Lending Club Dataset Exploration

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As the P2P Lending sphere develops, a unique opportunity for economic analysis is presented. Many of these platforms are as transparent as possible to encourage investors to utilize public data and develop strategies. For Lending Club in particular, almost every single loan processed through their standard program is cleansed of identifying information and published to their site. For now, the dataset is mostly useful for investors in either Lending Club loans or Lending Club's equity, but eventually, the combined datasets of P2P lenders could provide an interesting look at consumer credit details. Currently, macro factors are likely influences on demand for P2P loans, but maybe one day P2P loan demand itself could be a macro factor. In the project, I'll be identifying some characteristics of the dataset that will help put the space in context.

In [106]:
```
%matplotlib inline

import pandas as pd
import datetime
import matplotlib.pyplot as plt
from pandas.tools.plotting import table
import matplotlib
import numpy as np
from pandas.stats.api import ols
```

Importing and Cleaning Data

The data I used came from https://www.lendingclub.com/info/download-data.action (https://www.lendingclub.com/info/download-data.action). I downloaded the quarterly zips and used the extracted files to simplify importing. Only accepted loans are included in this dataset, so most of the entries have a healthy amount of data reported.

State population data is from a recent census and macroeconomic data is from FRED.

In [107]:
```
def readZIPFiles(path2):
    path1 = '/Users/sashankparigi/Desktop/Data_Bootcamp/Lending Club/'
    df = pd.read_csv(path1 + path2, header=0,low_memory = False, encoding = "ISO-88
59-1")
    return df;

def PullLoanDF(month,count):
    #This function is used for tracking the purpose of each loan in each month of d
ata
    g = df_full[df_full['issue_d'] == month]
    a = g[g['title'] == 'Debt consolidation'].count()['title']
    b = g[g['title'] == 'Credit card refinancing'].count()['title']
    c = g[g['title'] == 'Home improvement'].count()['title']
    d = g[g['title'] == 'Business'].count()['title']
    e = g[g['title'] == 'Medical expenses'].count()['title']
    f = g[g['title'] == 'Major purchase'].count()['title']
    g = g[g['title'] == 'Other'].count()['title']
    total = a+b+c+d+e+f+g
    df_monthly2.set_value(count,'Date',month)
    df_monthly2.set_value(count,'Debt',a)
    df_monthly2.set_value(count,'Credit Card',b)
    df_monthly2.set_value(count,'Home Improvement',c)
    df_monthly2.set_value(count,'Business',d)
    df_monthly2.set_value(count,'Medical Expenses',e)
```

```
    df_monthly2.set_value(count,'Major Purchase',f);

    df_monthly2.set_value(count,'Other',g);

def PullLoanDF2(month,count):
    #Similar function as above, but returns percentages instead of full loan count
s.
    #In retrospect, I should have just added a boolean to the first...
    g = df_full[df_full['issue_d'] == month]
    a = g[g['title'] == 'Debt consolidation'].count()['title']
    b = g[g['title'] == 'Credit card refinancing'].count()['title']
    c = g[g['title'] == 'Home improvement'].count()['title']
    d = g[g['title'] == 'Business'].count()['title']
    e = g[g['title'] == 'Medical expenses'].count()['title']
    f = g[g['title'] == 'Major purchase'].count()['title']
    g = g[g['title'] == 'Other'].count()['title']
    total = a+b+c+d+e+f+g
    df_monthly3.set_value(count,'Date',month)
    df_monthly3.set_value(count,'Debt',a/total)
    df_monthly3.set_value(count,'Credit Card',b/total)
    df_monthly3.set_value(count,'Home Improvement',c/total)
    df_monthly3.set_value(count,'Business',d/total)
    df_monthly3.set_value(count,'Medical Expenses',e/total)
    df_monthly3.set_value(count,'Major Purchase',f/total);

    df_monthly3.set_value(count,'Other',g/total);

#Calling function to read in each quarterly file
path2 = 'LoanStats_2016Q1.csv'
df_2016Q1 = readZIPFiles(path2)
path2 = 'LoanStats_2016Q2.csv'
df_2016Q2 = readZIPFiles(path2)
path2 = 'LoanStats_2016Q3.csv'
df_2016Q3 = readZIPFiles(path2)
path2 = 'LoanStats_2016Q4.csv'
df_2016Q4 = readZIPFiles(path2)
path2 = 'LoanStats_2017Q1.csv'
df_2017Q1 = readZIPFiles(path2)
path2 = 'LoanStats_2017Q2.csv'
df_2017Q2 = readZIPFiles(path2)
path2 = 'LoanStats_2017Q3.csv'
df_2017Q3 = readZIPFiles(path2)

#Combining all the quarterly files into one dataset, makes it easier to split back
 into months later
frames = [df_2016Q1,df_2016Q2,df_2016Q3,df_2016Q4,df_2017Q1,df_2017Q2,df_2017Q3]
df_full = pd.concat(frames)
```

In [108]:
```
#Builds new dataframe for Loan purpose breakdowns
columns_monthly2 = ['Date','Debt','Credit Card','Home Improvement','Business','Medi
cal Expenses','Major Purchase','Other']
df_monthly2 = pd.DataFrame(columns=columns_monthly2)

#Runs previously defined fucntion for every month
months = ["Jan-16","Feb-16","Mar-16","Apr-16","May-16","Jun-16","Jul-16","Aug-16",
"Sep-16","Oct-16","Nov-16","Dec-16","Jan-17","Feb-17","Mar-17","Apr-17","May-17","J
un-17","Jul-17","Aug-17","Sep-17"]
count = 1
for month in months:
    PullLoanDF(month,count)
    count = count + 1

df_monthly2
```

Out[108]:

	Date	Debt	Credit Card	Home Improvement	Business	Medical Expenses	Major Purchase	Other
1	Jan-16	17028	7639	1732	307	329	561	1514
2	Feb-16	20763	8778	2244	347	411	778	1853
3	Mar-16	32646	12874	4114	637	636	1398	3463
4	Apr-16	18603	7139	2567	366	390	853	2494
5	May-16	14819	5383	2107	343	346	672	1802
6	Jun-16	16956	6126	2748	336	454	920	2232
7	Jul-16	19163	6126	2486	335	410	799	2432
8	Aug-16	19552	6572	2427	340	373	859	2528
9	Sep-16	15284	5018	2066	325	391	721	2044
10	Oct-16	18902	6308	2508	363	475	781	2325
11	Nov-16	20150	7058	2417	351	488	779	2363
12	Dec-16	20697	7162	2468	502	505	910	2695
13	Jan-17	18431	6858	2123	395	423	655	1982
14	Feb-17	15652	6100	2005	336	399	622	1758
15	Mar-17	20724	8059	2930	415	531	890	2390
16	Apr-17	16227	6107	2706	311	446	734	2124
17	May-17	20872	7738	3353	395	600	909	2404
18	Jun-17	21465	7409	3163	330	602	974	2611
19	Jul-17	22195	7861	3164	364	592	986	2769
20	Aug-17	24426	8597	3396	458	689	1146	3180
21	Sep-17	22638	7436	3174	444	638	992	2990

To interpret results better, I build a pie chart using cumulative data for the entire time period.

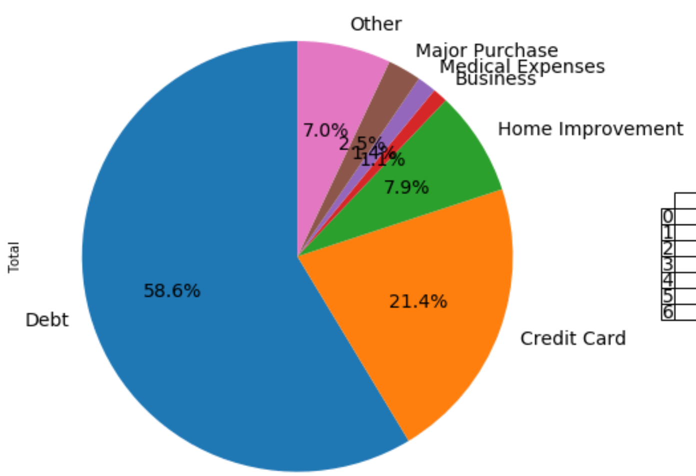
In [109]:
```python
rows_plot = ['Debt','Credit Card','Home Improvement','Business','Medical Expenses',
'Major Purchase','Other']
columns_plot = ['Title','Total']
raw_data = {'Title': ['Debt','Credit Card','Home Improvement','Business','Medical E
xpenses','Major Purchase','Other'],
        'Total': [0,0,0,0,0,0,0]}


df_plot = pd.DataFrame(raw_data,columns=columns_plot)
df_plot.index.name = "index"

#Plugs cumulative numbers for each category into a new dataframe
count = 0
for row in rows_plot:
    sum1 = df_monthly2.sum()[row]
    df_plot.set_value(count,'Total',sum1)
    count = count + 1

plt.figure(figsize=(16,8))
# plot chart
ax1 = plt.subplot(121, aspect='equal')
df_plot.plot(kind='pie', y = 'Total', ax=ax1, autopct='%1.1f%%',
 startangle=90, shadow=False, labels=df_plot['Title'], legend = False, fontsize=14)

# plot table
ax2 = plt.subplot(122)
plt.axis('off')
tbl = table(ax2, df_plot, loc='center')
tbl.auto_set_font_size(False)
tbl.set_fontsize(14)
plt.show()
```



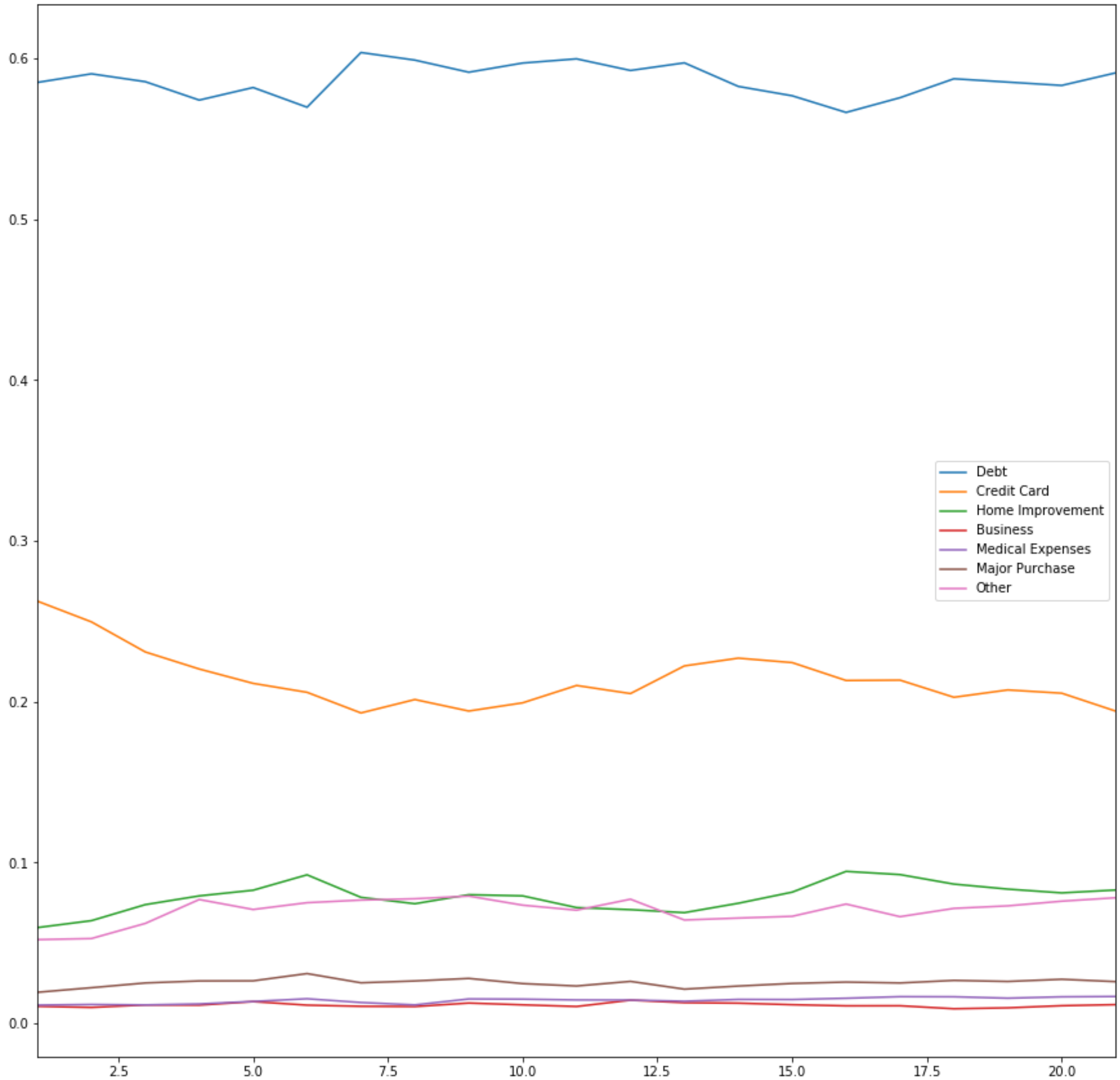
	Title	Total
0	Debt	417193
1	Credit Card	152348
2	Home Improvement	55898
3	Business	8000
4	Medical Expenses	10128
5	Major Purchase	17939
6	Other	49953

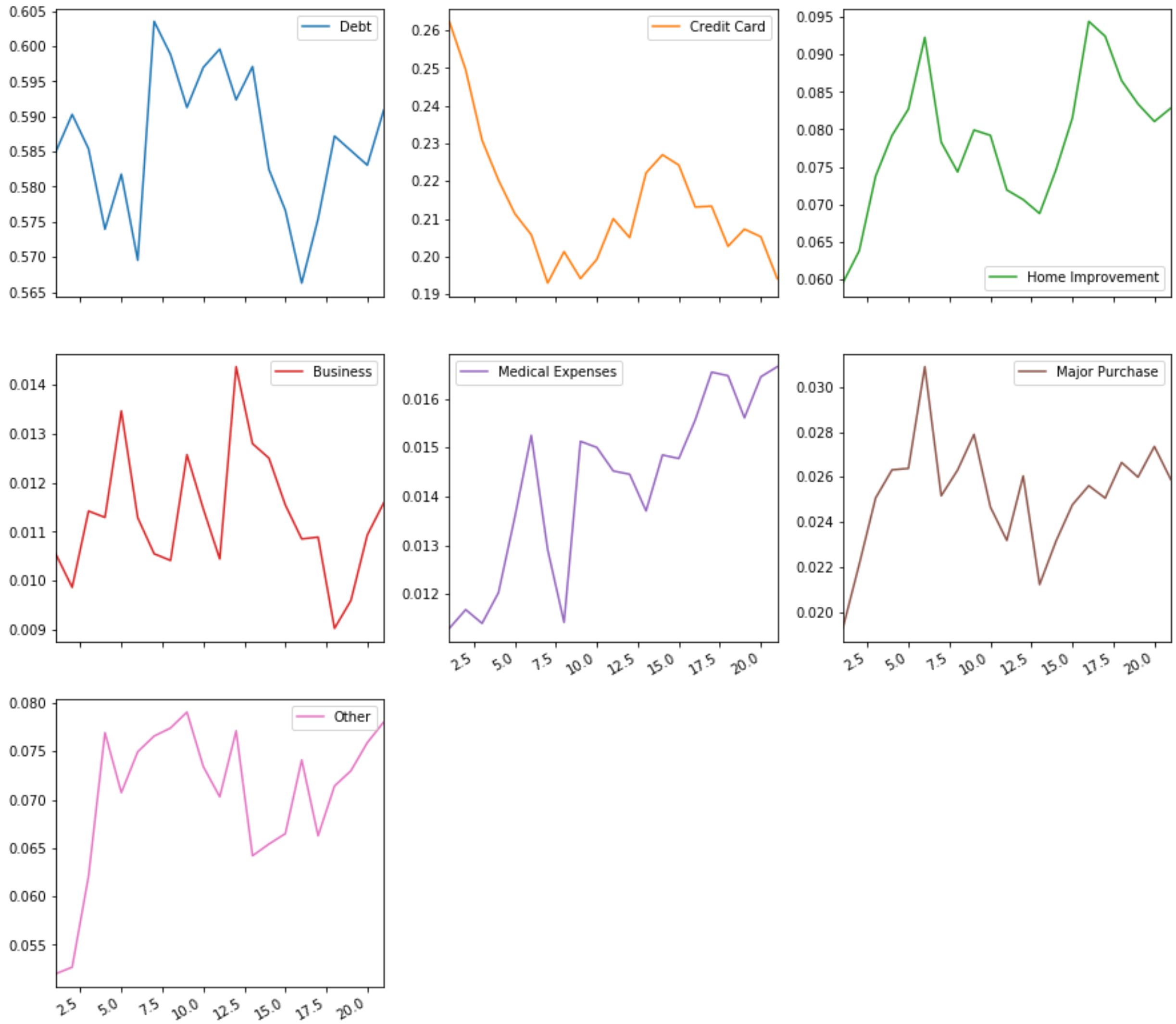
The pie chart above shows a clear preference in uses for the loans. Credit card refinancing and debt consolidation are the favorites, but other uses still make up a solid 20% of the loans. The credit card and debt consolidation categories could effectively be put together as they are driven by similar motivations. High interest rates and debts spread out across multiple cards make lending club an attractive choice for someone looking to simplify their finances.

To see how this split has been changing over time, I construct line charts below.

In [110]:
```
#Create new dataframe to hold category percentages over time
df_monthly3 = pd.DataFrame(columns=columns_monthly2)

count = 1
for month in months:
    PullLoanDF2(month,count)
    count = count + 1
#full plot
df_monthly3.plot(figsize =(15,15))
#sub plots
df_monthly3.plot(subplots=True, layout = (3,3), figsize = (15,15));
```


0.6
0.5
0.4
0.3
0.2
0.1
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Debt
Credit Card
Home Improvement
Business
Medical Expenses
Major Purchase
Other



As evidenced in the first full chart, the relative strength of each category has remained unchanged since the beginning of 2016. However, looking at the individual sub plots, there are still some interesting trends. Credit card refinancing has fallen from 26% to 20%. Meanwhile, all the "consumer spending" uses of loans have picked up. Perhaps customers initially treated Lending Club as primarily a vehicle for getting a better deal on credit cards and after success with that, they began to get comfortable using lending club for day-to-day purposes. From lending club's perspective, diversification is great for business. From the perspective of macroeconomists, more diversification in use means the dataset is becoming more useful for understanding consumer behavior.

Next, I want to look at income and debt levels of the people taking out these loans to get a better sense of the audience.

In [111]:
```
def PopulateMonthlyDF(month,count):
    g = df_full[df_full['issue_d'] == month]
    loan_sum = g['loan_amnt'].sum()
    average_income = g['annual_inc'].sum()
    average_incomec = g['annual_inc'].count()
    average_debt = g['tot_cur_bal'].sum()
    average_debtc = g['tot_cur_bal'].count()
    df_monthly.set_value(count,'Date',month)
    df_monthly.set_value(count,'Total Loans',loan_sum)
    df_monthly.set_value(count,'Average Income',average_income/average_incomec)
    df_monthly.set_value(count,'Average Outstanding Debt',average_debt/average_debt
c)
    df_monthly.set_value(count,'Coverage Ratio',(average_income/average_incomec)/(a
verage_debt/average_debtc));

columns_monthly = ['Date','Average Income','Average Outstanding Debt','Total Loans'
,'Coverage Ratio']
df_monthly = pd.DataFrame(columns=columns_monthly)

months = ["Jan-16","Feb-16","Mar-16","Apr-16","May-16","Jun-16","Jul-16","Aug-16",
"Sep-16","Oct-16","Nov-16","Dec-16","Jan-17","Feb-17","Mar-17","Apr-17","May-17","J
un-17","Jul-17","Aug-17","Sep-17"]
count = 0

for month in months:
    PopulateMonthlyDF(month,count)
    count = count + 1

df_monthly
```

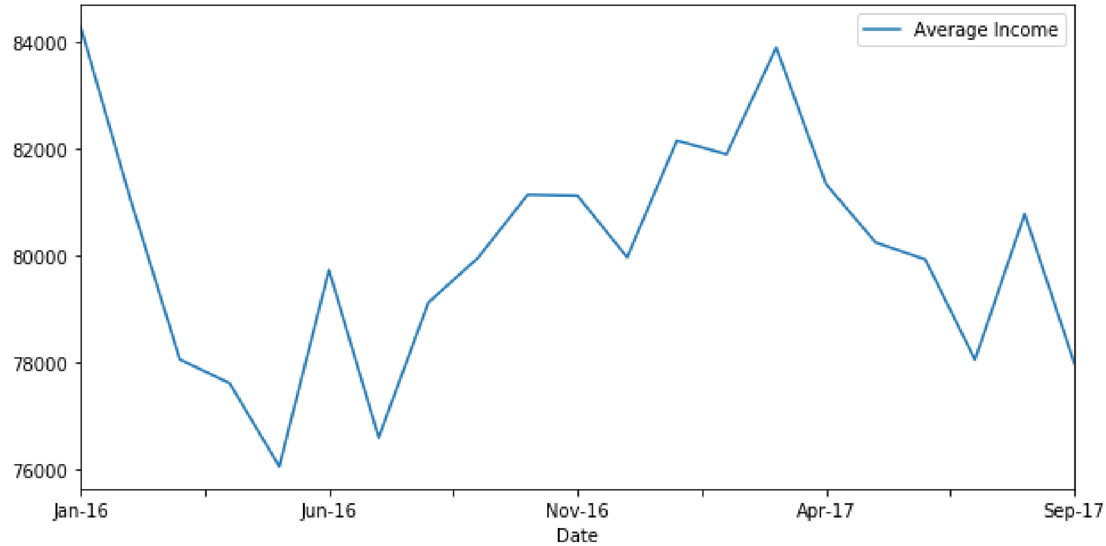
Out[111]:

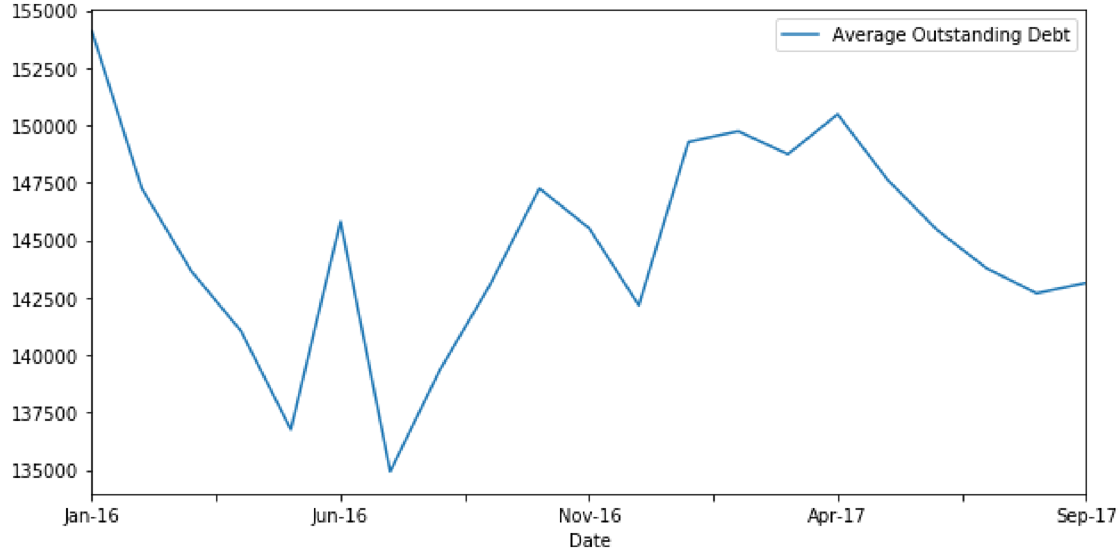
	Date	Average Income	Average Outstanding Debt	Total Loans	Coverage Ratio
0	Jan-16	84302.4	154088	5.18403e+08	0.547107
1	Feb-16	81079.4	147266	6.19446e+08	0.550562
2	Mar-16	78067.5	143648	9.49368e+08	0.543466
3	Apr-16	77626	141035	5.37278e+08	0.550401
4	May-16	76068.4	136753	4.17539e+08	0.556247
5	Jun-16	79741.8	145812	4.88624e+08	0.546882
6	Jul-16	76609.5	134929	4.88021e+08	0.567778
7	Aug-16	79134.6	139352	5.17054e+08	0.567875
8	Sep-16	79973.2	143021	3.99512e+08	0.55917
9	Oct-16	81153.7	147251	4.64761e+08	0.551125
10	Nov-16	81135	145518	4.92691e+08	0.557559
11	Dec-16	79981.4	142159	5.07873e+08	0.562618
12	Jan-17	82165.5	149276	4.70401e+08	0.550427
13	Feb-17	81909.4	149738	4.17331e+08	0.547018
14	Mar-17	83906.8	148738	5.50237e+08	0.564125
15	Apr-17	81353.3	150475	4.37931e+08	0.540643
16	May-17	80259.2	147635	5.49519e+08	0.543635
17	Jun-17	79940.2	145440	5.50983e+08	0.549644
18	Jul-17	78063.9	143765	5.69394e+08	0.542995
19	Aug-17	80792.7	142686	6.20409e+08	0.566229
20	Sep-17	77995.3	143135	6.01398e+08	0.544908

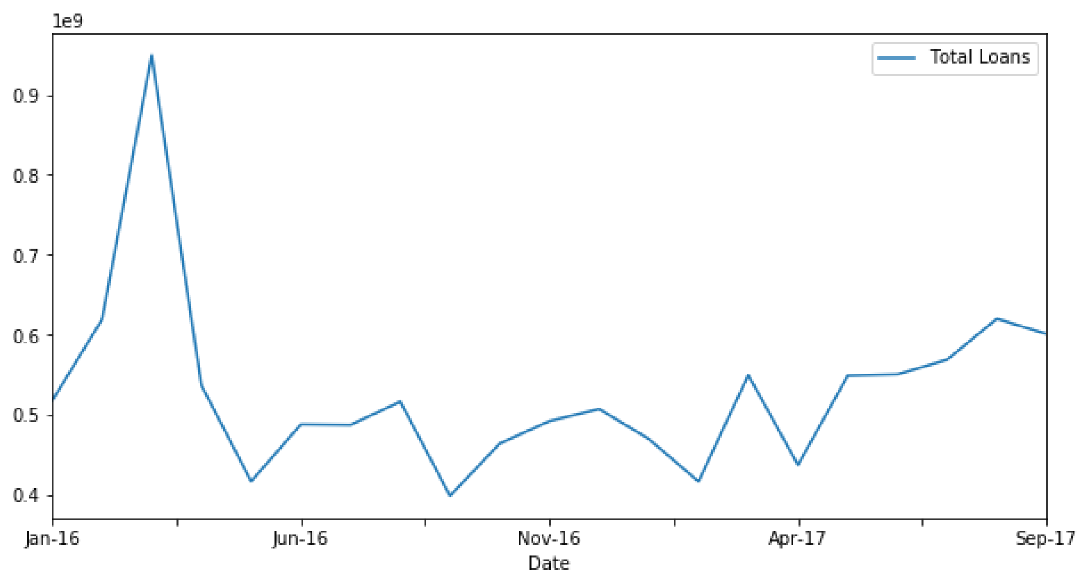
It might not be obvious from the output, but these Americans in the lending club dataset have very healthy finances. The average American is making an income of 55,000 with a total debt of 205,000. This translates to a coverage ratio about half as strong as that of Lending Club's customers.

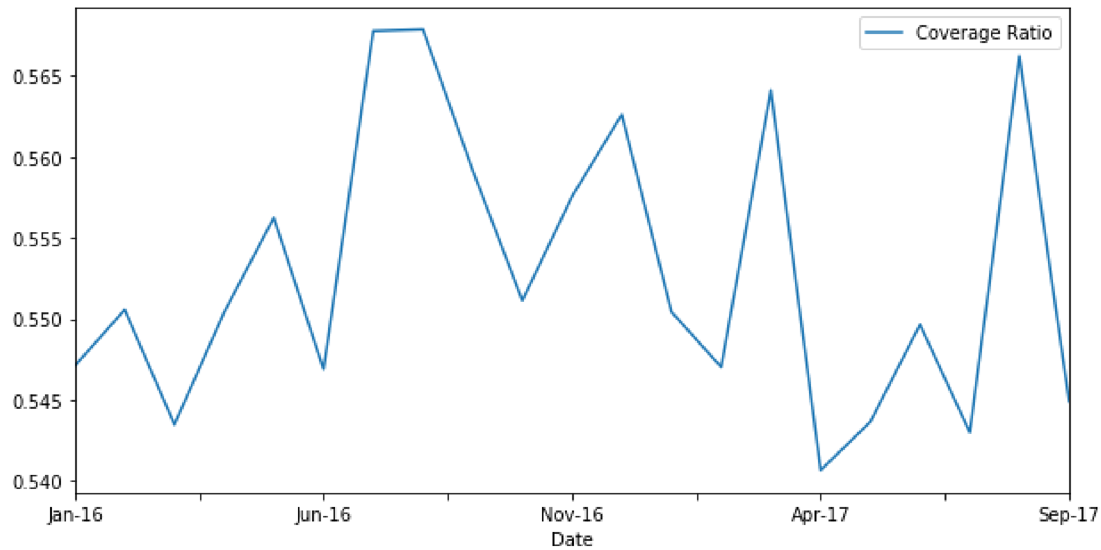
In [112]:
```
df_monthly.plot(x = 'Date',y = 'Average Income', figsize = (10,5))
df_monthly.plot(x = 'Date',y = 'Average Outstanding Debt', figsize = (10,5))
df_monthly.plot(x = 'Date',y = 'Total Loans', figsize = (10,5))
df_monthly.plot(x = 'Date',y = 'Coverage Ratio', figsize = (10,5))
```

```
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x1104a15c0>
```









The time series of these metrics show that average income and average outstanding debt have fallen slightly, but total originations (a proxy for overall demand) and coverage ratio have fluctuated around a mean during this period.

Next, I want to see if there are any geographic patterns with demand for lending club loans.

In [113]:
```
# Geographic Density of Loans

#Pulls the number of loans made in each state for the entire time period
def pullStateLoans(state,count):
    g = df_full[df_full['addr_state'] == state]
    loans = g['addr_state'].count()
    df_pops.set_value(count,'Loan Count',loans);

#Link provides population data in order to get a per capita figure that can be comp
ared across states
df_pops = pd.read_csv('http://www.101computing.net/wp/wp-content/uploads/US-States.
txt',header = -1)
df_pops.columns = ['State','Abr','Population']
df_pops['Loan Count']=""
df_pops['Loans per Capita']=""
#df_pops = df_pops.set_index('Abr')



states = ["AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE", "FL", "GA",
          "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD",
          "MA", "MI", "MN", "MS", "MO", "MT", "NE", "NV", "NH", "NJ",
          "NM", "NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
          "SD", "TN", "TX", "UT", "VT", "VA", "WA","DC", "WV", "WI", "WY"]
count = 0
for state in states:
    pullStateLoans(state, count)
    count = count+1

df_pops['Loans per Capita'] = df_pops['Loan Count']/df_pops['Population']
```

In [114]:
```
df_pops.sort_values('Loans per Capita',ascending = False)
```

Out[114]:

	State	Abr	Population	Loan Count	Loans per Capita
27	Nevada	NV	1998257	10875	0.00544224
5	Colorado	CO	4301261	15641	0.00363638
6	Connecticut	CT	3405565	12317	0.00361673
2	Arizona	AZ	5130632	18251	0.00355726
8	Florida	FL	15982378	54773	0.00342709
19	Maryland	MD	5296486	18078	0.00341321
31	New York	NY	18976457	62974	0.00331853
29	New Jersey	NJ	8414350	27830	0.00330745
38	Rhode Island	RI	1048319	3369	0.00321372
50	Wyoming	WY	493782	1538	0.00311473
42	Texas	TX	20851820	64425	0.00308966
28	New Hampshire	NH	1235786	3798	0.00307335
9	Georgia	GA	8186453	24828	0.00303282
4	California	CA	33871648	101377	0.00299298
47	Washington D.C.	DC	572059	1689	0.00295249
45	Virginia	VA	7078515	20670	0.0029201
10	Hawaii	HI	1211537	3485	0.00287651
44	Vermont	VT	608827	1716	0.00281853
33	North Dakota	ND	642200	1803	0.00280754
1	Alaska	AK	626932	1729	0.00275787
7	Delaware	DE	783600	2154	0.00274885
22	Minnesota	MN	4919479	13452	0.00273444
20	Massachusetts	MA	6349097	17312	0.00272669
32	North Carolina	NC	8049313	21231	0.00263762
46	Washington	WA	5894121	14989	0.00254304
12	Illinois	IL	12419293	31063	0.00250119
36	Oregon	OR	3421399	8509	0.00248699
39	South Carolina	SC	4012012	9474	0.00236141
15	Kansas	KS	2688418	6246	0.0023233
25	Montana	MT	902195	2049	0.00227113
34	Ohio	OH	11353140	25782	0.00227091
41	Tennessee	TN	5689283	12527	0.00220186
13	Indiana	IN	6080485	13305	0.00218815
24	Missouri	MO	5595211	12083	0.00215953
30	New Mexico	NM	1819046	3915	0.00215223
26	Nebraska	NE	1711263	3680	0.00215046

	State	Abr	Population	Loan Count	Loans per Capita
3	Arkansas	AR	2673400	5742	0.00214783
43	Utah	UT	2233169	4769	0.00213553
37	Pennsylvania	PA	12281054	25639	0.00208769
0	Alabama	AL	4447100	9133	0.0020537
21	Michigan	MI	9938444	20112	0.00202366
35	Oklahoma	OK	3450654	6958	0.00201643
40	South Dakota	SD	754844	1501	0.00198849
17	Louisiana	LA	4468976	8657	0.00193713
18	Maine	ME	1274923	2457	0.00192718
49	Wisconsin	WI	5363675	10147	0.0018918
16	Kentucky	KY	4041769	7417	0.00183509
23	Mississippi	MS	2844658	4933	0.00173413
11	Idaho	ID	1293953	2166	0.00167394
48	West Virginia	WV	1808344	770	0.000425804
14	Iowa	IA	2926324	0	0

Nevada, Arizona, and Florida stand out as three states whose housing markets were disproportionately hit during the housing crisis. Therefore, it makes sense that people in these states would have the worst debt situations and be most upon to considering new alternatives like P2P lending. The bottom few states tend to be more southern/midwestern. Iowa is the one state where P2P lending is still not legal.

Next, I want to see if macro factors have any relationship with overall originations by building a regression.

In [115]:
```
path2 = 'UNRATE.csv'
df_UNRATE = readZIPFiles(path2)
path2 = 'REVOLSL.csv'
df_REVOLSL = readZIPFiles(path2)
path2 = 'FEDFUNDS.csv'
df_FEDFUNDS = readZIPFiles(path2)


df_macro = pd.concat([df_monthly, df_UNRATE], axis=1)
df_macro = df_macro.drop('DATE', 1)
df_macro = pd.concat([df_macro, df_REVOLSL], axis=1)
df_macro = df_macro.drop('DATE', 1)
df_macro = pd.concat([df_macro, df_FEDFUNDS], axis=1)
df_macro = df_macro.drop('DATE', 1)


df_macro=df_macro.drop(df_macro.index[len(df_macro)-1])
df_macro=df_macro.drop(df_macro.index[len(df_macro)-1])


#Change in outstanding consumer credit is more relevant than the total amount
df_macro['Delta REVOLSL'] = df_macro['REVOLSL'].diff()
df_macro
```

Out[115]:

	Date	Average Income	Average Outstanding Debt	Total Loans	Coverage Ratio	UNRATE	REVOLSL	FEDFUNDS	Delta REVOLSL
0	Jan-16	84302.4	154088	5.18403e+08	0.547107	4.9	911.7307	0.34	NaN
1	Feb-16	81079.4	147266	6.19446e+08	0.550562	4.9	913.6404	0.38	1.9097
2	Mar-16	78067.5	143648	9.49368e+08	0.543466	5.0	924.8057	0.36	11.1653
3	Apr-16	77626	141035	5.37278e+08	0.550401	5.0	927.3958	0.37	2.5901
4	May-16	76068.4	136753	4.17539e+08	0.556247	4.7	931.6313	0.37	4.2355
5	Jun-16	79741.8	145812	4.88624e+08	0.546882	4.9	939.5301	0.38	7.8988
6	Jul-16	76609.5	134929	4.88021e+08	0.567778	4.9	942.6965	0.39	3.1664
7	Aug-16	79134.6	139352	5.17054e+08	0.567875	4.9	948.3063	0.40	5.6098
8	Sep-16	79973.2	143021	3.99512e+08	0.55917	4.9	952.2508	0.40	3.9445
9	Oct-16	81153.7	147251	4.64761e+08	0.551125	4.8	955.3078	0.40	3.0570
10	Nov-16	81135	145518	4.92691e+08	0.557559	4.6	967.6337	0.41	12.3259
11	Dec-16	79981.4	142159	5.07873e+08	0.562618	4.7	969.6323	0.54	1.9986
12	Jan-17	82165.5	149276	4.70401e+08	0.550427	4.8	970.5187	0.65	0.8864
13	Feb-17	81909.4	149738	4.17331e+08	0.547018	4.7	975.4803	0.66	4.9616
14	Mar-17	83906.8	148738	5.50237e+08	0.564125	4.5	979.8672	0.79	4.3869
15	Apr-17	81353.3	150475	4.37931e+08	0.540643	4.4	980.6683	0.90	0.8011
16	May-17	80259.2	147635	5.49519e+08	0.543635	4.3	987.4624	0.91	6.7941
17	Jun-17	79940.2	145440	5.50983e+08	0.549644	4.4	991.8880	1.04	4.4256
18	Jul-17	78063.9	143765	5.69394e+08	0.542995	4.3	992.0818	1.15	0.1938
19	Aug-17	80792.7	142686	6.20409e+08	0.566229	4.4	997.1717	1.16	5.0899

	Date	Average Income	Average Outstanding Debt	Total Loans	Coverage Ratio	UNRATE	REVOLSL	FEDFUNDS	Delta REVOLSL
20	Sep-17	77995.3	143135	6.01398e+08	0.544908	4.2	1003.2173	1.15	6.0456

In [116]:

```
result = ols(y=df_macro['Total Loans'], x=df_macro[['UNRATE','FEDFUNDS','Delta REVO
LSL']])
print(result)
```

```
/Users/sashankparigi/anaconda/lib/python3.6/site-packages/IPython/core/interactive
shell.py:2881: FutureWarning: The pandas.stats.ols module is deprecated and will b
e removed in a future version. We refer to external packages like statsmodels, see
some examples here: http://www.statsmodels.org/stable/regression.html
  exec(code_obj, self.user_global_ns, self.user_ns)

-------------------------Summary of Regression Analysis-------------------------

Formula: Y ~ <UNRATE> + <FEDFUNDS> + <Delta REVOLSL> + <intercept>

Number of Observations:         20
Number of Degrees of Freedom:   4

R-squared:         0.4206
Adj R-squared:     0.3120

Rmse:          97780319.8496

F-stat (3, 16):     3.8718, p-value:     0.0295

Degrees of Freedom: model 3, resid 16

-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
        UNRATE 542033181.8250 222297237.8232       2.44     0.0268 106330595.6915
977735767.9586
      FEDFUNDS 504178678.7052 191888751.8865       2.63     0.0183 128076725.0076
880280632.4028
 Delta REVOLSL 22384869.9245 7567972.1367       2.96     0.0093 7551644.5366 37218
095.3124
     intercept -2421418556.4662 1162487388.7300      -2.08     0.0537 -4699893838.
3771 -142943274.5553
---------------------------------End of Summary---------------------------------
```

According to the regression, all three of the factors are significant at a 5% level in predicting total originations. As unemployment goes up, credit refinancing becomes more important as more debt goes bad and marginal savings on interest payments matter more. As interest rates go up, credit card interest rates go up faster than lending club's, making incentive to refinance stronger. Finally, an increase in overall consumer credit is also a positive influence on lending club loan demand. However, more data and factors would be necessary to draw concrete conclusions from this regression. The January 2016 to September 2017 period is effectively the same macro environment, so the results would gain significance if they held true throughout different stages of the business cycle.

Conclusion

To summarize, the lending club dataset reveals that the bulk of loans are still concentrated in debt consolidation and credit card refinancing. However, there is a noticeable trend in more consumption-oriented loans. The average lending club customer has a far healthier debt and income profile than the average American, meaning that it is not yet as reflective of general American consumption trends as it could be. Geaographic breakdowns show that states that were hit hardest in the housing crisis have a particular demand for P2P lending. Finally, the regression output shows that Change in Consumer Credit, Unemployment, and interest rates all have a significant impact on demand for loans.

In [ ]: