

The graph above depicts the amount corporate debt from China in comparison to the rest of the world. It helps contextualize China's rising corporate debt historically (with two Asian countries who experienced debt crises--Japan and Thailand--for reference). Several interesting trends appear. Firstly, it's clear that over time, the median country's corporations have become more leveraged--median corporate debt-to-GDP ratios have increased from ~60% to over 85% by 2016. This seems to be driven largely by the top-end growth of the 90th percentile. This graph also makes it evident that Chinese corporate debt has rapidly increased since its first recorded corporate debt level. Towards the end, it surpasses the 90th percentile of the world, becoming one of the countries with the highest corporate debt. We depict Japan and Thailand as well, as they have shown similar rapid growths in the past as well. Both countries reached or surpassed the 90th percentile level but subsequently experienced a crisis, leading corporate debt levels to drastically decrease. Japan's corporate data fell below the 90th percentile level for the first time since its data was recorded, and Thailand's nearly reached the bottom 10%. An advanced economy like Japan and an emerging economy like Thailand were both unable to sustain high levels of growth in corporate debt for long, although Japan's time with outlier-amounts of corporate debt levels was substantial, as evidenced by the wide swath of light red shading above.

Conclusions

Chinese Bond Data

Now that we've looked at this data extensively, we can recap with the key takeaways from each portion of this project. In the **Chinese Bond Data** portion, we first see that all of China's bonds have grown substantially over time, but when looking at multiples of the initial observations, we see that China's corporate debt has grown at a far faster rate than any of the five other bond types. So China clearly does have rising corporate debt relative to its other debt markets. Interestingly enough, this rising corporate debt has come despite state-owned enterprises taking a much smaller portion of the Chinese corporate bond market, a trend that seemed to truly kick off in 2012. So China's rising corporate debt has truly come from private corporations, at least according to examinations of the aggregate Chinese bond market. In order to truly contextualize China's rising corporate debt to determine if it poses a problem for China going forward, we looked at China's debt relative to that of other countries.

BIS Data

After formatting the **BIS data** that we used for the second half of the presentation, we were able to glean a whole host of potential conclusions. In our comparisons of China to aggregate emerging markets and advanced economies, we see that China (as a large portion of the aggregate economic output of emerging markets) has debt trends that are highly correlated with those of emerging markets. Despite its designation as an emerging market, its corporate debt levels are much higher than the average of either advanced economies or emerging markets--and that China's corporate debt growth was likely a significant factor in allowing corporate leverage in emerging markets to eclipse that of advanced economies by June 2014. An indicator that China's debt growth was strongly negatively correlated with, however, was the credit to households and non-corporate private institutions. This could be linked to the fact that after the global financial crisis, households in advanced economies experienced significant deleveraging, while China's corporations actually continued levering at a greater rate than before the crisis. After examining this, we looked at world maps of 2007 and 2017 colorized by the severity of the countries' debt to GDP ratios. From these graphs, we saw that China had high rates of private non-financial sector debt and corporate debt, and was able to identify other regions that had high private non-financial and corporate debt levels--namely Canada, the United States, western European/Scandinavian countries, and Australia. But all of these countries had seen deleveraging relative to GDP from 2007 to 2017--while China's leverage had increased. Thus China's increased debt was coming despite 10-year trends in the traditionally most leveraged countries, not because of it.
The world maps emphasized the importance of differentiating China's general non-financial sector debt from its corporate debt, and in the weighted scatter plots we saw that China's corporate debt is the largest in the world, while its private non-financial debt lags behind the United States. Relative to the United States, in particular, China's credit growth has not come primarily from its households, but from its private corporations.

Lastly, we circled back to the two case studies we mentioned at the beginning of the BIS data section: Japan and Thailand. Japan was an advanced economy, while Thailand was an emerging market and both experienced rapid growth in corporate debt followed by practical economic crises. The aim of this graph was to determine how serious China's corporate debt issue is relative to these two historical benchmarks. The results certainly do not paint a pleasant picture for China's medium-term economic outlook. While both countries' corporate leverage peaked between 10-15 years after the beginning of their credit booms, neither country reached corporate debt levels as high as China's today. When their corporate debt to GDP ratios declined substantially, the subsequent credit crunch hampered economic growth in both countries. If China *is* indeed headed towards a credit crisis, it seems unlikely that its corporate leverage would rebound for quite some time afterward.

One point that could indicate that China is *Not* necessarily headed towards a crisis, however, is that Japan's peak corporate debt to GDP ratio may have been lower than China's is currently, but Japan was--at the time--much more of a global outlier than China is today. Thus, in the context of contemporary credit, China is not as outrageously leveraged as Japan was. But Thailand only briefly crossed the global 90th percentile before it rapidly delevered following the Asian Financial Crisis. Because of China's global stature, it seems more likely that its credit growth would mirror Japan than that of Thailand, but as we've already seen, that is not at all an encouraging sign.

Concluding Comments

This analysis cannot definitively predict whether China will experience a credit crisis--there are far too many confounding variables that have yet to be considered. What this project does show definitively, however, is that China has some of the telltale signs of a corporate credit bubble--a bubble which has been developing over the past 15 years. China corporate debt is an issue for the whole world to monitor over the coming few years. If it keeps trending upwards, and China becomes as much of a global outlier as Japan was in 1991, then China could indeed be heading for a credit crunch.