Stock Market Informativeness of Iranian Banks

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Data Initialization

In [1]:
```
import os
import pandas as pd
import copy
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator
import statsmodels.formula.api as smf
import math
import jdatetime
import datetime
import pickle
import warnings
import statsmodels.api as sm
warnings.filterwarnings("ignore")
```

In [2]:
```
data_address = 'D:\Masters\Term3\Banking\Project\Data\Banks'
files = os.listdir(data_address)
all_raw = {}

for file in files:
    if file.endswith('.csv'):
        address = data_address + '\\' + file
        name = file.replace('-a.csv', '').replace('.csv', '').replace(' ', '_')
        all_raw[name] = pd.read_csv(address)
```

In [3]:
```
initial_dic = copy.deepcopy(all_raw)
deleted_banks = []
print('Proportion of open Days:')
for dataframe in initial_dic:
    proportion = round(100 * np.count_nonzero(initial_dic[dataframe]['<VOL>']) / len(initial_dic[dataframe]), 1)
    print(dataframe, ': ', proportion)
    if proportion <= 70:
        deleted_banks.append(dataframe)
for bank in deleted_banks:
        del initial_dic[bank]
print(initial_dic.keys())
```

```
Proportion of open Days:
Bank_of_M.E. :  95.2
Index_Group_57 :  99.5
Karafarin_Bank :  91.2
Overall_Index :  99.8
Parsian_Bank :  82.7
Post_Bank :  82.2
S_Mellat_Bank :  85.5
S_Pasargad_Bank :  74.1
S_Tejarat_Bank :  84.2
Saderat_Bank :  79.9
Sina_Fin._Ins. :  87.2
dict_keys(['Bank_of_M.E.', 'Index_Group_57', 'Karafarin_Bank', 'Overall_Index', 'Parsian_Bank', 'Post_Bank', 'S_Mellat_Bank', 'S_
Pasargad_Bank', 'S_Tejarat_Bank', 'Saderat_Bank', 'Sina_Fin._Ins.'])
```

In [4]:
```
for bank in initial_dic:
    initial_dic[bank]['return_d'] = 0.0
    for i in range(1, len(initial_dic[bank])):
        initial_dic[bank]['return_d'][i] = 100 * (initial_dic[bank]['<CLOSE>'][i] - initial_dic[bank]['<CLOSE>'][i - 1]) / initial

overall_index = pd.DataFrame()
overall_index['date'] = pd.to_datetime(initial_dic['Overall_Index']['<DTYYYYMMDD>'], format='%Y%m%d')
overall_index['overall_close'] = initial_dic['Overall_Index']['<CLOSE>']
overall_index['overall_return_w'] = initial_dic['Overall_Index']['return_d']
overall_index['overall_value'] = initial_dic['Overall_Index']['<VALUE>']

bank_index = pd.DataFrame()
bank_index['date'] = pd.to_datetime(initial_dic['Index_Group_57']['<DTYYYYMMDD>'], format='%Y%m%d')
overall_index['industry_close'] = initial_dic['Index_Group_57']['<CLOSE>']
bank_index['industry_return_w'] = initial_dic['Index_Group_57']['return_d']
bank_index['industry_value'] = initial_dic['Index_Group_57']['<VALUE>']
```

SMI Measure No.1

Stock return non-synchronicity (Roll 1988 JF)

It equals $Ln(\frac{1-R^2}{R^2})$ where R^2 is calculated from estimating:

$$r_{i,j,t} = a_i + b_i r_{j,t} + c_i r_{m,t} + \epsilon_{i,j,t}$$

- $r_{i,j,t}$: return of firm *i* from industry *j* in week *t*.
- $r_{j,t}$: return of industry *j* in week *t* excluding firm *i*.
- $r_{m,t}$: return of market *m* in week *t* excluding firm *i*.

In [5]:
```python
results_folder_m1 = r'D:\Masters\Term3\Banking\Project\Results\Measure_1'
tables_1 = open(results_folder_m1 + '\\tables_1.txt', 'a') #regression results for each bank over all periods
tables_1_y = open(results_folder_m1 + '\\tables_1_y.txt', 'a') #regression results for each bank at each year

banks = []
measure1 = []
measures_y = {}

for bank in initial_dic:
    if bank == 'Index_Group_57' or bank == 'Overall_Index':
        continue
    banks.append(bank)
    df = pd.DataFrame()
    df['date'] = pd.to_datetime(initial_dic[bank]['<DTYYYYMMDD>'], format='%Y%m%d')
    df['close'] = initial_dic[bank]['<CLOSE>']
    df['return_w'] = np.nan
    df['vol'] = initial_dic[bank]['<VOL>']
    df['value'] = initial_dic[bank]['<VALUE>']
    df = pd.merge(df, bank_index, how='left', on="date", suffixes=('', ''))
    df = pd.merge(df, overall_index, how='left', on="date", suffixes=('', ''))
    df['overall_close_r'] = 0.0
    df['overall_return_w_r'] = 0.0
    df['industry_close_r'] = 0.0
    df['industry_return_w_r'] = 0.0
    for i in range(len(df)):
        df.loc[i, 'overall_close_r'] = \
        df.loc[i, 'overall_close'] - (df.loc[i, 'close'] * df.loc[i, 'value'] / df.loc[i, 'overall_value'])
        df.loc[i, 'industry_close_r'] = \
        df.loc[i, 'industry_close'] - (df.loc[i, 'close'] * df.loc[i, 'value'] / df.loc[i, 'industry_value'])
    df['year'] = [df.loc[ii, 'date'].year for ii in range(len(df))]
    df['date_w'] =df['date']
    df = df.set_index('date')
    df_w = df.resample("W").last()
    year_w = df_w.columns.get_loc('year')
    return_w = df_w.columns.get_loc('return_w')
    close_w = df_w.columns.get_loc('close')
    overall_return_w_r = df_w.columns.get_loc('overall_return_w_r')
    overall_close_r = df_w.columns.get_loc('overall_close_r')
    industry_return_w_r = df_w.columns.get_loc('industry_return_w_r')
    industry_close_r = df_w.columns.get_loc('industry_close_r')
    for j in range(1, len(df_w)):
        df_w.iloc[j, return_w] = (df_w.iloc[j, close_w] - df_w.iloc[j - 1, close_w]) / df_w.iloc[j - 1, close_w]
        df_w.iloc[j, overall_return_w_r] = \
        100 * (df_w.iloc[j, overall_close_r] - df_w.iloc[j - 1, overall_close_r]) / df_w.iloc[j - 1, overall_close_r]
        df_w.iloc[j, industry_return_w_r] = \
        100 * (df_w.iloc[j, industry_close_r] - df_w.iloc[j - 1, industry_close_r]) / df_w.iloc[j - 1, industry_close_r]
    df_w.to_csv(results_folder_m1 + f'\\{bank}_1st_measure.csv')
    mod = smf.ols('return_w ~ overall_return_w_r + industry_return_w_r', data=df_w)
    res = mod.fit()
    summary = res.summary()
    measure1.append(math.log((1 - res.rsquared_adj) / res.rsquared_adj))
    tables_1.write(f'Bank: {bank} \n')
    tables_1.write(f'{str(summary)} \n')
    tables_1.write(f"{'-' * 100} \n")
#     print('Bank: ', bank)
#     print(summary)
#     print('-' * 100)
#     print('\n')
    start_years = int(df_w.iloc[0, year_w])
    final_years = int(df_w.iloc[-1, year_w])
    years = []
    m1_y = []
    for y in range(start_years, final_years + 1):
        df_y = pd.DataFrame(df_w[df_w['year'] == y])
        df_y = df_y.dropna().reset_index(drop=True)
        df_y = df_y.reset_index(drop=True)
        if len(df_y) < 30:
            continue
        years.append(y)
        mod_y = smf.ols('return_w ~ overall_return_w_r + industry_return_w_r', data=df_y)
        res_y = mod_y.fit()
        summary_y = res_y.summary()
        m1_y.append(math.log((1 - res_y.rsquared) / res_y.rsquared))
        tables_1_y.write(f'Bank: {bank} \n')
        tables_1_y.write(f'year: {y} \n')
        tables_1_y.write(f'{str(summary_y)} \n')
        tables_1_y.write(f"{'-' * 100} \n")
    measures_y[bank] = pd.DataFrame(columns = ['year', '1st_measure'])
    measures_y[bank]['year'] = years
    measures_y[bank]['1st_measure'] = m1_y
tables_1.close()
tables_1_y.close()

results_list = pd.DataFrame(banks, columns = ['bank'])
results_list['1st_measure'] = measure1
```

SMI Measure No.2

Amihud illiquidity ratio (2002)

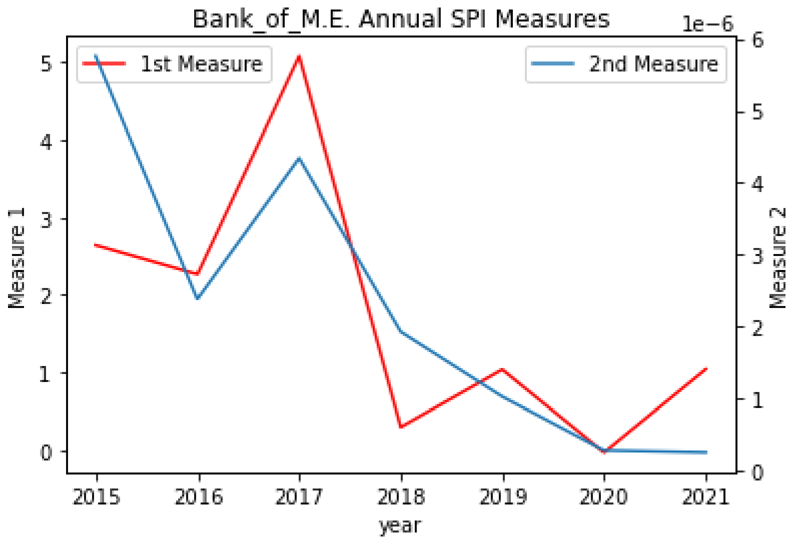
$$ILLIQi,y = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \frac{|R_{i,y,d}|}{VOLD_{i,y,d}}$$

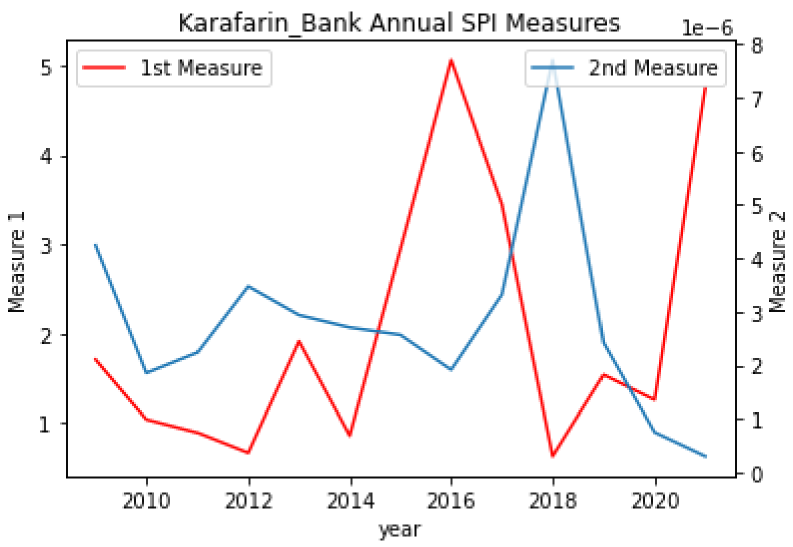
- $R_{i,y,d}$: the return of stock *i* in year *y* in day *d*.
- $VOLD_{i,y,d}$: the volume of trading (in Rials) of stock *i* in year *y* in day *d*.
- $D_{i,y}$: the number of days of available data on stock *i* in year *y*.

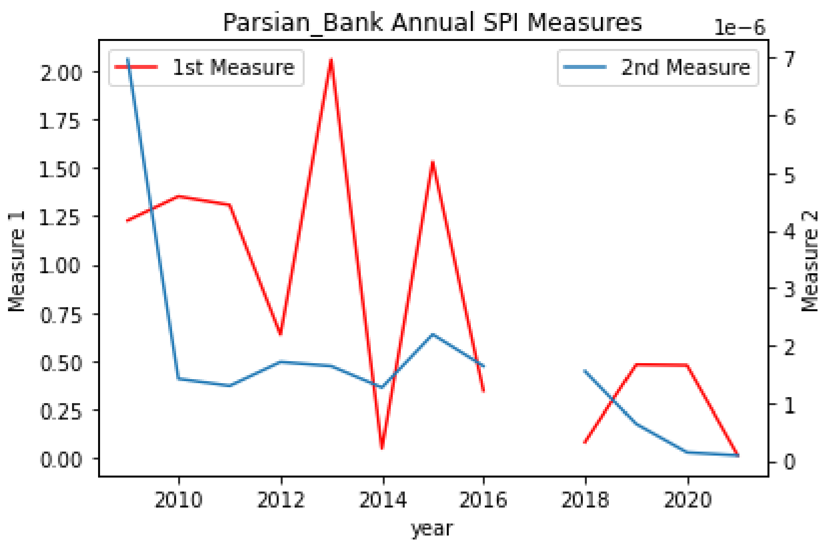
In [6]:
```
min_years = []
max_years = []

for bank in initial_dic:
    if bank == 'Index_Group_57' or bank == 'Overall_Index':
        continue
    date = pd.DataFrame()
    date['date'] = pd.to_datetime(initial_dic[bank]['<DTYYYYMMDD>'], format='%Y%m%d')
    date['year'] = pd.DatetimeIndex(date['date']).year
    min_years.append(np.min(date['year']))
    max_years.append(np.max(date['year']))
```

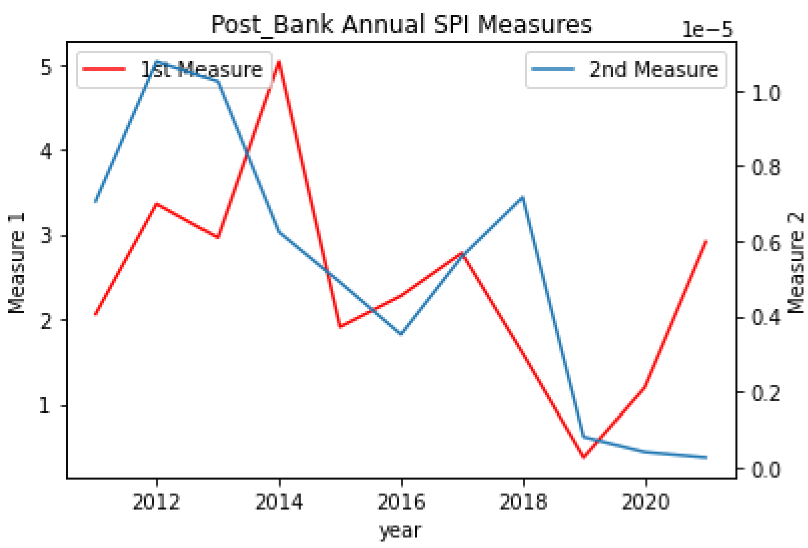
In [7]:
```
results_folder_2 = r'D:\Masters\Term3\Banking\Project\Results\Measure_2'

banks = []
measure2_df = pd.DataFrame()
measure2_df['year'] = list(range(np.min(min_years), np.max((max_years)) + 1))
measure2_df = measure2_df.set_index('year')
measure_2 = []

for bank in initial_dic:
    if bank == 'Index_Group_57' or bank == 'Overall_Index':
        continue
    measure2_df[bank] = np.nan
    banks.append(bank)
    df = pd.DataFrame()
    df['date'] = pd.to_datetime(initial_dic[bank]['<DTYYYYMMDD>'], format='%Y%m%d')
    df['close'] = initial_dic[bank]['<CLOSE>']
    df['return_d'] = initial_dic[bank]['return_d']
    df['vol'] = initial_dic[bank]['<VOL>']
    df['value'] = initial_dic[bank]['<VALUE>']
    df['year'] = pd.DatetimeIndex(df['date']).year
    df_nonzero = pd.DataFrame(df[[df.loc[i, 'value'] != 0 for i in range(len(df))]]).reset_index(drop=True)
    min_year = np.min(df_nonzero['year'])
    max_year = np.max(df_nonzero['year'])
    years = list(range(min_year, max_year + 1))
    measures_y[bank]['2nd_measure'] = np.nan
    #calculating Amihud's yearly illiquidity ratio for each bank:
    for y in years:
        df_branch = \
        pd.DataFrame(df_nonzero[[df_nonzero.loc[j, 'year'] == y for j in range(len(df_nonzero))]]).reset_index(drop=True)
        if len(df_branch) < 30:
            continue
        #illiquidity ratio for every 1000 Tomans (10k Rials):
        illiq = (1 / len(df_branch)) * np.sum(np.abs(10000 * df_branch['return_d']) / df_branch['value'])
        measure2_df.loc[y, bank] = illiq
        for yy in range(len(measures_y[bank]['year'])):
            if measures_y[bank].loc[yy, 'year'] == y:
                measures_y[bank].loc[yy, '2nd_measure'] = illiq
                break
    #calculating Amihud's total illiquidity ratio for each bank:
    illiq_t = (1 / len(df_branch)) * np.sum(np.abs(10000 * df_branch['return_d']) / df_branch['value'])
    measure_2.append(illiq_t)
results_list['2nd_measure'] = measure_2
measure2_df = measure2_df.reset_index()
```

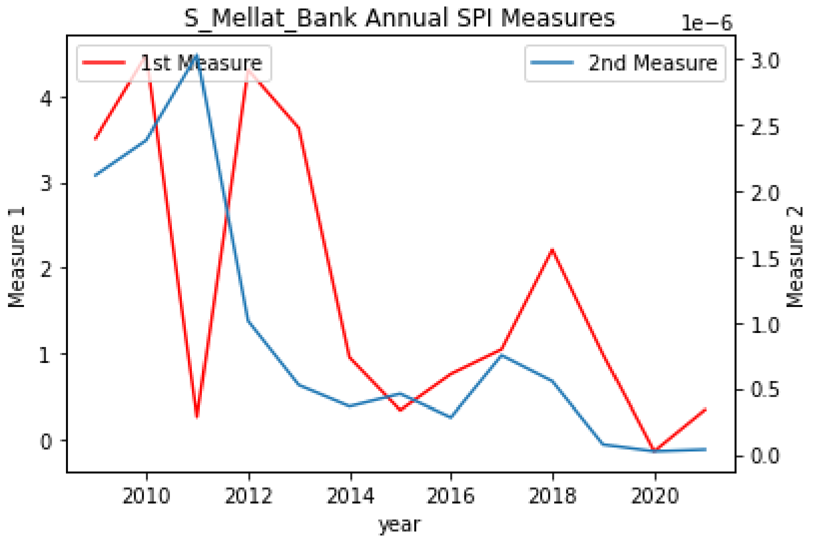
In [8]:
```python
for bank in results_list['bank']:
    fig, ax1 = plt.subplots()
    ax1.set_xlabel('year')
    ax1.set_ylabel('Measure 1')
    ax1.xaxis.set_major_locator(MaxNLocator(integer=True))
    ax1.plot(measures_y[bank]['year'], measures_y[bank]['1st_measure'], color='red',label='1st Measure')
    ax1.legend(loc=2)
    ax2 = ax1.twinx()
    ax2.set_ylabel('Measure 2')
    ax2.plot(measures_y[bank]['year'], measures_y[bank]['2nd_measure'], label='2nd Measure')
    ax2.legend(loc=1)
    plt.title(f'{bank} Annual SPI Measures')
    plt.savefig(results_folder_2 + f'\\{bank}_1stvs2nd_measure.png')
    plt.show()
```

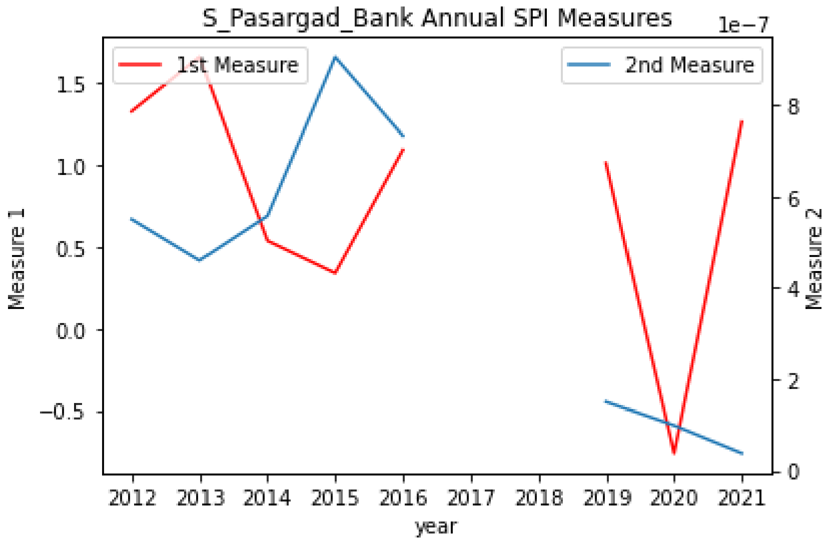


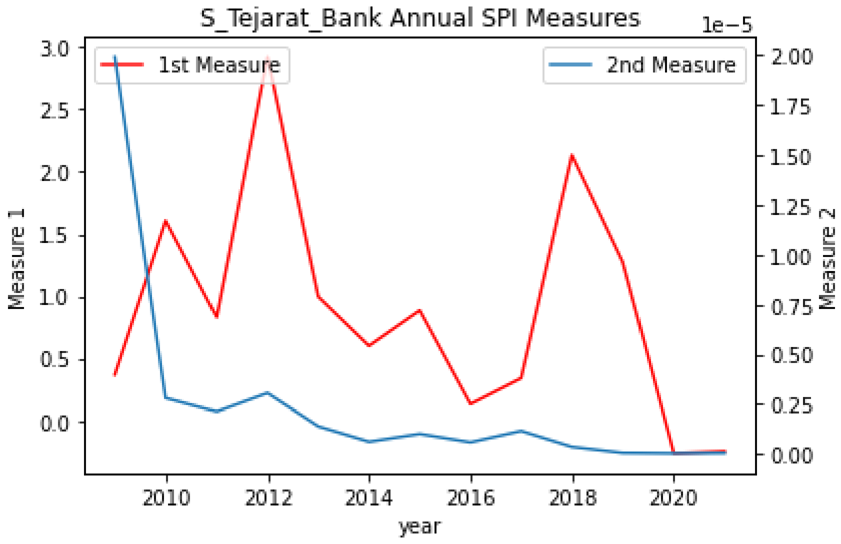


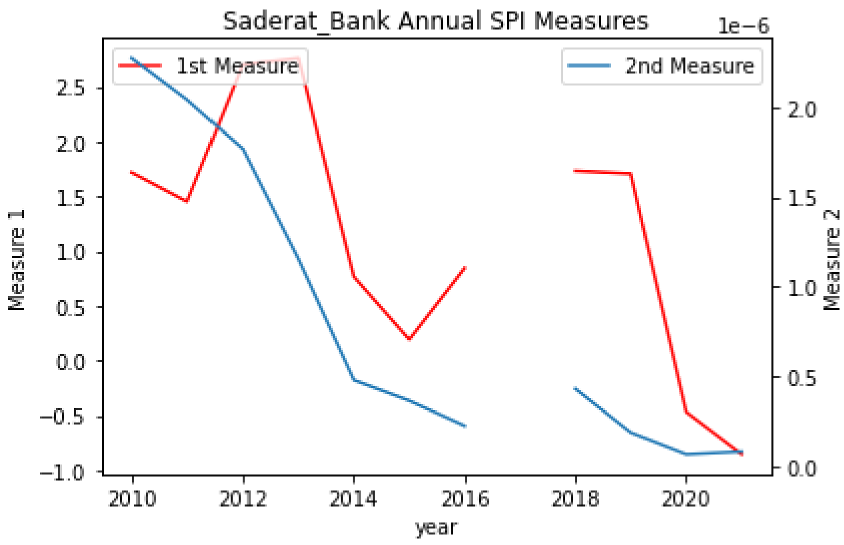


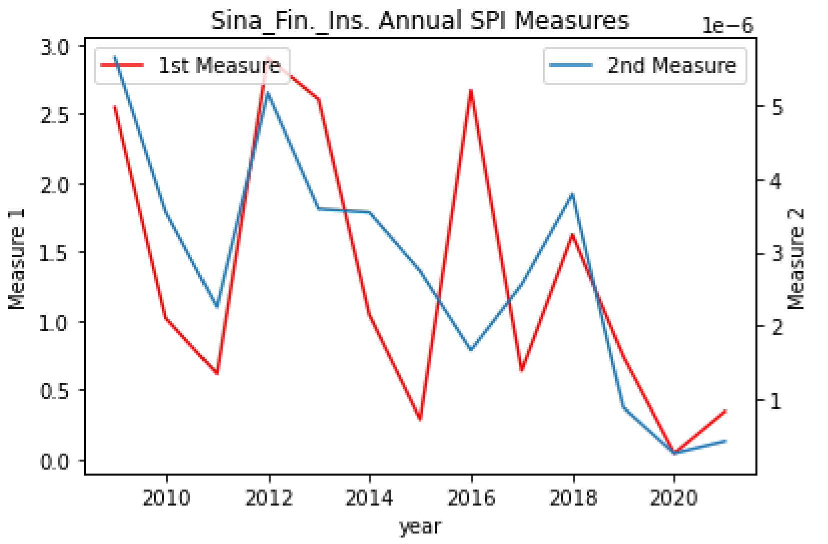



S_Mellat_Bank Annual SPI Measures
1e−6
1st Measure
2nd Measure
Measure 1
Measure 2
0
1
2
3
4
0.0
0.5
1.0
1.5
2.0
2.5
3.0
2010
2012
2014
2016
2018
2020
year

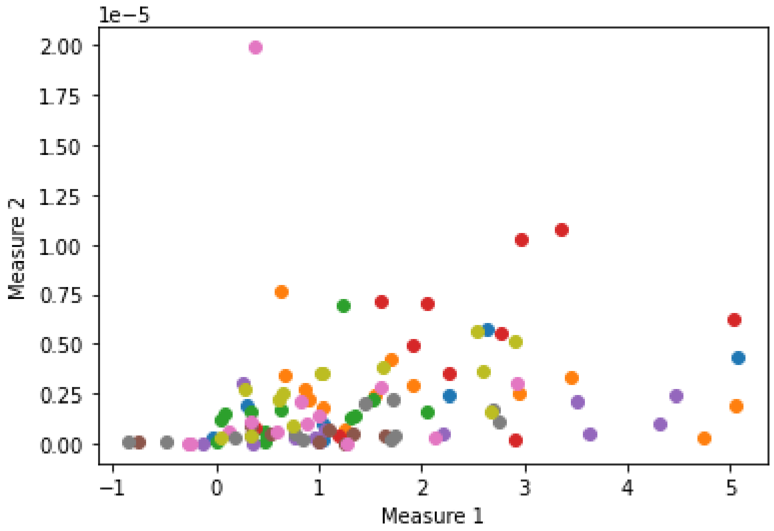

S_Pasargad_Bank Annual SPI Measures
1e−7
1st Measure
2nd Measure
Measure 1
Measure 2
−0.5
0.0
0.5
1.0
1.5
0
2
4
6
8
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
year


S_Tejarat_Bank Annual SPI Measures
1e−5
1st Measure
2nd Measure
Measure 1
Measure 2
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2010
2012
2014
2016
2018
2020
year

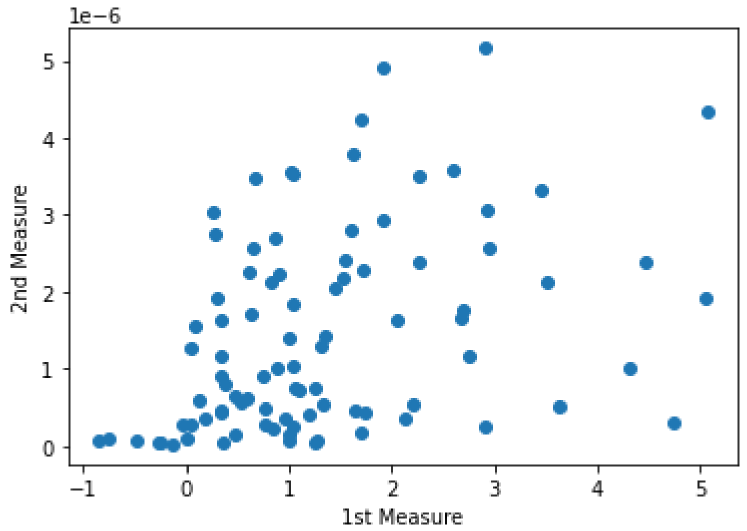

Saderat_Bank Annual SPI Measures
1e−6
1st Measure
2nd Measure
Measure 1
Measure 2
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.5
1.0
1.5
2.0
2010
2012
2014
2016
2018
2020
year


Sina_Fin._Ins. Annual SPI Measures
1e−6
1st Measure
2nd Measure
Measure 1
Measure 2
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1
2
3
4
5
2010
2012
2014
2016
2018
2020
year

In [9]:
```
fig, ax1 = plt.subplots()
ax1.set_xlabel('Measure 1')
ax1.set_ylabel('Measure 2')
for bank in results_list['bank']:
    ax1.scatter(measures_y[bank]['1st_measure'], measures_y[bank]['2nd_measure'])
plt.show()
```



In [10]:
```python
m_1 = []
m_2 = []
m1v2_i = pd.DataFrame()

for bank in results_list['bank']:
    for i in range(len(measures_y[bank])):
        m_1.append(measures_y[bank].loc[i, '1st_measure'])
        m_2.append(measures_y[bank].loc[i, '2nd_measure'])

m1v2_i['1st_measure'] = m_1
m1v2_i['2nd_measure'] = m_2

qh2 = m1v2_i["2nd_measure"].quantile(0.9)
ql2 = m1v2_i["2nd_measure"].quantile(0.1)
m1v2 = pd.DataFrame(m1v2_i[m1v2_i['2nd_measure'] < qh2])

plt.scatter(m1v2['1st_measure'], m1v2['2nd_measure'])
plt.xlabel('1st Measure')
plt.ylabel('2nd Measure')
plt.show()

m1v2 = m1v2[m1v2['2nd_measure'] > ql2].reset_index(drop=True)
mod_1v2 = sm.GLS(m1v2['2nd_measure'], m1v2['1st_measure'])
res_1v2 = mod_1v2.fit()
summary_1v2 = res_1v2.summary()
print(summary_1v2)
```




```
                            GLS Regression Results
=======================================================================================
Dep. Variable:            2nd_measure   R-squared (uncentered):                   0.527
Model:                            GLS   Adj. R-squared (uncentered):              0.521
Method:                 Least Squares   F-statistic:                              86.90
Date:                Fri, 31 Dec 2021   Prob (F-statistic):                    2.56e-14
Time:                        14:54:18   Log-Likelihood:                          951.50
No. Observations:                  79   AIC:                                     -1901.
Df Residuals:                      78   BIC:                                     -1899.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
1st_measure  7.717e-07   8.28e-08      9.322      0.000    6.07e-07    9.37e-07
==============================================================================
Omnibus:                        0.454   Durbin-Watson:                   1.277
Prob(Omnibus):                  0.797   Jarque-Bera (JB):                0.154
Skew:                          -0.092   Prob(JB):                        0.926
Kurtosis:                       3.113   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [11]:
```python
results_list
```

Out[11]:

	bank	1st_measure	2nd_measure
0	Bank_of_M.E.	1.843570	2.546993e-07
1	Karafarin_Bank	2.001226	3.000202e-07
2	Parsian_Bank	0.690010	8.992139e-08
3	Post_Bank	2.719908	2.659309e-07
4	S_Mellat_Bank	1.491802	3.803368e-08
5	S_Pasargad_Bank	1.810723	3.777567e-08
6	S_Tejarat_Bank	0.869873	5.889360e-08
7	Saderat_Bank	0.717849	8.258254e-08
8	Sina_Fin._Ins.	0.979439	4.384202e-07

SMI Measures No.3 and 4

Two other measures are expressed from the regression below:

$$r_t = a + b_0 \Delta E_t + \sum_{\tau} b_\tau \Delta E_{t+\tau} + \sum_{\tau} c_\tau r_{t+\tau} + \varepsilon_t$$

where ΔE_t are changes in ***EBITDA*** devided by the market value of the equity in the beginning of the fiscal year, $\Delta E_{t+\tau}$ is the ***EPS*** change in τ periods ahead, and $r_{t+\tau}$ is the annual return of the stock at time τ.

-Measure 3: $FERC = \sum b_\tau$

-Measure 4: $FINC = R^2_{r_t = a + b_0 \Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\tau c_\tau r_{t+\tau} + \varepsilon_t} - R^2_{r_t = a + b_0 \Delta E_t + \varepsilon_t}$

In [12]:
```
data_address = 'D:\Masters\Term3\Banking\Project\Data'
high_r = []
low_r = []

for hindex in list(results_list['1st_measure'].nlargest(4).index):
    high_r.append(results_list.loc[hindex, 'bank'])
for lindex in list(results_list['1st_measure'].nsmallest(4).index):
    low_r.append(results_list.loc[lindex, 'bank'])

with open(data_address + '\\high_r.txt', 'wb') as fh:
    pickle.dump(high_r, fh)
with open(data_address + '\\low_r.txt', 'wb') as fl:
    pickle.dump(low_r, fl)
```

P.S.:

```
Earnings per share have been collected semi-manually. Another option would be to use BeautifulSoup for web-scraping. Howe
ver, due to the small size of needed data, the better option seemed to be the manual one.
```

In [13]:
```
eps_high_r = pd.read_csv(data_address + '\\eps_high_r.csv')
eps_high_r = eps_high_r.astype({'date' : 'datetime64',
                                'MV' : 'float',
                                'EBIT' : 'float'})

eps_low_r = pd.read_csv(data_address + '\\eps_low_r.csv')
eps_low_r = eps_low_r.astype({'date' : 'datetime64',
                              'MV' : 'float',
                             'EBIT' : 'float'})
```

In [14]:
```
# High "1st measure" firms:

eps_high_r['dE'] = np.nan
eps_high_r['EPS1'] = np.nan
eps_high_r['EPS2'] = np.nan
eps_high_r['EPS3'] = np.nan
eps_high_r['return0'] = np.nan
eps_high_r['return1'] = np.nan
eps_high_r['return2'] = np.nan
eps_high_r['return3'] = np.nan

for bank in high_r:
    df = pd.DataFrame(eps_high_r[eps_high_r['bank'] == bank])
    df_w = pd.read_csv(results_folder_m1 + f'\\{bank}_1st_measure.csv')
    df_w = df_w.astype({'date' : 'datetime64'})
    n = 0
    for i in list(df.index):
        curr_date = df.loc[i, 'date']
        ym1 = datetime.datetime(curr_date.year - 1, curr_date.month, curr_date.day)
        y1 = datetime.datetime(curr_date.year + 1, curr_date.month, curr_date.day)
        y2 = datetime.datetime(curr_date.year + 2, curr_date.month, curr_date.day)
        y3 = datetime.datetime(curr_date.year + 3, curr_date.month, curr_date.day)
        df_y0 = pd.DataFrame(df_w[df_w['date'] <= curr_date])
        df_y0 = pd.DataFrame(df_y0[df_y0['date'] >= ym1]).reset_index(drop=True)
        df_y1 = pd.DataFrame(df_w[df_w['date'] <= y1])
        df_y1 = pd.DataFrame(df_y1[df_y1['date'] >= curr_date]).reset_index(drop=True)
        df_y2 = pd.DataFrame(df_w[df_w['date'] <= y2])
        df_y2 = pd.DataFrame(df_y2[df_y2['date'] >= y1]).reset_index(drop=True)
        df_y3 = pd.DataFrame(df_w[df_w['date'] <= y3])
        df_y3 = pd.DataFrame(df_y3[df_y3['date'] >= y2]).reset_index(drop=True)
        if n > 0:
            eps_high_r.loc[i, 'dE'] = (eps_high_r.loc[i, 'EBIT'] - eps_high_r.loc[i - 1, 'EBIT']) / eps_high_r.loc[i, 'MV']
        if len(df_y0) != 0:
            eps_high_r.loc[i, 'return0'] = 100 * (list(df_y0['close'])[-1] - df_y0.loc[0, 'close']) / df_y0.loc[0, 'close']
            curr_price = df_y0.loc[0, 'close']
            if i <= list(df.index)[-1] - 3:
                eps_high_r.loc[i, 'EPS1'] = (eps_high_r.loc[i + 1, 'EPS'] - eps_high_r.loc[i, 'EPS']) / curr_price
                eps_high_r.loc[i, 'EPS2'] = (eps_high_r.loc[i + 2, 'EPS'] - eps_high_r.loc[i + 1, 'EPS']) / curr_price
                eps_high_r.loc[i, 'EPS3'] = (eps_high_r.loc[i + 3, 'EPS'] - eps_high_r.loc[i + 2, 'EPS']) / curr_price
        if len(df_y1) != 0:
            eps_high_r.loc[i, 'return1'] = 100 * (list(df_y1['close'])[-1] - df_y1.loc[0, 'close']) / df_y1.loc[0, 'close']
        if len(df_y2) != 0:
            eps_high_r.loc[i, 'return2'] = 100 * (list(df_y2['close'])[-1] - df_y2.loc[0, 'close']) / df_y2.loc[0, 'close']
        if len(df_y3) != 0:
            eps_high_r.loc[i, 'return3'] = 100 * (list(df_y3['close'])[-1] - df_y3.loc[0, 'close']) / df_y3.loc[0, 'close']
        n += 1
```

In [15]:
```
# Regression without EPS and future annual returns for calculating FINC:
eps_high_r = eps_high_r.dropna()
mod_high_e = smf.ols('return0 ~ dE', data=eps_high_r)
res_high_e = mod_high_e.fit()
summary_high_e = res_high_e.summary()
print(summary_high_e)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.270
Model:                            OLS   Adj. R-squared:                  0.218
Method:                 Least Squares   F-statistic:                     5.179
Date:                Fri, 31 Dec 2021   Prob (F-statistic):             0.0391
Time:                        14:54:35   Log-Likelihood:                -83.718
No. Observations:                  16   AIC:                             171.4
Df Residuals:                      14   BIC:                             173.0
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     16.6375     12.477      1.333      0.204     -10.124      43.399
dE             0.1781      0.078      2.276      0.039       0.010       0.346
==============================================================================
Omnibus:                        2.275   Durbin-Watson:                   2.449
Prob(Omnibus):                  0.321   Jarque-Bera (JB):                1.783
Skew:                           0.720   Prob(JB):                        0.410
Kurtosis:                       2.224   Cond. No.                         164.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [16]:
```
# Regression of high "1st measure" firms without future stock returns as controls:
mod_high = smf.ols('return0 ~ dE + EPS1 + EPS2 + EPS3', data=eps_high_r)
res_high = mod_high.fit()
summary_high = res_high.summary()
print(summary_high)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.328
Model:                            OLS   Adj. R-squared:                  0.083
Method:                 Least Squares   F-statistic:                     1.341
Date:                Fri, 31 Dec 2021   Prob (F-statistic):              0.315
Time:                        14:54:36   Log-Likelihood:                -83.058
No. Observations:                  16   AIC:                             176.1
Df Residuals:                      11   BIC:                             180.0
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     15.5602     15.471      1.006      0.336     -18.490      49.611
dE             0.1634      0.103      1.591      0.140      -0.063       0.390
EPS1         -23.2255     51.606     -0.450      0.661    -136.810      90.359
EPS2         -13.8863     37.999     -0.365      0.722     -97.522      69.749
EPS3         -11.2680     27.754     -0.406      0.693     -72.353      49.817
==============================================================================
Omnibus:                        2.412   Durbin-Watson:                   2.372
Prob(Omnibus):                  0.299   Jarque-Bera (JB):                1.504
Skew:                           0.510   Prob(JB):                        0.472
Kurtosis:                       1.898   Cond. No.                         668.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [17]:
```python
# Regression of high "1st measure" firms with 3 future stock returns as controls:
mod_high_c = smf.ols('return0 ~ dE + EPS1 + EPS2 + EPS3 + return1 + return2 + return3', data=eps_high_r)
res_high_c = mod_high_c.fit()
summary_high_c = res_high_c.summary()
print(summary_high_c)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.511
Model:                            OLS   Adj. R-squared:                  0.083
Method:                 Least Squares   F-statistic:                     1.194
Date:                Fri, 31 Dec 2021   Prob (F-statistic):              0.401
Time:                        14:54:37   Log-Likelihood:                -80.514
No. Observations:                  16   AIC:                             177.0
Df Residuals:                       8   BIC:                             183.2
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     10.7865     21.936      0.492      0.636     -39.798      61.371
dE             0.1094      0.109      1.007      0.343      -0.141       0.360
EPS1          21.5500     62.157      0.347      0.738    -121.784     164.884
EPS2         -48.1927     49.623     -0.971      0.360    -162.624      66.238
EPS3           5.2998     33.002      0.161      0.876     -70.804      81.403
return1       -1.3152      0.781     -1.685      0.130      -3.115       0.485
return2        0.2993      0.233      1.283      0.235      -0.239       0.837
return3       -0.0917      0.195     -0.471      0.650      -0.541       0.358
==============================================================================
Omnibus:                        1.610   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.447   Jarque-Bera (JB):                0.986
Skew:                          -0.259   Prob(JB):                        0.611
Kurtosis:                       1.900   Cond. No.                         872.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [18]:
```python
ferc_h = res_high.params['EPS1'] + res_high.params['EPS2'] + res_high.params['EPS3']
ferc_h_c = res_high_c.params['EPS1'] + res_high_c.params['EPS2'] + res_high_c.params['EPS3']

finc_h = res_high.rsquared - res_high_e.rsquared
finc_h_c = res_high_c.rsquared - res_high_e.rsquared
```

In [19]:
```python
# Low "1st measure" firms:

eps_low_r['dE'] = np.nan
eps_low_r['EPS1'] = np.nan
eps_low_r['EPS2'] = np.nan
eps_low_r['EPS3'] = np.nan
eps_low_r['return0'] = np.nan
eps_low_r['return1'] = np.nan
eps_low_r['return2'] = np.nan
eps_low_r['return3'] = np.nan

for bank in low_r:
    df = pd.DataFrame(eps_low_r[eps_low_r['bank'] == bank])
    df_w = pd.read_csv(results_folder_m1 + f'\\{bank}_1st_measure.csv')
    df_w = df_w.astype({'date' : 'datetime64'})
    n = 0
    for i in list(df.index):
        curr_date = df.loc[i, 'date']
        ym1 = datetime.datetime(curr_date.year - 1, curr_date.month, curr_date.day)
        y1 = datetime.datetime(curr_date.year + 1, curr_date.month, curr_date.day)
        y2 = datetime.datetime(curr_date.year + 2, curr_date.month, curr_date.day)
        y3 = datetime.datetime(curr_date.year + 3, curr_date.month, curr_date.day)
        df_y0 = pd.DataFrame(df_w[df_w['date'] <= curr_date])
        df_y0 = pd.DataFrame(df_y0[df_y0['date'] >= ym1]).reset_index(drop=True)
        df_y1 = pd.DataFrame(df_w[df_w['date'] <= y1])
        df_y1 = pd.DataFrame(df_y1[df_y1['date'] >= curr_date]).reset_index(drop=True)
        df_y2 = pd.DataFrame(df_w[df_w['date'] <= y2])
        df_y2 = pd.DataFrame(df_y2[df_y2['date'] >= y1]).reset_index(drop=True)
        df_y3 = pd.DataFrame(df_w[df_w['date'] <= y3])
        df_y3 = pd.DataFrame(df_y3[df_y3['date'] >= y2]).reset_index(drop=True)
        if n > 0:
            eps_low_r.loc[i, 'dE'] = (eps_low_r.loc[i, 'EBIT'] - eps_low_r.loc[i - 1, 'EBIT']) / eps_low_r.loc[i, 'MV']
        if len(df_y0) != 0:
            eps_low_r.loc[i, 'return0'] = 100 * (list(df_y0['close'])[-1] - df_y0.loc[0, 'close']) / df_y0.loc[0, 'close']
            curr_price = df_y0.loc[0, 'close']
            if i <= list(df.index)[-1] - 3:
                eps_low_r.loc[i, 'EPS1'] = (eps_low_r.loc[i + 1, 'EPS'] - eps_low_r.loc[i, 'EPS']) / curr_price
                eps_low_r.loc[i, 'EPS2'] = (eps_low_r.loc[i + 2, 'EPS'] - eps_low_r.loc[i + 1, 'EPS']) / curr_price
                eps_low_r.loc[i, 'EPS3'] = (eps_low_r.loc[i + 3, 'EPS'] - eps_low_r.loc[i + 2, 'EPS']) / curr_price
        if len(df_y1) != 0:
            eps_low_r.loc[i, 'return1'] = 100 * (list(df_y1['close'])[-1] - df_y1.loc[0, 'close']) / df_y1.loc[0, 'close']
        if len(df_y2) != 0:
            eps_low_r.loc[i, 'return2'] = 100 * (list(df_y2['close'])[-1] - df_y2.loc[0, 'close']) / df_y2.loc[0, 'close']
        if len(df_y3) != 0:
            eps_low_r.loc[i, 'return3'] = 100 * (list(df_y3['close'])[-1] - df_y3.loc[0, 'close']) / df_y3.loc[0, 'close']
        n += 1
```

In [20]:
```python
# Regression without EPS and future annual returns for calculating FINC:
eps_low_r = eps_low_r.dropna()
mod_low_e = smf.ols('return0 ~ dE', data=eps_low_r)
res_low_e = mod_low_e.fit()
summary_low_e = res_low_e.summary()
print(summary_low_e)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.044
Model:                            OLS   Adj. R-squared:                 -0.029
Method:                 Least Squares   F-statistic:                    0.6027
Date:                Fri, 31 Dec 2021   Prob (F-statistic):              0.451
Time:                        14:54:41   Log-Likelihood:                -81.703
No. Observations:                  15   AIC:                             167.4
Df Residuals:                      13   BIC:                             168.8
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     11.6150     16.749      0.693      0.500     -24.570      47.800
dE             0.0270      0.035      0.776      0.451      -0.048       0.102
==============================================================================
Omnibus:                       20.307   Durbin-Watson:                   2.321
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20.305
Skew:                           2.010   Prob(JB):                     3.90e-05
Kurtosis:                       7.041   Cond. No.                         519.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [21]:
```python
# Regression of low "1st measure" firms without future stock returns as controls:
mod_low = smf.ols('return0 ~ dE + EPS1 + EPS2 + EPS3', data=eps_low_r)
res_low = mod_low.fit()
summary_low = res_low.summary()
print(summary_low)
```

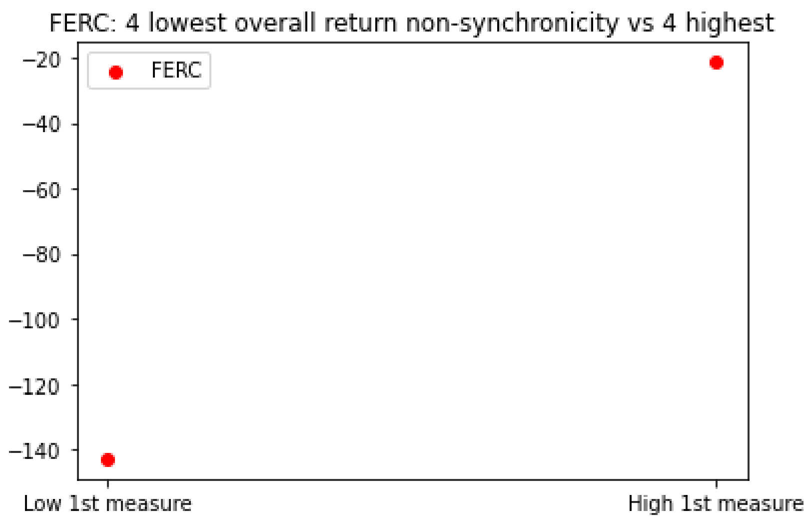
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.609
Model:                            OLS   Adj. R-squared:                  0.453
Method:                 Least Squares   F-statistic:                     3.898
Date:                Fri, 31 Dec 2021   Prob (F-statistic):             0.0369
Time:                        14:54:42   Log-Likelihood:                -74.995
No. Observations:                  15   AIC:                             160.0
Df Residuals:                      10   BIC:                             163.5
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -23.6807     16.037     -1.477      0.171     -59.414      12.053
dE            -0.0400      0.069     -0.582      0.573      -0.193       0.113
EPS1         -50.9387     14.106     -3.611      0.005     -82.370     -19.508
EPS2         -24.5104     24.740     -0.991      0.345     -79.636      30.615
EPS3           7.5735     21.298      0.356      0.730     -39.881      55.028
==============================================================================
Omnibus:                        0.348   Durbin-Watson:                   2.588
Prob(Omnibus):                  0.840   Jarque-Bera (JB):                0.479
Skew:                          -0.103   Prob(JB):                        0.787
Kurtosis:                       2.149   Cond. No.                     1.19e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.19e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

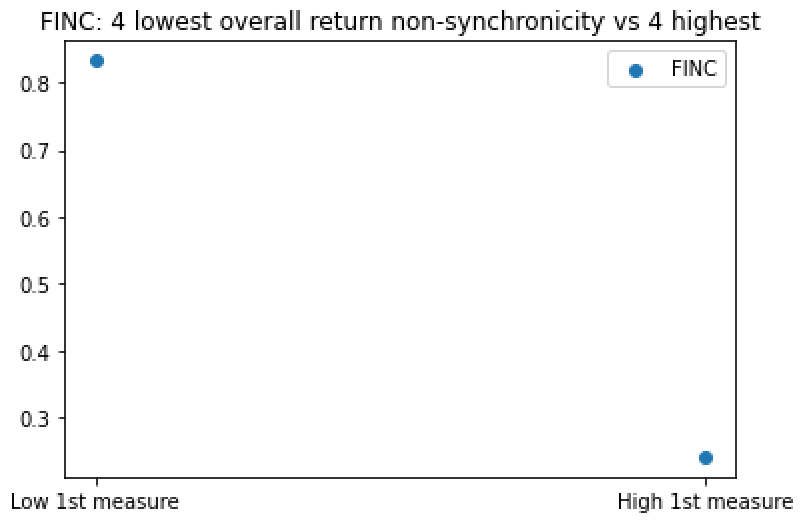
In [22]:
```python
# Regression of low "1st measure" firms with 3 future stock returns as controls:
mod_low_c = smf.ols('return0 ~ dE + EPS1 + EPS2 + EPS3 + return1 + return2 + return3', data=eps_low_r)
res_low_c = mod_low_c.fit()
summary_low_c = res_low_c.summary()
print(summary_low_c)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                return0   R-squared:                       0.877
Model:                            OLS   Adj. R-squared:                  0.754
Method:                 Least Squares   F-statistic:                     7.130
Date:                Fri, 31 Dec 2021   Prob (F-statistic):            0.00947
Time:                        14:54:43   Log-Likelihood:                -66.327
No. Observations:                  15   AIC:                             148.7
Df Residuals:                       7   BIC:                             154.3
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -55.4164     15.279     -3.627      0.008     -91.546     -19.287
dE            -0.2301      0.067     -3.410      0.011      -0.390      -0.071
EPS1         -66.4787     10.416     -6.382      0.000     -91.108     -41.849
EPS2         -58.1915     27.615     -2.107      0.073    -123.492       7.109
EPS3         -18.2099     18.961     -0.960      0.369     -63.045      26.626
return1       -0.9502      0.285     -3.338      0.012      -1.623      -0.277
return2        0.2691      0.128      2.103      0.074      -0.033       0.572
return3        0.0191      0.078      0.245      0.813      -0.165       0.203
==============================================================================
Omnibus:                        2.080   Durbin-Watson:                   1.046
Prob(Omnibus):                  0.353   Jarque-Bera (JB):                1.038
Skew:                          -0.215   Prob(JB):                        0.595
Kurtosis:                       1.785   Cond. No.                     2.13e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.13e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [23]:
```python
ferc_l = res_low.params['EPS1'] + res_low.params['EPS2'] + res_low.params['EPS3']
ferc_l_c = res_low_c.params['EPS1'] + res_low_c.params['EPS2'] + res_low_c.params['EPS3']

finc_l = res_low.rsquared - res_low_e.rsquared
finc_l_c = res_low_c.rsquared - res_low_e.rsquared
```

In [24]:
```
results_folder_3 = r'D:\Masters\Term3\Banking\Project\Results\Measure_3'

plt.scatter(['Low 1st measure', 'High 1st measure'], [ferc_l_c, ferc_h_c], label='FERC', color='red')
plt.title('FERC: 4 lowest overall return non-synchronicity vs 4 highest')
plt.legend()
plt.savefig(results_folder_3 + '\\FERC.png')
plt.show()
plt.scatter(['Low 1st measure', 'High 1st measure'], [finc_l_c, finc_h_c], label='FINC')
plt.title('FINC: 4 lowest overall return non-synchronicity vs 4 highest')
plt.legend()
plt.savefig(results_folder_3 + '\\FINC.png')
plt.show()
```





In [ ]: