TimeSeries2021_VAR

March 24, 2021

[1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
plt.rc("figure", figsize=(16, 6))
```

[3]:
```
div_url = "https://www.multpl.com/s-p-500-dividend/table/by-year"
earn_url = "https://www.multpl.com/s-p-500-earnings/table/by-year"
price_url = "https://www.multpl.com/inflation-adjusted-s-p-500/table/by-year"
```

[4]:
```
divs = pd.read_html(div_url, header=0, index_col=0, parse_dates=True)[0]["Value␣
↪Value"].sort_index().to_period("Y")["1945":"2019"].rename("divs")
divs.head()
```

[4]:
```
Date
1945     9.54
1946     8.69
1947     9.44
1948    10.15
1949    12.70
Freq: A-DEC, Name: divs, dtype: float64
```

[5]:
```
divs.tail()
```

[5]:
```
Date
2015    48.25
2016    49.79
2017    52.21
2018    56.27
2019    59.61
Freq: A-DEC, Name: divs, dtype: float64
```

[6]:
```
earnings = pd.read_html(earn_url, header=0, index_col=0,␣
↪parse_dates=True)[0]["Value Value"].sort_index().to_period("Y")["1945":
↪"2019"].rename("earnings")
earnings.head()
```

```
[6]: Date
1945    13.87
1946    12.97
1947    18.10
1948    24.99
1949    25.86
Freq: A-DEC, Name: earnings, dtype: float64
```

```
[41]: earnings.tail()
```

```
[41]: Date
2015     96.22
2016    103.00
2017    117.23
2018    138.60
2019    142.75
Freq: A-DEC, Name: earnings, dtype: float64
```

```
[8]: prices = pd.read_html(price_url, header=0, index_col=0,␣
 ↪parse_dates=True)[0]["Value Value"].sort_index().shift(-1,freq="D").
 ↪to_period("Y")["1945":"2019"].rename("prices")
prices.head()
```

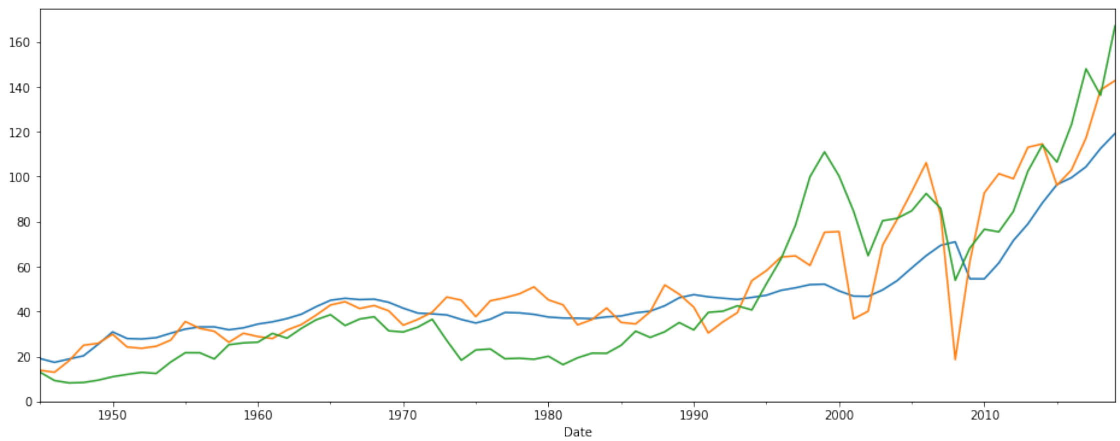
```
[8]: Date
1945    260.41
1946    186.07
1947    164.58
1948    168.33
1949    188.92
Freq: A-DEC, Name: prices, dtype: float64
```

```
[40]: prices.tail()
```

```
[40]: Date
2015    2129.95
2016    2464.14
2017    2960.28
2018    2724.46
2019    3342.29
Freq: A-DEC, Name: prices, dtype: float64
```

```
[10]: plt.figure()
(divs*2).plot()
earnings.plot()
(prices/20).plot().set_ylim(0,None)
```

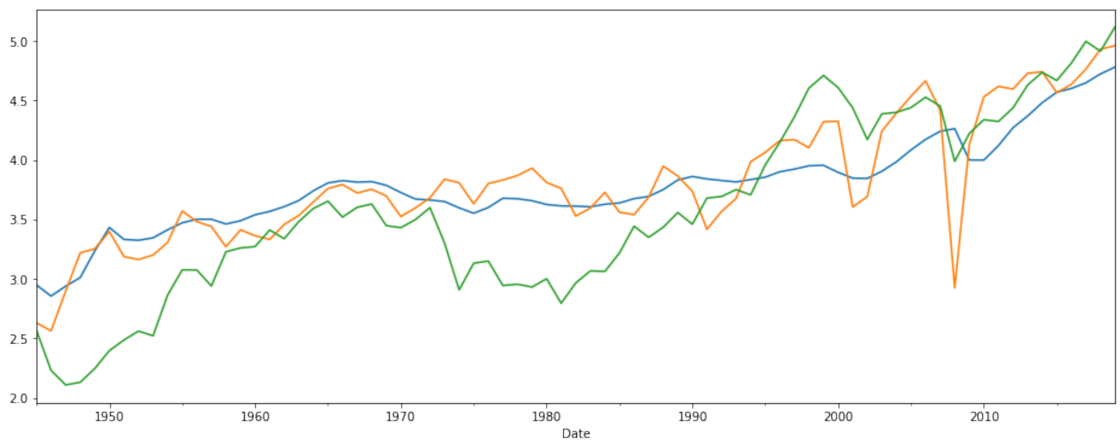
```
[10]: (0, 175.058775)
```



[11]:
```
logdivs = np.log(divs)
logearnings = np.log(earnings)
logprices = np.log(prices)
```

[12]:
```
plt.figure()
(logdivs+np.log(2)).plot()
logearnings.plot()
(logprices-np.log(20)).plot()
```

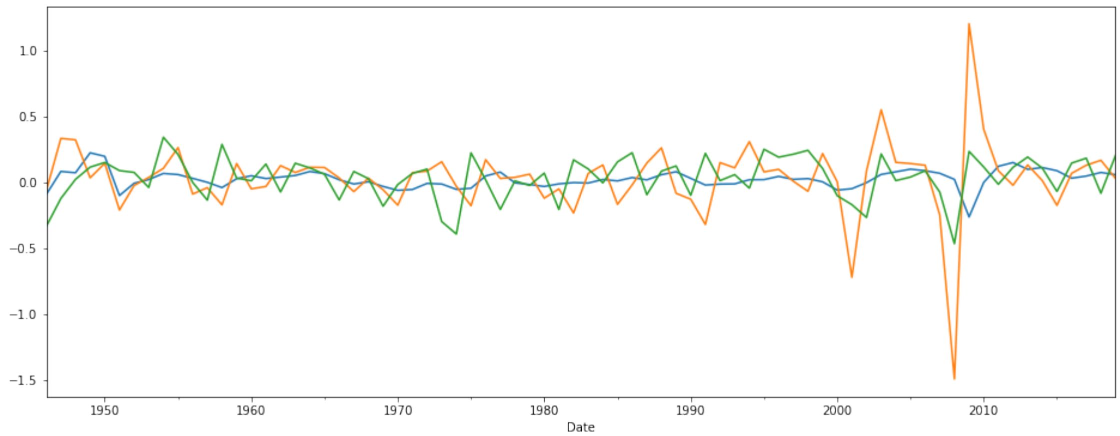
[12]: <matplotlib.axes._subplots.AxesSubplot at 0x12795a750>



[13]:
```
divGrowth = logdivs.diff().dropna()
earnGrowth = logearnings.diff().dropna()
returns = logprices.diff().dropna().rename("returns")
```

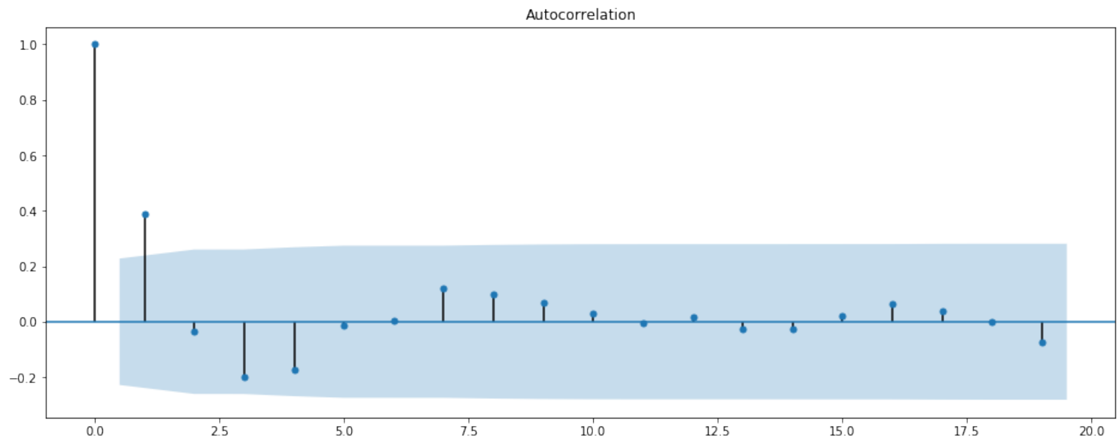
[14]:
```
plt.figure()
divGrowth.plot()
earnGrowth.plot()
returns.plot()
```

[14]: <matplotlib.axes._subplots.AxesSubplot at 0x127cb7a90>

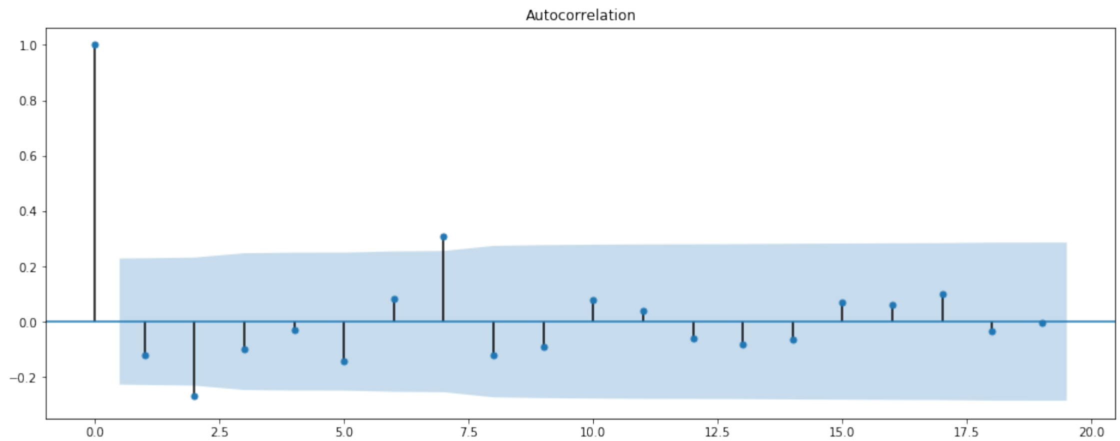


[15]:
```
from statsmodels.graphics.tsaplots import plot_acf
```

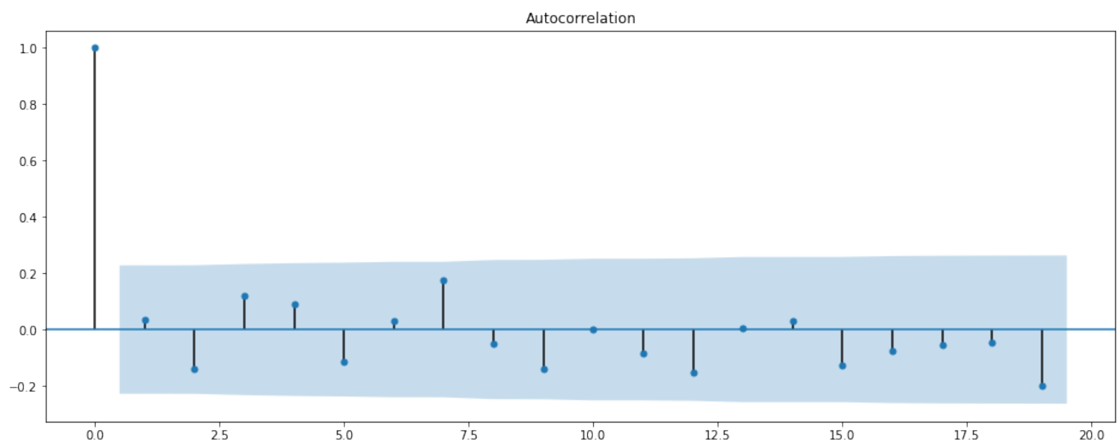
[16]:
```
plot_acf(divGrowth);
```



[17]:
```
plot_acf(earnGrowth);
```



[18]:
```
plot_acf(returns);
```



[19]:
```
df = pd.concat([divGrowth, earnGrowth, returns], axis=1)
df.describe()
```

[19]:

	divs	earnings	returns
count	74.000000	74.000000	74.000000
mean	0.024761	0.031505	0.034489
std	0.067610	0.286360	0.162472
min	-0.263294	-1.493037	-0.465843
25%	-0.010887	-0.054911	-0.062923
50%	0.022310	0.049897	0.064437
75%	0.064197	0.131911	0.145565
max	0.224128	1.204188	0.342731

[20]:
```
df.corr()
```

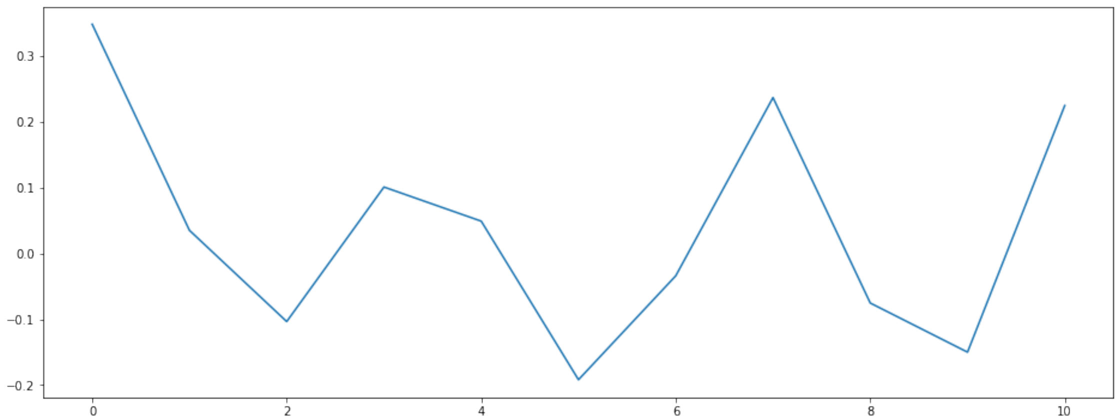
[20]:
```
              divs  earnings   returns
divs      1.000000 -0.049263  0.139044
earnings -0.049263  1.000000  0.347752
returns   0.139044  0.347752  1.000000
```

[21]:
```
from statsmodels.tsa.stattools import ccf
```

[22]:
```
plt.plot(ccf(returns,earnGrowth)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(returns,earnGrowth)[0:11])     # Only shift 0 is significant
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[ 0.34775194  0.0348649  -0.10358045  0.10063521  0.04882275 -0.19185602
 -0.03416783  0.23642307 -0.07544957 -0.15003368  0.22437801]
```

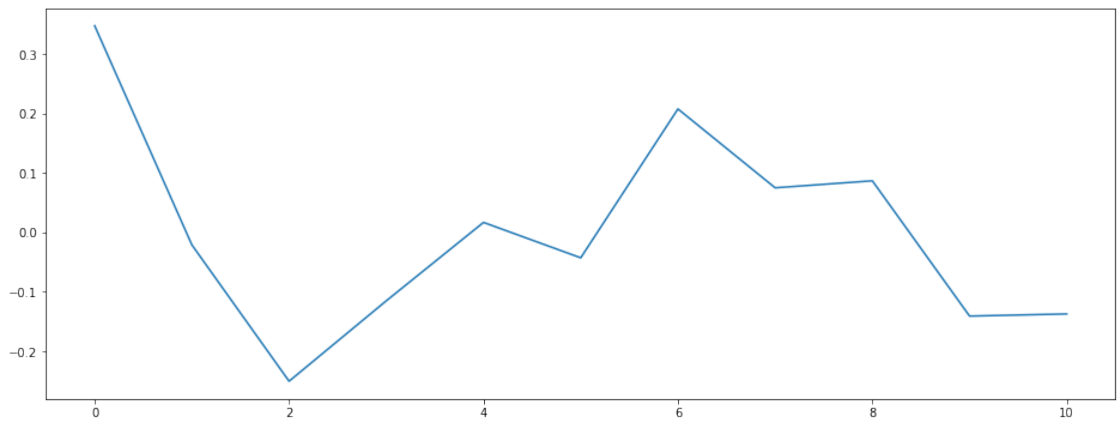
[22]: 0.23249527748763857



[23]:
```
plt.plot(ccf(earnGrowth,returns)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(earnGrowth,returns)[0:11])     # Shift 0 and shift 2 is significant␣
 ↪but not shift 1?  Ignore shift 2?
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[ 0.34775194 -0.02100698 -0.25044343 -0.11514607  0.01676789 -0.0427807
  0.20771867  0.0750129   0.08677466 -0.14086962 -0.13721904]
```

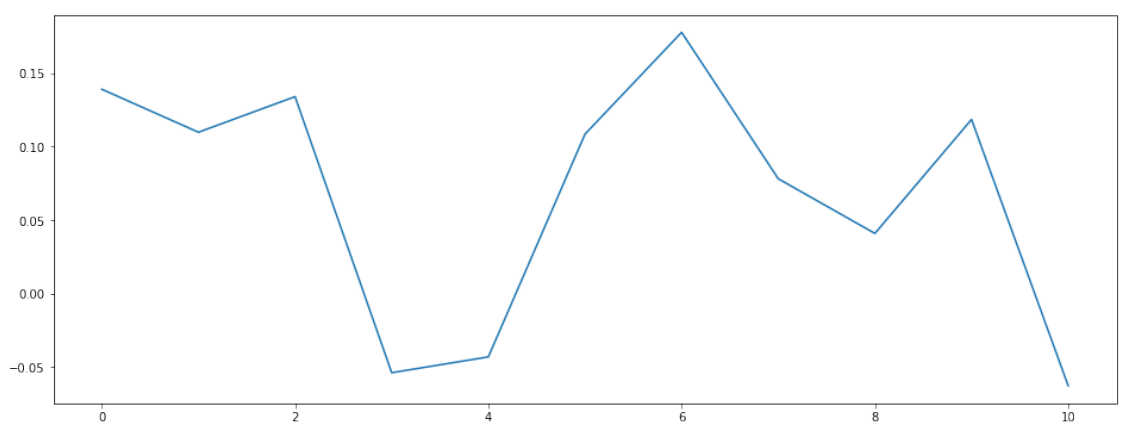
[23]: 0.23249527748763857



[24]:
```
plt.plot(ccf(returns,divGrowth)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(returns,divGrowth)[0:11])     # Not signficant.
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[ 0.13904353  0.10981227  0.13401037 -0.05372792 -0.04298127  0.10850214
  0.17774915  0.07816819  0.04099802  0.11852604 -0.06258222]
```

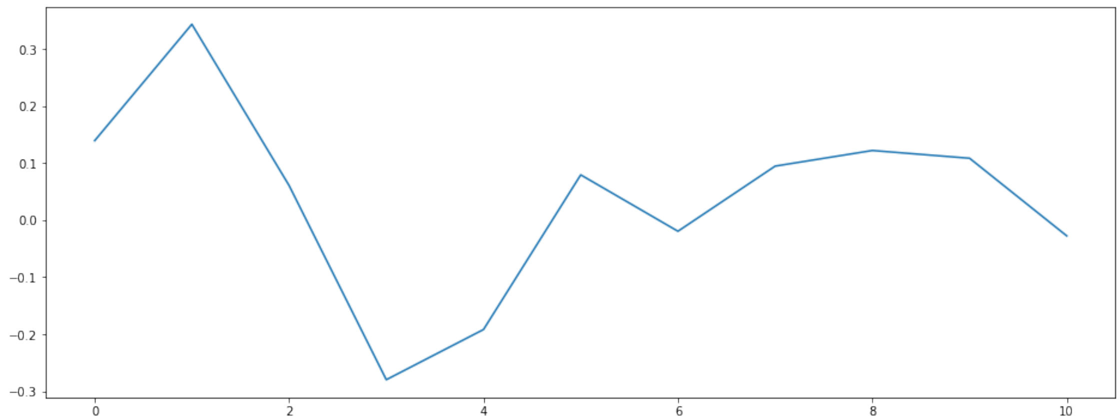
[24]: 0.23249527748763857



[25]:
```
plt.plot(ccf(divGrowth,returns)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(divGrowth,returns)[0:11])     # Shift 1 is signficant, i.e. div(t)␣
↪correl w/ returns(t-1)
# i.e. returns predict divs 1 year ahead
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[ 0.13904353  0.34317063  0.06057096 -0.27981402 -0.19185129  0.07920651
 -0.01963221  0.09450513  0.12188187  0.10829615 -0.02780556]
```

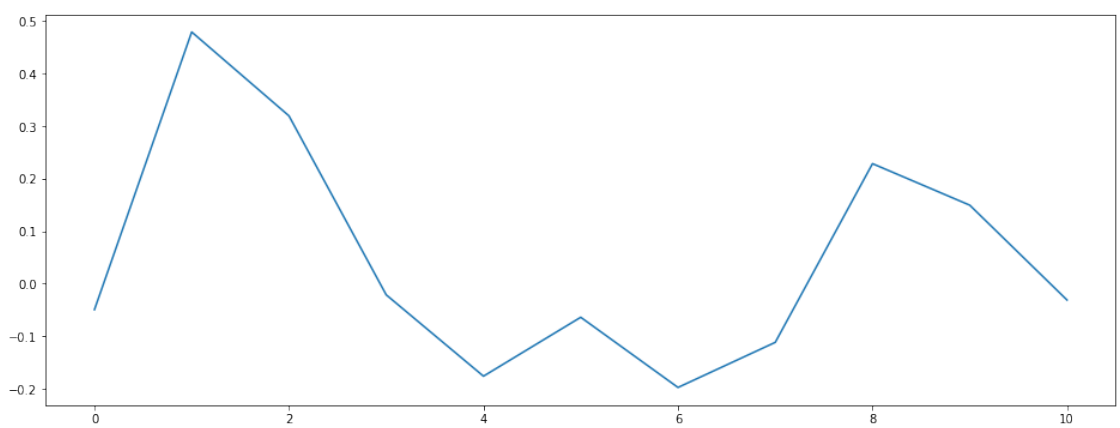
[25]: 0.23249527748763857



[26]:
```
plt.plot(ccf(divGrowth,earnGrowth)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(divGrowth,earnGrowth)[0:11])
# Shift 1,2 signficant, i.e. div(t) correl w/ earn(t-1), (t-2)
# i.e. earnings predict divs 1- and 2-years ahead
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[-0.04926259  0.47938877  0.31969605 -0.02107093 -0.17596079 -0.06378437
 -0.1974257  -0.11154092  0.22867684  0.14963013 -0.03092855]
```

[26]: 0.23249527748763857

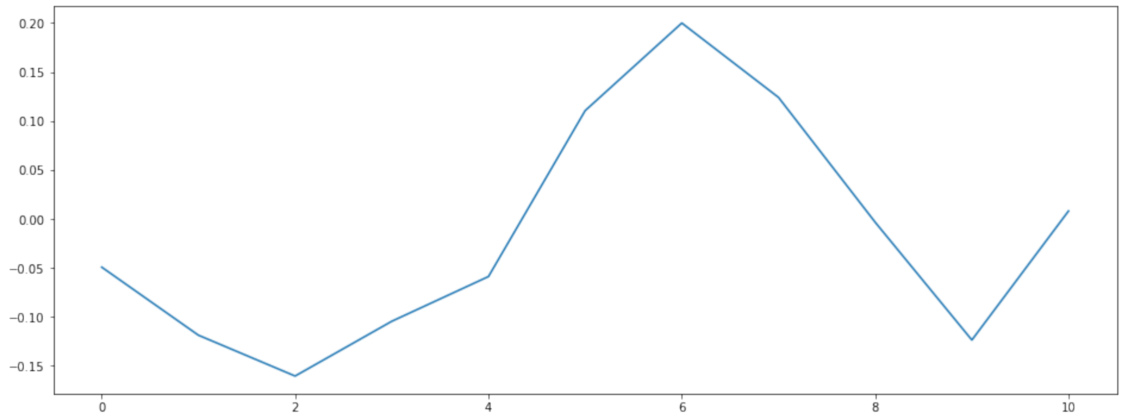


[27]:
```
plt.plot(ccf(earnGrowth,divGrowth)[0:11])  # 2nd series shift 0, 1, 2, 3, ...
print(ccf(earnGrowth,divGrowth)[0:11])      # Insignificant
2/len(returns)**0.5 # 95% confidence bands +/- 2 / sqrt(n)
```

```
[-0.04926259 -0.11874393 -0.16044432 -0.10452656 -0.05885002  0.11055937
```

```
 0.20001561  0.12408141 -0.00339224 -0.12366642  0.00813759]
```

[27]: 0.23249527748763857



Some conclusions: change in earnings roughly contemporaneous with returns, and divs lag 1-2 years behind.

Also, Python handles data much more elegantly than (base) R. Perhaps an unfair comparison of pandas vs base R though, since R also its own add-on packages. Also R is ahead on time series analysis functionality and visualization (e.g. ggplot2 and the rest of the "tidyverse").

[28]:
```
from statsmodels.tsa.api import VAR
```

[29]:
```
model = VAR(df)
```

[30]:
```
results = model.fit(0)   # vector random walk with drift
```

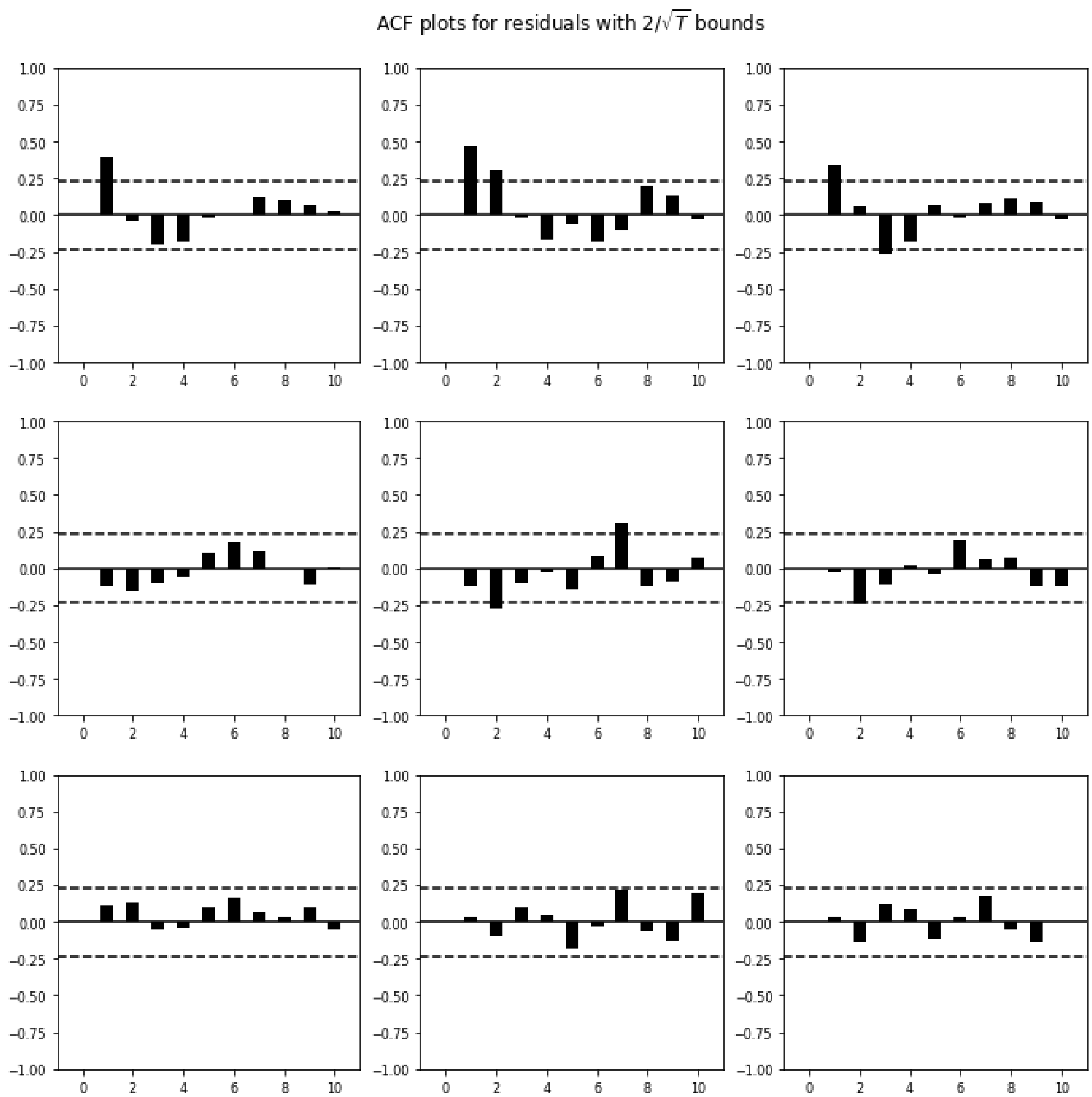
[31]:
```
results.summary()
```

[31]:
```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Wed, 24, Mar, 2021
Time:                     14:25:45
--------------------------------------------------------------------
No. of Equations:         3.00000    BIC:                  -11.5494
Nobs:                     74.0000    HQIC:                 -11.6055
Log likelihood:           118.778    FPE:               8.78246e-06
AIC:                     -11.6428    Det(Omega_mle):    8.43583e-06
--------------------------------------------------------------------
Results for equation divs
========================================================================
```

```
             coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const           0.024761         0.007860            3.150           0.002
==============================================================================

Results for equation earnings
==============================================================================
             coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const           0.031505         0.033289            0.946           0.344
==============================================================================

Results for equation returns
==============================================================================
             coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const           0.034489         0.018887            1.826           0.068
==============================================================================

Correlation matrix of residuals
                divs  earnings   returns
divs        1.000000 -0.049263  0.139044
earnings   -0.049263  1.000000  0.347752
returns     0.139044  0.347752  1.000000
```

[32]:

```
results.plot_acorr();
# How to intrepret this:  The 1st row, 2nd col is the ccf of divs and earnings,
# i.e. corr(divs(t),earnings(t-k)), k > 0
# The signficant correlations at lag 1 and 2 mean earnings lead dividends at␣
↪those lags.
# Important:  In these plots, the column leads the row.
```



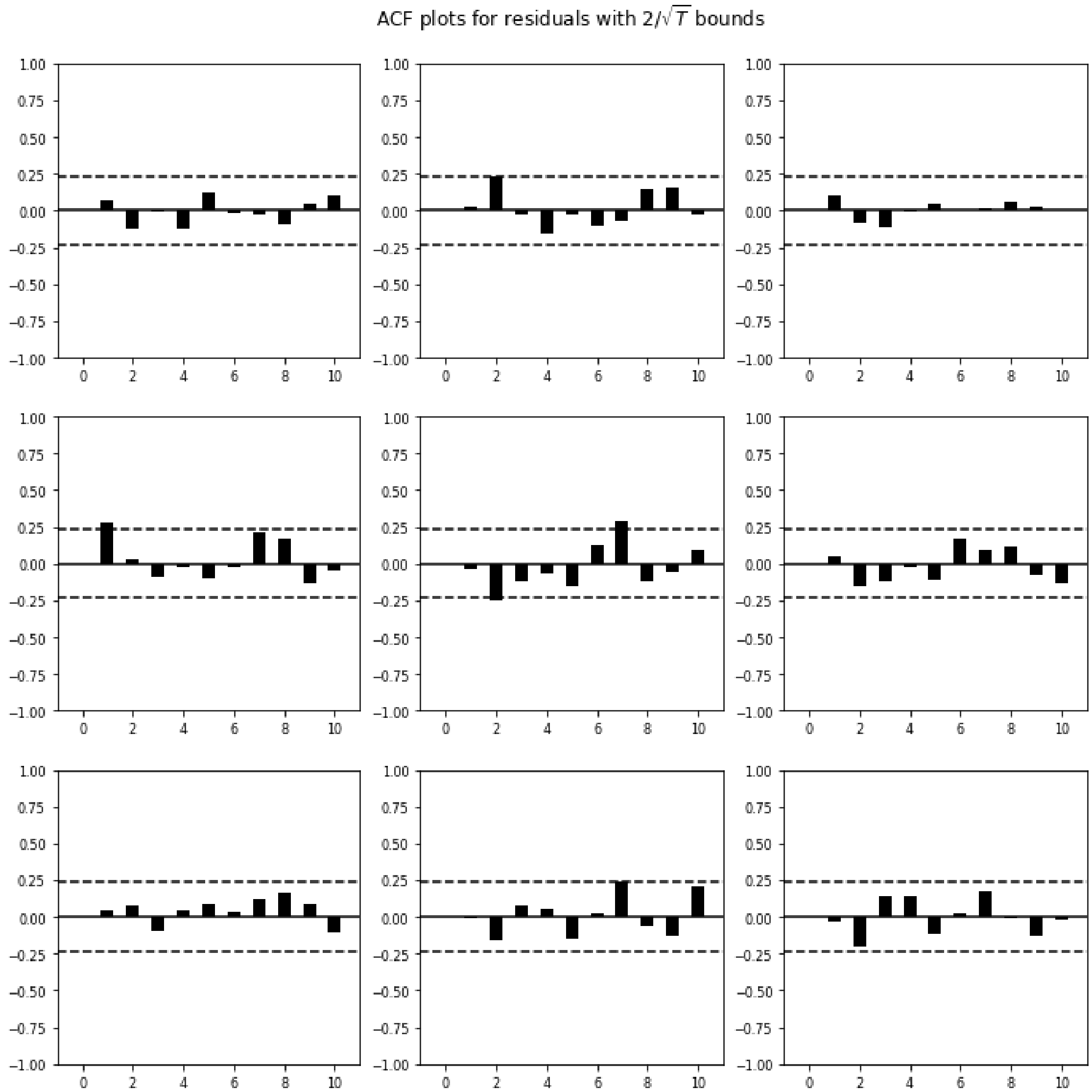
[33]:
```
results = model.fit(1)   # VAR(1)
```

[34]:
```
results.summary()
```

[34]:
```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Wed, 24, Mar, 2021
Time:                     14:25:49
--------------------------------------------------------------------
No. of Equations:         3.00000    BIC:                   -11.7039
Nobs:                     73.0000    HQIC:                  -11.9303
```

```
Log likelihood:           142.187    FPE:                 5.67148e-06
AIC:                     -12.0804    Det(Omega_mle):      4.83273e-06
--------------------------------------------------------------------
Results for equation divs
==============================================================================
                 coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const               0.011638         0.006479            1.796           0.072
L1.divs             0.396305         0.090444            4.382           0.000
L1.earnings         0.105299         0.022560            4.667           0.000
L1.returns          0.055538         0.040380            1.375           0.169
==============================================================================

Results for equation earnings
==============================================================================
                 coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const               0.048233         0.036480            1.322           0.186
L1.divs            -0.555327         0.509210           -1.091           0.275
L1.earnings        -0.146343         0.127017           -1.152           0.249
L1.returns          0.085108         0.227341            0.374           0.708
==============================================================================

Results for equation returns
==============================================================================
                 coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const               0.032255         0.020136            1.602           0.109
L1.divs             0.263855         0.281075            0.939           0.348
L1.earnings         0.021179         0.070111            0.302           0.763
L1.returns          0.007089         0.125488            0.056           0.955
==============================================================================

Correlation matrix of residuals
                divs  earnings   returns
divs        1.000000  0.063923  0.029378
earnings    0.063923  1.000000  0.377156
returns     0.029378  0.377156  1.000000
```

[35]:
```
results.plot_acorr();
```


ACF plots for residuals with $2/\sqrt{T}$ bounds

[ ]: