

Remote Data Access

Warning

Yahoo! Finance has been immediately deprecated. Yahoo! substantially altered their API in late 2017 and the csv endpoint was retired.

Functions from `pandas_datareader.data` and `pandas_datareader.wb` extract data from various Internet sources into a pandas DataFrame. Currently the following sources are supported:

- [Google Finance](#)
- [Morningstar](#)
- [IEX](#)
- [Robinhood](#)
- [Enigma](#)
- [Quandl](#)
- [St.Louis FED \(FRED\)](#)
- [Kenneth French's data library](#)
- [World Bank](#)
- [OECD](#)
- [Eurostat](#)
- [Thrift Savings Plan](#)
- [Nasdaq Trader symbol definitions](#)
- [Stooq](#)
- [MOEX](#)

It should be noted, that various sources support different kinds of data, so not all sources implement the same methods and the data elements returned might also differ.

Google Finance

⚠ Warning

Google's API has become less reliable during 2017. While the google datareader often works as expected, it is not uncommon to experience a range of errors when attempting to read data, especially in bulk.

```
In [1]: import pandas_datareader.data as web

In [2]: import datetime

In [3]: start = datetime.datetime(2010, 1, 1)

In [4]: end = datetime.datetime(2013, 1, 27)

In [5]: f = web.DataReader('F', 'google', start, end)

In [6]: f.ix['2010-01-04']
Out[6]:
Open           10.17
High           10.28
Low            10.05
Close          10.28
Volume      60855796.00
Name: 2010-01-04 00:00:00, dtype: float64
```

Tiingo

[Tiingo](#) is a trading platform that provides a data api with historical end-of-day prices on equities, mutual funds and ETFs. Free registration is required to get an API key. Free accounts are rate limited and can access a limited number of symbols (500 at the time of writing).

```

In [7]: import os

In [8]: import pandas_datareader as pdr

In [9]: df = pdr.get_data_tingo('GOOG', api_key=os.getenv('TIINGO_API_KEY'))
-----
AttributeError                                Traceback (most recent call last)
<ipython-input-9-c390cc1bcafe> in <module>()
----> 1 df = pdr.get_data_tingo('GOOG', api_key=os.getenv('TIINGO_API_KEY'))

AttributeError: module 'pandas_datareader' has no attribute 'get_data_tingo'

In [10]: df.head()
-----
NameError                                Traceback (most recent call last)
<ipython-input-10-c42a15b2c7cf> in <module>()
----> 1 df.head()

NameError: name 'df' is not defined

```

Morningstar

OHLC and Volume data is available from Morningstar using the same API which powers their charts.

```

In [11]: import pandas_datareader.data as web

In [12]: from datetime import datetime

In [13]: start = datetime(2015, 2, 9)

In [14]: end = datetime(2017, 5, 24)

In [15]: f = web.DataReader('F', 'morningstar', start, end)

In [16]: f.head()
Out[16]:

```

Symbol	Date	Close	High	Low	Open	Volume
F	2015-02-09	15.92	16.03	15.72	15.76	20286720
	2015-02-10	16.09	16.14	15.91	16.05	27928530
	2015-02-11	16.25	16.31	16.01	16.08	34285331
	2015-02-12	16.36	16.45	16.30	16.34	23738806
	2015-02-13	16.30	16.36	16.19	16.33	19954568

IEX

The Investors Exchange (IEX) provides a wide range of data through an [API](#). Historical stock prices are available for up to 5 years:

```
In [17]: import pandas_datareader.data as web

In [18]: from datetime import datetime

In [19]: start = datetime(2015, 2, 9)

In [20]: end = datetime(2017, 5, 24)

In [21]: f = web.DataReader('F', 'iex', start, end)
5y

In [22]: f.loc['2015-02-09']
Out[22]:
open           15.76
high           16.03
low            15.72
close          15.92
volume      20286720.00
Name: 2015-02-09, dtype: float64
```

There are additional interfaces to this API that are directly exposed: tops (*'iex-tops'*) and last (*'iex-lasts'*). A third interface to the deep API is exposed through *Deep* class or the *get_iex_book* function.

```
In [23]: import pandas_datareader.data as web

In [24]: f = web.DataReader('gs', 'iex-tops')

In [25]: f[:10]
Out[25]:
```

	0
askPrice	0
askSize	0
bidPrice	0
bidSize	0
lastSalePrice	272.48
lastSaleSize	3
lastSaleTime	1517518796044
lastUpdated	1517518800000
marketPercent	0.02056
sector	diversifiedfinancials

Robinhood

[Robinhood](#) is a stock trading platform with an API that provides a limited set of data. Historical daily data is limited to 1 year relative to today.

```

In [26]: import pandas_datareader.data as web

In [27]: from datetime import datetime

In [28]: f = web.DataReader('F', 'robinhood')

In [29]: f.head()
Out[29]:

```

		close_price	high_price	interpolated	low_price	open_price	\
symbol	begins_at						
F	2017-02-02	11.5323	11.6169	False	11.4854	11.5511	
	2017-02-03	11.7953	11.8516	False	11.6356	11.6638	
	2017-02-06	11.7577	11.8469	False	11.7014	11.7859	
	2017-02-07	11.5887	11.7577	False	11.5605	11.7389	
	2017-02-08	11.6263	11.6920	False	11.5230	11.5887	

		session	volume
symbol	begins_at		
F	2017-02-02	reg	29035383
	2017-02-03	reg	38245251
	2017-02-06	reg	26916768
	2017-02-07	reg	32914413
	2017-02-08	reg	26411417

Enigma

Access datasets from [Enigma](#), the world's largest repository of structured public data. Note that the Enigma URL has changed from [app.enigma.io](#) as of release `0.6.0`, as the old API deprecated.

Datasets are unique identified by the `uuid4` at the end of a dataset's web address. For example, the following code downloads from [USDA Food Recalls 1996 Data](#).

```

In [30]: import os

In [31]: import pandas_datareader as pdr

In [32]: df = pdr.get_data_enigma('292129b0-1275-44c8-a6a3-2a0881f24fe1',
os.getenv('ENIGMA_API_KEY'))
-----
ValueError                                Traceback (most recent call last)
<ipython-input-32-f46ac2b42095> in <module>()
----> 1 df = pdr.get_data_enigma('292129b0-1275-44c8-a6a3-2a0881f24fe1', os.getenv('ENIGMA_API_KEY'))

~/checkouts/readthedocs.org/user_builds/pandas-datareader/envs/latest/lib/python3.5/site-
packages/pandas_datareader-0.6.0-py3.5.egg/pandas_datareader/data.py in get_data_enigma(*args,
**kwargs)
    66
    67 def get_data_enigma(*args, **kwargs):
----> 68     return EnigmaReader(*args, **kwargs).read()
    69
    70

~/checkouts/readthedocs.org/user_builds/pandas-datareader/envs/latest/lib/python3.5/site-
packages/pandas_datareader-0.6.0-py3.5.egg/pandas_datareader/enigma.py in __init__(self, dataset_id,
api_key, retry_count, pause, session)
    41         self._api_key = os.getenv('ENIGMA_API_KEY')
    42         if self._api_key is None:
----> 43             raise ValueError("Please provide an Enigma API key or set "
    44                             "the ENIGMA_API_KEY environment variable\n"
    45                             "If you do not have an API key, you can get ")

ValueError: Please provide an Enigma API key or set the ENIGMA_API_KEY environment variable
If you do not have an API key, you can get one here: http://public.enigma.com/signup

In [33]: df.columns
-----
NameError                                Traceback (most recent call last)
<ipython-input-33-b666bf274d0a> in <module>()
----> 1 df.columns

NameError: name 'df' is not defined

```

Quandl

Daily financial data (prices of stocks, ETFs etc.) from [Quandl](#). The symbol names consist of two parts: DB name and symbol name. DB names can be all the [free ones listed on the Quandl website](#). Symbol names vary with DB name; for WIKI (US stocks), they are the common ticker symbols, in

some other cases (such as FSE) they can be a bit strange. Some sources are also mapped to suitable ISO country codes in the dot suffix style shown above, currently available for [BE](#), [CN](#), [DE](#), [FR](#), [IN](#), [JP](#), [NL](#), [PT](#), [UK](#), [US](#).

As of June 2017, each DB has a different data schema, the coverage in terms of time range is sometimes surprisingly small, and the data quality is not always good.

```
In [34]: import pandas_datareader.data as web

In [35]: symbol = 'WIKI/AAPL' # or 'AAPL.US'

In [36]: df = web.DataReader(symbol, 'quandl', '2015-01-01', '2015-01-05')

In [37]: df.loc['2015-01-02']
Out[37]:
```

	Open	High	Low	Close	Volume	ExDividend	\
Date							
2015-01-02	111.39	111.44	107.35	109.33	53204626.0	0.0	

	SplitRatio	AdjOpen	AdjHigh	AdjLow	AdjClose	\
Date						
2015-01-02	1.0	105.820966	105.868466	101.982949	103.863957	

	AdjVolume
Date	
2015-01-02	53204626.0

FRED


```

In [38]: import pandas_datareader.data as web

In [39]: import datetime

In [40]: start = datetime.datetime(2010, 1, 1)

In [41]: end = datetime.datetime(2013, 1, 27)

In [42]: gdp = web.DataReader('GDP', 'fred', start, end)

In [43]: gdp.ix['2013-01-01']
Out[43]:
GDP      16475.44
Name: 2013-01-01 00:00:00, dtype: float64

# Multiple series:
In [44]: inflation = web.DataReader(['CPIAUCSL', 'CPILFESL'], 'fred', start, end)

In [45]: inflation.head()
Out[45]:
           CPIAUCSL  CPILFESL
DATE
2010-01-01    217.488    220.633
2010-02-01    217.281    220.731
2010-03-01    217.353    220.783
2010-04-01    217.403    220.822
2010-05-01    217.290    220.962

```

Fama/French

Access datasets from the [Fama/French Data Library](#). The `get_available_datasets` function returns a list of all available datasets.

```

In [46]: from pandas_datareader.famafrench import get_available_datasets

In [47]: import pandas_datareader.data as web

In [48]: len(get_available_datasets())
Out[48]: 262

In [49]: ds = web.DataReader('5_Industry_Portfolios', 'famafrench')

In [50]: print(ds['DESCR'])
5 Industry Portfolios
-----

This file was created by CMPT_IND_RETs using the 201712 CRSP database. It contains value- and equal-
weighted returns for 5 industry portfolios. The portfolios are constructed at the end of June. The
annual returns are from January to December. Missing data are indicated by -99.99 or -999. Copyright
2017 Kenneth R. French

0 : Average Value Weighted Returns -- Monthly (96 rows x 5 cols)
1 : Average Equal Weighted Returns -- Monthly (96 rows x 5 cols)
2 : Average Value Weighted Returns -- Annual (8 rows x 5 cols)
3 : Average Equal Weighted Returns -- Annual (8 rows x 5 cols)
4 : Number of Firms in Portfolios (96 rows x 5 cols)
5 : Average Firm Size (96 rows x 5 cols)
6 : Sum of BE / Sum of ME (8 rows x 5 cols)
7 : Value-Weighted Average of BE/ME (8 rows x 5 cols)

In [51]: ds[4].head()
Out[51]:
      Cnsmr  Manuf  HiTec  Hlth  Other
Date
2010-01    622    737    830    467   1232
2010-02    620    734    821    464   1221
2010-03    614    729    818    458   1215
2010-04    614    726    807    458   1203
2010-05    611    723    804    457   1195

```

World Bank

`pandas` users can easily access thousands of panel data series from the [World Bank's World Development Indicators](#) by using the `wb` I/O functions.

Indicators

Either from exploring the World Bank site, or using the search function included, every world bank indicator is accessible.

For example, if you wanted to compare the Gross Domestic Products per capita in constant dollars in North America, you would use the `search` function:

```
In [1]: from pandas_datareader import wb
In [2]: mathces = wb.search('gdp.*capita.*const')
```

Then you would use the `download` function to acquire the data from the World Bank's servers:

```
In [3]: dat = wb.download(indicator='NY.GDP.PCAP.KD', country=['US', 'CA', 'MX'], start=2005,
end=2008)
```

```
In [4]: print(dat)
```

		NY.GDP.PCAP.KD
Canada	year	
	2008	36005.5004978584
	2007	36182.9138439757
	2006	35785.9698172849
	2005	35087.8925933298
Mexico	2008	8113.10219480083
	2007	8119.21298908649
	2006	7961.96818458178
	2005	7666.69796097264
United States	2008	43069.5819857208
	2007	43635.5852068142
	2006	43228.111147107
	2005	42516.3934699993

The resulting dataset is a properly formatted `DataFrame` with a hierarchical index, so it is easy to apply `.groupby` transformations to it:

```
In [6]: dat['NY.GDP.PCAP.KD'].groupby(level=0).mean()
Out[6]:
country
Canada      35765.569188
Mexico       7965.245332
United States 43112.417952
dtype: float64
```

Now imagine you want to compare GDP to the share of people with cellphone contracts around the world.

```
In [7]: wb.search('cell.*%').iloc[:, :2]
Out[7]:
```

	id	name
3990	IT.CEL.SETS.FE.ZS	Mobile cellular telephone users, female (% of...
3991	IT.CEL.SETS.MA.ZS	Mobile cellular telephone users, male (% of po...
4027	IT.MOB.COV.ZS	Population coverage of mobile cellular telepho...

Notice that this second search was much faster than the first one because `pandas` now has a cached list of available data series.

```
In [13]: ind = ['NY.GDP.PCAP.KD', 'IT.MOB.COV.ZS']
In [14]: dat = wb.download(indicator=ind, country='all', start=2011, end=2011).dropna()
In [15]: dat.columns = ['gdp', 'cellphone']
In [16]: print(dat.tail())
```

		gdp	cellphone
country	year		
Swaziland	2011	2413.952853	94.9
Tunisia	2011	3687.340170	100.0
Uganda	2011	405.332501	100.0
Zambia	2011	767.911290	62.0
Zimbabwe	2011	419.236086	72.4

Finally, we use the `statsmodels` package to assess the relationship between our two variables using ordinary least squares regression. Unsurprisingly, populations in rich countries tend to use cellphones at a higher rate:

```
In [17]: import numpy as np
In [18]: import statsmodels.formula.api as smf
In [19]: mod = smf.ols('cellphone ~ np.log(gdp)', dat).fit()
In [20]: print(mod.summary())
```

OLS Regression Results

Dep. Variable:	cellphone	R-squared:	0.297
Model:	OLS	Adj. R-squared:	0.274
Method:	Least Squares	F-statistic:	13.08
Date:	Thu, 25 Jul 2013	Prob (F-statistic):	0.00105
Time:	15:24:42	Log-Likelihood:	-139.16
No. Observations:	33	AIC:	282.3
Df Residuals:	31	BIC:	285.3
Df Model:	1		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	16.5110	19.071	0.866	0.393	-22.384 55.406
np.log(gdp)	9.9333	2.747	3.616	0.001	4.331 15.535

Omnibus:	36.054	Durbin-Watson:	2.071
Prob(Omnibus):	0.000	Jarque-Bera (JB):	119.133
Skew:	-2.314	Prob(JB):	1.35e-26
Kurtosis:	11.077	Cond. No.	45.8

Country Codes

The `country` argument accepts a string or list of mixed [two](#) or [three](#) character ISO country codes, as well as dynamic [World Bank exceptions](#) to the ISO standards.

For a list of the the hard-coded country codes (used solely for error handling logic) see

`pandas_datareader.wb.country_codes`.

Problematic Country Codes & Indicators

! Note

The World Bank's country list and indicators are dynamic. As of 0.15.1, `wb.download()` is more flexible. To achieve this, the warning and exception logic changed.

The world bank converts some country codes, in their response, which makes error checking by pandas difficult. Retired indicators still persist in the search.

Given the new flexibility of 0.15.1, improved error handling by the user may be necessary for fringe cases.

To help identify issues:

There are at least 4 kinds of country codes:

1. Standard (2/3 digit ISO) - returns data, will warn and error properly.
2. Non-standard (WB Exceptions) - returns data, but will falsely warn.
3. Blank - silently missing from the response.
4. Bad - causes the entire response from WB to fail, always exception inducing.

There are at least 3 kinds of indicators:

1. Current - Returns data.
2. Retired - Appears in search results, yet won't return data.
3. Bad - Will not return data.

Use the `errors` argument to control warnings and exceptions. Setting errors to ignore or warn, won't stop failed responses. (ie, 100% bad indicators, or a single 'bad' (#4 above) country code).

See docstrings for more info.

OECD

OECD Statistics are available via `DataReader`. You have to specify OECD's data set code.

To confirm data set code, access to `each data -> Export -> SDMX Query`. Following example is to download 'Trade Union Density' data which set code is 'TUD'.


```
names=['Country', 'Frequency', 'Source', 'Series', 'Measure'])
```

Out[56]:

Country	Frequency	Source	Administrative data	Trade union density
Series	Measure	Percentage	Union members Thousands	Percentage Thousands
Year				
2010-01-01	NaN		12417.5	NaN
2011-01-01	NaN		12271.9	NaN
2012-01-01	NaN		12227.1	NaN

```
Country      ...      United States
```

Frequency	...	Annual			
Source	...	Survey data			
Series	...	Trade union density		Employees	
Measure	Percentage	Thousands	Percentage	Thousands	
Year	...				
2010-01-01	28.9	...	NaN	17.4	97406.0
2011-01-01	27.6	...	NaN	16.5	102403.0
2012-01-01	25.9	...	NaN	15.9	106924.0

Country					
Frequency					
Source		Administrative data			
Series		Union members		Trade union density	
Measure	Percentage	Thousands	Percentage	Thousands	
Year					
2010-01-01	NaN	NaN	NaN		NaN
2011-01-01	NaN	NaN	NaN		NaN
2012-01-01	NaN	NaN	NaN		NaN

Country				
Frequency				
Source				
Series		Employees		
Measure	Percentage	Thousands	Percentage	
Year				
2010-01-01	NaN	97406.0	NaN	
2011-01-01	NaN	102403.0	NaN	
2012-01-01	NaN	106924.0	NaN	

[3 rows x 24 columns]

Eurostat

Eurostat are available via `DataReader`.

Get [Rail accidents by type of accident \(ERA data\)](#) data. The result will be a `DataFrame` which has `DatetimeIndex` as index and `MultiIndex` of attributes or countries as column. The target URL is:

- http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=tran_sf_railac&lang=en

You can specify dataset ID 'tran_sf_railac' to get corresponding data via `DataReader`.

```
In [57]: import pandas_datareader.data as web
```

```
In [58]: df = web.DataReader('tran_sf_railac', 'eurostat')
```

```
In [59]: df
```

```
Out[59]:
```

```
ACCIDENT    Collisions of trains, including collisions with obstacles within the clearance gauge \
UNIT                                                Number
GEO                                                Austria
FREQ                                                Annual
TIME_PERIOD
2010-01-01                    3.0
2011-01-01                    2.0
2012-01-01                    1.0
2013-01-01                    4.0
2014-01-01                    1.0
2015-01-01                    7.0
2016-01-01                    7.0
```

```
ACCIDENT \
UNIT
GEO      Belgium Bulgaria Switzerland Channel Tunnel Czech Republic
FREQ      Annual      Annual      Annual      Annual      Annual
TIME_PERIOD
2010-01-01      5.0      2.0      5.0      0.0      3.0
2011-01-01      0.0      0.0      4.0      0.0      6.0
2012-01-01      3.0      3.0      4.0      0.0      6.0
2013-01-01      1.0      2.0      6.0      0.0      5.0
2014-01-01      3.0      4.0      0.0      0.0      13.0
2015-01-01      0.0      3.0      3.0      0.0      14.0
2016-01-01      2.0      3.0      2.0      0.0      6.0
```

```
ACCIDENT \
UNIT
GEO      Germany (until 1990 former territory of the FRG) Denmark Estonia
FREQ      Annual      Annual      Annual
TIME_PERIOD
2010-01-01      13.0      0.0      1.0
2011-01-01      18.0      1.0      0.0
2012-01-01      23.0      1.0      3.0
2013-01-01      29.0      0.0      0.0
2014-01-01      32.0      0.0      0.0
2015-01-01      40.0      3.0      0.0
2016-01-01      29.0      0.0      3.0
```

```
ACCIDENT \
UNIT
GEO      Greece ... Unknown
FREQ      Annual ... Number
TIME_PERIOD
2010-01-01      4.0 ... Netherlands Norway Poland Portugal Romania
2011-01-01      1.0 ... Annual Annual Annual Annual Annual
2012-01-01      2.0 ...      NaN      NaN      NaN      NaN      NaN
```

2013-01-01	2.0	...		NaN	NaN	NaN	NaN	NaN
2014-01-01	1.0	...		NaN	NaN	NaN	NaN	NaN
2015-01-01	2.0	...		NaN	NaN	NaN	NaN	NaN
2016-01-01	1.0	...		NaN	NaN	NaN	NaN	NaN
ACCIDENT								
UNIT								
GEO	Sweden	Slovenia	Slovakia	Turkey	United Kingdom			
FREQ	Annual	Annual	Annual	Annual	Annual			
TIME_PERIOD								
2010-01-01	NaN	NaN	NaN	0.0		NaN		
2011-01-01	NaN	NaN	NaN	0.0		NaN		
2012-01-01	NaN	NaN	NaN	0.0		NaN		
2013-01-01	NaN	NaN	NaN	0.0		NaN		
2014-01-01	NaN	NaN	NaN	0.0		NaN		
2015-01-01	NaN	NaN	NaN	0.0		NaN		
2016-01-01	NaN	NaN	NaN	0.0		NaN		
[7 rows x 264 columns]								

TSP Fund Data

Download mutual fund index prices for the TSP.

```

In [60]: import pandas_datareader.tsp as tsp

In [61]: tspreader = tsp.TSPReader(start='2015-10-1', end='2015-12-31')

In [62]: tspreader.read()
Out[62]:

```

	L Income	L 2020	L 2030	L 2040	L 2050	G Fund	F Fund \
date							
2015-10-01	17.5164	22.5789	24.2159	25.5690	14.4009	14.8380	17.0467
2015-10-02	17.5707	22.7413	24.4472	25.8518	14.5805	14.8388	17.0924
2015-10-05	17.6395	22.9582	24.7571	26.2306	14.8233	14.8413	17.0531
2015-10-06	17.6338	22.9390	24.7268	26.1898	14.7979	14.8421	17.0790
2015-10-07	17.6639	23.0324	24.8629	26.3598	14.9063	14.8429	17.0725
2015-10-08	17.6957	23.1364	25.0122	26.5422	15.0240	14.8437	17.0363
2015-10-09	17.7048	23.1646	25.0521	26.5903	15.0554	14.8445	17.0511
...
2015-12-22	17.7493	23.1452	24.9775	26.4695	14.9611	14.9076	16.9607
2015-12-23	17.8015	23.3149	25.2208	26.7663	15.1527	14.9084	16.9421
2015-12-24	17.7991	23.3039	25.2052	26.7481	15.1407	14.9093	16.9596
2015-12-28	17.7950	23.2811	25.1691	26.7015	15.1101	14.9128	16.9799
2015-12-29	17.8270	23.3871	25.3226	26.8905	15.2319	14.9137	16.9150
2015-12-30	17.8066	23.3216	25.2267	26.7707	15.1556	14.9146	16.9249
2015-12-31	17.7733	23.2085	25.0635	26.5715	15.0263	14.9154	16.9549

	C Fund	S Fund	I Fund
date			
2015-10-01	25.7953	34.0993	23.3202
2015-10-02	26.1669	34.6504	23.6367
2015-10-05	26.6467	35.3565	24.1475
2015-10-06	26.5513	35.1320	24.2294
2015-10-07	26.7751	35.6035	24.3671
2015-10-08	27.0115	35.9016	24.6406
2015-10-09	27.0320	35.9772	24.7723
...
2015-12-22	27.4848	35.0903	23.8679
2015-12-23	27.8272	35.5749	24.3623
2015-12-24	27.7831	35.6084	24.3272
2015-12-28	27.7230	35.4625	24.2816
2015-12-29	28.0236	35.8047	24.4757
2015-12-30	27.8239	35.5126	24.4184
2015-12-31	27.5622	35.2356	24.0952


```

[62 rows x 11 columns]

```

Nasdaq Trader Symbol Definitions

Download the latest symbols from [Nasdaq](#).

Note that Nasdaq updates this file daily, and historical versions are not available. More information on the [field](#) definitions.

```
In [12]: from pandas_datareader.nasdaq_trader import get_nasdaq_symbols
In [13]: symbols = get_nasdaq_symbols()
In [14]: print(symbols.ix['IBM'])
```

Nasdaq Traded	True
Security Name	International Business Machines Corporation Co...
Listing Exchange	N
Market Category	
ETF	False
Round Lot Size	100
Test Issue	False
Financial Status	NaN
CQS Symbol	IBM
NASDAQ Symbol	IBM
NextShares	False
Name: IBM, dtype: object	

Stooq Index Data

Google finance doesn't provide common index data download. The Stooq site has the data for download.

```
In [63]: import pandas_datareader.data as web

In [64]: f = web.DataReader('^DJI', 'stooq')

In [65]: f[:10]
Out[65]:
```

	Open	High	Low	Close	Volume
Date					
2018-02-01	26083.04	26306.70	26014.44	26186.71	NaN
2018-01-31	26268.17	26338.03	26050.98	26149.39	140120144.0
2018-01-30	26198.45	26256.99	26028.42	26076.89	111840144.0
2018-01-29	26584.28	26608.90	26435.34	26439.48	110919888.0
2018-01-26	26466.74	26616.71	26425.35	26616.71	123610888.0
2018-01-25	26313.06	26458.25	26259.72	26392.79	95732448.0
2018-01-24	26282.07	26392.80	26106.94	26252.12	123271104.0
2018-01-23	26214.87	26246.19	26143.90	26210.81	109272288.0
2018-01-22	26025.32	26215.23	25974.65	26214.60	126357768.0
2018-01-19	25987.35	26071.72	25942.83	26071.72	171541424.0

MOEX Data

The Moscow Exchange (MOEX) provides historical data.

```
In [66]: import pandas_datareader.data as web
```

```
In [67]: f = web.DataReader('USD000UTSTOM', 'moex', start='2017-07-01', end='2017-07-31')
```

```
In [68]: f.head()
```

```
Out[68]:
```

	BOARDID	SHORTNAME	SECID	OPEN	LOW	HIGH	CLOSE	\
TRADEDATE								
2017-07-03	CETS	USDRUB_TOM	USD000UTSTOM	58.95	58.790	59.4825	59.2650	
2017-07-04	CETS	USDRUB_TOM	USD000UTSTOM	59.30	59.135	59.4575	59.4125	
2017-07-04	CNGD	USDRUB_TOM	USD000UTSTOM	59.36	58.930	59.3600	59.3575	
2017-07-05	CETS	USDRUB_TOM	USD000UTSTOM	59.30	59.300	60.2600	59.9825	
2017-07-05	CNGD	USDRUB_TOM	USD000UTSTOM	59.34	59.265	60.1800	60.1800	

	NUMTRADES	VOLRUR	WAPRICE
TRADEDATE			
2017-07-03	29108	1.472424e+11	59.1903
2017-07-04	21053	1.090265e+11	59.2700
2017-07-04	37	1.046416e+09	NaN
2017-07-05	50108	2.874226e+11	59.9234
2017-07-05	35	6.339036e+09	NaN