The Latin American Agriculture Sector as Related With a Country's Macroeconomy

Daniel Fridman (df1647) and Samantha Ruilova Vallejo (srv261)

21 December 2018

Outline:

The World Bank has an immense compendium of economic data for over 300 nations, regions, and disputed states. There's a lot to be done with such data, and economists, data scientists, and hedge funds comb through the over 26,000,000 pieces of data. We have decided to join them in their pursuits.

This project analyzes the agricultural industry of thirty two countries in Latin America. Agriculture is of great importance to the economy overall. Especially in developing countries, agriculture has a strategic impotance in social and economic welfare. Oftentimes, the sector can contribute up to fifty percent to Gross National Income. However, the agricultural sector is often not given enough analytical attention. Thus, we decided to analyze this sector by assesing the relevant macroeconomic trends and country-specific factors that affect this industry across the region.

Specifically, we aim to evaluate any potential correlations between pure macroeconomic factors, such as interest rates, and agricultural indicators, such as percentage velue added. We start by finding these correlations on a country-level basis (e.g. what's the correlation between interest rates and value added in Antigua and Barbuda?), and then generalize our programming to be able to find the average of all correlation pairs in all countries. We will thus be able to compare all correlations at once, instead of fishing blindly for factors we believe *might* be correlated.

Generalization is a big theme here. The World Bank has so much data, and we aimed to create a program that doesn't just work for LatAm, or macro indicators, or agricultural indicators. We seek scalability, so that adding another country or another indicator constitututes nothing more than changing a couple of lines.

The effect of this is that we avoided hardcoding like the plague, and thus have *lots* of seemingly complicated lines of code. We tried to explain these as best as possible. Overall, we have less lines of code than comparable projects due to a liberal usage of loops. Most of our time spent on this project regarded figuring out the logic behind the methods.

Let's start off with some simple imports and definitions

In [2361]:
```
import sys
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import datetime as dt
import numpy as np
import seaborn as sns
import math as math
from scipy.stats.stats import pearsonr

%matplotlib inline
```

Import WDI data as dataframe:

In [2362]:
```
file = '/Users/danielfridman/Downloads/WDI_csv/WDIData.csv'
WDI = pd.read_csv(file)
```

Create dictionary of countries/keys and convert to dataframe. *Note: We have not included Venezuela due to lack of data.*

In [2363]:
```
countries_dict = {
    'country': {1: 'Antigua and Barbuda',
                2: 'Argentina',
                3: 'Bahamas',
                4: 'Barbados',
                5: 'Belize',
                6: 'Bolivia',
                7: 'Brazil',
                8: 'Chile',
                9: 'Colombia',
                10: 'Costa Rica',
                11: 'Cuba',
                12: 'Dominica',
                13: 'Dominican Republic',
                14: 'Ecuador',
                15: 'El Salvador',
                16: 'Grenada',
                17: 'Guatemala',
                18: 'Guyana',
                19: 'Haiti',
                20: 'Honduras',
                21: 'Jamaica',
                22: 'Mexico',
                23: 'Nicaragua',
                24: 'Panama',
                25: 'Paraguay',
                26: 'Peru',
                27: 'Saint Kitts & Nevis',
                28: 'Saint Lucia',
                29: 'Saint Vincent & Grenadines',
                30: 'Suriname',
                31: 'Trinidad and Tobago',
                32: 'Uruguay',
               },
    'code': {1: 'ATG', 2: 'ARG', 3: 'BHS', 4: 'BRB', 5: 'BLZ', 6: 'BOL', 7: 'BRA'
, 8: 'CHL', 9: 'COL', 10: 'CRI',
             11: 'CUB', 12: 'DMA', 13: 'DOM', 14: 'ECU', 15: 'SLV', 16: 'GRD', 17
: 'GTM', 18: 'GUY', 19: 'HTI',
             20: 'HND', 21: 'JAM', 22: 'MEX', 23: 'NIC', 24: 'PAN', 25: 'PRY', 26
: 'PER', 27: 'KNA', 28: 'LCA',
             29: 'VCT', 30: 'SUR', 31: 'TTO', 32: 'URY'
            }
}
countries = pd.DataFrame(countries_dict)
```

Select relevant indicators:

In [2364]:
```
indicators_macro = {
               'NY.GNP.PCAP.CD':'GNI per Capita',
               'NY.GDP.MKTP.KD.ZG':'GDP Growth (%)',
               'BX.KLT.DINV.CD.WD': 'Foreign direct investment, net inflows (BoP,
current US$)',
               'FP.CPI.TOTL.ZG': 'Inflation, consumer prices (annual %)',
               'FR.INR.RINR': 'Real interest rate (%)',
               'SM.POP.NETM': 'Net migration',
               'PA.NUS.FCRF': 'Official exchange rate (LCU per US$, period average
)',
               'SL.UEM.TOTL.ZS': 'Unemployment, total (% of total labor force) (mo
deled ILO estimate)',
               'IC.PRP.PROC': 'Procedures to register property (number)',
               'FR.INR.RISK': 'Risk premium on lending (lending rate minus treasur
y bill rate, %)',
              }

indicators_agro = { 'NV.AGR.TOTL.ZS' : 'Agriculture, forestry, and fishing, value
added (% of GDP)',
                    'NV.AGR.TOTL.KD.ZG' : 'Agriculture, forestry, and fishing, va
lue added (annual % growth)',
                    'NV.AGR.TOTL.KD' : 'Agriculture, forestry, and fishing, value
added (constant 2010 US$)',
                    'NV.AGR.TOTL.KN' : 'Agriculture, forestry, and fishing, value
added (constant LCU)',
                    'NV.AGR.TOTL.CN' : 'Agriculture, forestry, and fishing, value
added (current LCU)',
                    'NV.AGR.TOTL.CD' : 'Agriculture, forestry, and fishing, value
added (current US$)',
                    'NV.AGR.EMPL.KD' : 'Agriculture, forestry, and fishing, value
added per worker (constant 2010 US$)',
                    'ER.H2O.FWAG.ZS' : 'Annual freshwater withdrawals, agricultur
e (% of total freshwater withdrawal)',
                    'SL.AGR.0714.ZS' : 'Child employment in agriculture (% of eco
nomically active children ages 7-14)',
                    'SL.AGR.0714.FE.ZS' : 'Child employment in agriculture, femal
e (% of female economically active children ages 7-14)',
                    'SL.AGR.0714.MA.ZS' : 'Child employment in agriculture, male
(% of male economically active children ages 7-14)',
                    'SL.AGR.EMPL.ZS' : 'Employment in agriculture (% of total emp
loyment) (modeled ILO estimate)',
                    'SL.AGR.EMPL.FE.ZS' : 'Employment in agriculture, female (% o
f female employment) (modeled ILO estimate)',
                    'SL.AGR.EMPL.MA.ZS' : 'Employment in agriculture, male (% of
female employment) (modeled ILO estimate)',
}
```

Now let's take a look at our data and clean it up a bit

In [2365]:
```
WDI.tail(10)
```

Out[2365]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	...	2009
422390	Zimbabwe	ZWE	Women participating in the three decisions (ow...	SG.DMK.ALLD.FN.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422391	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.REAS.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422392	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.ARGU.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422393	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.BURN.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422394	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.GOES.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422395	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.NEGL.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422396	Zimbabwe	ZWE	Women who believe a husband is justified in be...	SG.VAW.REFU.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422397	Zimbabwe	ZWE	Women who were first married by age 15 (% of w...	SP.M15.2024.FE.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
422398	Zimbabwe	ZWE	Women who were first married by age 18 (% of w...	SP.M18.2024.FE.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	30.1
422399	Zimbabwe	ZWE	Women's share of population ages 15+ living wi...	SH.DYN.AIDS.FE.ZS	NaN	NaN	NaN	NaN	NaN	NaN	...	57.4

10 rows × 63 columns

In [2366]:
```
WDI.shape
```

Out[2366]: (422400, 63)

In [2367]:
```
WDI.dtypes
```

Out[2367]:
```
Country Name       object
Country Code       object
Indicator Name     object
Indicator Code     object
1960              float64
1961              float64
1962              float64
1963              float64
1964              float64
1965              float64
1966              float64
1967              float64
1968              float64
1969              float64
1970              float64
1971              float64
1972              float64
1973              float64
1974              float64
1975              float64
1976              float64
1977              float64
1978              float64
1979              float64
1980              float64
1981              float64
1982              float64
1983              float64
1984              float64
1985              float64
                   ...
1989              float64
1990              float64
1991              float64
1992              float64
1993              float64
1994              float64
1995              float64
1996              float64
1997              float64
1998              float64
1999              float64
2000              float64
2001              float64
2002              float64
2003              float64
2004              float64
2005              float64
2006              float64
2007              float64
2008              float64
2009              float64
2010              float64
2011              float64
2012              float64
2013              float64
2014              float64
2015              float64
2016              float64
2017              float64
Unnamed: 62       float64
Length: 63, dtype: object
```

Set all columns lowercase, set index as country code, drop any unsorted columns, and remove all rows with less than 10 non-NaN values for more reliable data

In [2368]:
```
WDI.columns = [i.lower() for i in WDI.columns]
WDI = WDI.set_index('country code')
WDI = WDI.drop('unnamed: 62', 1)
WDI = WDI.dropna(how = 'all', subset = [[str(i) for i in list(range(1960, 2018, 1
))]], thresh = 10) #removes all rows with less than 10 non-NaN values
```

In [2369]:
```
WDI.shape
```

Out[2369]: (225787, 61)

Looks like we got rid of 150,000 lines!

Now let's create our LatAm dataframe from the list of countries we created a dictionary of earlier – this is the only part that is *not* scalable, e.g. if we were to create a WDI_Europe DataFrame, we'd have to change some of the code.

It's possible to get around this by adding countries to countries_dict, instead of creating a separate dictionary for different countries.

In [2370]:
```
WDI_LatAm = WDI.loc[(WDI['country name'].isin(countries['country'])),:]
WDI_LatAm.shape
```

Out[2370]: (28953, 61)

In [2371]:
```
WDI_LatAm_Macro = WDI_LatAm.loc[(WDI_LatAm['indicator code'].isin(list(indicators
_macro))),:]
WDI_LatAm_Macro = WDI_LatAm_Macro.reset_index()
WDI_LatAm_Macro.shape
```

Out[2371]: (250, 62)

In [2372]:
```
WDI_LatAm_Agro = WDI_LatAm.loc[(WDI_LatAm['indicator code'].isin(list(indicators_
agro))),:]
WDI_LatAm_Agro = WDI_LatAm_Agro.reset_index()
WDI_LatAm_Agro.shape
```

Out[2372]: (268, 62)

And now, from the LatAm dataframe, let's create a sample country dataframe – obviously not scalable, but for now. Our first country is Antigua and Barbuda, so let's check out its Macroeconomic indicators!

In [2373]:
```
WDI_LatAm_Macro_ATG = WDI_LatAm_Macro.loc[(WDI_LatAm_Macro['country code'] == 'AT
G')][[str(i) for i in list(range(1960, 2018, 1))]]
WDI_LatAm_Macro_ATG
```

Out[2373]:

	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	...	2(
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.587838e+
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-3.013327e-
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.407000e+
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	5.333806e+
4	NaN	NaN	-1703.00000	NaN	NaN	NaN	NaN	-1625.000000	NaN	NaN	...	N
5	1.71429	1.71429	1.71429	1.71429	1.71429	1.71429	1.71429	1.761908	2.0	2.0	...	2.700000e+
6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	6.000000e+
7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	5.795052e+
8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4.414101e+

9 rows × 58 columns

Clean it up a bit and set an index...

In [2374]:
```
WDI_LatAm_Macro_ATG['indicator code'] = list(WDI_LatAm_Macro.loc[(WDI_LatAm_Macro
['country code'] == 'ATG')]['indicator code'])
WDI_LatAm_Macro_ATG = WDI_LatAm_Macro_ATG.set_index('indicator code')
WDI_LatAm_Macro_ATG
```

Out[2374]:

	1960	1961	1962	1963	1964	1965	1966	1967	1968	19
indicator code										
BX.KLT.DINV.CD.WD	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
NY.GDP.MKTP.KD.ZG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
NY.GNP.PCAP.CD	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
SM.POP.NETM	NaN	NaN	-1703.00000	NaN	NaN	NaN	NaN	-1625.000000	NaN	N
PA.NUS.FCRF	1.71429	1.71429	1.71429	1.71429	1.71429	1.71429	1.71429	1.761908	2.0	
IC.PRP.PROC	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
FR.INR.RINR	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
FR.INR.RISK	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

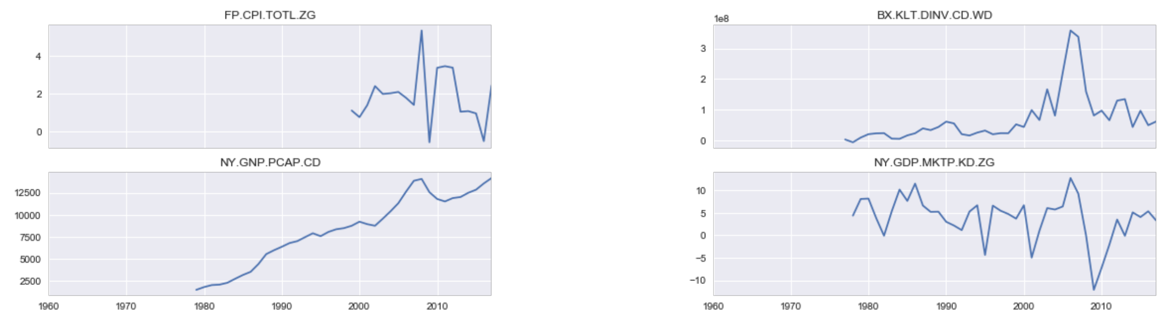
9 rows × 58 columns

Now let's plot the data!

In [2375]:
```
fig, ax = plt.subplots(nrows = 2, ncols = 2, sharex = True)
fig.subplots_adjust(wspace = 0.5)

WDI_LatAm_Macro_ATG.T[WDI_LatAm_Macro_ATG.T.columns[0]].plot(ax = ax[0, 1], title
= WDI_LatAm_Macro_ATG.T.columns[0], figsize = (20, 5))
WDI_LatAm_Macro_ATG.T[WDI_LatAm_Macro_ATG.T.columns[1]].plot(ax = ax[1, 1], title
= WDI_LatAm_Macro_ATG.T.columns[1])
WDI_LatAm_Macro_ATG.T[WDI_LatAm_Macro_ATG.T.columns[2]].plot(ax = ax[1, 0], title
= WDI_LatAm_Macro_ATG.T.columns[2])
WDI_LatAm_Macro_ATG.T[WDI_LatAm_Macro_ATG.T.columns[3]].plot(ax = ax[0, 0], title
= WDI_LatAm_Macro_ATG.T.columns[3])
```

Out[2375]: <matplotlib.axes._subplots.AxesSubplot at 0x167764a90>



It's taking too long to do all the graphs one by one...why not automate it with a loop?

We will be using this logic throughout the project.

This is also not scalable due to hardcoding the number of indicators (nrows * ncols) and due to the title. We leave it as is since it only exists for demonstration purposes.

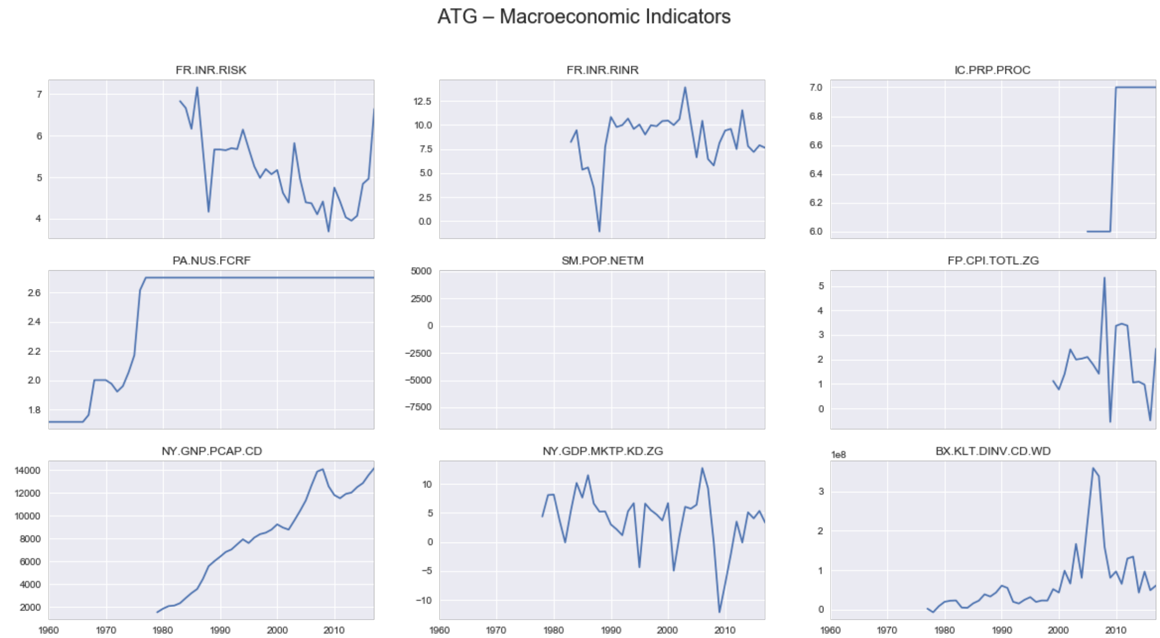
In [2376]:
```
ncols = len(WDI_LatAm_Macro_ATG.index) - 1

fig, ax = plt.subplots(nrows = 3, ncols = 3, sharex = True)

while ncols > -1:

    for i in range(3):
        for j in range(3):
            WDI_LatAm_Macro_ATG.T[WDI_LatAm_Macro_ATG.T.columns[ncols]].plot(ax =
ax[i, j], title = WDI_LatAm_Macro_ATG.T.columns[ncols], figsize = (20, 5))
            ncols-=1

fig.set_figwidth(20)
fig.set_figheight(10)
fig = fig.suptitle('ATG – Macroeconomic Indicators', fontsize = 20)
```



Interesting! A couple of conclusions:

– SM.POP.NETM seems to not exist, but looking up the dataframe shows that there's only a value every five years. Perhaps that is messing with it.

– FR.INR.RISK and FR.INR.RINR seem to be directly correlated. This is not a surprise since .RISR is the risk-free rate, while .RISK is the risk-free rate.

– PA.NUS.FCRF evens out. This is the exchange rate. Antigua and Barbuda fixed its currency to the dollar in 1976, so reliability is not compromised.

– Rest of the data has at least 20 datapoints – looking good!

Same thing for the Agricultural indicators...

In [2377]:

```
WDI_LatAm_Agro_ATG['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['c
ountry code'] == 'ATG')]['indicator code'])
WDI_LatAm_Agro_ATG = WDI_LatAm_Agro_ATG.set_index('indicator code')
WDI_LatAm_Agro_ATG
```

Out[2377]:

	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	...	2008	2009
indicator code													
NV.AGR.TOTL.ZS	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.549311e+00	1.49670
NV.AGR.TOTL.KD.ZG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-6.868142e+00	-1.40573
NV.AGR.TOTL.KD	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.146312e+07	1.84459
NV.AGR.TOTL.KN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4.764570e+07	4.09480
NV.AGR.TOTL.CN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	5.724340e+07	4.94734
NV.AGR.TOTL.CD	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.120126e+07	1.83234

6 rows × 58 columns

In [2378]:

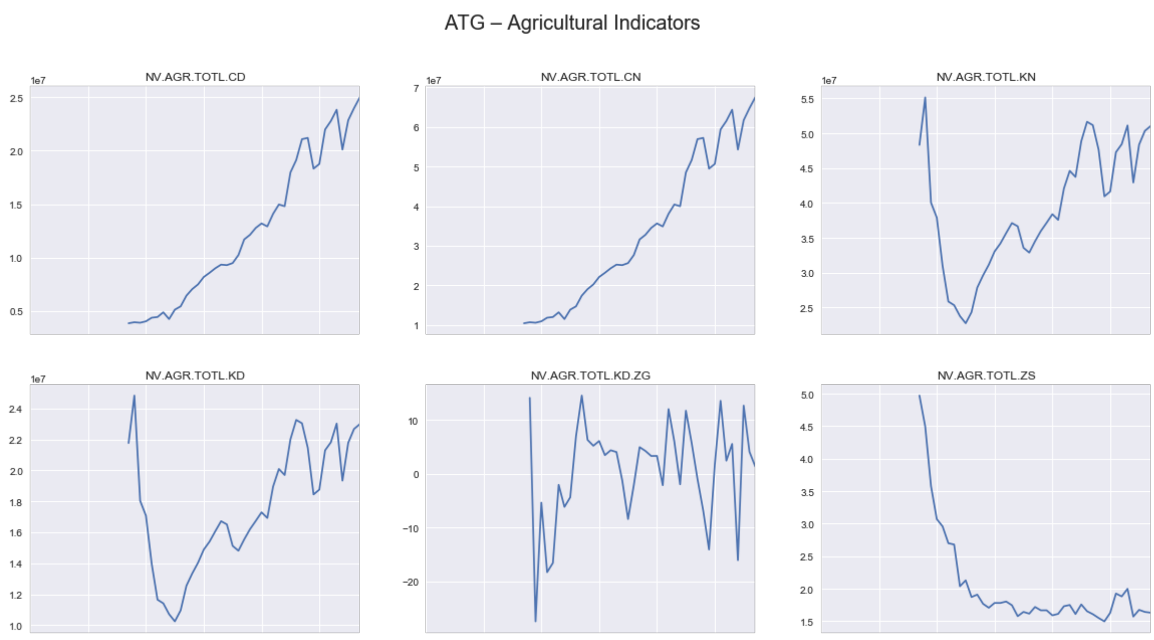
```
ncols = len(WDI_LatAm_Agro_ATG.index) - 1

fig, ax = plt.subplots(nrows = 2, ncols = 3, sharex = True)

while ncols > -1:

    for i in range(2):
        for j in range(3):
            WDI_LatAm_Agro_ATG.T[WDI_LatAm_Agro_ATG.T.columns[ncols]].plot(ax = a
x[i, j], title = WDI_LatAm_Agro_ATG.T.columns[ncols], figsize = (20, 5))
            ncols-=1

fig.set_figwidth(20)
fig.set_figheight(10)
fig = fig.suptitle('ATG – Agricultural Indicators', fontsize = 20)
```



Some conclusions:

– At a first glance, NV.AGR.TOTL.CD and NY.GNP.PCAP.CD seem to have a positive correlation – will be looking out for this later.

– NV_AGR.TOTL.KD and FR.INR.RINR also seem to be correlated.

– Data is quite reliable, going back further than 1980 in all cases.

And now, for the main event: finding the correlations between all graphs.

Many of the other projects find the correlations one by one, drawing conclusions one by one.

We want to do it all at once.

Lots going on below.

First: Set up the correlation statement

This is tricky because we need the correlations between two *time series*. We are actually working with a 3D data set here: we don't just want the correlation between WDI_LatAm_Agro_ATG and WDI_LatAm_Macro_ATG – we want the correlation between those two *across the time series*.

Hence, a simple .corr() doesn't work – there is no use to finding the correlation between just two datapoints – Macro_ATG in 2018 and Agro_ATG in 2018. Thus, pearsonr, which returns (r, p-value). We will only be looking at the r here since we want to average it later on across countries.

Additionally, we want to make this scalable, so we can add and remove indicators without breaking the project. Different indicators have different amounts of data. Thus, we generalize the correlations to make sure the time series lines up across rows, setting it up through .tail(len(WDI_LatAm_Macro_ATG.iloc[j].dropna()))

Finally, we drop NaN values so the correlation actually works.

In [2379]:
```
pearsonr(WDI_LatAm_Agro_ATG.iloc[i].dropna().tail(len(WDI_LatAm_Macro_ATG.iloc[j]
.dropna())), WDI_LatAm_Macro_ATG.iloc[j].dropna())
```

Out[2379]:
```
(0.31561217591734325, 0.0503217431556l7528)
```

Second: Use if statement to account for differing NA values

Additionally, earlier on, we dropped any rows that had less than 10 data points across time. We need to account for this:

If the **length of the list of non-NA values in Agro_ATG** is greater than **the length of the list of non-NA values in Macro_ATG**, then:

Find the correlation

between

the last x values in Agro_ATG, with *x* being equal to *the length of the list of non-NA values in Macro_ATG*

and

the list of non-NA values in Macro_ATG

else:

the reverse

This makes sure that we are actually lined up across time series.

In [2380]:
```
i = WDI_LatAm_Agro_ATG.shape[0] - 1
j = WDI_LatAm_Macro_ATG.shape[0] - 1

if len(WDI_LatAm_Agro_ATG.iloc[i].dropna()) > len(WDI_LatAm_Macro_ATG.iloc[j].dro
pna()):
    print(pearsonr(WDI_LatAm_Agro_ATG.iloc[i].dropna().tail(len(WDI_LatAm_Macro_A
TG.iloc[j].dropna())), WDI_LatAm_Macro_ATG.iloc[j].dropna()))
else:
    print(pearsonr(WDI_LatAm_Agro_ATG.iloc[i].dropna(), WDI_LatAm_Macro_ATG.iloc[
j].dropna().tail(len(WDI_LatAm_Agro_ATG.iloc[i].dropna()))))
```

```
(-0.63013520161223313, 4.9789575746451641e-05)
```

Third: use nested loops to loop through master country dataframe

We have our master country dataframe WDI_LatAm_Macro_ATG. We now want to loop through every row and find its correlation with every column.

All we have to do is use nested loops.

The rest of the code is the same – the text exists to verify that this strategy works.

In [2381]:
```
i = WDI_LatAm_Agro_ATG.shape[0] - 1

while i > -1:

    j = WDI_LatAm_Macro_ATG.shape[0] - 1

    while j > -1:

        print('i = ' + str(i))
        print('j = ' + str(j))

        if len(WDI_LatAm_Agro_ATG.iloc[i].dropna()) > len(WDI_LatAm_Macro_ATG.ilo
c[j].dropna()):
            print('Correlation between ' + WDI_LatAm_Macro_ATG.index[j] + ' and '
+ WDI_LatAm_Agro_ATG.index[i])
            print(pearsonr(WDI_LatAm_Agro_ATG.iloc[i].dropna().tail(len(WDI_LatAm
_Macro_ATG.iloc[j].dropna())), WDI_LatAm_Macro_ATG.iloc[j].dropna()))
            print('n = ' + str(len(WDI_LatAm_Agro_ATG.iloc[i].dropna().tail(len(W
DI_LatAm_Macro_ATG.iloc[j].dropna())))))
        else:
            print('Correlation between ' + WDI_LatAm_Macro_ATG.index[j] + ' and '
+ WDI_LatAm_Agro_ATG.index[i])
            print(pearsonr(WDI_LatAm_Agro_ATG.iloc[i].dropna(), WDI_LatAm_Macro_A
TG.iloc[j].dropna().tail(len(WDI_LatAm_Agro_ATG.iloc[i].dropna()))))
            print('n = ' + str(len(WDI_LatAm_Agro_ATG.iloc[i].dropna().tail(len(W
DI_LatAm_Macro_ATG.iloc[j].dropna())))))
        print('********************************************************************
**********')
        j-=1

    i-=1
```

```
i = 5
j = 8
Correlation between FR.INR.RISK and NV.AGR.TOTL.CD
(-0.63013520161223313, 4.9789575746451641e-05)
n = 35
****************************************************************************
i = 5
j = 7
Correlation between FR.INR.RINR and NV.AGR.TOTL.CD
(0.11764303182267173, 0.50091399843320095)
n = 35
****************************************************************************
i = 5
j = 6
Correlation between IC.PRP.PROC and NV.AGR.TOTL.CD
(0.62511382899079038, 0.022337001502883161)
n = 13
****************************************************************************
i = 5
j = 5
Correlation between PA.NUS.FCRF and NV.AGR.TOTL.CD
(nan, 1.0)
n = 41
****************************************************************************
i = 5
j = 4
Correlation between SM.POP.NETM and NV.AGR.TOTL.CD
(0.57656315358815857, 0.049715865512860599)
n = 12
****************************************************************************
i = 5
j = 3
Correlation between FP.CPI.TOTL.ZG and NV.AGR.TOTL.CD
(0.11181005128754874, 0.64859470202147884)
n = 19
****************************************************************************
i = 5
j = 2
Correlation between NY.GNP.PCAP.CD and NV.AGR.TOTL.CD
(0.95901238341293593, 7.3939402314023583e-22)
n = 39
****************************************************************************
i = 5
j = 1
Correlation between NY.GDP.MKTP.KD.ZG and NV.AGR.TOTL.CD
(-0.26935061393672621, 0.092816025551934897)
n = 40
****************************************************************************
i = 5
j = 0
Correlation between BX.KLT.DINV.CD.WD and NV.AGR.TOTL.CD
(0.59938390183932899, 3.4589956773934924e-05)
n = 41
****************************************************************************
i = 4
j = 8
Correlation between FR.INR.RISK and NV.AGR.TOTL.CN
(-0.63013520161223324, 4.9789575746451478e-05)
n = 35
****************************************************************************
i = 4
j = 7
Correlation between FR.INR.RINR and NV.AGR.TOTL.CN
(0.11764303182267266, 0.50091399843319739)
n = 35
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den
```

```
i = 4
j = 5
Correlation between PA.NUS.FCRF and NV.AGR.TOTL.CN
(nan, 1.0)
n = 41
***************************************************************************
i = 4
j = 4
Correlation between SM.POP.NETM and NV.AGR.TOTL.CN
(0.57656315358816013, 0.049715865512859898)
n = 12
***************************************************************************
i = 4
j = 3
Correlation between FP.CPI.TOTL.ZG and NV.AGR.TOTL.CN
(0.11181005128754817, 0.64859470202148173)
n = 19
***************************************************************************
i = 4
j = 2
Correlation between NY.GNP.PCAP.CD and NV.AGR.TOTL.CN
(0.95901238341293604, 7.3939402314019793e-22)
n = 39
***************************************************************************
i = 4
j = 1
Correlation between NY.GDP.MKTP.KD.ZG and NV.AGR.TOTL.CN
(-0.26935061393672677, 0.092816025551934078)
n = 40
***************************************************************************
i = 4
j = 0
Correlation between BX.KLT.DINV.CD.WD and NV.AGR.TOTL.CN
(0.59938390183932855, 3.4589956773935534e-05)
n = 41
***************************************************************************
i = 3
j = 8
Correlation between FR.INR.RISK and NV.AGR.TOTL.KN
(-0.63023987268391035, 4.9602881682317532e-05)
n = 35
***************************************************************************
i = 3
j = 7
Correlation between FR.INR.RINR and NV.AGR.TOTL.KN
(0.23200541546286474, 0.17988866455240193)
n = 35
***************************************************************************
i = 3
j = 6
Correlation between IC.PRP.PROC and NV.AGR.TOTL.KN
(-0.055516817863305049, 0.85704539673990932)
n = 13
***************************************************************************
i = 3
j = 5
Correlation between PA.NUS.FCRF and NV.AGR.TOTL.KN
(nan, 1.0)
n = 41
***************************************************************************
i = 3
j = 4
Correlation between SM.POP.NETM and NV.AGR.TOTL.KN
(0.53946228679731401, 0.07027017403089468)
n = 12
```

Now, we generalize away from WDI_LatAm_Agro_ATG to enable loop usage across countries:

We start off by locating the time series in the dataframe WDI_Lat_Am_Agro, generalized to *country_code*

We then set the index equal to the indicator code, so that we know what we're actually looking at!

In [2382]:
```
current_country_agro = WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['country code'] == coun
try_code)][[str(i) for i in list(range(1960, 2018, 1))]]
current_country_agro['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_Agro[
'country code'] == country_code)]['indicator code'])
current_country_agro = current_country_agro.set_index('indicator code')
current_country_agro
```

Out[2382]:

indicator code	1960	1961	1962	1963	1964	1965
NV.AGR.TOTL.ZS	9.909312e+00	9.545033e+00	8.727907e+00	7.575173e+00	8.168961e+00	8.441750e+00
NV.AGR.TOTL.KD.ZG	NaN	-1.836386e+00	-4.556404e+00	6.202341e+00	1.294433e+00	1.123147e+00
NV.AGR.TOTL.KD	1.117711e+09	1.097186e+09	1.047193e+09	1.112144e+09	1.126540e+09	1.139193e+09
NV.AGR.TOTL.KN	6.192410e+11	6.078694e+11	5.801724e+11	6.161567e+11	6.241324e+11	6.311423e+11
NV.AGR.TOTL.CN	4.480000e+05	4.840000e+05	5.200000e+05	6.870000e+05	1.124000e+06	1.628000e+06
NV.AGR.TOTL.CD	4.072727e+08	4.400000e+08	4.727273e+08	4.293750e+08	4.886957e+08	5.087500e+08
NV.AGR.EMPL.KD	NaN	NaN	NaN	NaN	NaN	NaN
SL.AGR.EMPL.ZS	NaN	NaN	NaN	NaN	NaN	NaN
SL.AGR.EMPL.FE.ZS	NaN	NaN	NaN	NaN	NaN	NaN
SL.AGR.EMPL.MA.ZS	NaN	NaN	NaN	NaN	NaN	NaN

10 rows × 58 columns

Fourth: implement generalization and define as method

The method doesn't return anything yet. For readability reasons, we will add that in the next step. All we did here was copy-paste the above code inside the loop, and put the whole thing inside a method.

In [2383]:
```
def crosscorrs(country_code):

    current_country_macro = WDI_LatAm_Macro.loc[(WDI_LatAm_Macro['country code']
== country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_macro['indicator code'] = list(WDI_LatAm_Macro.loc[(WDI_LatAm
_Macro['country code'] == country_code)]['indicator code'])
    current_country_macro = current_country_macro.set_index('indicator code')

    current_country_agro = WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['country code'] ==
country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_agro['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_A
gro['country code'] == country_code)]['indicator code'])
    current_country_agro = current_country_agro.set_index('indicator code')

    i = current_country_agro.shape[0] - 1

    while i > -1:

        j = current_country_macro.shape[0] - 1

        while j > -1:

            print('i = ' + str(i))
            print('j = ' + str(j))

            if len(current_country_agro.iloc[i].dropna()) > len(current_country_m
acro.iloc[j].dropna()):
                print('Correlation between ' + current_country_macro.index[j] + '
and ' + current_country_agro.index[i])
                print(pearsonr(current_country_agro.iloc[i].dropna().tail(len(cur
rent_country_macro.iloc[j].dropna())), current_country_macro.iloc[j].dropna()))
                print('n = ' + str(len(current_country_agro.iloc[i].dropna().tail
(len(current_country_macro.iloc[j].dropna())))))
            else:
                print('Correlation between ' + current_country_macro.index[j] + '
and ' + current_country_agro.index[i])
                print(pearsonr(current_country_agro.iloc[i].dropna(), current_cou
ntry_macro.iloc[j].dropna().tail(len(current_country_agro.iloc[i].dropna()))))
                print('n = ' + str(len(current_country_agro.iloc[i].dropna().tail
(len(current_country_macro.iloc[j].dropna())))))
            print('**************************************************************
**************')
            j-=1

        i-=1

# crosscorrs(countries.iloc[7][0])
# We won't run this because the output is the same as the output in Step 3. Every
thing that goes on is behind-the-scenes.
```

Fifth: store correlation results in lists

We create two lists here. The first list, *list1*, stores the correlations for pairs across one single row. *list1* is cleared every time we move to the next row, with its contents added to a master list *list_crosscorr*.

We return *list_crosscorr*, depicting all correlation pairs in a very unreadable format.

In [2384]:
```
list_crosscorr = []

def crosscorrs(country_code):

    current_country_macro = WDI_LatAm_Macro.loc[(WDI_LatAm_Macro['country code']
== country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_macro['indicator code'] = list(WDI_LatAm_Macro.loc[(WDI_LatAm
_Macro['country code'] == country_code)]['indicator code'])
    current_country_macro = current_country_macro.set_index('indicator code')

    current_country_agro = WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['country code'] ==
country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_agro['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_A
gro['country code'] == country_code)]['indicator code'])
    current_country_agro = current_country_agro.set_index('indicator code')

    i = current_country_agro.shape[0] - 1

    while i > -1:

        j = current_country_macro.shape[0] - 1
        list1.clear()

        while j > -1:

            if len(current_country_agro.iloc[i].dropna()) > len(current_country_m
acro.iloc[j].dropna()):
                corr = pearsonr(current_country_agro.iloc[i].dropna().tail(len(cu
rrent_country_macro.iloc[j].dropna())), current_country_macro.iloc[j].dropna())

            else:
                corr = pearsonr(current_country_agro.iloc[i].dropna(), current_co
untry_macro.iloc[j].dropna().tail(len(current_country_agro.iloc[i].dropna())))

            list1.append(corr[0])

            j-=1

        list_crosscorr.append(list1.copy())
        i-=1

    print(list_crosscorr)

crosscorrs(countries.iloc[7][0])
```

```
[[-0.30599489555335296, 0.41777456716679445, nan, -0.61300107182723418, -0.83176
680422827287, 0.72772656920708323, -0.93033521089255711, 0.54279265740158167, -0
.80779767824250837], [-0.20131601992979045, -0.19554572401650358, nan, -0.383208
72609977275, -0.75430054999572049, 0.42988193345456688, -0.3170895192437917, 0.2
9470688634263331, -0.25147258466291134], [-0.3130483011107415, 0.397234155554001
93, nan, -0.61989920086586037, -0.8259287213547708, 0.73466617411901014, -0.9278
4615453478925, 0.55220586192878351, -0.80572994138865872], [0.28278717835592876,
-0.46888822126060964, nan, 0.57820690109178785, 0.85511511815663899, -0.64349382
926958265, 0.93556059940677994, -0.50887189875035943, 0.82086925336309369], [-0.
052262720737316928, -0.26994232466679818, nan, 0.82622404952853157, 0.8718583790
3104257, -0.40612368071238697, 0.98148506761712195, 0.044571529288059457, 0.8649
9122355289504], [0.090645017397428265, -0.35400286884191812, nan, 0.850595319361
55086, 0.93325138453494128, -0.3756083265531206, 0.96565467169224106, -0.0120784
37397979012, 0.80690190364396375], [0.27761390559670462, -0.36594579925497811, n
an, 0.90012504138750637, 0.85056639390032041, -0.42675840346489241, 0.9525148859
8621914, 0.032459424134316954, 0.85847622830789239], [0.27761390559670474, -0.36
594579925497789, nan, 0.90012504138750649, 0.85056639390031985, -0.4267584034648
9236, 0.95251488598621903, 0.032459424134316878, 0.8584762283078925], [-0.152430
64787541694, -0.032699361168367753, nan, 0.095001953268814193, -0.10526931127960
384, 0.15579123671279982, -0.085671149403876587, 0.39142136274598099, -0.2417657
2459688822], [-0.56424817395046112, 0.35812636350471971, nan, -0.767711012352610
41, 0.23194377302300087, 0.18722799337813953, -0.82800769230501636, 0.2255624437
5356679, -0.76270285383531622]]
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den
```

Sixth: create a DataFrame depicting the correlation matrix stored in lists

This vastly improves the readability. Thanks to employing the nested list as our data structure, converting it to a dataframe is very easy.

We now have a beautiful dataframe return from the crosscorrs() method:

In [2385]:
```
def crosscorrs(country_code):

    list_crosscorr = []

    current_country_macro = WDI_LatAm_Macro.loc[(WDI_LatAm_Macro['country code']
== country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_macro['indicator code'] = list(WDI_LatAm_Macro.loc[(WDI_LatAm
_Macro['country code'] == country_code)]['indicator code'])
    current_country_macro = current_country_macro.set_index('indicator code')

    current_country_agro = WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['country code'] ==
country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_agro['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_A
gro['country code'] == country_code)]['indicator code'])
    current_country_agro = current_country_agro.set_index('indicator code')

    i = current_country_agro.shape[0] - 1

    while i > -1:

        j = current_country_macro.shape[0] - 1
        list1.clear()

        while j > -1:

            if len(current_country_agro.iloc[i].dropna()) > len(current_country_m
acro.iloc[j].dropna()):
                corr = pearsonr(current_country_agro.iloc[i].dropna().tail(len(cu
rrent_country_macro.iloc[j].dropna())), current_country_macro.iloc[j].dropna())

            else:
                corr = pearsonr(current_country_agro.iloc[i].dropna(), current_co
untry_macro.iloc[j].dropna().tail(len(current_country_agro.iloc[i].dropna())))

            list1.append(corr[0])

            j-=1

        list_crosscorr.append(list1.copy())
        i-=1

    df = pd.DataFrame(list_crosscorr, columns = list(reversed(current_country_mac
ro.index)))
    df[''] = list(reversed(current_country_agro.index))
    df = df.set_index('')
    df.index.name = country_code

    return df

crosscorrs(countries.iloc[7][0])
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den
```

Out[2385]:

CHL	SL.UEM.TOTL.ZS	FR.INR.RINR	IC.PRP.PROC	PA.NUS.FCRF	SM.POP.NETM	FP.CPI.TOTL.
SL.AGR.EMPL.MA.ZS	-0.305995	0.417775	NaN	-0.613001	-0.831767	0.727
SL.AGR.EMPL.FE.ZS	-0.201316	-0.195546	NaN	-0.383209	-0.754301	0.429
SL.AGR.EMPL.ZS	-0.313048	0.397234	NaN	-0.619899	-0.825929	0.734
NV.AGR.EMPL.KD	0.282787	-0.468888	NaN	0.578207	0.855115	-0.643
NV.AGR.TOTL.CD	-0.052263	-0.269942	NaN	0.826224	0.871858	-0.406
NV.AGR.TOTL.CN	0.090645	-0.354003	NaN	0.850595	0.933251	-0.375
NV.AGR.TOTL.KN	0.277614	-0.365946	NaN	0.900125	0.850566	-0.426
NV.AGR.TOTL.KD	0.277614	-0.365946	NaN	0.900125	0.850566	-0.426
NV.AGR.TOTL.KD.ZG	-0.152431	-0.032699	NaN	0.095002	-0.105269	0.155
NV.AGR.TOTL.ZS	-0.564248	0.358126	NaN	-0.767711	0.231944	0.187

Seventh: change World Bank indicator codes into human-readable labels

Just increasing visibility here by moving away from the World Bank jargon to the actual keys stored in our _indicators dictionaries at the very begining.

In [2386]:
```
def crosscorrs(country_code):

    list_crosscorr = []

    current_country_macro = WDI_LatAm_Macro.loc[(WDI_LatAm_Macro['country code']
== country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_macro['indicator code'] = list(WDI_LatAm_Macro.loc[(WDI_LatAm
_Macro['country code'] == country_code)]['indicator code'])
    current_country_macro = current_country_macro.set_index('indicator code')

    current_country_agro = WDI_LatAm_Agro.loc[(WDI_LatAm_Agro['country code'] ==
country_code)][[str(i) for i in list(range(1960, 2018, 1))]]
    current_country_agro['indicator code'] = list(WDI_LatAm_Agro.loc[(WDI_LatAm_A
gro['country code'] == country_code)]['indicator code'])
    current_country_agro = current_country_agro.set_index('indicator code')

    list_indicators_macro = [indicators_macro.get(i) for i in list(reversed(curre
nt_country_macro.index))]
    list_indicators_agro = [indicators_agro.get(i) for i in list(reversed(current
_country_agro.index))]

    i = current_country_agro.shape[0] - 1

    while i > -1:

        j = current_country_macro.shape[0] - 1
        list1.clear()

        while j > -1:

            if len(current_country_agro.iloc[i].dropna()) > len(current_country_m
acro.iloc[j].dropna()):
                corr = pearsonr(current_country_agro.iloc[i].dropna().tail(len(cu
rrent_country_macro.iloc[j].dropna())), current_country_macro.iloc[j].dropna())

            else:
                corr = pearsonr(current_country_agro.iloc[i].dropna(), current_co
untry_macro.iloc[j].dropna().tail(len(current_country_agro.iloc[i].dropna())))

            list1.append(corr[0])

            j-=1

        list_crosscorr.append(list1.copy())
        i-=1

    df = pd.DataFrame(list_crosscorr, columns = list_indicators_macro)
    df[''] = list_indicators_agro
    df = df.set_index('')
    df.index.name = country_code

    return df
```

In [2387]:
```
crosscorrs(countries.iloc[8][0])
```

Out[2387]:

COL	Unemployment, total (% of total labor force) (modeled ILO estimate)	Real interest rate (%)	Procedures to register property (number)	Official exchange rate (LCU per US$, period average)	Net migration	Inflation, consumer prices (annual %)	GNI per Capita	GDP Growth (%)	Fo di in ne (B cu U
Employment in agriculture, male (% of female employment) (modeled ILO estimate)	0.285841	0.277638	0.677011	-0.734466	-0.938903	0.839712	-0.920766	-0.182541	
Employment in agriculture, female (% of female employment) (modeled ILO estimate)	-0.470581	0.044500	-0.140641	0.165110	0.497582	-0.056026	0.174609	0.191525	
Employment in agriculture (% of total employment) (modeled ILO estimate)	0.224292	0.272378	0.705420	-0.755619	-0.919964	0.886783	-0.910303	-0.182544	
Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)	-0.409550	0.122252	-0.382249	-0.386178	0.846857	0.558723	-0.138648	-0.124942	
Agriculture, forestry, and fishing, value added (current US$)	-0.469452	-0.141325	-0.704225	0.762896	0.476606	-0.487035	0.953982	-0.235890	
Agriculture, forestry, and fishing, value added (current LCU)	-0.282814	-0.254634	-0.742499	0.906470	0.863307	-0.689767	0.939783	-0.210037	
Agriculture, forestry, and fishing, value added (constant LCU)	-0.671990	-0.068325	-0.655452	0.710960	0.941742	-0.171702	0.759083	-0.285173	
Agriculture, forestry, and fishing, value added (constant 2010 US$)	-0.671990	-0.068325	-0.655452	0.710960	0.941742	-0.171702	0.759083	-0.285173	

Done for now!

We can now create 32 DataFrames, one for each country. We won't bore and show you every one, but just to prove it:

In [2388]:
```
crosscorrs(countries.iloc[0][0])
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den
```

Out[2388]:

ATG	Risk premium on lending (lending rate minus treasury bill rate, %)	Real interest rate (%)	Procedures to register property (number)	Official exchange rate (LCU per US$, period average)	Net migration	Inflation, consumer prices (annual %)	GNI per Capita	GDP Growth (%)	Foreign direct investme net inflow (BoP, current US$)
Agriculture, forestry, and fishing, value added (current US$)	-0.630135	0.117643	0.625114	NaN	0.576563	0.111810	0.959012	-0.269351	0.5993
Agriculture, forestry, and fishing, value added (current LCU)	-0.630135	0.117643	0.625114	NaN	0.576563	0.111810	0.959012	-0.269351	0.5993
Agriculture, forestry, and fishing, value added (constant LCU)	-0.630240	0.232005	-0.055517	NaN	0.539462	0.159257	0.855614	-0.119933	0.5479
Agriculture, forestry, and fishing, value added (constant 2010 US$)	-0.630240	0.232005	-0.055517	NaN	0.539462	0.159257	0.855614	-0.119933	0.5479
Agriculture, forestry, and fishing, value added (annual % growth)	0.027707	-0.034931	0.220433	NaN	-0.022967	0.150932	0.315612	0.131195	0.1831
Agriculture, forestry, and fishing, value added (% of GDP)	0.433871	-0.102180	0.433233	NaN	0.288119	0.216924	-0.711005	0.165610	-0.3406

In [2389]:
```
crosscorrs(countries.iloc[31][0])
```

Out[2389]:

	Unemployment, total (% of total labor force) (modeled ILO estimate)	Risk premium on lending (lending rate minus treasury bill rate, %)	Real interest rate (%)	Procedures to register property (number)	Official exchange rate (LCU per US$, period average)	Net migration	Inflation, consumer prices (annual %)	GNI per Capita	G G (%
URY									
Employment in agriculture, male (% of female employment) (modeled ILO estimate)	-0.694933	-0.860384	-0.781335	0.183202	0.587684	-0.232654	-0.406612	0.685737	0
Employment in agriculture, female (% of female employment) (modeled ILO estimate)	-0.682706	-0.834117	-0.748602	0.306379	0.627484	-0.083539	-0.499207	0.814835	0
Employment in agriculture (% of total employment) (modeled ILO estimate)	-0.700200	-0.857225	-0.778738	0.200060	0.587321	-0.210253	-0.414751	0.706260	0
Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)	0.728176	0.899030	0.797361	-0.205348	-0.516942	0.365506	0.217073	-0.626979	-0
Agriculture, forestry, and fishing, value added (current US$)	-0.726483	-0.755183	-0.521755	0.014636	0.654171	-0.037265	-0.611265	0.926229	0
Agriculture, forestry, and fishing, value added (current LCU)	-0.567714	-0.803147	-0.545992	0.407907	0.844811	0.035789	-0.686827	0.925607	0
Agriculture, forestry, and fishing, value added (constant LCU)	-0.421893	-0.811507	-0.331617	0.363436	0.879131	0.291430	-0.834850	0.872471	0
Agriculture, forestry, and fishing									

We will deal with the NaN values later.

Let's make it pretty! Thanks to seaborn for the heatmap:

[https://seaborn.pydata.org/generated/seaborn.heatmap.html (https://seaborn.pydata.org/generated/seaborn.heatmap.html)](https://seaborn.pydata.org/generated/seaborn.heatmap.html)

In [2390]:
```
def visualize(df):

    sns.set()

    # Draw a heatmap with the numeric values in each cell
    f, ax = plt.subplots(figsize=(9, 6))
    sns.heatmap(df, annot=True, linewidths=.5, ax=ax)
```

In [2391]:
```
visualize(crosscorrs(countries.iloc[8][0]))
```

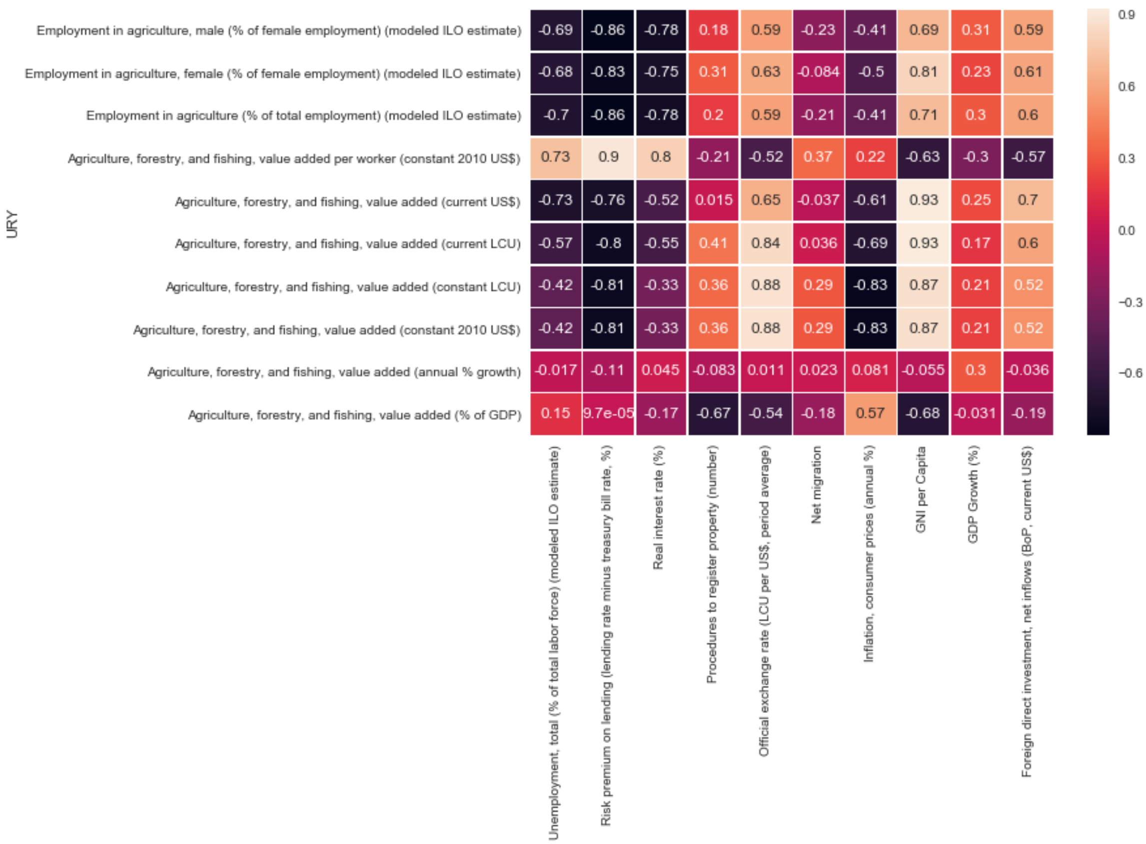
Just like there's potentially 32 DataFrames, we can also create 32 of these.

Again, proof:

In [2392]:
```
visualize(crosscorrs(countries.iloc[0][0]))
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den
```

In [2393]:
```
visualize(crosscorrs(countries.iloc[31][0]))
```



As mentioned, ATG pegged their currency to the U.S. Dollar. Guess that broke the correlation statement. No worries – we will deal with it later.

Overall, it seems like Agriculture Employment is negatively correlated with Unemployment and Interest Rates. This makes macroeconomic theoretical sense: when the economy is going better, it usually diversifies away from primary sectors such as agriculture!

Let's find the average of each indicator pair so that we can conclude which factors are most correlated.

Start by creating an empty Master DataFrame (master_df) with row labels = macro_indicators and columns labels = agro_indicators. We do this using some funky list magic:

We create a nested list master_list holding all possible correlation pairs:

In [2394]:
```
master_list = []

for i in list(indicators_macro.values()):
    master_list.append([i])
    idx = master_list.index([i])

    for j in list(indicators_agro.values()):
        master_list[idx].append(j)

master_list
```

```
Out[2394]: [['GNI per Capita',
             'Agriculture, forestry, and fishing, value added (% of GDP)',
             'Agriculture, forestry, and fishing, value added (annual % growth)',
             'Agriculture, forestry, and fishing, value added (constant 2010 US$)',
             'Agriculture, forestry, and fishing, value added (constant LCU)',
             'Agriculture, forestry, and fishing, value added (current LCU)',
             'Agriculture, forestry, and fishing, value added (current US$)',
             'Agriculture, forestry, and fishing, value added per worker (constant 2010 US$
           )',
             'Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)
           ',
             'Child employment in agriculture (% of economically active children ages 7-14)
           ',
             'Child employment in agriculture, female (% of female economically active chil
           dren ages 7-14)',
             'Child employment in agriculture, male (% of male economically active children
           ages 7-14)',
             'Employment in agriculture (% of total employment) (modeled ILO estimate)',
             'Employment in agriculture, female (% of female employment) (modeled ILO estim
           ate)',
             'Employment in agriculture, male (% of female employment) (modeled ILO estimat
           e)'],
            ['GDP Growth (%)',
             'Agriculture, forestry, and fishing, value added (% of GDP)',
             'Agriculture, forestry, and fishing, value added (annual % growth)',
             'Agriculture, forestry, and fishing, value added (constant 2010 US$)',
             'Agriculture, forestry, and fishing, value added (constant LCU)',
             'Agriculture, forestry, and fishing, value added (current LCU)',
             'Agriculture, forestry, and fishing, value added (current US$)',
             'Agriculture, forestry, and fishing, value added per worker (constant 2010 US$
           )',
             'Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)
           ',
             'Child employment in agriculture (% of economically active children ages 7-14)
           ',
             'Child employment in agriculture, female (% of female economically active chil
           dren ages 7-14)',
             'Child employment in agriculture, male (% of male economically active children
           ages 7-14)',
             'Employment in agriculture (% of total employment) (modeled ILO estimate)',
             'Employment in agriculture, female (% of female employment) (modeled ILO estim
           ate)',
             'Employment in agriculture, male (% of female employment) (modeled ILO estimat
           e)'],
            ['Foreign direct investment, net inflows (BoP, current US$)',
             'Agriculture, forestry, and fishing, value added (% of GDP)',
             'Agriculture, forestry, and fishing, value added (annual % growth)',
             'Agriculture, forestry, and fishing, value added (constant 2010 US$)',
             'Agriculture, forestry, and fishing, value added (constant LCU)',
             'Agriculture, forestry, and fishing, value added (current LCU)',
             'Agriculture, forestry, and fishing, value added (current US$)',
             'Agriculture, forestry, and fishing, value added per worker (constant 2010 US$
           )',
             'Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)
           ',
             'Child employment in agriculture (% of economically active children ages 7-14)
           ',
             'Child employment in agriculture, female (% of female economically active chil
           dren ages 7-14)',
             'Child employment in agriculture, male (% of male economically active children
           ages 7-14)',
             'Employment in agriculture (% of total employment) (modeled ILO estimate)',
             'Employment in agriculture, female (% of female employment) (modeled ILO estim
           ate)',
             'Employment in agriculture, male (% of female employment) (modeled ILO estimat
```

And now we turn the nested list into a DataFrame. We also make the cells empty – or, well, fully populate them by zeroes:

In [2395]:
```
master_df = pd.DataFrame(master_list)
master_df = dfc.set_index(master_df.pop(0))
master_df.columns = (list(master_df.iloc[0]))

idx = len(indicators_macro) - 1

while idx > -1:
    master_df.iloc[idx] = 0
    idx -= 1

master_df
```

Out[2395]:

	Agriculture, forestry, and fishing, value added (% of GDP)	Agriculture, forestry, and fishing, value added (annual % growth)	Agriculture, forestry, and fishing, value added (constant 2010 US$)	Agriculture, forestry, and fishing, value added (constant LCU)	Agriculture, forestry, and fishing, value added (current LCU)	Agriculture, forestry, and fishing, value added (current US$)	Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)	Annu fresh withc agric (% of fresh withc
0								
GNI per Capita	0	0	0	0	0	0	0	
GDP Growth (%)	0	0	0	0	0	0	0	
Foreign direct investment, net inflows (BoP, current US$)	0	0	0	0	0	0	0	
Inflation, consumer prices (annual %)	0	0	0	0	0	0	0	
Real interest rate (%)	0	0	0	0	0	0	0	
Net migration	0	0	0	0	0	0	0	
Official exchange rate (LCU per US$, period average)	0	0	0	0	0	0	0	
Unemployment, total (% of total labor force) (modeled ILO estimate)	0	0	0	0	0	0	0	
Procedures to register property (number)	0	0	0	0	0	0	0	
Risk premium on lending (lending rate minus treasury bill rate, %)	0	0	0	0	0	0	0	

Now comes the meat of filling in the correlations for each [macro, agro] pair.

Essentially, we create a DataFrame of each country's correlations, and then add the cells from those DataFrames ('current') to the corresponding cell in the Master DataFrame (master_df) we just created.

The end goal is to find the average, and to find the average, we need to keep track of the number of times we added something to the cell ('n'). *n* is not the same for each cell because some countries have more data than others. Instead of creating yet another variable to keep track of this, we cheat by adding 1000 to the correlations, essentially tracking *n* in the first digit or two of the cells. On the way we also remove any NaN values.

Note: this takes a while to run and is wasteful computationally, but it was the best way we found to do this given our data structures.

In [2396]:

```
jdx = countries.shape[0] - 1

while jdx > -1:
    current = crosscorrs(countries.iloc[jdx][0])
    current = current.fillna(0, downcast='infer')
    print('country ' + str(jdx)) #since it takes so long, we want to make sure it
's actually running!

    for row in current.iterrows():
        idx = 0

        while idx < len(row[1]):
            if np.isnan(master_df.loc[list(row[1].index)[idx]][row[1].name]) == F
alse:
                master_df.loc[list(row[1].index)[idx]][row[1].name] = master_df.l
oc[list(row[1].index)[idx]][row[1].name] + row[1][idx] + 1000
            else:
                print('NaN')
            idx += 1

    jdx -= 1
```

```
country 31

/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:3021: RuntimeWarning
: invalid value encountered in double_scalars
  r = r_num / r_den

country 30
country 29
country 28
country 27
country 26
country 25
country 24
country 23
country 22
country 21
country 20
country 19
country 18
country 17
country 16
country 15
country 14
country 13
country 12
country 11
country 10
country 9
country 8
country 7
country 6
country 5
country 4
country 3
country 2
country 1
country 0
```

And here's the DataFrame of correlations...plus the temporary math stuff:

In [2397]:
```
master_df
```

Out[2397]:

0	Agriculture, forestry, and fishing, value added (% of GDP)	Agriculture, forestry, and fishing, value added (annual % growth)	Agriculture, forestry, and fishing, value added (constant 2010 US$)	Agriculture, forestry, and fishing, value added (constant LCU)	Agriculture, forestry, and fishing, value added (current LCU)	Agriculture, forestry, and fishing, value added (current US$)	Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)	Annu fresh withc agric (% of fresh withc
GNI per Capita	27980.9	27999.8	28015.2	28015.2	28023.7	28023.3	25010.1	
GDP Growth (%)	28003	28010.2	28000.4	28000.4	27999.1	27998.5	24998.3	
Foreign direct investment, net inflows (BoP, current US$)	26985.6	27000.8	27013.6	27013.6	27017.6	27017.4	24008.4	
Inflation, consumer prices (annual %)	26006.7	25999.1	25996.6	25996.6	25991.9	25993.6	22997.1	
Real interest rate (%)	26000.9	26000.5	25997.3	25997.3	25995.8	25996.2	23000.4	
Net migration	27003.3	27000.4	27002.2	27002.2	27002.7	27001	25003.5	
Official exchange rate (LCU per US$, period average)	27988.6	27999.7	28014.1	28014.1	28016	28013.2	25005	
Unemployment, total (% of total labor force) (modeled ILO estimate)	25005.9	25000.1	24997.9	24997.9	24994.9	24994.6	24998	
Procedures to register property (number)	24002.3	24000.7	23999.7	23999.7	24000.4	23999.8	20999.9	
Risk premium on lending (lending rate minus treasury bill rate, %)	11001.1	10999.1	10998.2	10998.2	10998.2	10998.7	9001.05	

Due to the funky list magic earlier, the dtype of the cells is 'object'. Let's change this to numeric so we can use math to convert the sum of correlations + (number of correlations * 1000) into the average.

In [2398]:
```
master_df.dtypes
```

Out[2398]:
```
Agriculture, forestry, and fishing, value added (% of GDP)
object
Agriculture, forestry, and fishing, value added (annual % growth)
object
Agriculture, forestry, and fishing, value added (constant 2010 US$)
object
Agriculture, forestry, and fishing, value added (constant LCU)
object
Agriculture, forestry, and fishing, value added (current LCU)
object
Agriculture, forestry, and fishing, value added (current US$)
object
Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)
object
Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)
object
Child employment in agriculture (% of economically active children ages 7-14)
object
Child employment in agriculture, female (% of female economically active childre
n ages 7-14)    object
Child employment in agriculture, male (% of male economically active children ag
es 7-14)        object
Employment in agriculture (% of total employment) (modeled ILO estimate)
object
Employment in agriculture, female (% of female employment) (modeled ILO estimate
)               object
Employment in agriculture, male (% of female employment) (modeled ILO estimate)
object
dtype: object
```

In [2399]:
```
cols = master_df.columns[master_df.dtypes.eq(object)]
master_df[cols] = master_df[cols].apply(pd.to_numeric, errors='coerce', axis=0)
master_df
```

Out[2399]:

	Agriculture, forestry, and fishing, value added (% of GDP)	Agriculture, forestry, and fishing, value added (annual % growth)	Agriculture, forestry, and fishing, value added (constant 2010 US$)	Agriculture, forestry, and fishing, value added (constant LCU)	Agriculture, forestry, and fishing, value added (current LCU)	Agriculture, forestry, and fishing, value added (current US$)	Agricult forestry, fishing, added p worker (constar 2010 US
0							
GNI per Capita	27980.897705	27999.812038	28015.246316	28015.246316	28023.704389	28023.288998	25010.1
GDP Growth (%)	28002.997914	28010.156111	28000.421151	28000.421151	27999.090712	27998.466623	24998.2
Foreign direct investment, net inflows (BoP, current US$)	26985.589688	27000.773057	27013.641153	27013.641153	27017.646735	27017.389207	24008.4
Inflation, consumer prices (annual %)	26006.749178	25999.051251	25996.643712	25996.643712	25991.919194	25993.556043	22997.0
Real interest rate (%)	26000.894821	26000.528003	25997.278847	25997.278847	25995.777556	25996.222974	23000.4
Net migration	27003.272516	27000.350580	27002.226590	27002.226590	27002.725757	27001.033892	25003.4
Official exchange rate (LCU per US$, period average)	27988.596030	27999.676339	28014.143081	28014.143081	28016.018364	28013.203220	25004.9
Unemployment, total (% of total labor force) (modeled ILO estimate)	25005.906204	25000.093049	24997.881130	24997.881130	24994.939869	24994.642150	24998.0
Procedures to register property (number)	24002.324599	24000.653400	23999.727340	23999.727340	24000.380444	23999.817532	20999.8
Risk premium on lending (lending rate minus treasury bill rate, %)	11001.104976	10999.109459	10998.157857	10998.157857	10998.198167	10998.716831	9001.0

An explanation of the below math.

The first two digits 'store' the number of times we added a value to a cell. We access these through (round(x / 1000)), so e.g. round(27980.9) / 1000 returns 28, meaning we added 28 correlations to that cell.

All we have to do is subtract 28,000 from the total and then divide that by 28 to get the average!

In [2400]:
```
x = 27980.9
x = (x - (round(x / 1000) * 1000)) / (round(x / 1000))
x
```

Out[2400]: -0.6821428571428052

Let's implement this:

In [2401]:
```
idx = len(indicators_macro) - 1

while idx > -1:
    master_df.iloc[idx] = (master_df.iloc[idx] - (round(master_df.iloc[idx] / 100
0) * 1000)) / (round(master_df.iloc[idx] / 1000))
    idx -= 1
```

In [2402]:
```
master_df
```

Out[2402]:

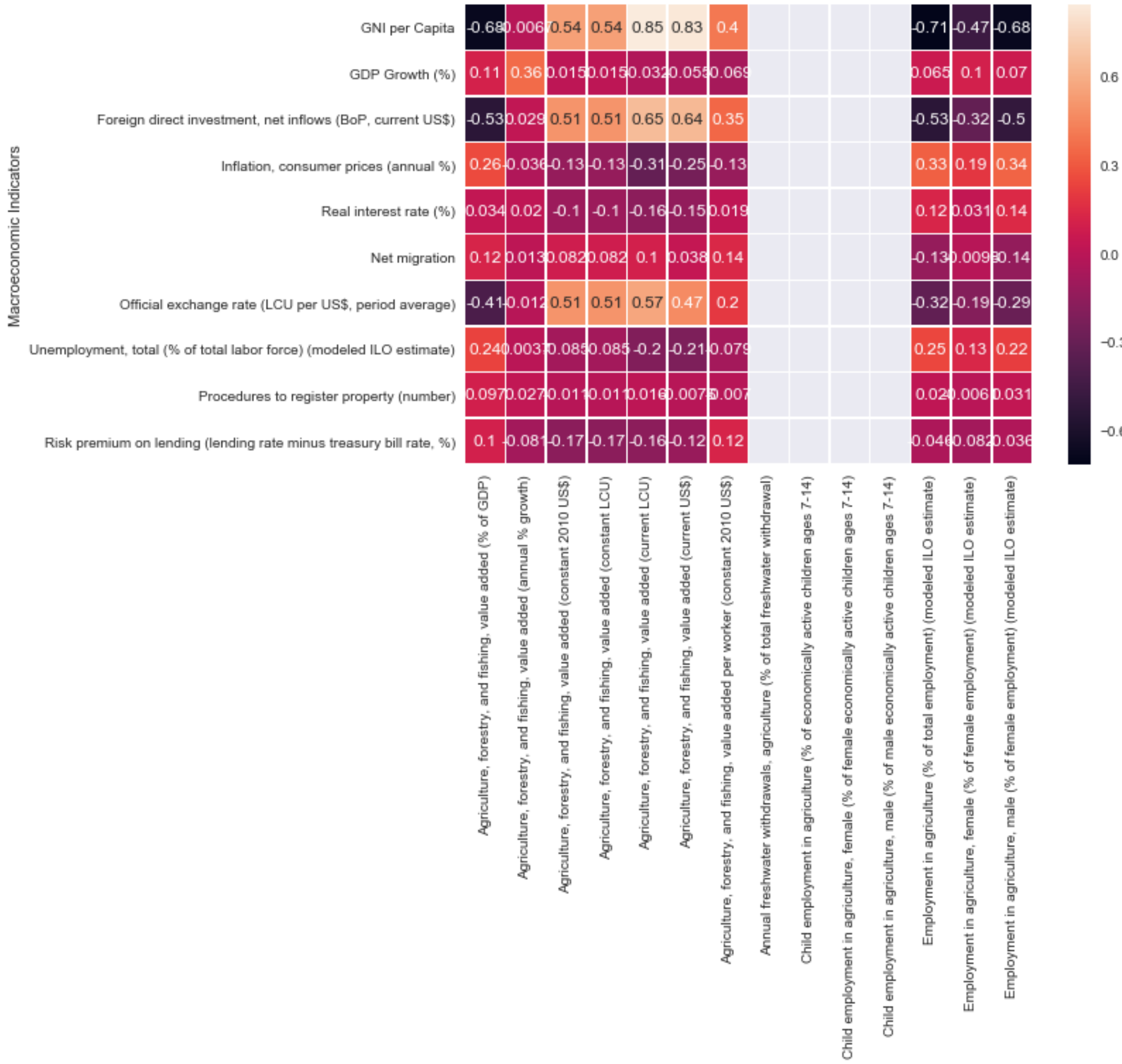
0	Agriculture, forestry, and fishing, value added (% of GDP)	Agriculture, forestry, and fishing, value added (annual % growth)	Agriculture, forestry, and fishing, value added (constant 2010 US$)	Agriculture, forestry, and fishing, value added (constant LCU)	Agriculture, forestry, and fishing, value added (current LCU)	Agriculture, forestry, and fishing, value added (current US$)	Agriculture, forestry, and fishing, value added per worker (constant 2010 US$)	Annu fresh withc agric (% of fresh withc
GNI per Capita	-0.682225	-0.006713	0.544511	0.544511	0.846585	0.831750	0.404729	
GDP Growth (%)	0.107068	0.362718	0.015041	0.015041	-0.032475	-0.054763	-0.068957	
Foreign direct investment, net inflows (BoP, current US$)	-0.533715	0.028632	0.505228	0.505228	0.653583	0.644045	0.351729	
Inflation, consumer prices (annual %)	0.259584	-0.036490	-0.129088	-0.129088	-0.310800	-0.247845	-0.126282	
Real interest rate (%)	0.034416	0.020308	-0.104660	-0.104660	-0.162402	-0.145270	0.019336	
Net migration	0.121204	0.012984	0.082466	0.082466	0.100954	0.038292	0.139138	
Official exchange rate (LCU per US$, period average)	-0.407285	-0.011559	0.505110	0.505110	0.572084	0.471544	0.198658	
Unemployment, total (% of total labor force) (modeled ILO estimate)	0.236248	0.003722	-0.084755	-0.084755	-0.202405	-0.214314	-0.079445	
Procedures to register property (number)	0.096858	0.027225	-0.011361	-0.011361	0.015852	-0.007603	-0.006961	
Risk premium on lending (lending rate minus treasury bill rate, %)	0.100452	-0.080958	-0.167468	-0.167468	-0.163803	-0.116652	0.116624	

Finally here is what we were ultimately looking for; the end goal of the project: the correlations of each [Agro, Macro] pair.

Now we can draw tons of conclusions at once, instead of fishing in the dark for correlations!

In [2403]:
```
master_df.index.name = 'Macroeconomic Indicators'
```

In [2404]:
```
visualize(master_df)
```



Finally, this last graph summarizes our conclusions by illustrating the total average corralations for all countries.

As we see in the graph, on the vertical axis we have different macroeconomics topics while in our horizontal axis we have the agriculture factors we wanted to analyze.

This graph demonstrates which economic factors have a positive or negative impact on the different agriculture factors. For example, the Gross National Income (GNI) per capita is highly negative corralated to the percentage of total employement in agriculture while it is highly correlated to the total amount of current USD.

This makes sense by simple logic, as the current amount of USD in the economy rises it should positively impact Gross National Income per capita making it rise as well.