Ranking Universes by Factors

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Part of the Quantopian Lecture Series:

- www.quantopian.com/lectures (https://www.quantopian.com/lectures)
- https://github.com/quantopian/research_public (https://github.com/quantopian/research_public)

One common technique in quantitative finance is that of ranking stocks in some way. This ranking can be whatever you come up with, but will often be a combination of fundamental factors and price-based signals. One example could be the following

1. Score stocks based on 0.5 x the PE Ratio of that stock + 0.5 x the 30 day price momentum
2. Rank stocks based on that score

These ranking systems can be used to construct long-short equity strategies. The Long-Short Equity Lecture is recommended reading before this Lecture.

In order to develop a good ranking system, we need to first understand how to evaluate ranking systems. We will show a demo here.

WARNING:

This notebook does analysis over thousands of equities and hundreds of timepoints. The resulting memory usage can crash the research server if you are running other notebooks. Please shut down other notebooks in the main research menu before running this notebook. You can tell if other notebooks are running by checking the color of the notebook symbol. Green indicates running, grey indicates not.

In [1]:
```
import numpy as np
import statsmodels.api as sm
import scipy.stats as stats
import scipy
from statsmodels import regression
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

Getting Data

The first thing we're gonna do is get monthly values for the Market Cap, P/E Ratio and Monthly Returns for every equity. Monthly Returns is a metric that takes the returns accrued over an entire month of trading by dividing the last close price by the first close price and subtracting 1.

In [2]:
```
from quantopian.pipeline import Pipeline
from quantopian.pipeline.data import morningstar
from quantopian.pipeline.data.builtin import USEquityPricing
from quantopian.pipeline.factors import CustomFactor, Returns

def make_pipeline():
    """
    Create and return our pipeline.

    We break this piece of logic out into its own function to make it easier to
    test and modify in isolation.
    """

    pipe = Pipeline(
        columns = {
            'Market Cap' : morningstar.valuation.market_cap.latest,
            'PE Ratio' : morningstar.valuation_ratios.pe_ratio.latest,
            'Monthly Returns': Returns(window_length=21),
        })

    return pipe

pipe = make_pipeline()
```

Let's take a look at the data to get a quick sense of what we have. This may take a while.

In [4]:
```
from quantopian.research import run_pipeline
```

```
In [4]: from quantopian.research import run_pipeline

start_date = '2013-01-01'
end_date = '2015-02-01'

data = run_pipeline(pipe, start_date, end_date)

# remove NaN values
data = data.dropna()

# show data
data
```

Out[4]:

		Market Cap	Monthly Returns	PE Ratio
2013-01-02 00:00:00+00:00	**Equity(2 [AA])**	8.975170e+09	0.032143	135.1351
	Equity(21 [AAME])	6.228180e+07	0.065580	16.0772
	Equity(24 [AAPL])	5.505680e+11	-0.089110	13.2626
	Equity(31 [ABAX])	8.283930e+08	0.008415	35.8423
	Equity(52 [ABM])	1.037840e+09	0.053308	16.7504
	Equity(53 [ABMD])	5.296030e+08	0.008621	39.8406
	Equity(62 [ABT])	4.916000e+10	0.008154	15.7978
	Equity(64 [ABX])	3.455270e+10	0.014778	10.2987
	Equity(66 [AB])	1.848950e+09	-0.007688	9.3284
	Equity(67 [ADSK])	7.444310e+09	0.066727	31.3480
	Equity(69 [ACAT])	4.985790e+08	-0.115538	14.9925
	Equity(76 [TAP])	7.513120e+09	0.034208	13.6054
	Equity(84 [ACET])	2.710310e+08	0.013798	14.3266
	Equity(88 [ACI])	1.426500e+09	0.089153	14.7493
	Equity(99 [ACO])	9.648460e+08	0.023727	14.8148
	Equity(100 [IEP])	4.212790e+09	0.107074	6.7204
	Equity(106 [ACU])	3.430780e+07	0.008284	10.1626
	Equity(110 [ACXM])	1.319010e+09	-0.012450	26.5957
	Equity(112 [ACY])	2.004690e+07	0.084681	4.3764
	Equity(114 [ADBE])	1.710190e+10	0.088099	20.8768
	Equity(122 [ADI])	1.223640e+10	0.044177	19.0476
	Equity(128 [ADM])	1.758370e+10	0.025843	18.7266
	Equity(153 [AE])	1.471520e+08	-0.003438	6.0277
	Equity(154 [AEM])	9.589180e+09	-0.059362	64.5161
	Equity(157 [AEG])	1.096140e+10	0.125654	4.2644
	Equity(161 [AEP])	2.069590e+10	0.000469	11.3636
	Equity(162 [AEPI])	3.346250e+08	-0.012629	14.5349
	Equity(166 [AES])	7.938060e+09	0.005162	128.2051
	Equity(168 [AET])	1.444710e+10	0.072222	8.2576
	Equity(185 [AFL])	2.484740e+10	0.003021	8.7108
...	**...**	...	...	...
	Equity(47858 [NMS])	6.352770e+07	0.075804	10.6952
	Equity(47873 [OMAM])	1.854000e+09	-0.067692	74.7579

Now, we need to take each of these individual factors, clean them to remove NaN values and aggregate them for each month.

```
In [5]: cap_data = data['Market Cap'].transpose().unstack() # extract series of data
cap_data = cap_data.T.dropna().T # remove NaN values
cap_data = cap_data.resample('M', how='last') # use last instance in month to aggregate
```

```
pe_data = data['PE Ratio'].transpose().unstack()
pe_data = pe_data.T.dropna().T
pe_data = pe_data.resample('M', how='last')

month_data = data['Monthly Returns'].transpose().unstack()
month_data = month_data.T.dropna().T
month_data = month_data.resample('M', how='last')
```

The next step is to figure out which equities we have data for. Data sources are never perfect, and stocks go in and out of existence with Mergers, Acquisitions, and Bankruptcies. We'll make a list of the stocks common to all three sources (our factor data sets) and then filter down both to just those stocks.

In [6]:
```
common_equities = cap_data.T.index.intersection(pe_data.T.index).intersection(month_data.T.index)
```

Now, we will make sure that each time series is being run over identical an identical set of securities.

In [7]:
```
cap_data_filtered = cap_data[common_equities][:-1]
month_forward_returns = month_data[common_equities][1:]
pe_data_filtered = pe_data[common_equities][:-1]
```

Here, is the filtered data for market cap over all equities for the first 5 months, as an example.

In [8]:
```
cap_data_filtered.head()
```

Out[8]:

	Equity(2 [AA])	Equity(24 [AAPL])	Equity(31 [ABAX])	Equity(52 [ABM])	Equity(62 [ABT])	Equity(64 [ABX])	Equity(66 [AB])	Equity(6 [ADSK])
2013-01-31 00:00:00+00:00	9263400000	4.996960e+11	828393000	1085530000	49412800000	35048800000	1833170000	7943140
2013-02-28 00:00:00+00:00	9434150000	4.277320e+11	852731000	1085530000	53214500000	31955400000	2141330000	8693570
2013-03-31 00:00:00+00:00	9110660000	4.145000e+11	937567000	1240500000	53073200000	30273500000	2422140000	8217940
2013-04-30 00:00:00+00:00	9110660000	4.161420e+11	1046720000	1215370000	55059100000	29433900000	2309700000	9231750
2013-05-31 00:00:00+00:00	9089870000	4.156150e+11	944303000	1215370000	57553300000	19732700000	2498490000	8813240

5 rows × 3203 columns

Because we're dealing with ranking systems, at several points we're going to want to rank our data. Let's check how our data looks when ranked to get a sense for this.

In [9]:
```
cap_data_filtered.rank().head()
```

Out[9]:

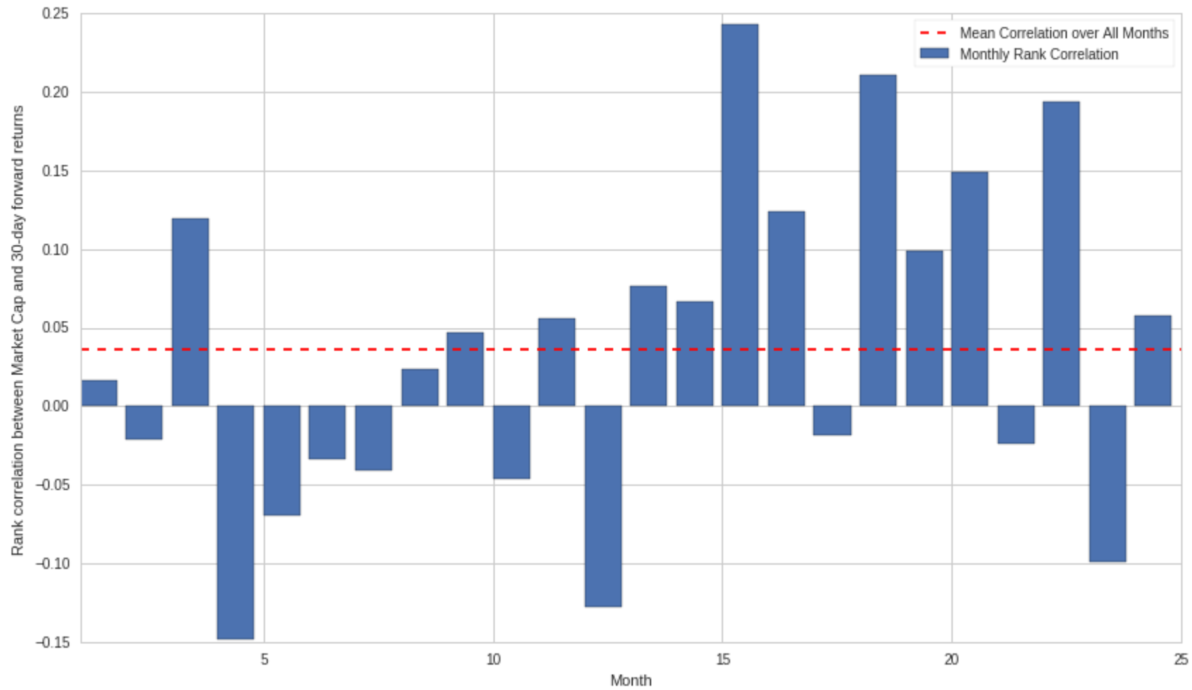
	Equity(2 [AA])	Equity(24 [AAPL])	Equity(31 [ABAX])	Equity(52 [ABM])	Equity(62 [ABT])	Equity(64 [ABX])	Equity(66 [AB])	Equity(67 [ADSK])	Equity(69 [ACAT])	Equity([TAP])
2013-01-31 00:00:00+00:00	9.0	14	3	1.5	1	25	2	2	4	1
2013-02-28 00:00:00+00:00	10.0	7	6	1.5	5	24	7	7	8	3
2013-03-31 00:00:00+00:00	7.5	3	11	5.0	4	23	14	5	9	2
2013-04-30 00:00:00+00:00	7.5	5	17	3.5	7	22	10	11	14	5
2013-05-31 00:00:00+00:00	5.5	4	14	3.5	12	12	18	8	15	11

5 rows × 3203 columns

Looking at Correlations Over Time

Now that we have the data, let's do something with it. Our first analysis will be to measure the monthly Spearman rank correlation coefficient between Market Cap and month-forward returns. In other words, how predictive of 30-day returns is ranking your universe by market cap.

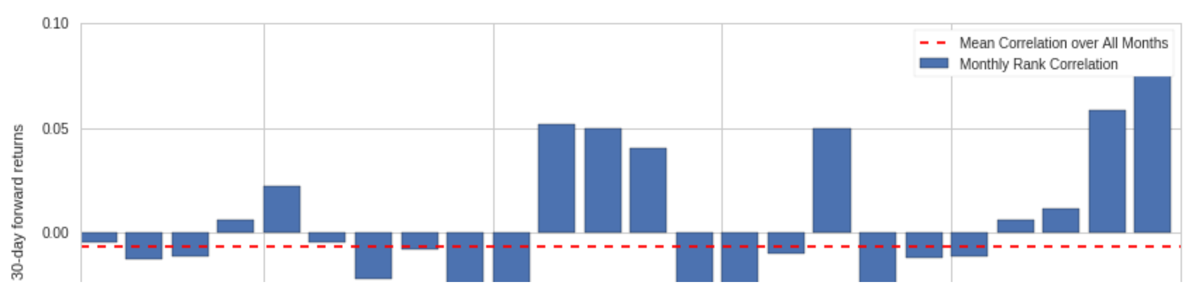
In [10]:
```
scores = np.zeros(24)
pvalues = np.zeros(24)
for i in range(24):
    score, pvalue = stats.spearmanr(cap_data_filtered.iloc[i], month_forward_returns.iloc[i])
    pvalues[i] = pvalue
    scores[i] = score

plt.bar(range(1,25),scores)
plt.hlines(np.mean(scores), 1, 25, colors='r', linestyles='dashed')
plt.xlabel('Month')
plt.xlim((1, 25))
plt.legend(['Mean Correlation over All Months', 'Monthly Rank Correlation'])
plt.ylabel('Rank correlation between Market Cap and 30-day forward returns');
```

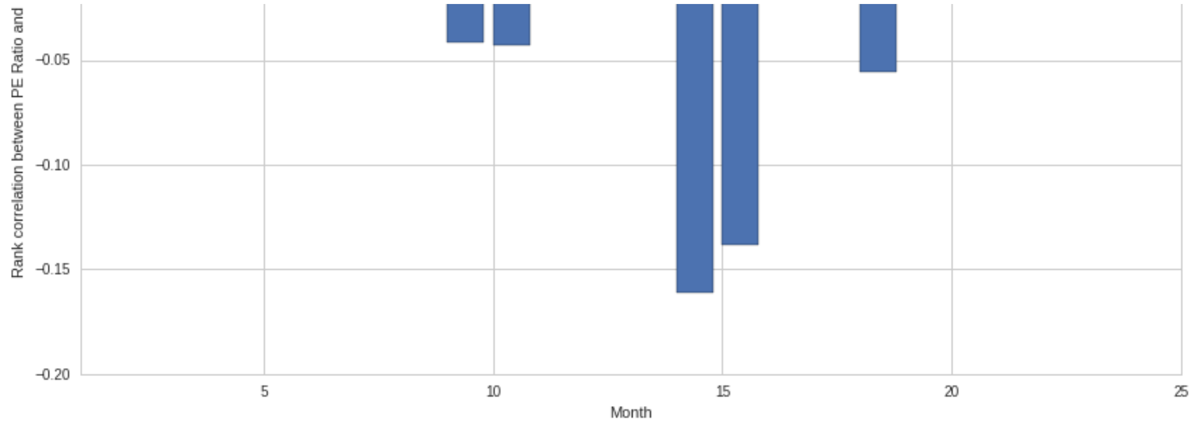


We can see that the average correlation is positive, but varies a lot from month to month.

Let's look at the same analysis, but with PE Ratio.

In [11]:
```
scores = np.zeros(24)
pvalues = np.zeros(24)
for i in range(24):
    score, pvalue = stats.spearmanr(pe_data_filtered.iloc[i], month_forward_returns.iloc[i])
    pvalues[i] = pvalue
    scores[i] = score

plt.bar(range(1,25),scores)
plt.hlines(np.mean(scores), 1, 25, colors='r', linestyles='dashed')
plt.xlabel('Month')
plt.xlim((1, 25))
plt.legend(['Mean Correlation over All Months', 'Monthly Rank Correlation'])
plt.ylabel('Rank correlation between PE Ratio and 30-day forward returns');
```





The correlation of PE Ratio and 30-day returns seems to be near 0 on average. It's important to note that this monthly and between 2012 and 2015. Different factors are predictive on differen timeframes and frequencies, so the fact that PE Ratio doesn't appear predictive here is not necessary throwing it out as a useful factor. Beyond it's usefulness in predicting returns, it can be used for risk exposure analysis as discussed in the Factor Risk Exposure Lecture.

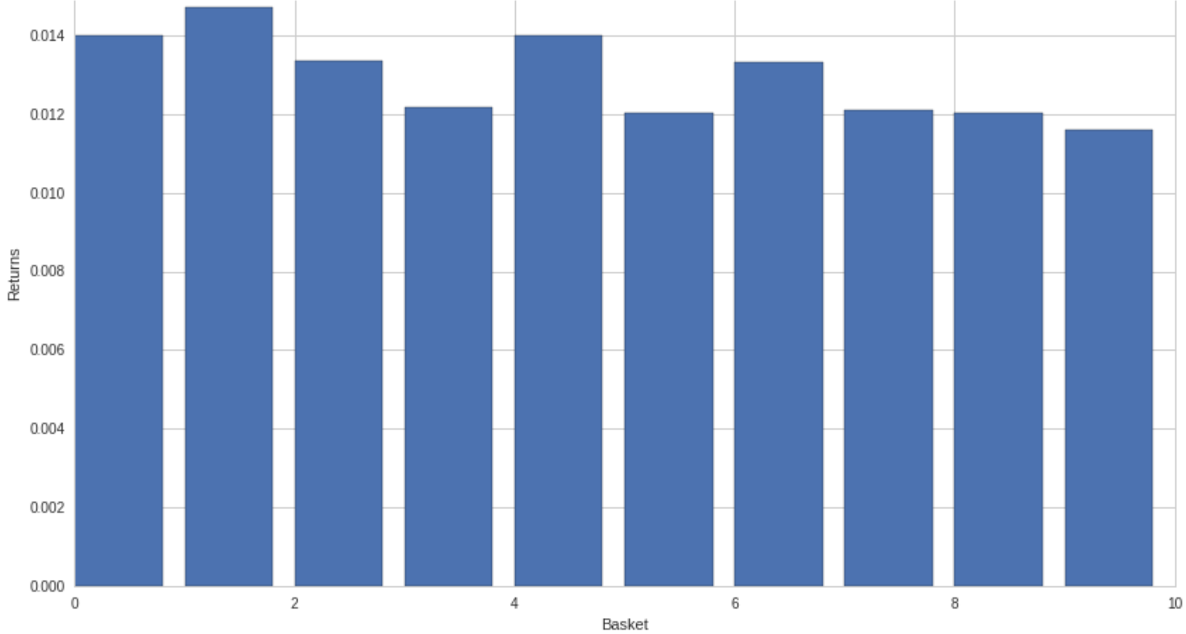
Basket Returns

The next step is to compute the returns of baskets taken out of our ranking. If we rank all equities and then split them into n groups, what would the mean return be of each group? We can answer this question in the following way. The first step is to create a function that will give us the mean return in each basket in a given the month and a ranking factor.

In [12]:
```
def compute_basket_returns(factor_data, forward_returns, number_of_baskets, month):

    data = pd.concat([factor_data.iloc[month-1],forward_returns.iloc[month-1]], axis=1)
    # Rank the equities on the factor values
    data.columns = ['Factor Value', 'Month Forward Returns']
    data.sort('Factor Value', inplace=True)

    # How many equities per basket
    equities_per_basket = np.floor(len(data.index) / number_of_baskets)

    basket_returns = np.zeros(number_of_baskets)

    # Compute the returns of each basket
    for i in range(number_of_baskets):
        start = i * equities_per_basket
        if i == number_of_baskets - 1:
            # Handle having a few extra in the last basket when our number of equities doesn't divide well
            end = len(data.index) - 1
        else:
            end = i * equities_per_basket + equities_per_basket
        # Actually compute the mean returns for each basket
        basket_returns[i] = data.iloc[start:end]['Month Forward Returns'].mean()

    return basket_returns
```

The first thing we'll do with this function is compute this for each month and then average. This should give us a sense of the relationship over a long timeframe.

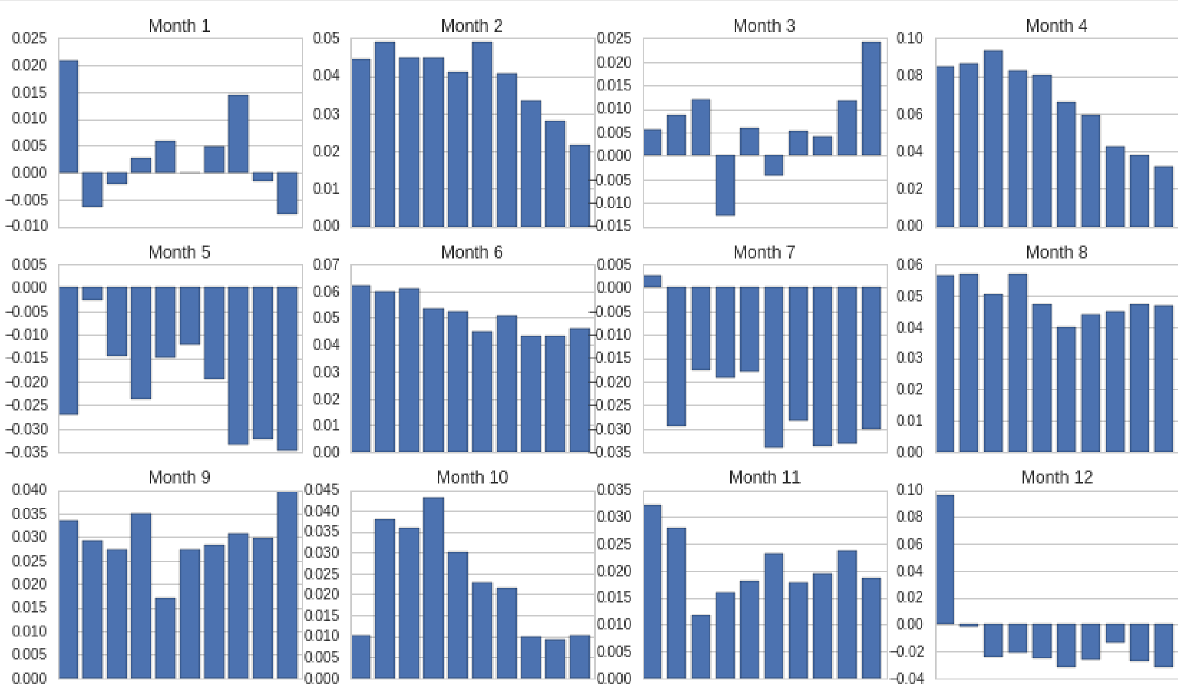
In [13]:
```
number_of_baskets = 10
mean_basket_returns = np.zeros(number_of_baskets)
for m in range(1, 25):
    basket_returns = compute_basket_returns(cap_data_filtered, month_forward_returns, number_of_baskets,
m)
    mean_basket_returns += basket_returns

mean_basket_returns /= 24

# Plot the returns of each basket
plt.bar(range(number_of_baskets), mean_basket_returns)
plt.ylabel('Returns')
plt.xlabel('Basket')
plt.legend(['Returns of Each Basket']);
```



Spread Consistency

Of course, that's just the average relationship. To get a sense of how consistent this is, and whether or not we would want to trade on it, we should look at it over time. Here we'll look at the monthly spreads for the first year. We can see a lot of variation, and further analysis should be done to determine whether Market Cap is tradeable.

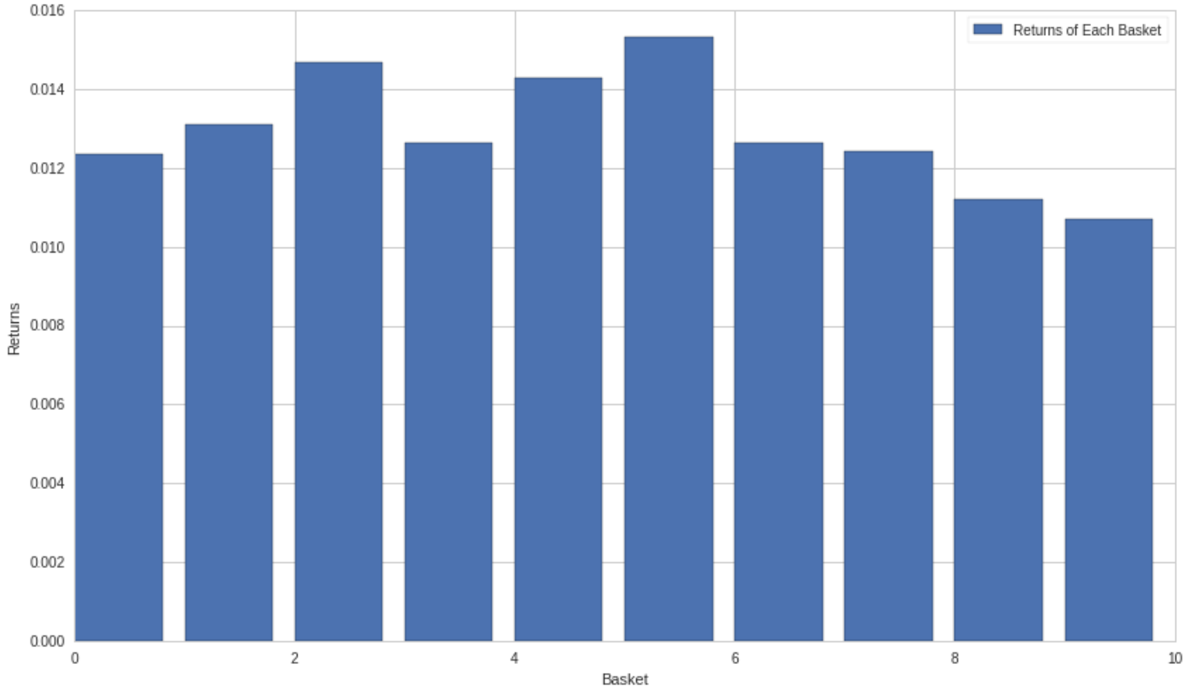
In [14]:
```
f, axarr = plt.subplots(3, 4)
for month in range(1, 13):
    basket_returns = compute_basket_returns(cap_data_filtered, month_forward_returns, 10, month)

    r = np.floor((month-1) / 4)
    c = (month-1) % 4
    axarr[r, c].bar(range(number_of_baskets), basket_returns)
    axarr[r, c].xaxis.set_visible(False) # Hide the axis lables so the plots aren't super messy
    axarr[r, c].set_title('Month ' + str(month))
```



We'll repeat the same analysis for PE Ratio.

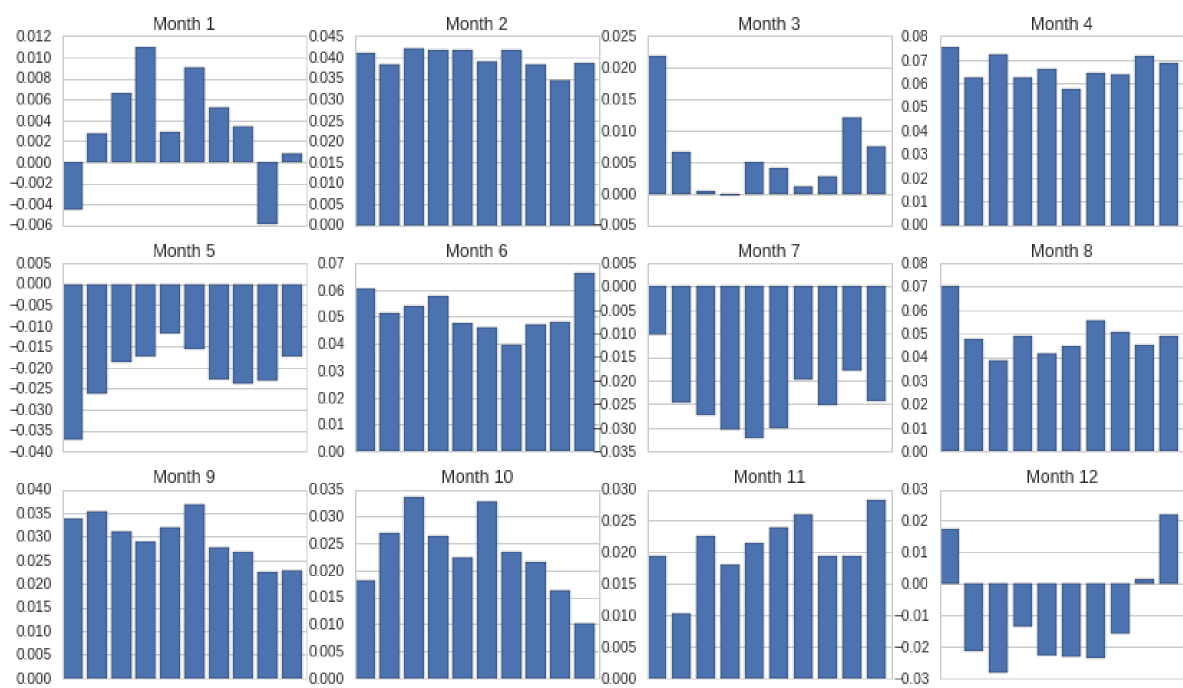
In [15]:
```
number_of_baskets = 10
mean_basket_returns = np.zeros(number_of_baskets)
for m in range(1, 25):
```

```
    basket_returns = compute_basket_returns(pe_data_filtered, month_forward_returns, number_of_baskets, m)
    mean_basket_returns += basket_returns

mean_basket_returns /= 24

# Plot the returns of each basket
plt.bar(range(number_of_baskets), mean_basket_returns)
plt.ylabel('Returns')
plt.xlabel('Basket')
plt.legend(['Returns of Each Basket']);
```



In [16]:

```
f, axarr = plt.subplots(3, 4)
for month in range(1, 13):
    basket_returns = compute_basket_returns(pe_data_filtered, month_forward_returns, 10, month)

    r = np.floor((month-1) / 4)
    c = (month-1) % 4
    axarr[r, c].bar(range(10), basket_returns)
    axarr[r, c].xaxis.set_visible(False) # Hide the axis lables so the plots aren't super messy
    axarr[r, c].set_title('Month ' + str(month))
```



Sometimes Factors are Just Other Factors

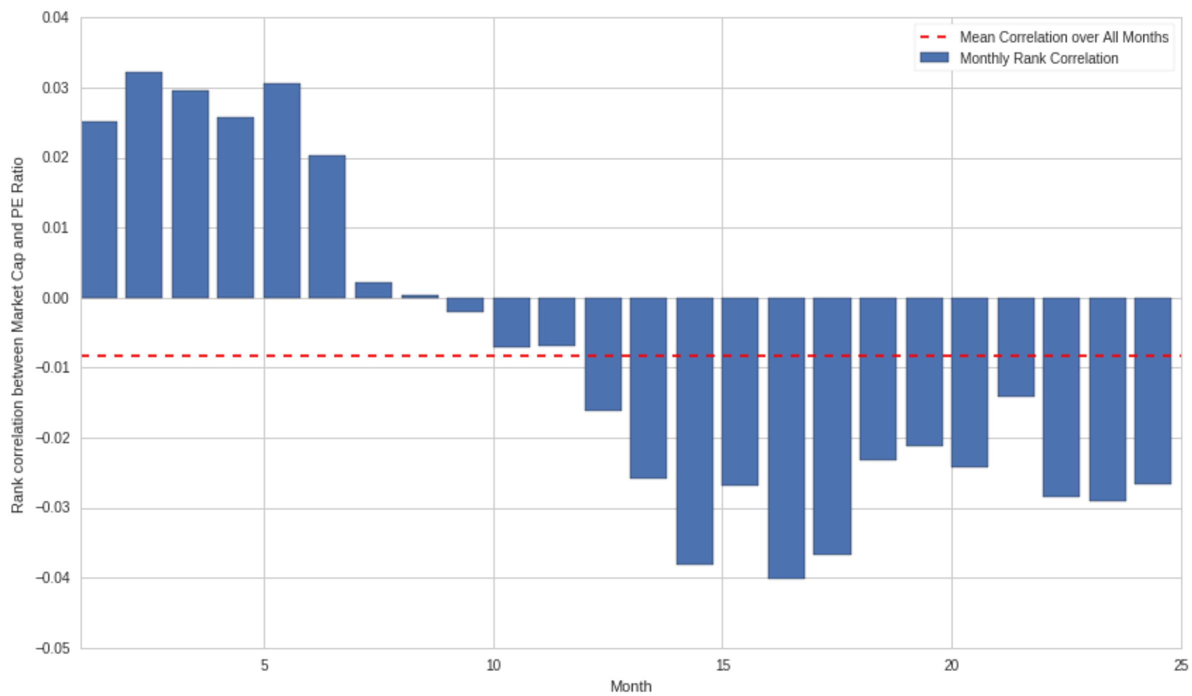
Often times a new factor will be discovered that seems to induce spread, but it turns out that it is just a new and potentially more complicated way to compute a well known factor. Consider for instance the case in which you have poured tons of resources into developing a new factor, it looks great, but how do you know it's not just another factor in disguise?

To check for this, there are many analyses that can be done.

Correlation Analysis

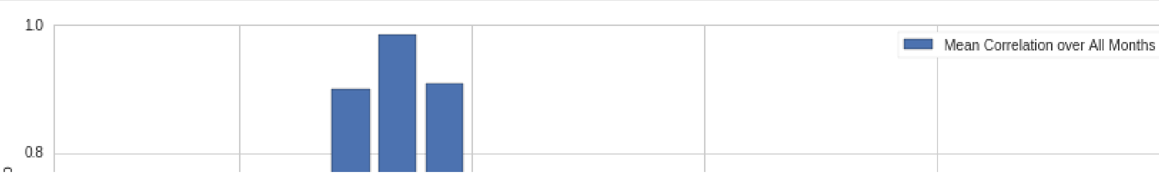
One of the most intuitive ways is to check what the correlation of the factors is over time. We'll plot that here.

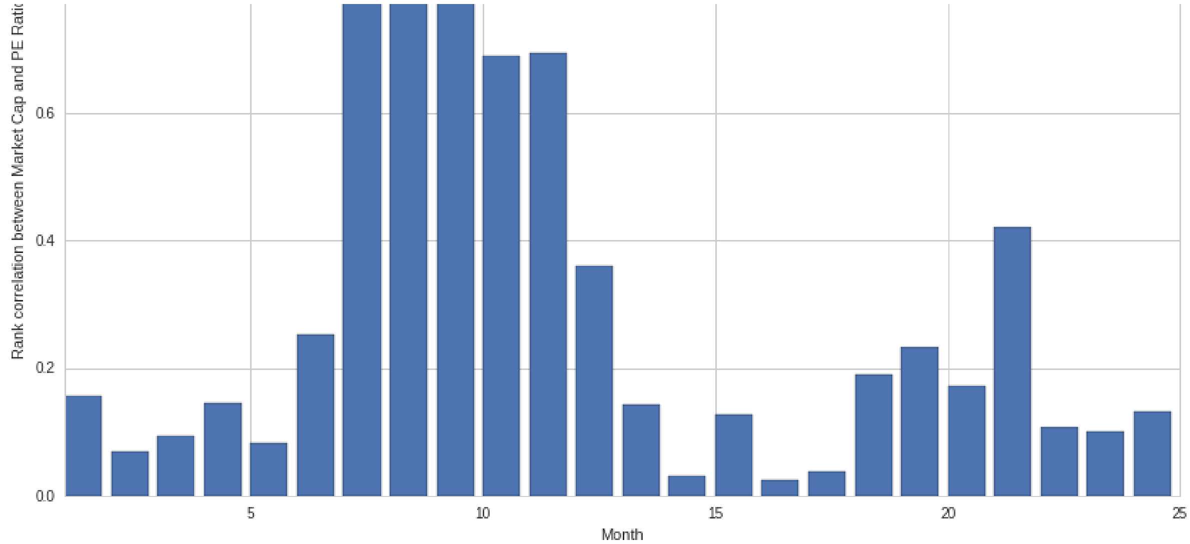
In [17]:
```
scores = np.zeros(24)
pvalues = np.zeros(24)
for i in range(24):
    score, pvalue = stats.spearmanr(cap_data_filtered.iloc[i], pe_data_filtered.iloc[i])
    pvalues[i] = pvalue
    scores[i] = score

plt.bar(range(1,25),scores)
plt.hlines(np.mean(scores), 1, 25, colors='r', linestyles='dashed')
plt.xlabel('Month')
plt.xlim((1, 25))
plt.legend(['Mean Correlation over All Months', 'Monthly Rank Correlation'])
plt.ylabel('Rank correlation between Market Cap and PE Ratio');
```



And also the p-values because the correlations may not be that meaningful by themselves.

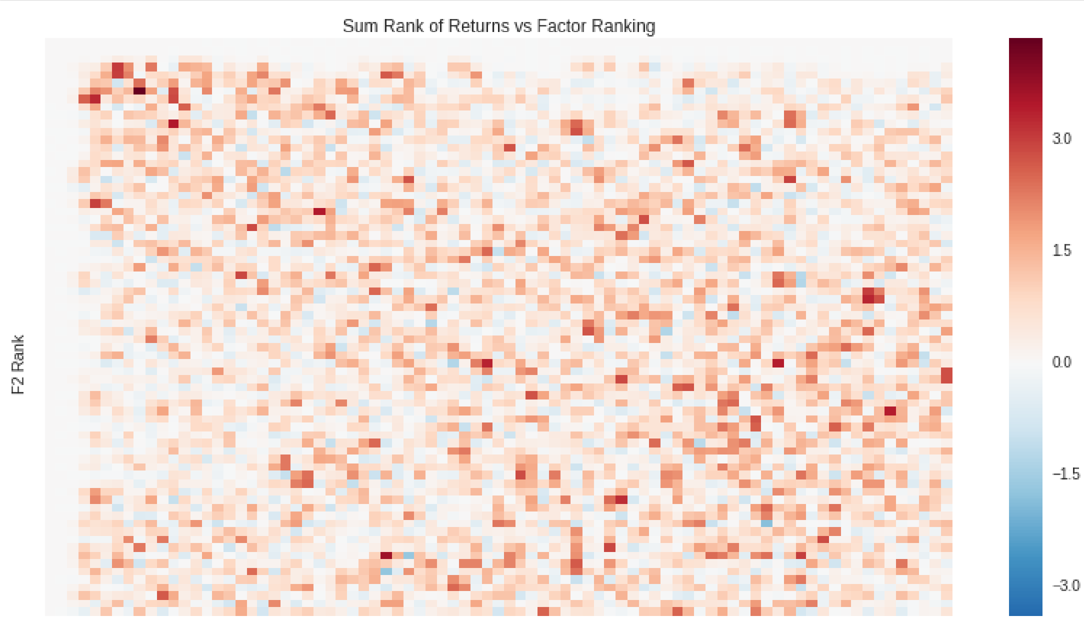
In [18]:
```
scores = np.zeros(24)
pvalues = np.zeros(24)
for i in range(24):
    score, pvalue = stats.spearmanr(cap_data_filtered.iloc[i], pe_data_filtered.iloc[i])
    pvalues[i] = pvalue
    scores[i] = score

plt.bar(range(1,25),pvalues)
plt.xlabel('Month')
plt.xlim((1, 25))
plt.legend(['Mean Correlation over All Months', 'Monthly Rank Correlation'])
plt.ylabel('Rank correlation between Market Cap and PE Ratio');
```

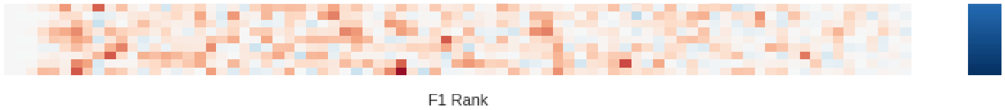




There is interesting behavior, and further analysis would be needed to determine whether a relationship existed.

In [19]:
```
pe_dataframe = pd.DataFrame(pe_data_filtered.iloc[0])
pe_dataframe.columns = ['F1']
cap_dataframe = pd.DataFrame(cap_data_filtered.iloc[0])
cap_dataframe.columns = ['F2']
returns_dataframe = pd.DataFrame(month_forward_returns.iloc[0])
returns_dataframe.columns = ['Returns']

data = pe_dataframe.join(cap_dataframe).join(returns_dataframe)

data = data.rank(method='first')

heat = np.zeros((len(data), len(data)))

for e in data.index:
    F1 = data.loc[e]['F1']
    F2 = data.loc[e]['F2']
    R = data.loc[e]['Returns']
    heat[F1-1, F2-1] += R

heat = scipy.signal.decimate(heat, 40)
heat = scipy.signal.decimate(heat.T, 40).T

p = sns.heatmap(heat, xticklabels=[], yticklabels=[])
# p.xaxis.set_ticks([])
# p.yaxis.set_ticks([])
p.xaxis.set_label_text('F1 Rank')
p.yaxis.set_label_text('F2 Rank')
p.set_title('Sum Rank of Returns vs Factor Ranking');
```





How to Choose Ranking System

The ranking system is the secret sauce of many strategies. Choosing a good ranking system, or factor, is not easy and the subject of much research. We'll discuss a few starting points here.

Clone and Tweak

Choose one that is commonly discussed and see if you can modify it slightly to gain back an edge. Often times factors that are public will have no signal left as they have been completely arbitraged out of the market. However, sometimes they lead you in the right direction of where to go.

Pricing Models

Any model that predicts future returns can be a factor. The future return predicted is now that factor, and can be used to rank your universe. You can take any complicated pricing model and transform it into a ranking.

Price Based Factors (Technical Indicators)

Price based factors take information about the historical price of each equity and use it to generate the factor value. Examples could be 30-day momentum, or volatility measures.

Reversion vs. Momentum

It's important to note that some factors bet that prices, once moving in a direction, will continue to do so. Some factors bet the opposite. Both are valid models on different time horizons and assets, and it's important to investigate whether the underlying behavior is momentum or reversion based.

Fundamental Factors (Value Based)

This is using combinations of fundamental values as we discussed today. Fundamental values contain information that is tied to real world facts about a company, so in many ways can be more robust than prices.

The Arms Race

Ultimately, developing predictive factors is an arms race in which you are trying to stay one step ahead. Factors get arbitraged out of markets and have a lifespan, so it's important that you are constantly doing work to determine how much decay your factors are experiencing, and what new factors might be used to take their place.