In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas_profiling
```

In [3]:

```
df = pd.read_csv('./price_ratio_cagr_sector.csv')
```

Prepare for model

In [4]:

```
df.head(5)
```

Out[4]:

_201701	P_201801	EPS_2012	...	CAGR_NPM	CAGR_IRD	CAGR_ROE	CAGR_ROA	CAGR_DPS
2.78	1.7	-0.15	...	6.267906	NaN	-5.872124	-1.052619	NaN
393.00	470.0	38.90	...	-1.434567	NaN	-11.896327	-9.105290	1.508768
5.90	5.5	0.57	...	-11.877138	20.262051	-12.538095	-14.011722	-12.944944
23.60	23.7	0.32	...	10.530804	-33.946925	9.544604	15.715264	48.123240
2.84	2.3	0.02	...	-262.712989	NaN	-242.192095	-238.517403	NaN

In [5]:

```
df.columns
```

Out[5]:

```
Index(['NAME', 'P_201101', 'P_201201', 'P_201301', 'P_201401', 'P_2015
01',
       'P_201601', 'P_201701', 'P_201801', 'EPS_2012', 'EPS_2013', 'EP
S_2014',
       'EPS_2015', 'EPS_2016', 'EPS_2017', 'GPM_2012', 'GPM_2013', 'GP
M_2014',
       'GPM_2015', 'GPM_2016', 'GPM_2017', 'Ops_2012', 'Ops_2013', 'Op
s_2014',
       'Ops_2015', 'Ops_2016', 'Ops_2017', 'EBIT_2012', 'EBIT_2013',
       'EBIT_2014', 'EBIT_2015', 'EBIT_2016', 'EBIT_2017', 'NPM_2012',
       'NPM_2013', 'NPM_2014', 'NPM_2015', 'NPM_2016', 'NPM_2017', 'IB
D_2012',
       'IBD_2013', 'IBD_2014', 'IBD_2015', 'IBD_2016', 'IBD_2017', 'RO
E_2012',
       'ROE_2013', 'ROE_2014', 'ROE_2015', 'ROE_2016', 'ROE_2017', 'RO
A_2012',
       'ROA_2013', 'ROA_2014', 'ROA_2015', 'ROA_2016', 'ROA_2017', 'DP
S_2012',
       'DPS_2013', 'DPS_2014', 'DPS_2015', 'DPS_2016', 'DPS_2017', 'BV
_2012',
       'BV_2013', 'BV_2014', 'BV_2015', 'BV_2016', 'BV_2017', 'Payout_
2012',
       'Payout_2013', 'Payout_2014', 'Payout_2015', 'Payout_2016',
       'Payout_2017', 'CAGR_P', 'CAGR_EPS', 'CAGR_GPM', 'CAGR_Ops',
       'CAGR_EBIT', 'CAGR_NPM', 'CAGR_IRD', 'CAGR_ROE', 'CAGR_ROA', 'C
AGR_DPS',
       'CAGR_BV', 'CAGR_Payout', 'sector', 'sector_code', 'business_gr
oup'],
      dtype='object')
```

Select feature

In [6]:

```
sf2012 = ['P_201201',
'EPS_2012',
'GPM_2012',
'Ops_2012',
'EBIT_2012',
'NPM_2012',
'IBD_2012',
'ROE_2012',
'ROA_2012',
'DPS_2012',
'BV_2012',
'Payout_2012']
```

In [7]:

```
sf2013 = ['P_201301',
'EPS_2013',
'GPM_2013',
'Ops_2013',
'EBIT_2013',
'NPM_2013',
'IBD_2013',
'ROE_2013',
'ROA_2013',
'DPS_2013',
'BV_2013',
'Payout_2013']
```

In [8]:

```
sf2014 = ['P_201401',
'EPS_2014',
'GPM_2014',
'Ops_2014',
'EBIT_2014',
'NPM_2014',
'IBD_2014',
'ROE_2014',
'ROA_2014',
'DPS_2014',
'BV_2014',
'Payout_2014']
```

In [9]:

```
sf2015 = ['P_201501',
'EPS_2015',
'GPM_2015',
'Ops_2015',
'EBIT_2015',
'NPM_2015',
'IBD_2015',
'ROE_2015',
'ROA_2015',
'DPS_2015',
'BV_2015',
'Payout_2015']
```

In [10]:

```
sf2016 = ['P_201601',
'EPS_2016',
'GPM_2016',
'Ops_2016',
'EBIT_2016',
'NPM_2016',
'IBD_2016',
'ROE_2016',
'ROA_2016',
'DPS_2016',
'BV_2016',
'Payout_2016']
```

In [11]:

```
sf2017 = ['P_201701',
'EPS_2017',
'GPM_2017',
'Ops_2017',
'EBIT_2017',
'NPM_2017',
'IBD_2017',
'ROE_2017',
'ROA_2017',
'DPS_2017',
'BV_2017',
'Payout_2017']
```

Feature correlation

In [12]:

```
df[sf2012]
```

Out[12]:

	P_201201	EPS_2012	GPM_2012	Ops_2012	EBIT_2012	NPM_2012	IBD_2012	ROE_2012
0	1.87	-0.15	16.18	10.85	0.00	-17.88	NaN	-5.30
1	179.00	38.90	16.43	12.24	0.00	8.96	NaN	21.32
2	5.70	0.57	40.62	28.38	0.01	13.53	0.03	16.96
3	111.00	0.32	49.74	NaN	0.12	5.54	0.45	8.45
4	3.18	0.02	17.14	16.64	-0.03	0.26	NaN	0.36
...	...	...	...	...	...	...	...	...
286	17.60	2.26	10.74	3.03	0.01	6.61	0.02	29.00
287	7.20	1.01	28.75	11.18	NaN	21.34	NaN	31.05
288	5.25	0.14	9.37	3.70	0.03	4.80	NaN	7.41
289	83.75	1.05	19.07	3.52	NaN	15.47	NaN	34.07
290	17.20	1.31	17.00	6.59	0.07	9.17	0.18	9.37

291 rows × 12 columns

In [13]:

```
df[sf2012].corr()
```

Out[13]:

	P_201201	EPS_2012	GPM_2012	Ops_2012	EBIT_2012	NPM_2012	IBD_2012	ROE
P_201201	1.000000	0.563938	0.069985	-0.102210	-0.013543	-0.003848	-0.026985	0.1
EPS_2012	0.563938	1.000000	0.073532	-0.057838	-0.018203	0.033257	-0.075496	0.1
GPM_2012	0.069985	0.073532	1.000000	0.505038	0.020379	0.273754	-0.091829	0.2
Ops_2012	-0.102210	-0.057838	0.505038	1.000000	0.033519	0.133756	-0.041585	0.0
EBIT_2012	-0.013543	-0.018203	0.020379	0.033519	1.000000	0.001710	0.092720	0.0
NPM_2012	-0.003848	0.033257	0.273754	0.133756	0.001710	1.000000	-0.113351	0.1
IBD_2012	-0.026985	-0.075496	-0.091829	-0.041585	0.092720	-0.113351	1.000000	-0.1
ROE_2012	0.119095	0.175302	0.254930	0.037570	0.015606	0.197830	-0.127444	1.0
ROA_2012	0.109181	0.160611	0.301000	-0.050143	-0.005032	0.213889	-0.252221	0.8
DPS_2012	0.576435	0.869124	0.052419	-0.070753	-0.066567	0.089429	-0.067948	0.2
BV_2012	0.578729	0.874431	0.004543	-0.063586	-0.014634	0.007011	-0.043949	0.0
Payout_2012	0.018071	-0.008437	0.043617	-0.013627	0.142240	-0.017353	0.197161	0.0

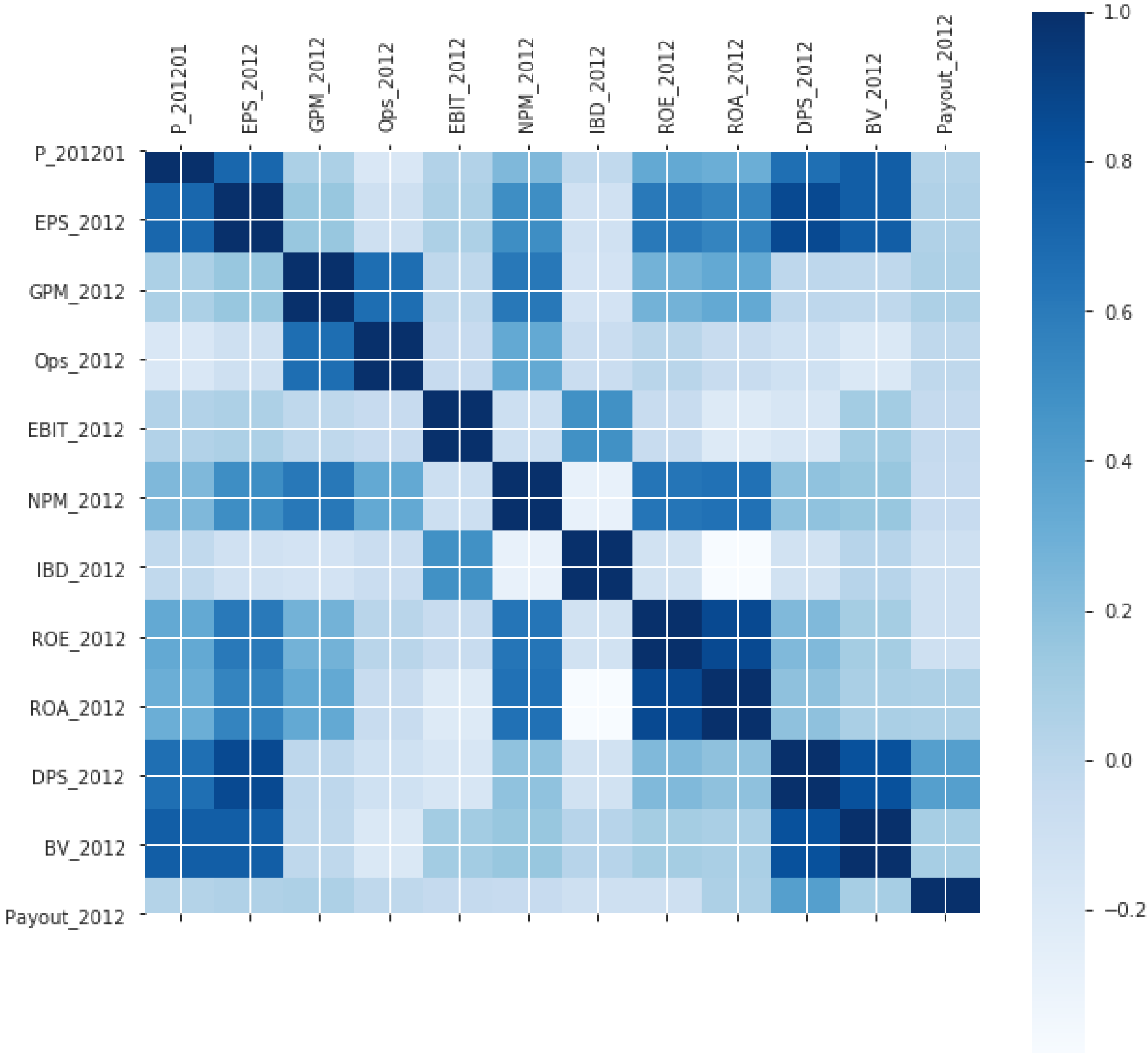
In [14]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2012].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2012].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2012].corr().columns,rotation=0)
plt.colorbar()
```

Out[14]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b29f98d0>
```

```
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu
Sans.
```

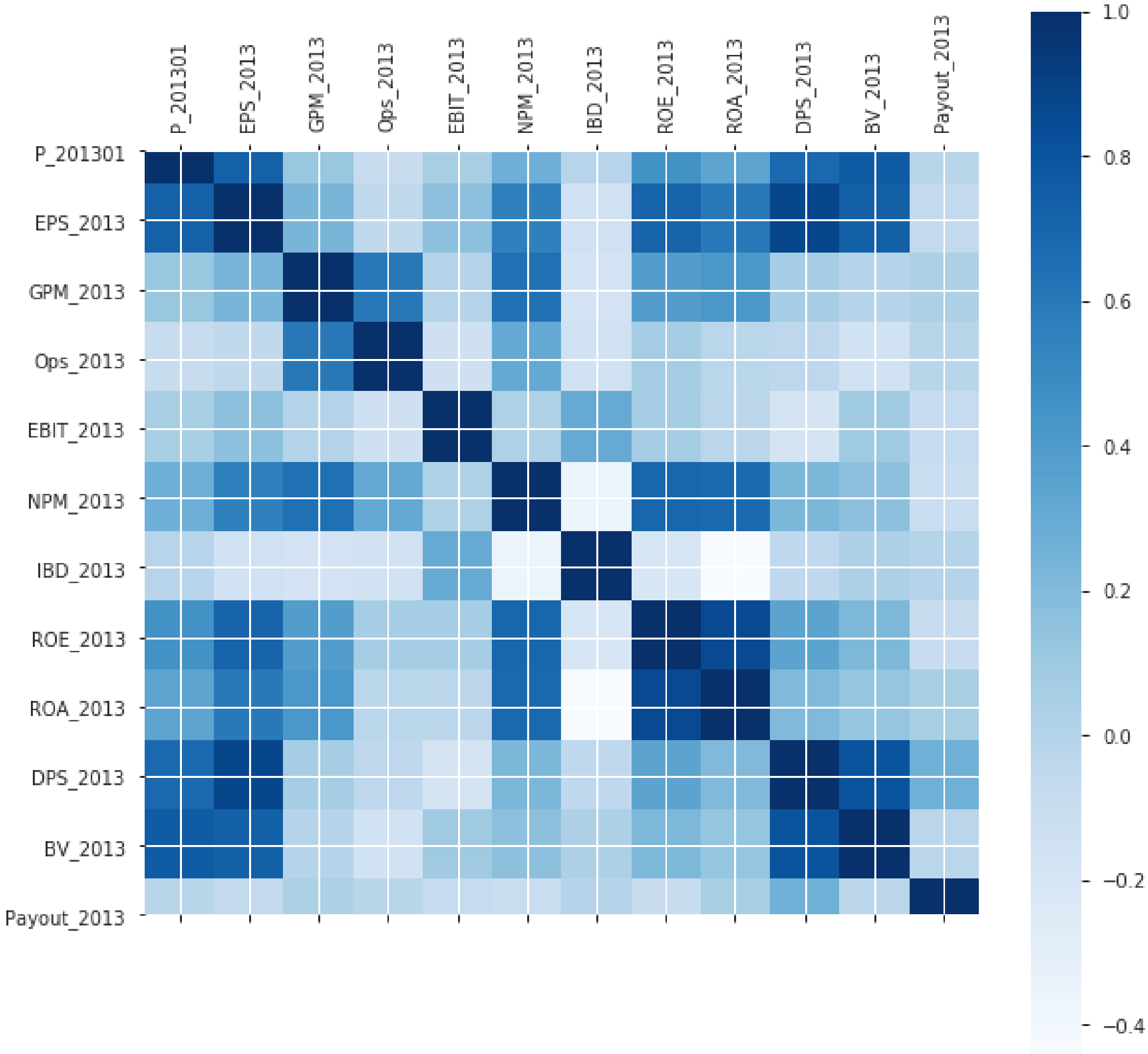


In [15]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2013].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2013].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2013].corr().columns,rotation=0)
plt.colorbar()
```

Out[15]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b293b2d0>
```

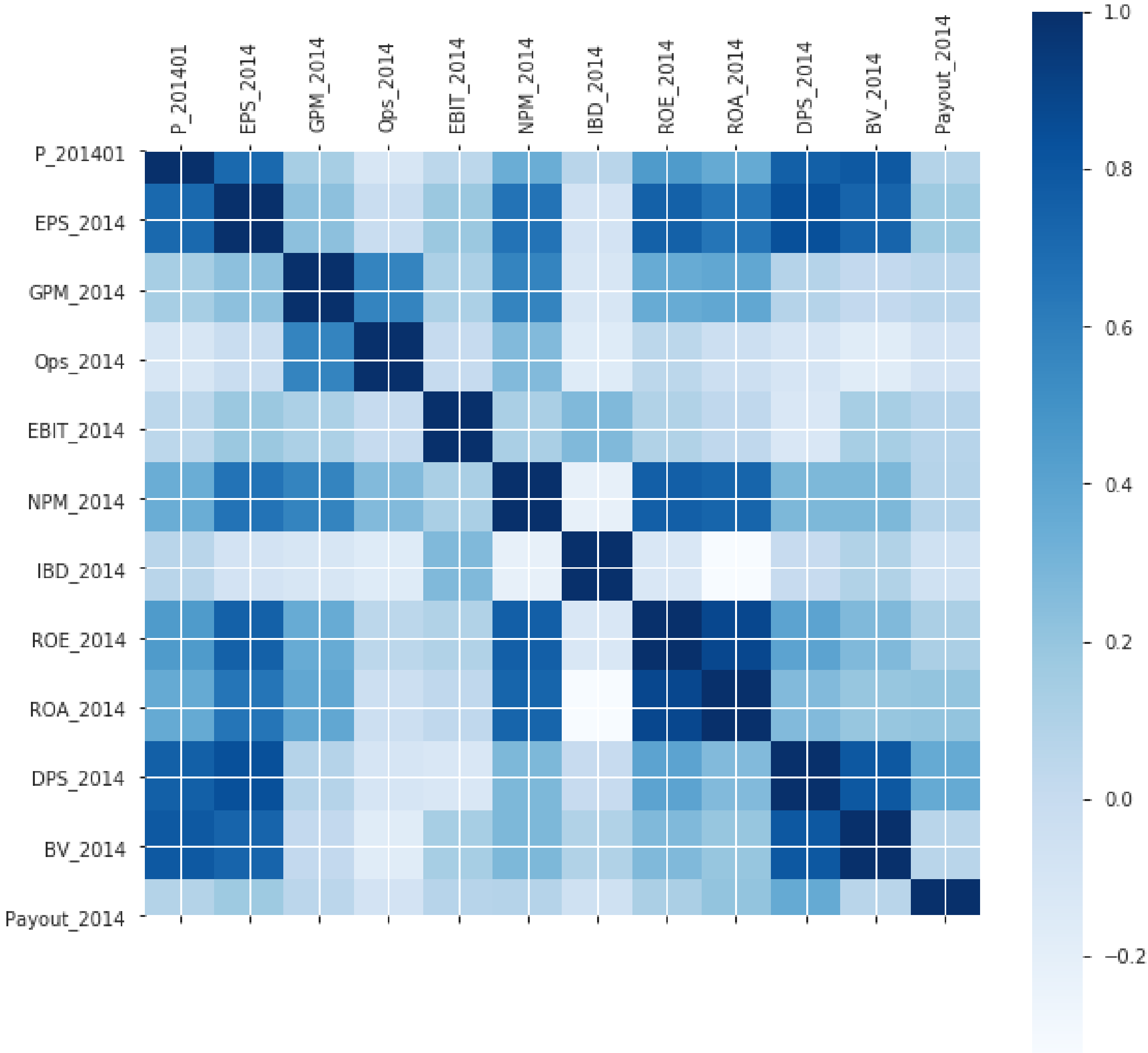


In [16]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2014].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2014].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2014].corr().columns,rotation=0)
plt.colorbar()
```

Out[16]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b2826a50>
```

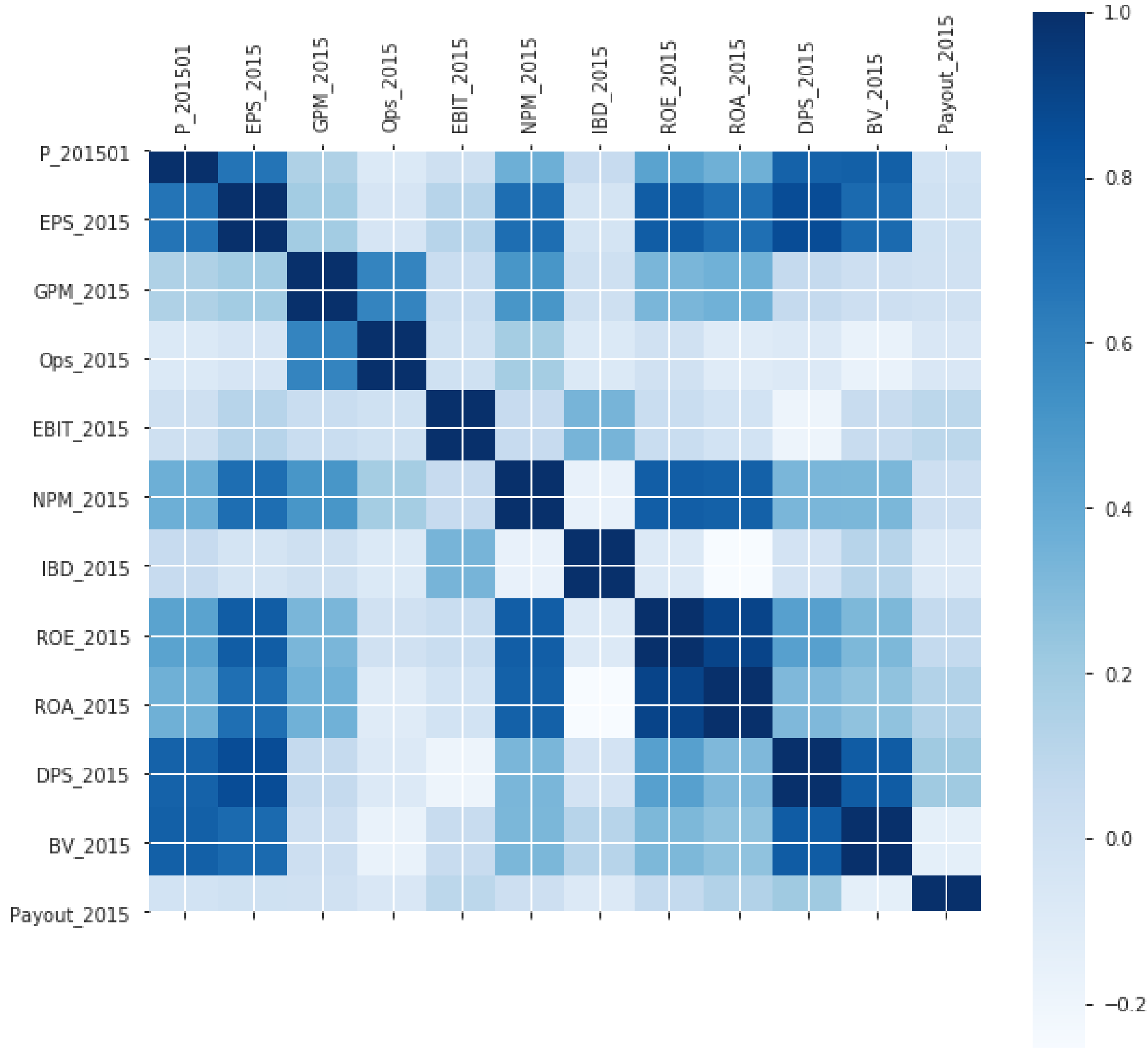


In [17]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2015].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2015].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2015].corr().columns,rotation=0)
plt.colorbar()
```

Out[17]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b206f790>
```

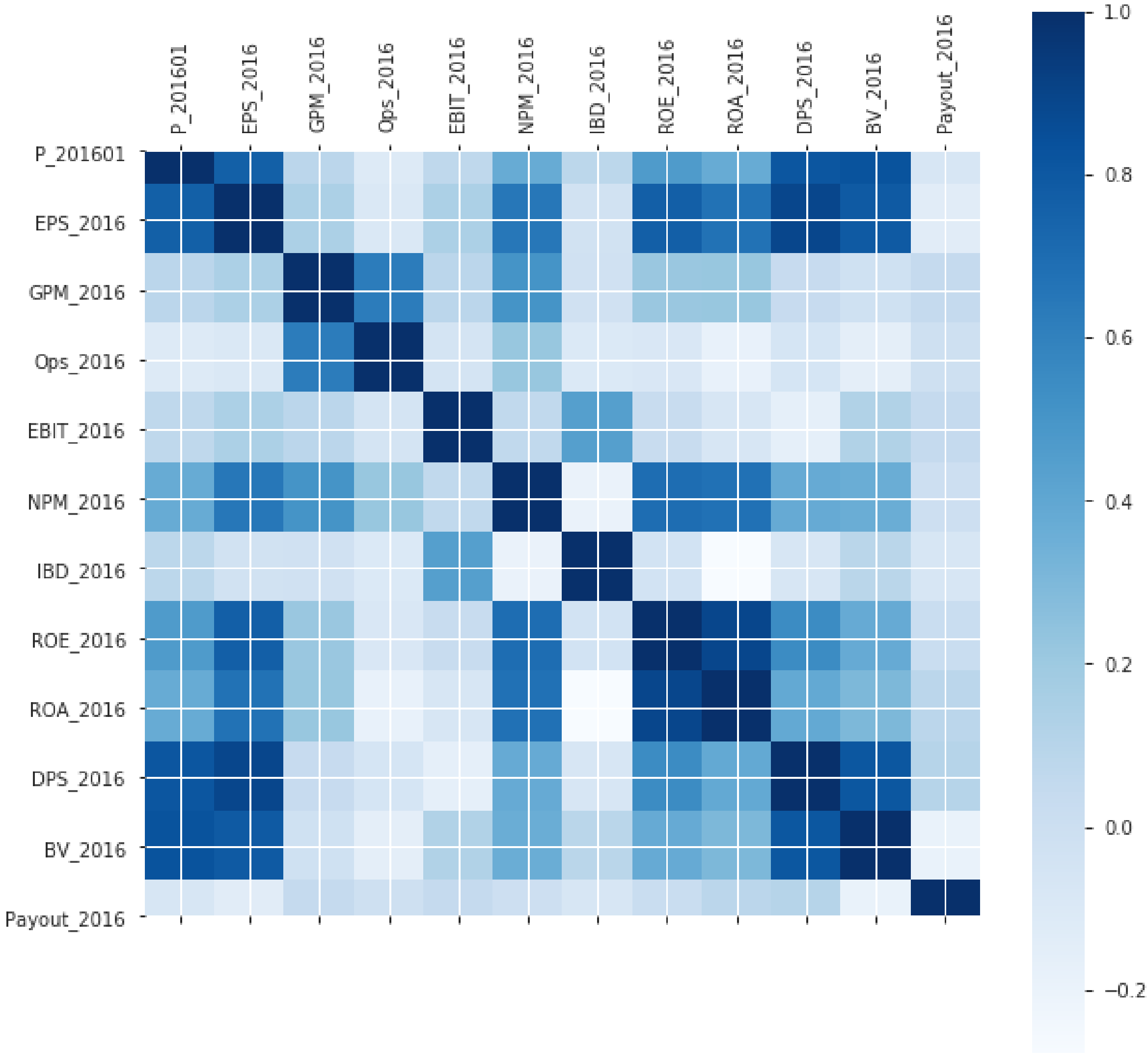


In [18]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2016].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2016].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2016].corr().columns,rotation=0)
plt.colorbar()
```

Out[18]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b1f57cd0>
```

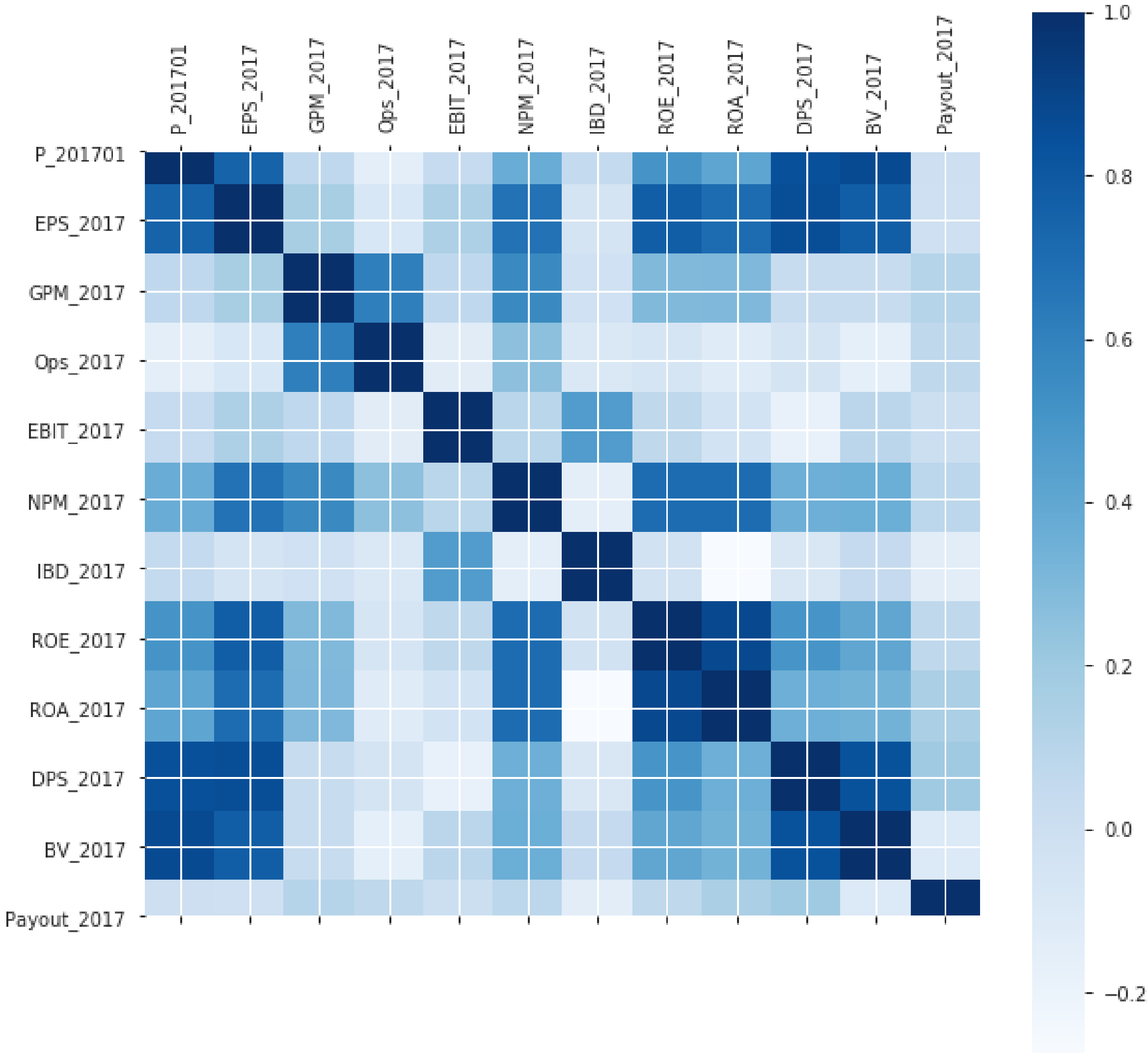


In [19]:

```
plt.figure(figsize=(10,10))
plt.matshow(df[sf2017].corr('spearman'),fignum=1,cmap='Blues')
plt.xticks(np.arange(12),df[sf2017].corr().columns,rotation=90)
plt.yticks(np.arange(12),df[sf2017].corr().columns,rotation=0)
plt.colorbar()
```

Out[19]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b1e43a10>
```



Price correlation

In [20]:

```
corr2012 = df[sf2012].corr()['P_201201'].rename({
    'P_201201' : 'P',
    'EPS_2012' : 'EPS',
    'GPM_2012' : 'GPM',
    'Ops_2012' : 'Ops',
    'EBIT_2012' : 'EBIT',
    'NPM_2012' : 'NPM',
    'IBD_2012' : 'IBD',
    'ROE_2012' : 'ROE',
    'ROA_2012' : 'ROA',
    'DPS_2012' : 'DPS',
    'BV_2012' : 'BV',
    'Payout_2012' : 'Payout'
}) #.sort_values(ascending=False)
```

In [21]:

```
corr2013 = df[sf2013].corr()['P_201301'].rename({
    'P_201301' : 'P',
    'EPS_2013' : 'EPS',
    'GPM_2013' : 'GPM',
    'Ops_2013' : 'Ops',
    'EBIT_2013' : 'EBIT',
    'NPM_2013' : 'NPM',
    'IBD_2013' : 'IBD',
    'ROE_2013' : 'ROE',
    'ROA_2013' : 'ROA',
    'DPS_2013' : 'DPS',
    'BV_2013' : 'BV',
    'Payout_2013' : 'Payout'
})
```

In [22]:

```
corr2014 = df[sf2014].corr()['P_201401'].rename({
    'P_201401' : 'P',
    'EPS_2014' : 'EPS',
    'GPM_2014' : 'GPM',
    'Ops_2014' : 'Ops',
    'EBIT_2014' : 'EBIT',
    'NPM_2014' : 'NPM',
    'IBD_2014' : 'IBD',
    'ROE_2014' : 'ROE',
    'ROA_2014' : 'ROA',
    'DPS_2014' : 'DPS',
    'BV_2014' : 'BV',
    'Payout_2014' : 'Payout'
})
```

In [23]:

```
corr2015 = df[sf2015].corr()['P_201501'].rename({
    'P_201501' : 'P',
    'EPS_2015' : 'EPS',
    'GPM_2015' : 'GPM',
    'Ops_2015' : 'Ops',
    'EBIT_2015' : 'EBIT',
    'NPM_2015' : 'NPM',
    'IBD_2015' : 'IBD',
    'ROE_2015' : 'ROE',
    'ROA_2015' : 'ROA',
    'DPS_2015' : 'DPS',
    'BV_2015' : 'BV',
    'Payout_2015' : 'Payout'
})
```

In [24]:

```
corr2016 = df[sf2016].corr()['P_201601'].rename({
    'P_201601' : 'P',
    'EPS_2016' : 'EPS',
    'GPM_2016' : 'GPM',
    'Ops_2016' : 'Ops',
    'EBIT_2016' : 'EBIT',
    'NPM_2016' : 'NPM',
    'IBD_2016' : 'IBD',
    'ROE_2016' : 'ROE',
    'ROA_2016' : 'ROA',
    'DPS_2016' : 'DPS',
    'BV_2016' : 'BV',
    'Payout_2016' : 'Payout'
})
```

In [25]:

```
corr2017 = df[sf2017].corr()['P_201701'].rename({
    'P_201701' : 'P',
    'EPS_2017' : 'EPS',
    'GPM_2017' : 'GPM',
    'Ops_2017' : 'Ops',
    'EBIT_2017' : 'EBIT',
    'NPM_2017' : 'NPM',
    'IBD_2017' : 'IBD',
    'ROE_2017' : 'ROE',
    'ROA_2017' : 'ROA',
    'DPS_2017' : 'DPS',
    'BV_2017' : 'BV',
    'Payout_2017' : 'Payout'
})
```

In [26]:

```
corr_mat = pd.DataFrame({
    'corr2012': corr2012,
    'corr2013': corr2013,
    'corr2014': corr2014,
    'corr2015': corr2015,
    'corr2016': corr2016,
    'corr2017': corr2017
})
```

In [27]:

```
corr_mat_sort = corr_mat.sort_values(by='corr2012', ascending=False)
corr_mat_sort
```

Out[27]:

	corr2012	corr2013	corr2014	corr2015	corr2016	corr2017
P	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
BV	0.578729	0.663245	0.795801	0.769508	0.772482	0.777747
DPS	0.576435	0.742352	0.829126	0.839421	0.814103	0.823045
EPS	0.563938	0.731008	0.808789	0.810396	0.784989	0.816188
ROE	0.119095	0.173135	0.204822	0.197250	0.178288	0.174591
ROA	0.109181	0.149564	0.181804	0.160212	0.161732	0.150948
GPM	0.069985	0.059269	0.086218	0.085111	0.051078	0.030134
Payout	0.018071	0.030429	-0.001076	-0.024985	0.008502	0.018074
NPM	-0.003848	0.039940	0.121712	0.052705	0.036564	0.013959
EBIT	-0.013543	0.019969	0.021032	0.003198	0.019040	0.018176
IBD	-0.026985	-0.025422	-0.027075	-0.014046	-0.004112	-0.034385
Ops	-0.102210	-0.052159	-0.032806	-0.029146	-0.036502	-0.034716

In [28]:

```
corr_mat_sort.T
```

Out[28]:

	P	BV	DPS	EPS	ROE	ROA	GPM	Payout	NPM
corr2012	1.0	0.578729	0.576435	0.563938	0.119095	0.109181	0.069985	0.018071	-0.003848
corr2013	1.0	0.663245	0.742352	0.731008	0.173135	0.149564	0.059269	0.030429	0.039940
corr2014	1.0	0.795801	0.829126	0.808789	0.204822	0.181804	0.086218	-0.001076	0.121712
corr2015	1.0	0.769508	0.839421	0.810396	0.197250	0.160212	0.085111	-0.024985	0.052705
corr2016	1.0	0.772482	0.814103	0.784989	0.178288	0.161732	0.051078	0.008502	0.036564
corr2017	1.0	0.777747	0.823045	0.816188	0.174591	0.150948	0.030134	0.018074	0.013959

In [29]:

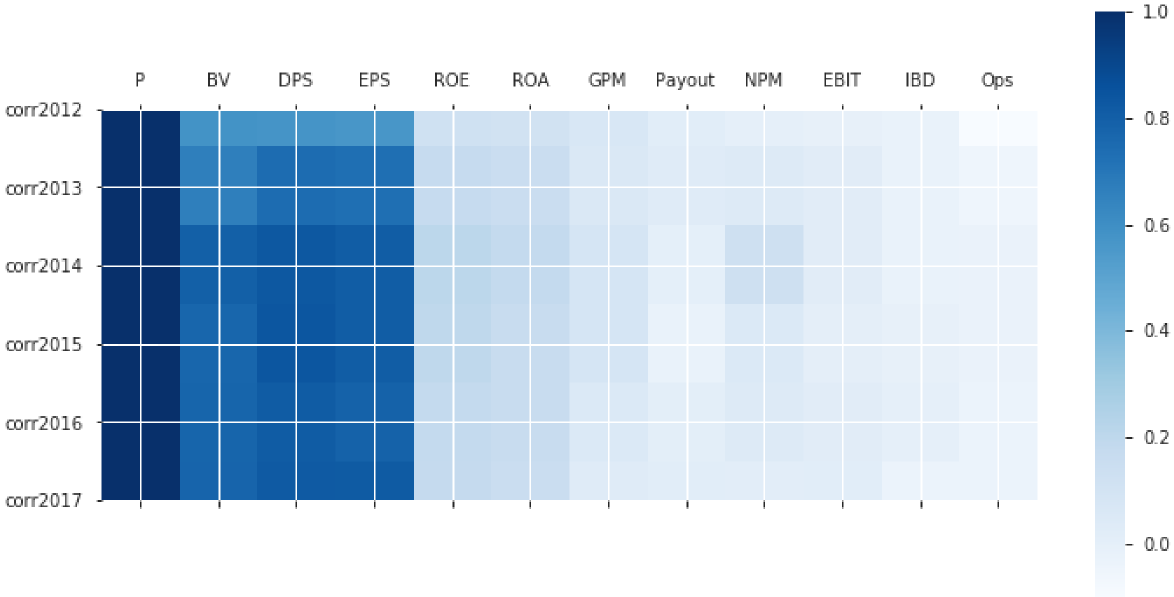
```
# plt.rcParams["axes.grid"] = True
```

In [30]:

```
plt.figure(figsize=(12,6))
plt.matshow(corr_mat_sort.T,fignum=1,cmap='Blues')
plt.xticks(np.arange(12), corr_mat_sort.T.columns,rotation=0)
plt.yticks(np.arange(6), corr_mat_sort.T.index,rotation=0)
plt.colorbar()
```

Out[30]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b1d370d0>
```



Diff

make diff column

In [31]:

```
diff_df = pd.DataFrame({
    'P_2013': df['P_201301'],
    'P_2014': df['P_201401'],
    'P_2015': df['P_201501'],
    'P_2016': df['P_201601'],
    'P_2017': df['P_201701'],

    'P_D_2013_2012':  df['P_201301'] - df['P_201201'],
    'P_D_2014_2013':  df['P_201401'] - df['P_201301'],
    'P_D_2015_2014':  df['P_201501'] - df['P_201401'],
    'P_D_2016_2015':  df['P_201601'] - df['P_201501'],
    'P_D_2017_2016':  df['P_201701'] - df['P_201601'],

    'EPS_D_2013_2012':  df['EPS_2013'] - df['EPS_2012'],
    'EPS_D_2014_2013':  df['EPS_2014'] - df['EPS_2013'],
    'EPS_D_2015_2014':  df['EPS_2015'] - df['EPS_2014'],
    'EPS_D_2016_2015':  df['EPS_2016'] - df['EPS_2015'],
    'EPS_D_2017_2016':  df['EPS_2017'] - df['EPS_2016'],

    'GPM_D_2013_2012':  df['GPM_2013'] - df['GPM_2012'],
    'GPM_D_2014_2013':  df['GPM_2014'] - df['GPM_2013'],
    'GPM_D_2015_2014':  df['GPM_2015'] - df['GPM_2014'],
    'GPM_D_2016_2015':  df['GPM_2016'] - df['GPM_2015'],
    'GPM_D_2017_2016':  df['GPM_2017'] - df['GPM_2016'],

    'Ops_D_2013_2012':  df['Ops_2013'] - df['Ops_2012'],
    'Ops_D_2014_2013':  df['Ops_2014'] - df['Ops_2013'],
    'Ops_D_2015_2014':  df['Ops_2015'] - df['Ops_2014'],
    'Ops_D_2016_2015':  df['Ops_2016'] - df['Ops_2015'],
    'Ops_D_2017_2016':  df['Ops_2017'] - df['Ops_2016'],

    'EBIT_D_2013_2012':  df['EBIT_2013'] - df['EBIT_2012'],
    'EBIT_D_2014_2013':  df['EBIT_2014'] - df['EBIT_2013'],
    'EBIT_D_2015_2014':  df['EBIT_2015'] - df['EBIT_2014'],
    'EBIT_D_2016_2015':  df['EBIT_2016'] - df['EBIT_2015'],
    'EBIT_D_2017_2016':  df['EBIT_2017'] - df['EBIT_2016'],

    'NPM_D_2013_2012':  df['NPM_2013'] - df['NPM_2012'],
    'NPM_D_2014_2013':  df['NPM_2014'] - df['NPM_2013'],
    'NPM_D_2015_2014':  df['NPM_2015'] - df['NPM_2014'],
    'NPM_D_2016_2015':  df['NPM_2016'] - df['NPM_2015'],
    'NPM_D_2017_2016':  df['NPM_2017'] - df['NPM_2016'],

    'IBD_D_2013_2012':  df['IBD_2013'] - df['IBD_2012'],
    'IBD_D_2014_2013':  df['IBD_2014'] - df['IBD_2013'],
    'IBD_D_2015_2014':  df['IBD_2015'] - df['IBD_2014'],
    'IBD_D_2016_2015':  df['IBD_2016'] - df['IBD_2015'],
    'IBD_D_2017_2016':  df['IBD_2017'] - df['IBD_2016'],

    'ROE_D_2013_2012':  df['ROE_2013'] - df['ROE_2012'],
    'ROE_D_2014_2013':  df['ROE_2014'] - df['ROE_2013'],
    'ROE_D_2015_2014':  df['ROE_2015'] - df['ROE_2014'],
    'ROE_D_2016_2015':  df['ROE_2016'] - df['ROE_2015'],
    'ROE_D_2017_2016':  df['ROE_2017'] - df['ROE_2016'],

    'ROA_D_2013_2012':  df['ROA_2013'] - df['ROA_2012'],
    'ROA_D_2014_2013':  df['ROA_2014'] - df['ROA_2013'],
    'ROA_D_2015_2014':  df['ROA_2015'] - df['ROA_2014'],
    'ROA_D_2016_2015':  df['ROA_2016'] - df['ROA_2015'],
```

```
    'ROA_D_2017_2016':  df['ROA_2017'] - df['ROA_2016'],

    'DPS_D_2013_2012':  df['DPS_2013'] - df['DPS_2012'],
    'DPS_D_2014_2013':  df['DPS_2014'] - df['DPS_2013'],
    'DPS_D_2015_2014':  df['DPS_2015'] - df['DPS_2014'],
    'DPS_D_2016_2015':  df['DPS_2016'] - df['DPS_2015'],
    'DPS_D_2017_2016':  df['DPS_2017'] - df['DPS_2016'],

    'BV_D_2013_2012':  df['BV_2013'] - df['BV_2012'],
    'BV_D_2014_2013':  df['BV_2014'] - df['BV_2013'],
    'BV_D_2015_2014':  df['BV_2015'] - df['BV_2014'],
    'BV_D_2016_2015':  df['BV_2016'] - df['BV_2015'],
    'BV_D_2017_2016':  df['BV_2017'] - df['BV_2016'],

    'Payout_D_2013_2012':  df['Payout_2013'] - df['Payout_2012'],
    'Payout_D_2014_2013':  df['Payout_2014'] - df['Payout_2013'],
    'Payout_D_2015_2014':  df['Payout_2015'] - df['Payout_2014'],
    'Payout_D_2016_2015':  df['Payout_2016'] - df['Payout_2015'],
    'Payout_D_2017_2016':  df['Payout_2017'] - df['Payout_2016']
})
```

In [32]:

```
diff_df
```

Out[32]:

	P_2013	P_2014	P_2015	P_2016	P_2017	P_D_2013_2012	P_D_2014_2013	P_D_2015_2014
0	1.75	1.68	2.00	2.70	2.78	-0.12	-0.07	0.32
1	263.00	240.00	260.00	273.00	393.00	84.00	-23.00	20.00
2	7.70	8.40	9.90	7.90	5.90	2.00	0.70	1.50
3	24.40	22.60	23.70	23.00	23.60	-86.60	-1.80	1.10
4	3.12	2.20	2.30	3.00	2.84	-0.06	-0.92	0.10
...	...	...	...	...	...	...	...	...
286	24.30	18.50	21.20	22.50	40.25	6.70	-5.80	2.70
287	11.30	9.80	9.95	4.56	7.15	4.10	-1.50	0.15
288	8.35	2.48	4.24	3.30	6.30	3.10	-5.87	1.76
289	95.25	10.20	10.60	7.80	7.75	11.50	-85.05	0.40
290	18.20	10.20	9.75	9.25	16.70	1.00	-8.00	-0.45

291 rows × 65 columns

feature selection

In [33]:

```
sf_d_2013_2012 = [
    'P_D_2013_2012',
    'EPS_D_2013_2012',
    'GPM_D_2013_2012',
    'Ops_D_2013_2012',
    'EBIT_D_2013_2012',
    'NPM_D_2013_2012',
    'IBD_D_2013_2012',
    'ROE_D_2013_2012',
    'ROA_D_2013_2012',
    'DPS_D_2013_2012',
    'BV_D_2013_2012',
    'Payout_D_2013_2012'
]
```

In [34]:

```
sf_d_2014_2013 = [
    'P_D_2014_2013',
    'EPS_D_2014_2013',
    'GPM_D_2014_2013',
    'Ops_D_2014_2013',
    'EBIT_D_2014_2013',
    'NPM_D_2014_2013',
    'IBD_D_2014_2013',
    'ROE_D_2014_2013',
    'ROA_D_2014_2013',
    'DPS_D_2014_2013',
    'BV_D_2014_2013',
    'Payout_D_2014_2013'
]
```

In [35]:

```
sf_d_2015_2014 = [
    'P_D_2015_2014',
    'EPS_D_2015_2014',
    'GPM_D_2015_2014',
    'Ops_D_2015_2014',
    'EBIT_D_2015_2014',
    'NPM_D_2015_2014',
    'IBD_D_2015_2014',
    'ROE_D_2015_2014',
    'ROA_D_2015_2014',
    'DPS_D_2015_2014',
    'BV_D_2015_2014',
    'Payout_D_2015_2014'
]
```

In [36]:

```
sf_d_2016_2015 = [
    'P_D_2016_2015',
    'EPS_D_2016_2015',
    'GPM_D_2016_2015',
    'Ops_D_2016_2015',
    'EBIT_D_2016_2015',
    'NPM_D_2016_2015',
    'IBD_D_2016_2015',
    'ROE_D_2016_2015',
    'ROA_D_2016_2015',
    'DPS_D_2016_2015',
    'BV_D_2016_2015',
    'Payout_D_2016_2015'
]
```

In [37]:

```
sf_d_2017_2016 = [
    'P_D_2017_2016',
    'EPS_D_2017_2016',
    'GPM_D_2017_2016',
    'Ops_D_2017_2016',
    'EBIT_D_2017_2016',
    'NPM_D_2017_2016',
    'IBD_D_2017_2016',
    'ROE_D_2017_2016',
    'ROA_D_2017_2016',
    'DPS_D_2017_2016',
    'BV_D_2017_2016',
    'Payout_D_2017_2016'
]
```

diff corr

In [38]:

```
corr_d_2013_2012 = diff_df[sf_d_2013_2012].corr()['P_D_2013_2012'].rename({
    'P_D_2013_2012' : 'P_D',
    'EPS_D_2013_2012' : 'EPS_D',
    'GPM_D_2013_2012' : 'GPM_D',
    'Ops_D_2013_2012' : 'Ops_D',
    'EBIT_D_2013_2012' : 'EBIT_D',
    'NPM_D_2013_2012' : 'NPM_D',
    'IBD_D_2013_2012' : 'IBD_D',
    'ROE_D_2013_2012' : 'ROE_D',
    'ROA_D_2013_2012' : 'ROA_D',
    'DPS_D_2013_2012' : 'DPS_D',
    'BV_D_2013_2012' : 'BV_D',
    'Payout_D_2013_2012' : 'Payout_D'
})
```

In [39]:

```
corr_d_2014_2013 = diff_df[sf_d_2014_2013].corr()['P_D_2014_2013'].rename({
    'P_D_2014_2013' : 'P_D',
    'EPS_D_2014_2013' : 'EPS_D',
    'GPM_D_2014_2013' : 'GPM_D',
    'Ops_D_2014_2013' : 'Ops_D',
    'EBIT_D_2014_2013' : 'EBIT_D',
    'NPM_D_2014_2013' : 'NPM_D',
    'IBD_D_2014_2013' : 'IBD_D',
    'ROE_D_2014_2013' : 'ROE_D',
    'ROA_D_2014_2013' : 'ROA_D',
    'DPS_D_2014_2013' : 'DPS_D',
    'BV_D_2014_2013' : 'BV_D',
    'Payout_D_2014_2013' : 'Payout_D'
})
```

In [40]:

```
corr_d_2015_2014 = diff_df[sf_d_2015_2014].corr()['P_D_2015_2014'].rename({
    'P_D_2015_2014' : 'P_D',
    'EPS_D_2015_2014' : 'EPS_D',
    'GPM_D_2015_2014' : 'GPM_D',
    'Ops_D_2015_2014' : 'Ops_D',
    'EBIT_D_2015_2014' : 'EBIT_D',
    'NPM_D_2015_2014' : 'NPM_D',
    'IBD_D_2015_2014' : 'IBD_D',
    'ROE_D_2015_2014' : 'ROE_D',
    'ROA_D_2015_2014' : 'ROA_D',
    'DPS_D_2015_2014' : 'DPS_D',
    'BV_D_2015_2014' : 'BV_D',
    'Payout_D_2015_2014' : 'Payout_D'
})
```

In [41]:

```
corr_d_2016_2015 = diff_df[sf_d_2016_2015].corr()['P_D_2016_2015'].rename({
    'P_D_2016_2015' : 'P_D',
    'EPS_D_2016_2015' : 'EPS_D',
    'GPM_D_2016_2015' : 'GPM_D',
    'Ops_D_2016_2015' : 'Ops_D',
    'EBIT_D_2016_2015' : 'EBIT_D',
    'NPM_D_2016_2015' : 'NPM_D',
    'IBD_D_2016_2015' : 'IBD_D',
    'ROE_D_2016_2015' : 'ROE_D',
    'ROA_D_2016_2015' : 'ROA_D',
    'DPS_D_2016_2015' : 'DPS_D',
    'BV_D_2016_2015' : 'BV_D',
    'Payout_D_2016_2015' : 'Payout_D'
})
```

In [42]:

```
corr_d_2017_2016 = diff_df[sf_d_2017_2016].corr()['P_D_2017_2016'].rename({
    'P_D_2017_2016' : 'P_D',
    'EPS_D_2017_2016' : 'EPS_D',
    'GPM_D_2017_2016' : 'GPM_D',
    'Ops_D_2017_2016' : 'Ops_D',
    'EBIT_D_2017_2016' : 'EBIT_D',
    'NPM_D_2017_2016' : 'NPM_D',
    'IBD_D_2017_2016' : 'IBD_D',
    'ROE_D_2017_2016' : 'ROE_D',
    'ROA_D_2017_2016' : 'ROA_D',
    'DPS_D_2017_2016' : 'DPS_D',
    'BV_D_2017_2016' : 'BV_D',
    'Payout_D_2017_2016' : 'Payout_D'
})
```

In [43]:

```
corr_d_mat = pd.DataFrame({
    'corr_d_2013_2012': corr_d_2013_2012,
    'corr_d_2014_2013': corr_d_2014_2013,
    'corr_d_2015_2014': corr_d_2015_2014,
    'corr_d_2016_2015': corr_d_2016_2015,
    'corr_d_2017_2016': corr_d_2017_2016
})
```

In [44]:

```
corr_d_mat_sort = corr_d_mat.sort_values(by='corr_d_2015_2014', ascending=False)
corr_d_mat_sort
```

Out[44]:

	corr_d_2013_2012	corr_d_2014_2013	corr_d_2015_2014	corr_d_2016_2015	corr_d_2017
P_D	1.000000	1.000000	1.000000	1.000000	1.0
DPS_D	0.011287	0.049399	0.285828	0.269028	0.2
BV_D	0.501151	0.025453	0.215925	-0.040319	0.1
EPS_D	0.199250	0.011876	0.096793	0.084282	-0.2
GPM_D	0.059069	-0.001343	0.062136	0.088238	0.0
Payout_D	-0.008055	0.016045	0.044653	-0.020422	0.0
Ops_D	0.062342	0.012979	0.017703	0.043921	0.0
EBIT_D	0.000281	-0.000649	0.006970	0.004688	-0.0
ROA_D	0.016251	0.001509	0.006662	0.089976	-0.0
NPM_D	0.015497	-0.027345	0.005839	-0.017572	-0.0
IBD_D	-0.002659	0.008940	0.003839	-0.110394	-0.0
ROE_D	0.037903	-0.002935	-0.006082	0.057021	-0.0

In [45]:

```
corr_d_mat_sort.T
```

Out[45]:

	P_D	DPS_D	BV_D	EPS_D	GPM_D	Payout_D	Ops_D	EBIT_D
corr_d_2013_2012	1.0	0.011287	0.501151	0.199250	0.059069	-0.008055	0.062342	0.000281
corr_d_2014_2013	1.0	0.049399	0.025453	0.011876	-0.001343	0.016045	0.012979	-0.000649
corr_d_2015_2014	1.0	0.285828	0.215925	0.096793	0.062136	0.044653	0.017703	0.006970
corr_d_2016_2015	1.0	0.269028	-0.040319	0.084282	0.088238	-0.020422	0.043921	0.004688
corr_d_2017_2016	1.0	0.268567	0.167284	-0.263004	0.004017	0.002062	0.022122	-0.007717

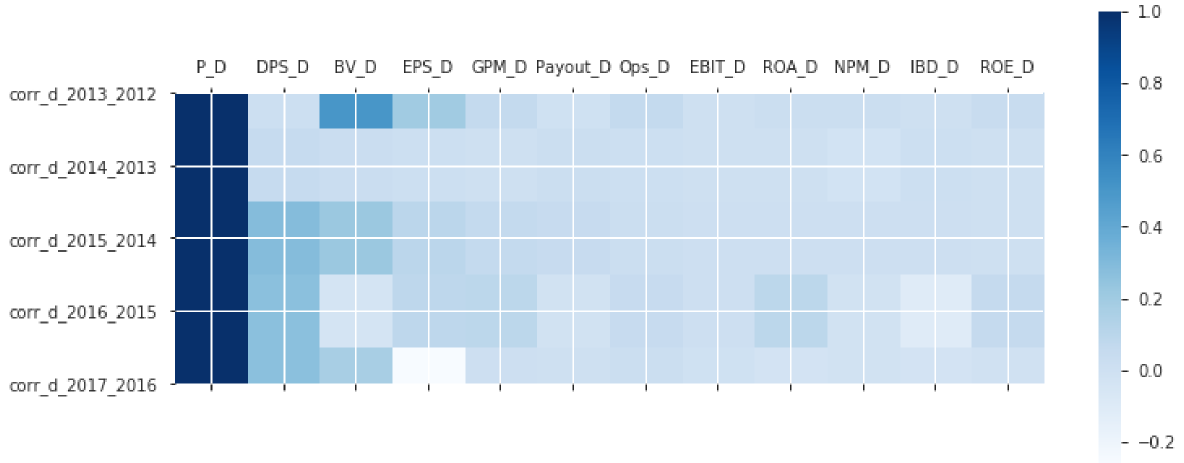
diff ratio vs diff price

In [46]:

```
plt.figure(figsize=(12,5))
plt.matshow(corr_d_mat_sort.T,fignum=1,cmap='Blues')
plt.xticks(np.arange(12), corr_d_mat_sort.T.columns,rotation=0)
plt.yticks(np.arange(5), corr_d_mat_sort.T.index,rotation=0)
plt.colorbar()
```

Out[46]:

```
<matplotlib.colorbar.Colorbar at 0x7f18b1c5b350>
```



In [47]:

```
sf_dnp_2013_2012 = [
    'P_2013',
    'EPS_D_2013_2012',
    'GPM_D_2013_2012',
    'Ops_D_2013_2012',
    'EBIT_D_2013_2012',
    'NPM_D_2013_2012',
    'IBD_D_2013_2012',
    'ROE_D_2013_2012',
    'ROA_D_2013_2012',
    'DPS_D_2013_2012',
    'BV_D_2013_2012',
    'Payout_D_2013_2012'
]
```

In [48]:

```
sf_dnp_2014_2013 = [
    'P_2014',
    'EPS_D_2014_2013',
    'GPM_D_2014_2013',
    'Ops_D_2014_2013',
    'EBIT_D_2014_2013',
    'NPM_D_2014_2013',
    'IBD_D_2014_2013',
    'ROE_D_2014_2013',
    'ROA_D_2014_2013',
    'DPS_D_2014_2013',
    'BV_D_2014_2013',
    'Payout_D_2014_2013'
]
```

In [49]:

```
sf_dnp_2015_2014 = [
    'P_2015',
    'EPS_D_2015_2014',
    'GPM_D_2015_2014',
    'Ops_D_2015_2014',
    'EBIT_D_2015_2014',
    'NPM_D_2015_2014',
    'IBD_D_2015_2014',
    'ROE_D_2015_2014',
    'ROA_D_2015_2014',
    'DPS_D_2015_2014',
    'BV_D_2015_2014',
    'Payout_D_2015_2014'
]
```

In [50]:

```
sf_dnp_2016_2015 = [
    'P_2016',
    'EPS_D_2016_2015',
    'GPM_D_2016_2015',
    'Ops_D_2016_2015',
    'EBIT_D_2016_2015',
    'NPM_D_2016_2015',
    'IBD_D_2016_2015',
    'ROE_D_2016_2015',
    'ROA_D_2016_2015',
    'DPS_D_2016_2015',
    'BV_D_2016_2015',
    'Payout_D_2016_2015'
]
```

In [51]:

```
sf_dnp_2017_2016 = [
    'P_2017',
    'EPS_D_2017_2016',
    'GPM_D_2017_2016',
    'Ops_D_2017_2016',
    'EBIT_D_2017_2016',
    'NPM_D_2017_2016',
    'IBD_D_2017_2016',
    'ROE_D_2017_2016',
    'ROA_D_2017_2016',
    'DPS_D_2017_2016',
    'BV_D_2017_2016',
    'Payout_D_2017_2016'
]
```

In [52]:

```
corr_dnp_2013_2012 = diff_df[sf_dnp_2013_2012].corr()['P_2013'].rename({
    'P_2013' : 'P',
    'EPS_D_2013_2012' : 'EPS_D',
    'GPM_D_2013_2012' : 'GPM_D',
    'Ops_D_2013_2012' : 'Ops_D',
    'EBIT_D_2013_2012' : 'EBIT_D',
    'NPM_D_2013_2012' : 'NPM_D',
    'IBD_D_2013_2012' : 'IBD_D',
    'ROE_D_2013_2012' : 'ROE_D',
    'ROA_D_2013_2012' : 'ROA_D',
    'DPS_D_2013_2012' : 'DPS_D',
    'BV_D_2013_2012' : 'BV_D',
    'Payout_D_2013_2012' : 'Payout_D'
})
```

In [53]:

```
corr_dnp_2014_2013 = diff_df[sf_dnp_2014_2013].corr()['P_2014'].rename({
    'P_2014' : 'P',
    'EPS_D_2014_2013' : 'EPS_D',
    'GPM_D_2014_2013' : 'GPM_D',
    'Ops_D_2014_2013' : 'Ops_D',
    'EBIT_D_2014_2013' : 'EBIT_D',
    'NPM_D_2014_2013' : 'NPM_D',
    'IBD_D_2014_2013' : 'IBD_D',
    'ROE_D_2014_2013' : 'ROE_D',
    'ROA_D_2014_2013' : 'ROA_D',
    'DPS_D_2014_2013' : 'DPS_D',
    'BV_D_2014_2013' : 'BV_D',
    'Payout_D_2014_2013' : 'Payout_D'
})
```

In [54]:

```
corr_dnp_2015_2014 = diff_df[sf_dnp_2015_2014].corr()['P_2015'].rename({
    'P_2015' : 'P',
    'EPS_D_2015_2014' : 'EPS_D',
    'GPM_D_2015_2014' : 'GPM_D',
    'Ops_D_2015_2014' : 'Ops_D',
    'EBIT_D_2015_2014' : 'EBIT_D',
    'NPM_D_2015_2014' : 'NPM_D',
    'IBD_D_2015_2014' : 'IBD_D',
    'ROE_D_2015_2014' : 'ROE_D',
    'ROA_D_2015_2014' : 'ROA_D',
    'DPS_D_2015_2014' : 'DPS_D',
    'BV_D_2015_2014' : 'BV_D',
    'Payout_D_2015_2014' : 'Payout_D'
})
```

In [55]:

```
corr_dnp_2016_2015 = diff_df[sf_dnp_2016_2015].corr()['P_2016'].rename({
    'P_2016' : 'P',
    'EPS_D_2016_2015' : 'EPS_D',
    'GPM_D_2016_2015' : 'GPM_D',
    'Ops_D_2016_2015' : 'Ops_D',
    'EBIT_D_2016_2015' : 'EBIT_D',
    'NPM_D_2016_2015' : 'NPM_D',
    'IBD_D_2016_2015' : 'IBD_D',
    'ROE_D_2016_2015' : 'ROE_D',
    'ROA_D_2016_2015' : 'ROA_D',
    'DPS_D_2016_2015' : 'DPS_D',
    'BV_D_2016_2015' : 'BV_D',
    'Payout_D_2016_2015' : 'Payout_D'
})
```

In [56]:

```
corr_dnp_2017_2016 = diff_df[sf_dnp_2017_2016].corr()['P_2017'].rename({
    'P_2017' : 'P',
    'EPS_D_2017_2016' : 'EPS_D',
    'GPM_D_2017_2016' : 'GPM_D',
    'Ops_D_2017_2016' : 'Ops_D',
    'EBIT_D_2017_2016' : 'EBIT_D',
    'NPM_D_2017_2016' : 'NPM_D',
    'IBD_D_2017_2016' : 'IBD_D',
    'ROE_D_2017_2016' : 'ROE_D',
    'ROA_D_2017_2016' : 'ROA_D',
    'DPS_D_2017_2016' : 'DPS_D',
    'BV_D_2017_2016' : 'BV_D',
    'Payout_D_2017_2016' : 'Payout_D'
})
```

In [57]:

```
corr_dnp_mat = pd.DataFrame({
    'corr_dnp_2013': corr_dnp_2013_2012,
    'corr_dnp_2014': corr_dnp_2014_2013,
    'corr_dnp_2015': corr_dnp_2015_2014,
    'corr_dnp_2016': corr_dnp_2016_2015,
    'corr_dnp_2017': corr_dnp_2017_2016
})
```

In [58]:

```
corr_dnp_mat_sort = corr_dnp_mat.sort_values(by='corr_dnp_2014', ascending=False)
corr_dnp_mat_sort
```

Out[58]:

	corr_dnp_2013	corr_dnp_2014	corr_dnp_2015	corr_dnp_2016	corr_dnp_2017
P	1.000000	1.000000	1.000000	1.000000	1.000000
BV_D	0.567832	0.664851	0.662971	0.519204	0.663381
DPS_D	-0.015303	0.201041	0.245843	0.039062	0.093670
EPS_D	0.160505	0.143639	0.001492	0.372671	-0.304225
NPM_D	0.018391	0.044439	0.028036	0.014732	-0.027189
ROA_D	-0.010590	-0.000708	-0.022049	0.005655	-0.036503
GPM_D	-0.007023	-0.008892	0.056626	-0.051470	-0.014981
Payout_D	0.023749	-0.012205	-0.004335	0.018829	0.017706
EBIT_D	0.022629	-0.020601	-0.011408	0.017642	-0.004643
ROE_D	0.021332	-0.021781	-0.020307	0.009141	-0.028299
IBD_D	0.038484	-0.024463	0.022398	0.022204	-0.040272
Ops_D	0.048979	-0.025359	0.015439	-0.030788	0.031046

In [59]:

```
corr_dnp_mat_sort.T
```

Out[59]:

	P	BV_D	DPS_D	EPS_D	NPM_D	ROA_D	GPM_D	Payout_D	
corr_dnp_2013	1.0	0.567832	-0.015303	0.160505	0.018391	-0.010590	-0.007023	0.023749	
corr_dnp_2014	1.0	0.664851	0.201041	0.143639	0.044439	-0.000708	-0.008892	-0.012205	-
corr_dnp_2015	1.0	0.662971	0.245843	0.001492	0.028036	-0.022049	0.056626	-0.004335	-
corr_dnp_2016	1.0	0.519204	0.039062	0.372671	0.014732	0.005655	-0.051470	0.018829	
corr_dnp_2017	1.0	0.663381	0.093670	-0.304225	-0.027189	-0.036503	-0.014981	0.017706	-

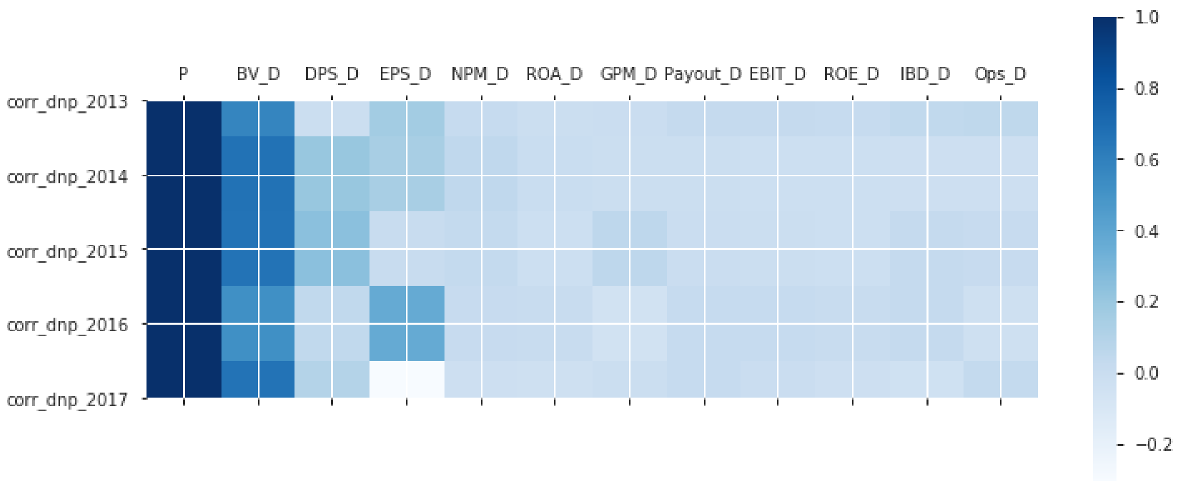
diff ratio vs price

In [60]:

```
plt.figure(figsize=(12,5))
plt.matshow(corr_dnp_mat_sort.T,fignum=1,cmap='Blues')
plt.xticks(np.arange(12), corr_dnp_mat_sort.T.columns,rotation=0)
plt.yticks(np.arange(5), corr_dnp_mat_sort.T.index,rotation=0)
plt.colorbar()
```

Out[60]:

<matplotlib.colorbar.Colorbar at 0x7f18b1d281d0>



Industry group

In [61]:

```
df.head()
```

Out[61]:

_201701	P_201801	EPS_2012	...	CAGR_NPM	CAGR_IRD	CAGR_ROE	CAGR_ROA	CAGR_DPS
2.78	1.7	-0.15	...	6.267906	NaN	-5.872124	-1.052619	NaN
393.00	470.0	38.90	...	-1.434567	NaN	-11.896327	-9.105290	1.508768
5.90	5.5	0.57	...	-11.877138	20.262051	-12.538095	-14.011722	-12.944944
23.60	23.7	0.32	...	10.530804	-33.946925	9.544604	15.715264	48.123240
2.84	2.3	0.02	...	-262.712989	NaN	-242.192095	-238.517403	NaN

In [370]:

```
df_set = df[df['sector_code']!=13]
```

In [63]:

```
df_mai = df[df['sector_code']==13]
```

In [64]:

```
df_fin = df[df['sector_code']==3]
```

In [65]:

```
df_tech = df[df['sector_code']==12]
```

In [66]:

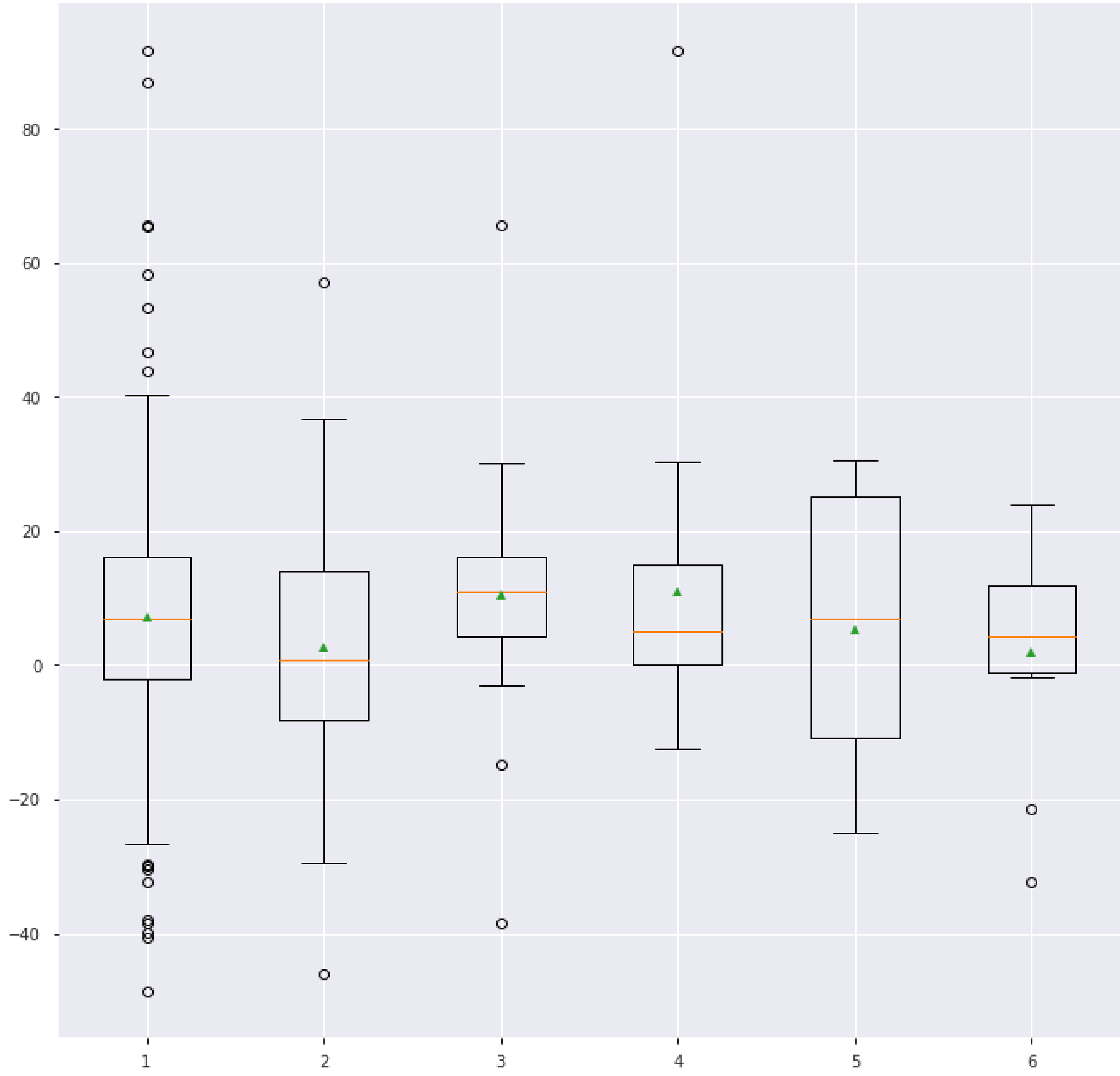
```
df_service_other = df[df['sector_code']==10]
```

In [174]:

```
df_service_commerce = df[df['sector_code']==5]
```

In [68]:

```
fig = plt.figure(1, figsize=(12, 12))
ax = fig.add_subplot()
bp = ax.boxplot([
        df_set['CAGR_P'],
        df_mai['CAGR_P'],
        df_fin['CAGR_P'],
        df_tech['CAGR_P'],
        df_service_other['CAGR_P'],
        df_service_commerce['CAGR_P']
    ],
    showmeans=True)
```



In [69]:

```
df_sector = pd.read_csv('./export_value_by_sactor.csv')
```

In [70]:

```
df_sector
```

Out[70]:

	sector_name	sector_code	2012	2013	2014	2015	
0	Business	10.0	4.112330e+03	4.872300e+03	4101.58000	4612.0100	
1	Charges for the use of intellectual property n...	10.0	3.714550e+03	4.655390e+03	4027.54000	4206.1600	
2	Commercial services	1.0	1.896750e+05	2.109916e+05	200232.82370	207206.0503	2
3	Commercial services (Services excl. government...	1.0	1.021608e+05	1.135886e+05	NaN	NaN	
4	Communications services	12.0	9.159850e+02	1.014124e+03	NaN	NaN	
5	Computer and information services	12.0	7.238700e+01	1.043130e+02	NaN	NaN	
6	Computer services	12.0	9.278200e+01	1.417180e+02	NaN	NaN	
7	Construction	4.0	1.329058e+03	3.051577e+03	1375.42000	1383.0200	
8	Construction abroad	4.0	4.405000e+02	8.171800e+02	612.83000	533.0300	
9	Construction in the reporting economy	4.0	2.240700e+02	7.092300e+02	762.59000	849.9900	
10	Education-related	7.0	1.985544e+03	1.835361e+03	1964.70300	2005.8250	
11	Financial services	3.0	2.105484e+03	2.292054e+03	1243.12000	1270.5200	
12	Freight (All modes of transport)	9.0	2.084079e+04	2.058463e+04	18247.97000	14826.9300	
13	Health-related	6.0	3.991380e+02	4.109230e+02	414.18400	476.9000	
14	Insurance and pension services	2.0	2.502090e+03	2.266240e+03	1899.69000	1629.7800	
15	Insurance services	2.0	3.456392e+03	3.225564e+03	NaN	NaN	
16	Memo item: Government goods and services n.i.e.	10.0	1.112320e+03	1.366840e+03	1333.08000	1348.1600	
17	Memo item: Government services n.i.e.	10.0	5.559190e+02	6.830750e+02	NaN	NaN	
18	Memo item: Other services	10.0	8.316675e+04	9.179696e+04	61014.80000	60461.7400	
19	Memo item: Total services	10.0	2.935040e+05	3.266301e+05	201565.90370	208554.2103	2
20	Other (All modes of transport- other than Post...	9.0	1.084010e+03	1.192200e+03	1158.11000	1153.0300	
21	Other (All modes of transport)	9.0	1.084010e+03	1.192200e+03	1158.11000	1153.0300	
22	Other (Personal)	10.0	3.360580e+04	4.114237e+04	39007.91000	45545.7800	
23	Other business services	10.0	3.530077e+04	3.725268e+04	20007.44000	19872.0000	

	sector_name	sector_code	2012	2013	2014	2015	
24	Other commercial services	11.0	5.410296e+04	5.948628e+04	59681.72000	59113.5800	
25	Other commercial services (Commercial services...	8.0	2.739555e+04	3.026076e+04	NaN	NaN	
26	Other personal, cultural, and recreational ser...	10.0	1.058770e+02	9.765800e+01	80.40500	87.4260	
27	Passenger (All modes of transport)	9.0	5.758430e+03	5.714830e+03	5381.09000	5425.7600	
28	Personal	10.0	3.599066e+04	4.338865e+04	41386.79700	48028.5050	
29	Personal, cultural and recreational services	8.0	1.057359e+02	9.753480e+01	NaN	NaN	
30	Personal, cultural, and recreational services	8.0	1.058800e+02	9.766000e+01	80.41000	87.4100	
31	Royalties and license fees	10.0	3.850446e+03	4.808572e+03	NaN	NaN	
32	Technical, trade-related, and other business s...	5.0	1.773103e+04	1.852366e+04	20007.44000	19872.0000	
33	Telecommunication services	12.0	9.159850e+02	1.014124e+03	NaN	NaN	
34	Telecommunications services	12.0	9.158500e+02	1.033751e+03	1038.76100	950.6120	
35	Telecommunications, computer, and information ...	12.0	9.882400e+02	1.138260e+03	1207.24000	1107.9000	
36	Transport	9.0	5.536644e+04	5.498332e+04	49574.35000	42811.4400	
37	Transportation	9.0	3.471971e+04	3.459626e+04	NaN	NaN	
38	Travel	8.0	1.202514e+05	1.452535e+05	90976.75366	105281.0303	1
39	Grand Total	NaN	1.141745e+06	1.272312e+06	829542.77100	859853.8289	9

In [186]:

```python
df_sector[df_sector['sector_code']==5]
```

Out[186]:

	sector_name	sector_code	2012	2013	2014	2015	2016	2017	
32	Technical, trade-related, and other business s...	5.0	17731.03	18523.66	20007.44	19872.0	22965.72	20694.51	2516

In [71]:

```python
df_fin_value = df_sector[df_sector['sector_code']==3][['2012', '2013', '2014', '201
```

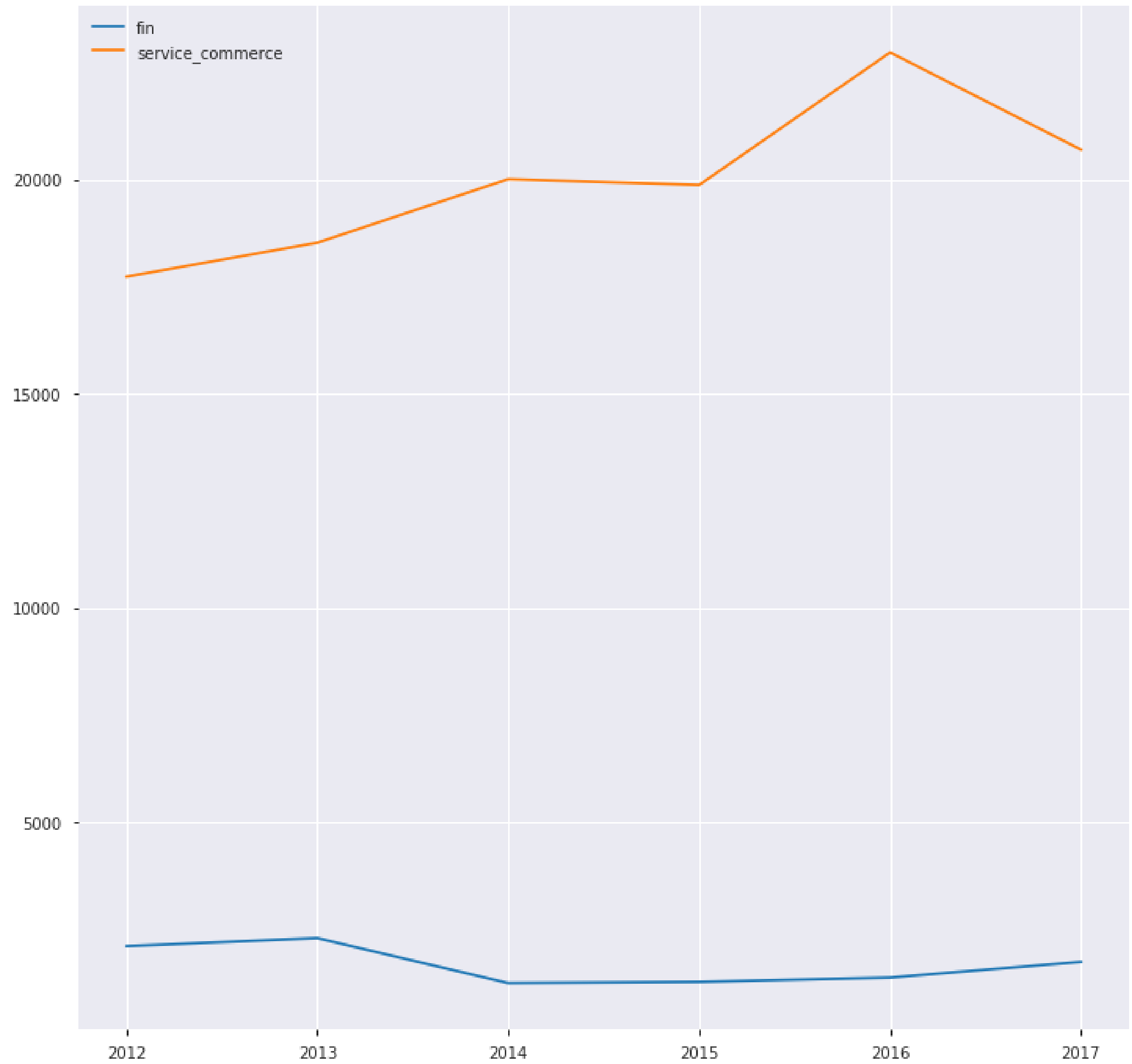
In [175]:

```
df_service_commerce = df_sector[df_sector['sector_code']==5][['2012', '2013', '2014
```

In [176]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], df_fin_value.values[0].to
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], df_service_commerce.value
plt.suptitle('Categorical Plotting')
plt.legend()
plt.show()
```

Categorical Plotting



In [152]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

In [153]:

```
df_fin_value.T
```

Out[153]:

	11
2012	2105.484
2013	2292.054
2014	1243.120
2015	1270.520
2016	1371.800
2017	1737.780

In [197]:

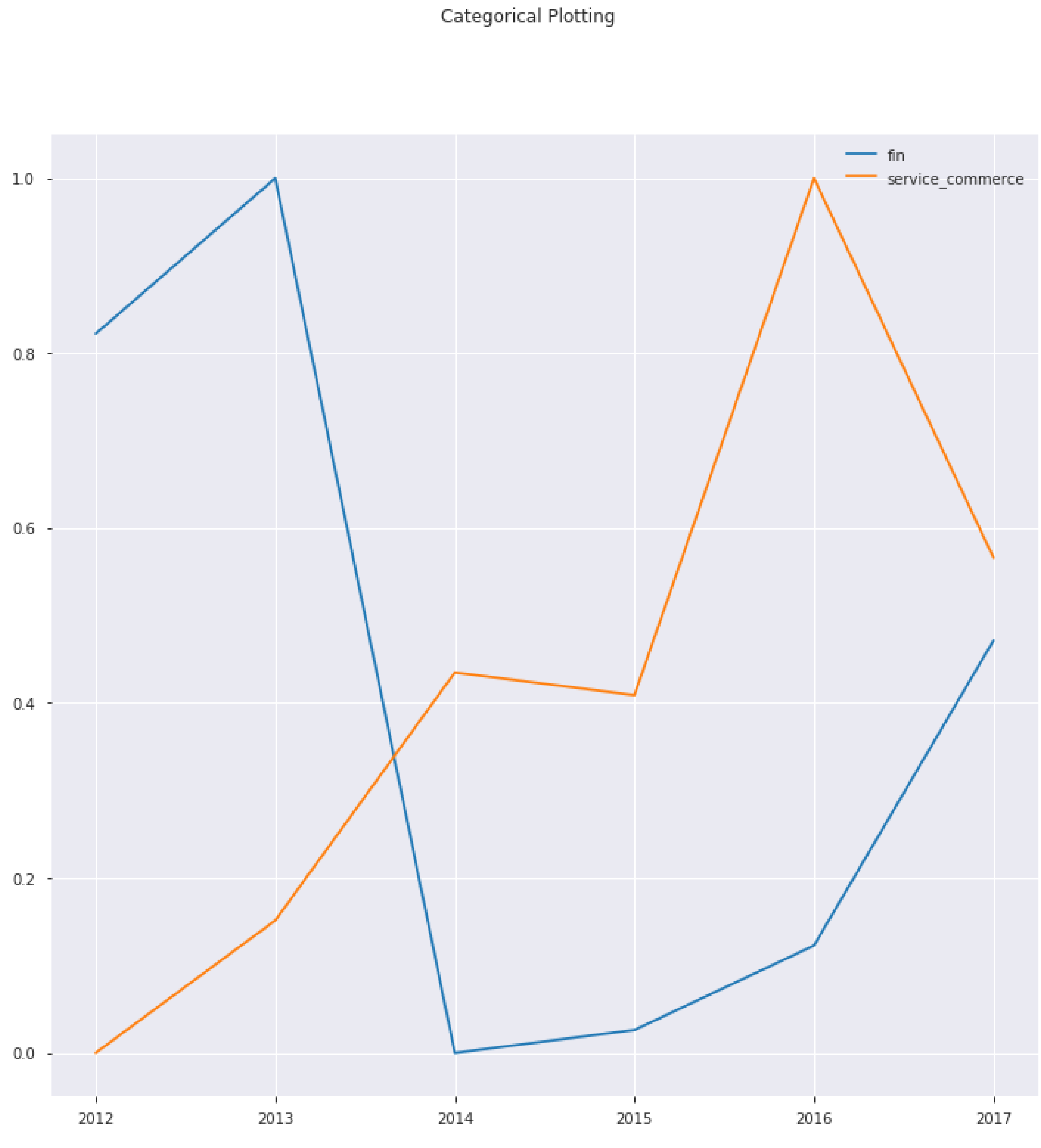
```
norm_df_fin = scaler.fit_transform(df_fin_value.T[[11]]).T
```

In [198]:

```
norm_df_service_commerce = scaler.fit_transform(df_service_commerce.T[[32]]).T
```

In [199]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], norm_df_fin.tolist()[0],
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], norm_df_service_commerce.
plt.suptitle('Categorical Plotting')
plt.legend()
plt.show()
```



Fin sector

In [327]:

```
# normalize
fin_companies = df[df['sector_code']==3][
    ['NAME', 'P_201201', 'P_201301', 'P_201401', 'P_201501', 'P_201601', 'P_201701']
]
tmp_df = fin_companies.copy().T
tmp_df.columns = a.iloc[0]
tmp_df = tmp_df.iloc[1:]
raster_arr_df = scaler.fit_transform(tmp_df)
norm_fin_companies = pd.DataFrame(data=raster_arr_df, index=tmp_df.index, columns=tr
norm_fin_companies
```

Out[327]:

	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
NAME						
AEONTS	0.000000	0.822430	0.775701	1.000000	0.859813	0.950156
ASK	0.000000	0.723577	0.414634	0.634146	0.707317	1.000000
ASP	0.000000	0.252336	0.542056	1.000000	0.663551	0.766355
BAY	0.000000	0.547619	0.392857	1.000000	0.369048	0.880952
BBL	0.032609	1.000000	0.347826	0.869565	0.000000	0.282609
CIMBT	1.000000	0.796791	0.422460	0.449198	0.000000	0.139037
CNS	0.891413	1.000000	0.000000	0.026395	0.027731	0.031073
ECL	0.000000	0.200935	0.158879	1.000000	0.500000	0.425234
FSS	0.000000	0.209524	1.000000	0.476190	0.342857	0.342857
GBX	0.000000	0.095238	1.000000	0.595238	0.071429	0.238095
GL	0.279444	1.000000	0.000000	0.010241	0.200439	0.839064
IFS	0.000000	0.814815	0.777778	0.975309	0.790123	1.000000
KBANK	0.000000	0.760000	0.255000	1.000000	0.275000	0.620000
KCAR	0.000000	1.000000	0.135135	0.243243	0.000000	0.418919
KGI	0.000000	0.172043	0.344086	0.774194	0.720430	1.000000
KKP	0.000000	0.657407	0.129630	0.259259	0.138889	1.000000
KTB	0.000000	0.676056	0.070423	1.000000	0.140845	0.422535
KTC	0.000000	0.169937	0.120879	0.415228	0.658556	1.000000
MBKET	0.035714	0.000000	0.690476	1.000000	0.940476	0.928571
ML	0.000000	0.285714	0.051948	1.000000	0.344156	0.766234
PE	0.000000	0.683673	0.306122	1.000000	0.438776	0.408163
PL	0.409091	1.000000	0.556818	0.181818	0.000000	0.068182
SCB	0.000000	1.000000	0.242857	0.921429	0.042857	0.592857
TCAP	0.000000	0.635135	0.243243	0.297297	0.513514	1.000000
THANI	0.000000	0.635659	0.764858	0.475452	0.408269	1.000000
TISCO	0.061947	0.530973	0.000000	0.230088	0.176991	1.000000

NAME	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
TK	0.143750	1.000000	0.000000	0.050000	0.162500	0.300000
TMB	0.000000	0.241667	0.266667	1.000000	0.600000	0.450000
ZMICO	0.000000	0.583333	0.333333	1.000000	0.083333	0.777778

In [338]:

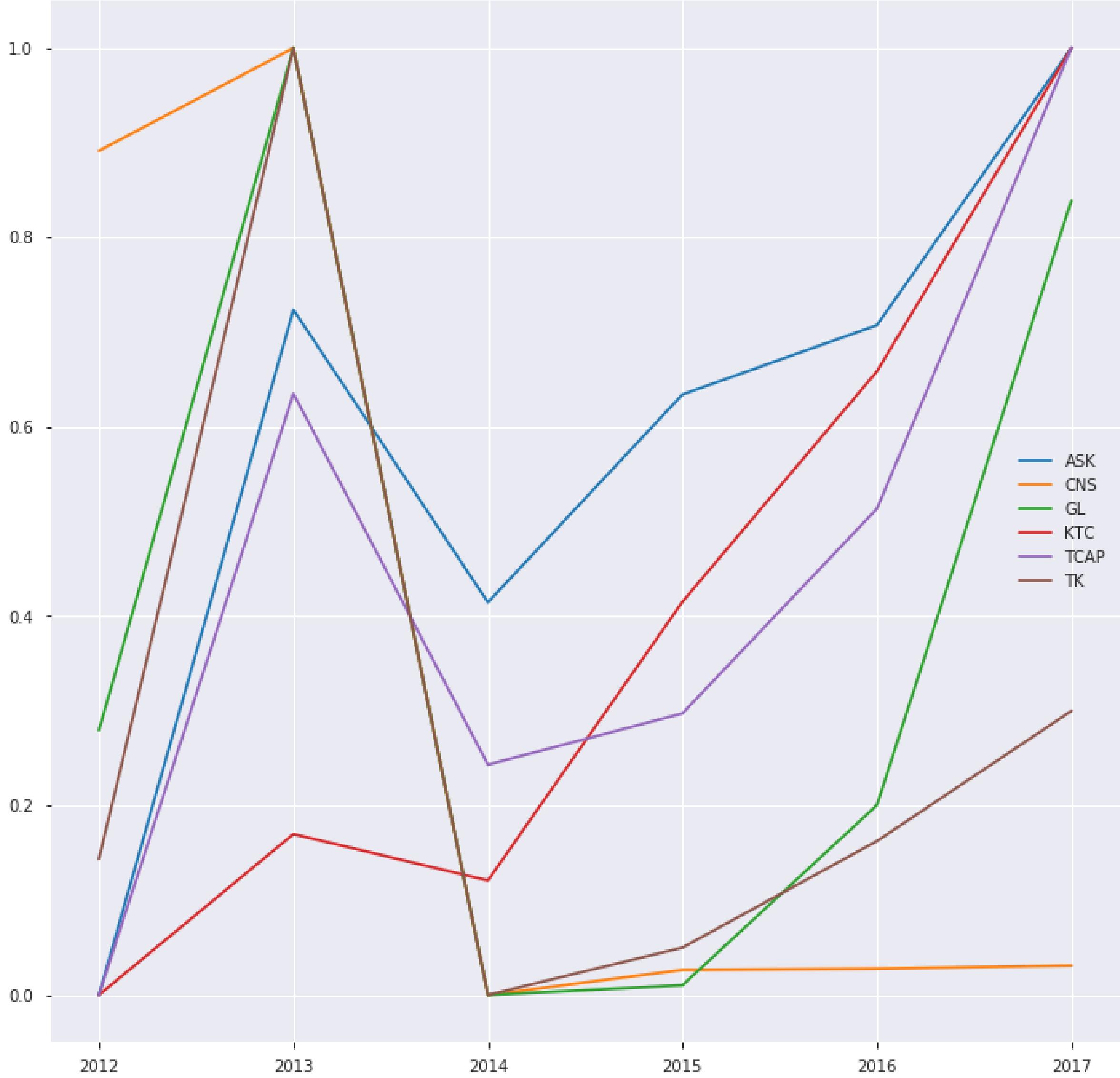
```
norm_fin_companies.values[0].tolist()
```

Out[338]:

```
[0.0,
 0.8224299065420562,
 0.7757009345794392,
 1.0,
 0.8598130841121496,
 0.9501557632398754]
```

In [342]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(norm_fin_companies.shape[0]):
    company = norm_fin_companies.values[i].tolist()
    if company[5] > company[4] and company[4] > company[3]:
        plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], company, label=no
plt.legend()
plt.show()
```



In [251]:

```
fin_companies
```

Out[251]:

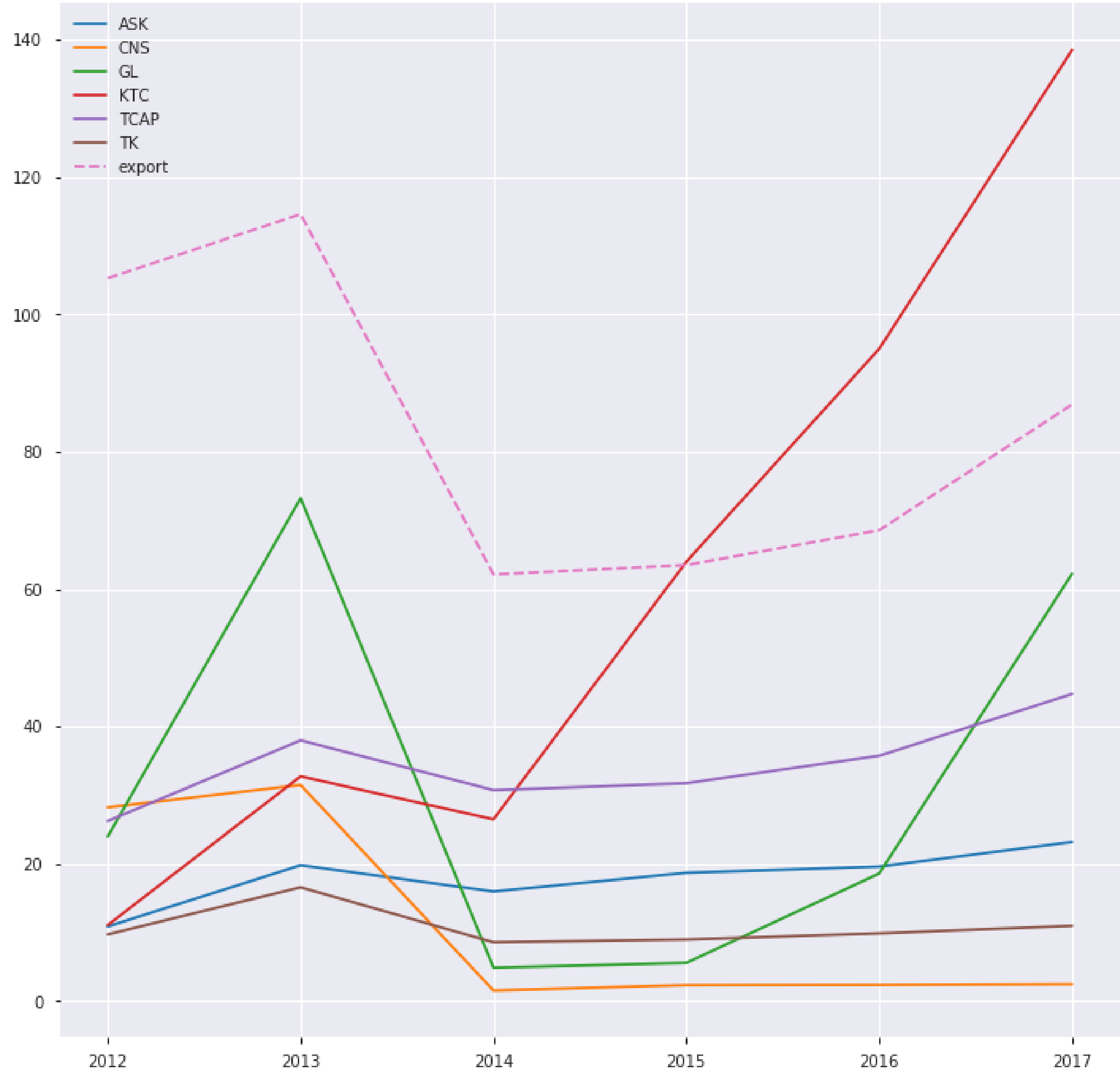
	NAME	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
13	AEONTS	27.75	93.75	90.00	108.00	96.75	104.00
14	ASK	10.90	19.80	16.00	18.70	19.60	23.20
15	ASP	2.02	2.56	3.18	4.16	3.44	3.66
16	BAY	21.50	33.00	29.75	42.50	29.25	40.00
17	BBL	151.50	196.00	166.00	190.00	150.00	163.00
18	CIMBT	2.92	2.54	1.84	1.89	1.05	1.31
19	CNS	28.25	31.50	1.57	2.36	2.40	2.50
20	ECL	0.70	1.13	1.04	2.84	1.77	1.61
21	FSS	2.20	2.64	4.30	3.20	2.92	2.92
22	GBX	0.70	0.74	1.12	0.95	0.73	0.80
23	GL	24.00	73.25	4.90	5.60	18.60	62.25
24	IFS	1.28	2.60	2.54	2.86	2.56	2.90
25	KBANK	120.00	196.00	145.50	220.00	147.50	182.00
26	KCAR	9.00	16.40	10.00	10.80	9.00	12.10
27	KGI	2.06	2.38	2.70	3.50	3.40	3.92
28	KKP	31.50	49.25	35.00	38.50	35.25	58.50
29	KTB	15.00	19.80	15.50	22.10	16.00	18.00
30	KTC	11.10	32.75	26.50	64.00	95.00	138.50
31	MBKET	14.90	14.60	20.40	23.00	22.50	22.40
32	ML	0.84	1.28	0.92	2.38	1.37	2.02
33	PE	0.47	1.14	0.77	1.45	0.90	0.87
34	PL	4.36	5.40	4.62	3.96	3.64	3.76
35	SCB	114.50	184.50	131.50	179.00	117.50	156.00
36	TCAP	26.25	38.00	30.75	31.75	35.75	44.75
37	THANI	1.48	3.94	4.44	3.32	3.06	5.35
38	TISCO	38.50	51.75	36.75	43.25	41.75	65.00
39	TK	9.75	16.60	8.60	9.00	9.90	11.00
40	TMB	1.62	1.91	1.94	2.82	2.34	2.16
41	ZMICO	1.18	1.39	1.30	1.54	1.21	1.46

In [741]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(fin_companies.shape[0]):
    company = fin_companies.values[i].tolist()
    if company[5] > company[4] and company[4] > company[3]:
        plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], company[1:], labe


fin_sector = df_sector[df_sector['sector_code']==3][['2012', '2013', '2014', '2015',
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], fin_sector/20, label='exp

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



In [76]:

```
fin_companies
```

Out[76]:

	NAME	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
13	AEONTS	27.75	93.75	90.00	108.00	96.75	104.00
14	ASK	10.90	19.80	16.00	18.70	19.60	23.20
15	ASP	2.02	2.56	3.18	4.16	3.44	3.66
16	BAY	21.50	33.00	29.75	42.50	29.25	40.00
17	BBL	151.50	196.00	166.00	190.00	150.00	163.00
18	CIMBT	2.92	2.54	1.84	1.89	1.05	1.31
19	CNS	28.25	31.50	1.57	2.36	2.40	2.50
20	ECL	0.70	1.13	1.04	2.84	1.77	1.61
21	FSS	2.20	2.64	4.30	3.20	2.92	2.92
22	GBX	0.70	0.74	1.12	0.95	0.73	0.80
23	GL	24.00	73.25	4.90	5.60	18.60	62.25
24	IFS	1.28	2.60	2.54	2.86	2.56	2.90
25	KBANK	120.00	196.00	145.50	220.00	147.50	182.00
26	KCAR	9.00	16.40	10.00	10.80	9.00	12.10
27	KGI	2.06	2.38	2.70	3.50	3.40	3.92
28	KKP	31.50	49.25	35.00	38.50	35.25	58.50
29	KTB	15.00	19.80	15.50	22.10	16.00	18.00
30	KTC	11.10	32.75	26.50	64.00	95.00	138.50
31	MBKET	14.90	14.60	20.40	23.00	22.50	22.40
32	ML	0.84	1.28	0.92	2.38	1.37	2.02
33	PE	0.47	1.14	0.77	1.45	0.90	0.87
34	PL	4.36	5.40	4.62	3.96	3.64	3.76
35	SCB	114.50	184.50	131.50	179.00	117.50	156.00
36	TCAP	26.25	38.00	30.75	31.75	35.75	44.75
37	THANI	1.48	3.94	4.44	3.32	3.06	5.35
38	TISCO	38.50	51.75	36.75	43.25	41.75	65.00
39	TK	9.75	16.60	8.60	9.00	9.90	11.00
40	TMB	1.62	1.91	1.94	2.82	2.34	2.16
41	ZMICO	1.18	1.39	1.30	1.54	1.21	1.46

service_commerce sector

In [77]:

```
service_commerce_companies = df[df['sector_code']==5][['NAME', 'P_201201', 'P_20130
```

In [749]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(service_commerce_companies.shape[0]):
    company = service_commerce_companies.values[i].tolist()
    if company[0] != 'MAKRO' and company[6] > company[5] and company[6] > company[1
        plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], company[1:], labe

service_commerce_sector = df_sector[df_sector['sector_code']==5][['2012', '2013', '2
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], service_commerce_sector/2

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

In [351]:

```
service_commerce_companies
```

Out[351]:

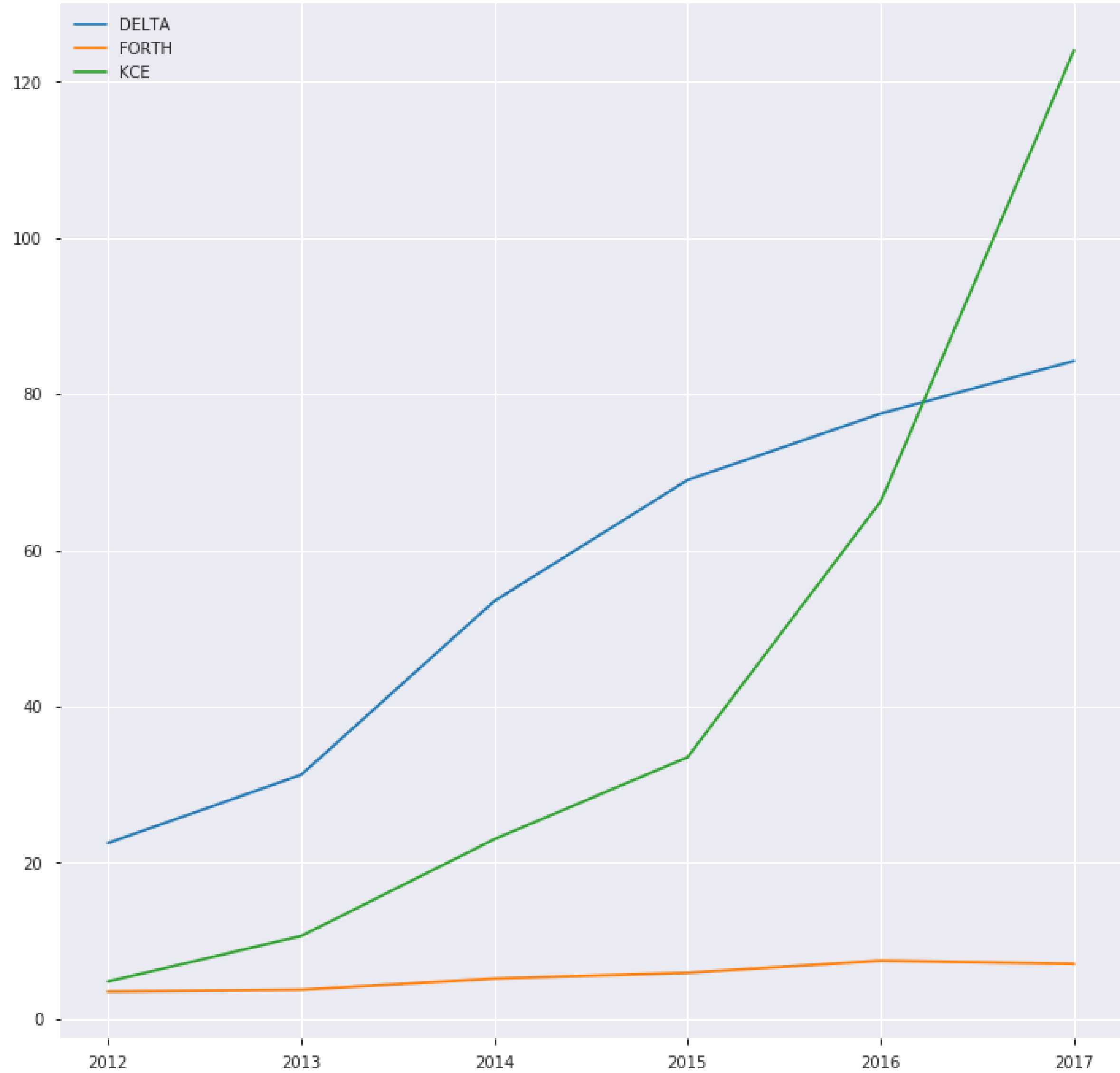
	NAME	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
104	BJC	30.25	61.00	46.50	40.75	33.50	49.50
105	CPALL	52.25	45.75	40.00	42.50	39.00	65.00
106	GLOBAL	9.05	18.10	14.60	10.40	8.95	17.90
107	HMPRO	11.10	12.80	8.55	8.05	6.90	10.10
108	IT	10.30	4.98	2.62	2.72	2.28	3.08
109	KAMART	4.36	7.00	4.70	6.00	6.60	12.80
110	LOXLEY	3.20	5.20	3.30	4.20	2.34	3.16
111	MAKRO	246.00	446.00	28.75	36.50	35.50	35.00
112	MIDA	0.70	1.44	1.35	1.40	0.90	0.81
113	ROBINS	42.25	67.00	45.00	44.50	42.25	65.00
114	SINGER	5.80	18.20	17.30	12.60	8.65	11.00

In [80]:

```
tech_companies = df[df['sector_code']==12][['NAME', 'P_201201', 'P_201301', 'P_2014(
```

In [364]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(tech_companies.shape[0]):
    company = tech_companies.values[i].tolist()
    if company[5] > company[4] and company[4] > company[3] and company[6] > company[
        plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], company[1:], labe
plt.legend()
plt.show()
```



In [82]:

```
tech_companies
```

Out[82]:

	NAME	P_201201	P_201301	P_201401	P_201501	P_201601	P_201701
147	ADVANC	146.50	209.00	187.00	249.00	143.00	149.50
148	AIT	48.00	58.75	23.00	37.50	26.75	24.60
149	CCET	2.58	3.22	2.80	2.78	3.28	2.80
150	DELTA	22.50	31.25	53.50	69.00	77.50	84.25
151	DTAC	67.50	87.50	93.00	95.50	28.25	40.75
152	FORTH	3.50	3.72	5.15	5.90	7.45	7.05
153	HANA	19.40	22.80	25.25	37.75	34.50	39.50
154	INTUCH	42.75	69.50	64.00	78.00	49.50	50.75
155	JAS	2.08	5.50	6.20	7.35	3.06	7.85
156	JMART	6.00	14.00	19.10	10.20	7.25	14.30
157	JTS	1.33	2.20	1.35	1.58	1.23	2.10
158	KCE	4.78	10.60	23.00	33.50	66.25	124.00
159	MFEC	4.58	6.00	5.95	8.05	4.88	5.35
160	PT	3.16	6.40	6.70	13.20	8.70	11.60
161	SAMART	7.25	12.60	14.00	38.00	14.90	12.70
162	SAMTEL	11.30	19.30	12.10	23.60	14.20	10.00
163	SMT	8.80	11.10	7.25	6.65	9.20	7.30
164	SVI	3.24	4.10	4.00	4.00	4.82	5.35
165	SVOA	1.19	1.15	1.09	1.70	1.44	1.39
166	SYMC	10.00	22.90	13.00	13.80	8.95	8.25
167	SYNEX	5.25	5.70	3.02	2.82	4.34	7.20
168	TEAM	1.52	1.74	1.15	3.34	1.20	1.49
169	THCOM	10.40	25.25	38.00	35.75	27.25	19.50
170	TWZ	0.28	0.41	0.30	0.50	0.23	0.29

Fin comp

-

In [583]:

```
fin_companies[['P_201701']]
```

Out[583]:

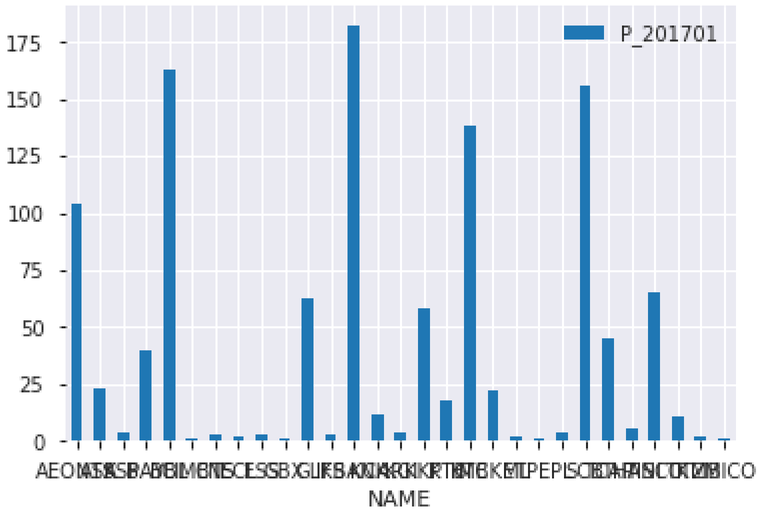
	P_201701
13	104.00
14	23.20
15	3.66
16	40.00
17	163.00
18	1.31
19	2.50
20	1.61
21	2.92
22	0.80
23	62.25
24	2.90
25	182.00
26	12.10
27	3.92
28	58.50
29	18.00
30	138.50
31	22.40
32	2.02
33	0.87
34	3.76
35	156.00
36	44.75
37	5.35
38	65.00
39	11.00
40	2.16
41	1.46

In [587]:

```
fin_companies.plot.bar(x='NAME', y='P_201701', rot=0)
```

Out[587]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f18aaa9b850>
```

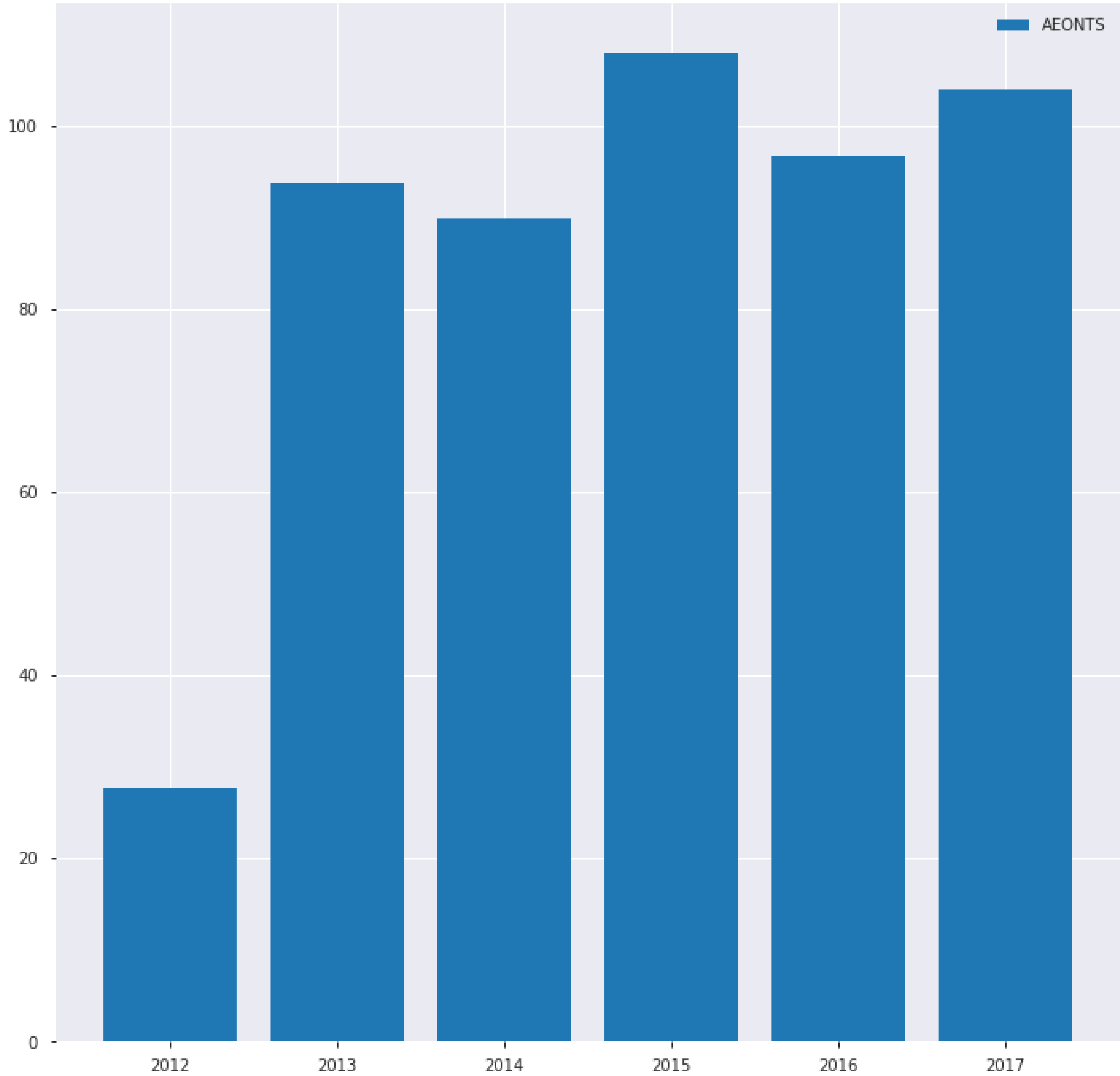


In [ ]:

```
company
```

In [593]:

```
plt.figure(figsize=(12, 12))
company = fin_companies.values[0].tolist()
plt.bar(['2012', '2013', '2014', '2015', '2016', '2017'], company[1:], label=company
plt.legend()
plt.show()
```



KTC

In [450]:

```
code = 'KTC'
ktc = pd.DataFrame({
    'NAME': ['P', 'BV', 'EPS', 'DPS'],
    '2012': df[df['NAME']==code][['P_201201', 'BV_2012', 'EPS_2012', 'DPS_2012']].va
    '2013': df[df['NAME']==code][['P_201301', 'BV_2013', 'EPS_2013', 'DPS_2013']].va
    '2014': df[df['NAME']==code][['P_201401', 'BV_2014', 'EPS_2014', 'DPS_2014']].va
    '2015': df[df['NAME']==code][['P_201501', 'BV_2015', 'EPS_2015', 'DPS_2015']].va
    '2016': df[df['NAME']==code][['P_201601', 'BV_2016', 'EPS_2016', 'DPS_2016']].va
    '2017': df[df['NAME']==code][['P_201701', 'BV_2017', 'EPS_2017', 'DPS_2017']].va
    '2018': [df[df['NAME']==code][['P_201801']].values[0][0], np.nan, np.nan, np.nan
})
ktc
```

Out[450]:

	NAME	2012	2013	2014	2015	2016	2017	2018
0	P	11.10	32.75	26.50	64.00	95.00	138.50	184.5
1	BV	20.13	23.77	28.58	33.87	40.03	48.78	NaN
2	EPS	0.99	4.97	6.81	8.04	9.68	12.82	NaN
3	DPS	0.40	2.00	2.75	3.25	4.00	5.30	NaN

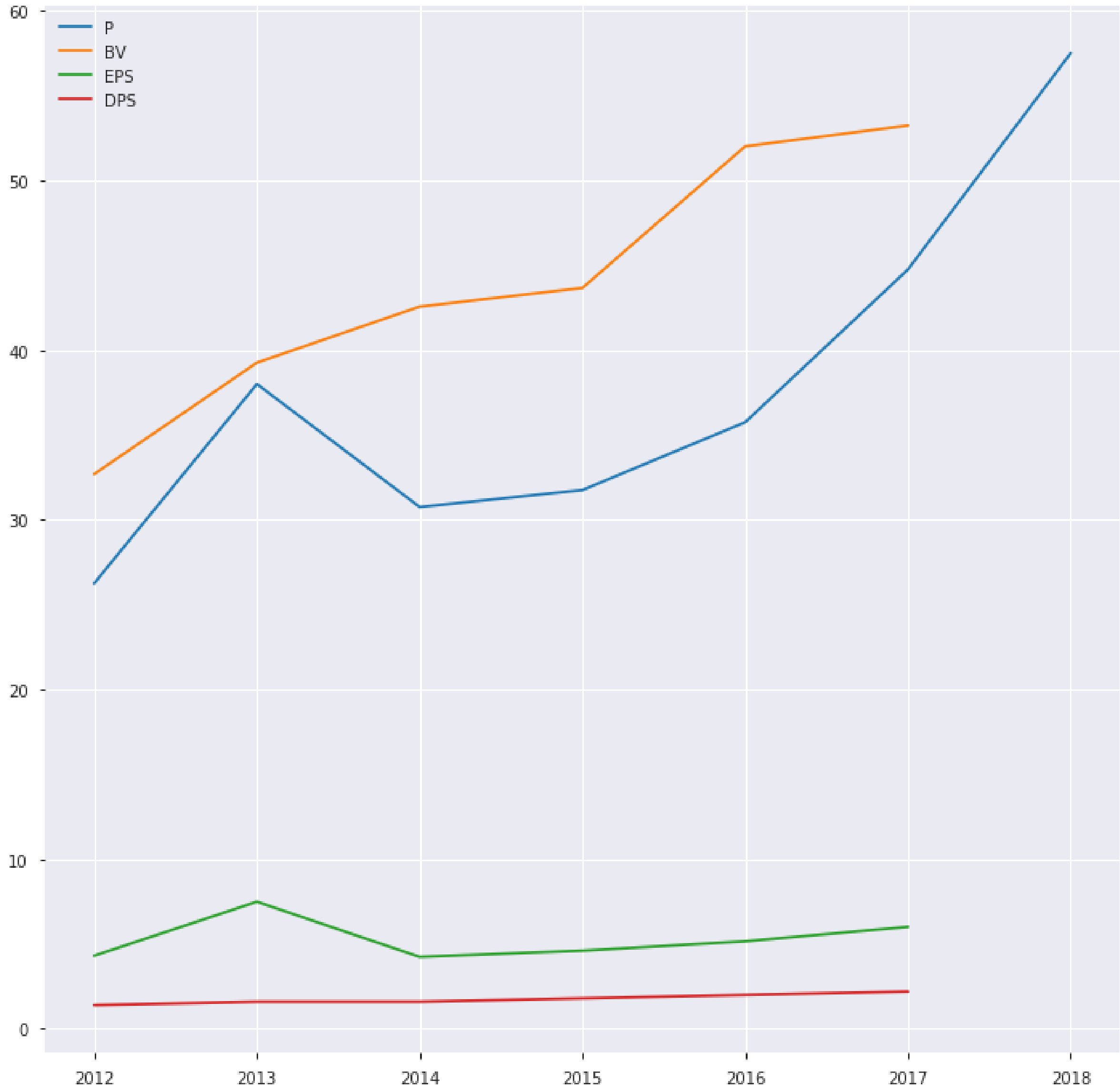
In [451]:

```
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(ktc.shape[0]):
    ratio = ktc.values[i].tolist()
    plt.plot(['2012', '2013', '2014', '2015', '2016', '2017', '2018'], ratio[1:], la
plt.legend()
plt.show()
```

GL

In [456]:

```
code = 'TCAP'
stock = pd.DataFrame({
    'NAME': ['P', 'BV', 'EPS', 'DPS'],
    '2012': df[df['NAME']==code][['P_201201', 'BV_2012', 'EPS_2012', 'DPS_2012']].va
    '2013': df[df['NAME']==code][['P_201301', 'BV_2013', 'EPS_2013', 'DPS_2013']].va
    '2014': df[df['NAME']==code][['P_201401', 'BV_2014', 'EPS_2014', 'DPS_2014']].va
    '2015': df[df['NAME']==code][['P_201501', 'BV_2015', 'EPS_2015', 'DPS_2015']].va
    '2016': df[df['NAME']==code][['P_201601', 'BV_2016', 'EPS_2016', 'DPS_2016']].va
    '2017': df[df['NAME']==code][['P_201701', 'BV_2017', 'EPS_2017', 'DPS_2017']].va
    '2018': [df[df['NAME']==code][['P_201801']].values[0][0], np.nan, np.nan, np.nan
})
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(stock.shape[0]):
    ratio = stock.values[i].tolist()
    plt.plot(['2012', '2013', '2014', '2015', '2016', '2017', '2018'], ratio[1:], la
plt.legend()
plt.show()
```



In [460]:

```
code = 'CPALL'
stock = pd.DataFrame({
    'NAME': ['P', 'BV', 'EPS', 'DPS'],
    '2012': df[df['NAME']==code][['P_201201', 'BV_2012', 'EPS_2012', 'DPS_2012']].va
    '2013': df[df['NAME']==code][['P_201301', 'BV_2013', 'EPS_2013', 'DPS_2013']].va
    '2014': df[df['NAME']==code][['P_201401', 'BV_2014', 'EPS_2014', 'DPS_2014']].va
    '2015': df[df['NAME']==code][['P_201501', 'BV_2015', 'EPS_2015', 'DPS_2015']].va
    '2016': df[df['NAME']==code][['P_201601', 'BV_2016', 'EPS_2016', 'DPS_2016']].va
    '2017': df[df['NAME']==code][['P_201701', 'BV_2017', 'EPS_2017', 'DPS_2017']].va
    '2018': [df[df['NAME']==code][['P_201801']].values[0][0], np.nan, np.nan, np.nan
})
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(stock.shape[0]):
    ratio = stock.values[i].tolist()
    plt.plot(['2012', '2013', '2014', '2015', '2016', '2017', '2018'], ratio[1:], la
plt.legend()
plt.show()
```

In [604]:

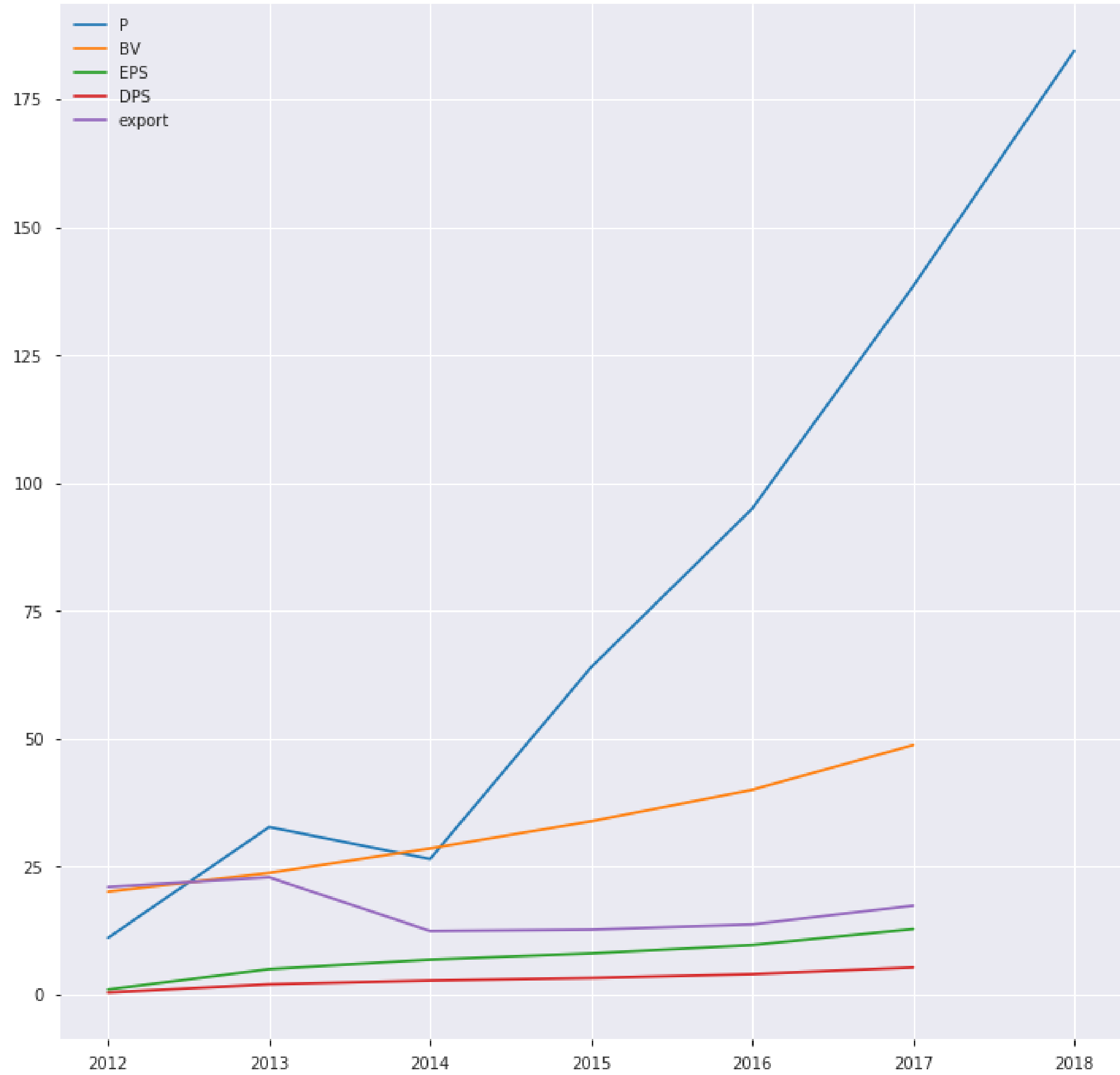
```
code = 'TK'
stock = pd.DataFrame({
    'NAME': ['P', 'BV', 'EPS', 'DPS'],
    '2012': df[df['NAME']==code][['P_201201', 'BV_2012', 'EPS_2012', 'DPS_2012']].va
    '2013': df[df['NAME']==code][['P_201301', 'BV_2013', 'EPS_2013', 'DPS_2013']].va
    '2014': df[df['NAME']==code][['P_201401', 'BV_2014', 'EPS_2014', 'DPS_2014']].va
    '2015': df[df['NAME']==code][['P_201501', 'BV_2015', 'EPS_2015', 'DPS_2015']].va
    '2016': df[df['NAME']==code][['P_201601', 'BV_2016', 'EPS_2016', 'DPS_2016']].va
    '2017': df[df['NAME']==code][['P_201701', 'BV_2017', 'EPS_2017', 'DPS_2017']].va
    '2018': [df[df['NAME']==code][['P_201801']].values[0][0], np.nan, np.nan, np.nan
})
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(stock.shape[0]):
    ratio = stock.values[i].tolist()
    plt.plot(['2012', '2013', '2014', '2015', '2016', '2017', '2018'], ratio[1:], la
plt.legend()
plt.show()
```

In [735]:

```
code = 'KTC'
stock = pd.DataFrame({
    'NAME': ['P', 'BV', 'EPS', 'DPS'],
    '2012': df[df['NAME']==code][['P_201201', 'BV_2012', 'EPS_2012', 'DPS_2012']].va
    '2013': df[df['NAME']==code][['P_201301', 'BV_2013', 'EPS_2013', 'DPS_2013']].va
    '2014': df[df['NAME']==code][['P_201401', 'BV_2014', 'EPS_2014', 'DPS_2014']].va
    '2015': df[df['NAME']==code][['P_201501', 'BV_2015', 'EPS_2015', 'DPS_2015']].va
    '2016': df[df['NAME']==code][['P_201601', 'BV_2016', 'EPS_2016', 'DPS_2016']].va
    '2017': df[df['NAME']==code][['P_201701', 'BV_2017', 'EPS_2017', 'DPS_2017']].va
    '2018': [df[df['NAME']==code][['P_201801']].values[0][0], np.nan, np.nan, np.nar
})
plt.figure(figsize=(12, 12))
plt.subplot()
for i in range(stock.shape[0]):
    ratio = stock.values[i].tolist()
    plt.plot(['2012', '2013', '2014', '2015', '2016', '2017', '2018'], ratio[1:], la


fin_sector = df_sector[df_sector['sector_code']==3][['2012', '2013', '2014', '2015',
plt.plot(['2012', '2013', '2014', '2015', '2016', '2017'], fin_sector/100, label='ex

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



In [ ]:

```

```