birth-times series

January 23, 2017

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

%matplotlib inline
```

In [2]:
```
ls
```

```
README.md                  images/                    pair.ipynb
birth-times series.ipynb   individual.md              pair.md
data/                      iterate.dat
```

In [3]:
```
df = pd.read_csv('data/birth.txt')
df.head()
```

Out[3]:

	num_births
0	295
1	286
2	300
3	278
4	272

In [4]:
```
print df.shape[0]/31 #31 years
print df.shape
```

```
12
(372, 1)
```

In [5]:
```
df['dates']=pd.date_range("1980-01-01", "2010-12-31", freq="1M")
```

In [6]:
```
df.head()
```

Out[6]:

	num_births	dates
0	295	1980-01-31
1	286	1980-02-29
2	300	1980-03-31
3	278	1980-04-30
4	272	1980-05-31

def acf_pacf(ts, lags): fig = plt.figure(figsize=(12,8)) ax1 = fig.add_subplot(211) fig = sm.graphics.tsa.plot_acf(ts, lags=lags, ax=ax1) ax2 = fig.add_subplot(212) fig = sm.graphics.tsa.plot_pacf(ts, lags=lags, ax=ax2)

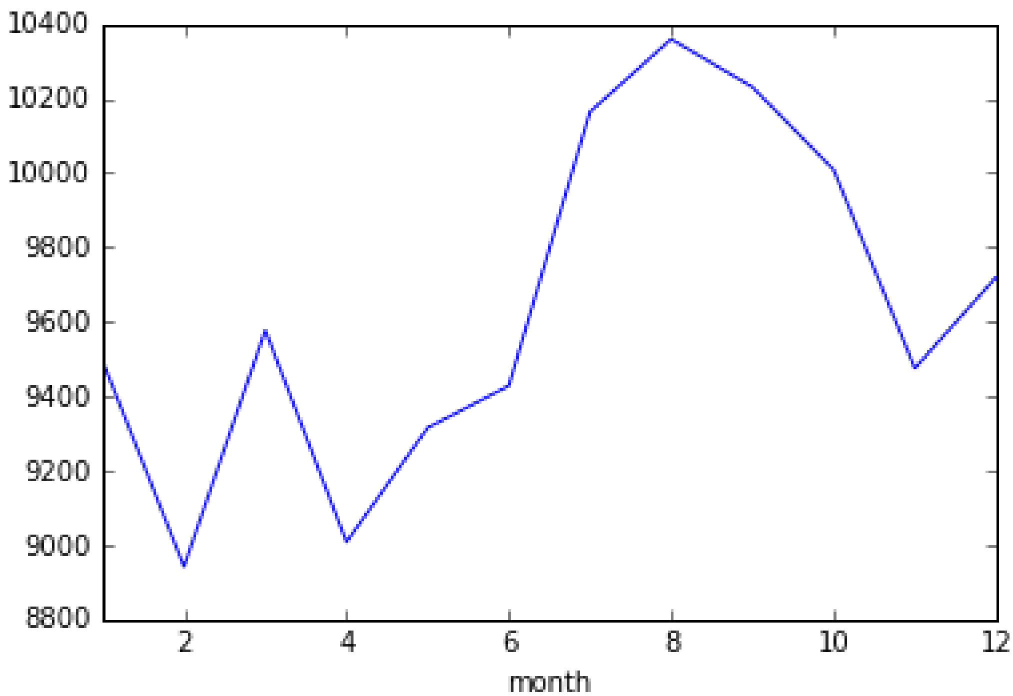
In [7]:
```
df['time'] = range(372)
```

```
In [8]: df['month'] = pd.DatetimeIndex(df.dates).month
        df['year'] = pd.DatetimeIndex(df.dates).year
        df['quarters'] = pd.DatetimeIndex(df['dates']).quarter

In [9]: df.head()

Out[9]:    num_births      dates  time  month  year  quarters
        0         295 1980-01-31     0      1  1980         1
        1         286 1980-02-29     1      2  1980         1
        2         300 1980-03-31     2      3  1980         1
        3         278 1980-04-30     3      4  1980         2
        4         272 1980-05-31     4      5  1980         2

In [10]: df = df.set_index('dates')

In [11]: df.head()

Out[11]:             num_births  time  month  year  quarters
         dates
         1980-01-31         295     0      1  1980         1
         1980-02-29         286     1      2  1980         1
         1980-03-31         300     2      3  1980         1
         1980-04-30         278     3      4  1980         2
         1980-05-31         272     4      5  1980         2

In [12]: df.info()

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 372 entries, 1980-01-31 to 2010-12-31
Data columns (total 5 columns):
num_births    372 non-null int64
time          372 non-null int64
month         372 non-null int32
year          372 non-null int32
quarters      372 non-null int32
dtypes: int32(3), int64(2)
memory usage: 13.1 KB

In [13]: sdf = df.groupby('month')['num_births'].mean()
         print sdf.max()
         print np.argmax(sdf)

334.161290323
8

In [14]: df_month = df.groupby('month').sum()

In [15]: df_month.head(12)

Out[15]:        num_births  time   year  quarters
         month
         1            9493  5580  61845        31
         2            8942  5611  61845        31
         3            9577  5642  61845        31
         4            9008  5673  61845        62
         5            9315  5704  61845        62
         6            9428  5735  61845        62
```

7	10164	5766	61845	93
8	10359	5797	61845	93
9	10231	5828	61845	93
10	10008	5859	61845	124
11	9475	5890	61845	124
12	9719	5921	61845	124

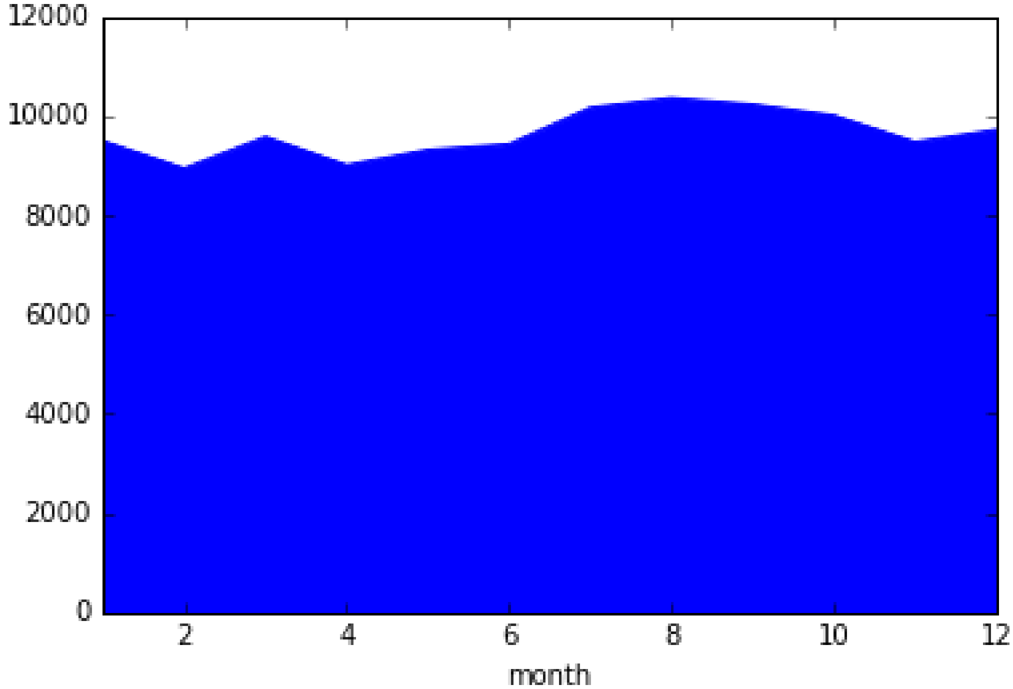
```
In [16]: df_month['num_births'].plot(kind = 'line')
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x117550790>
```

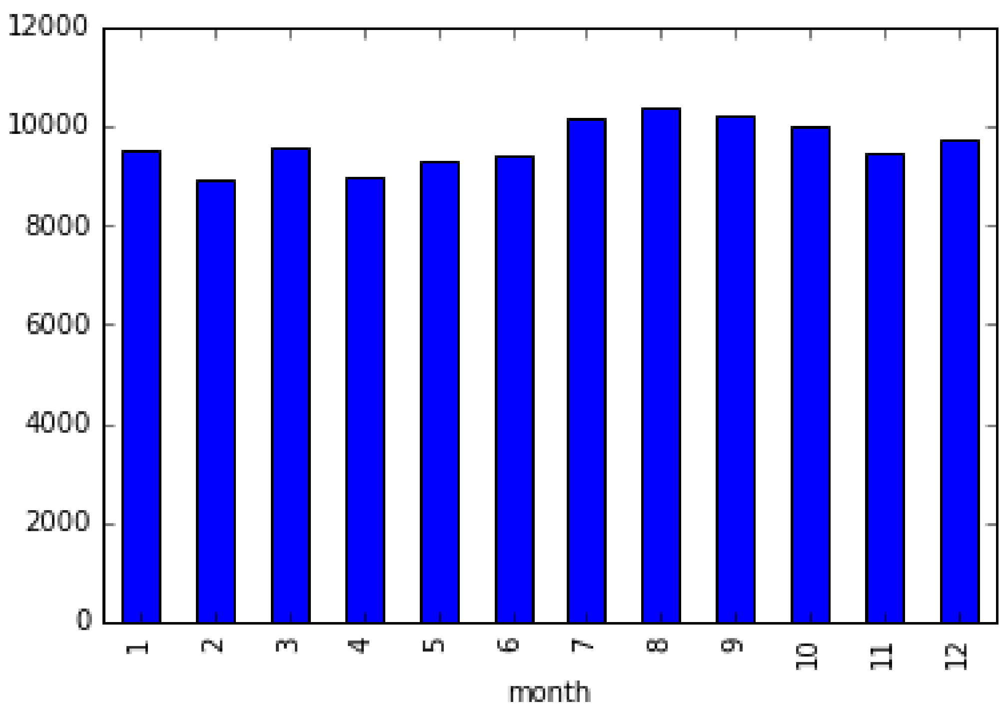



```
In [17]: df_month['num_births'].plot(kind = 'area')
```

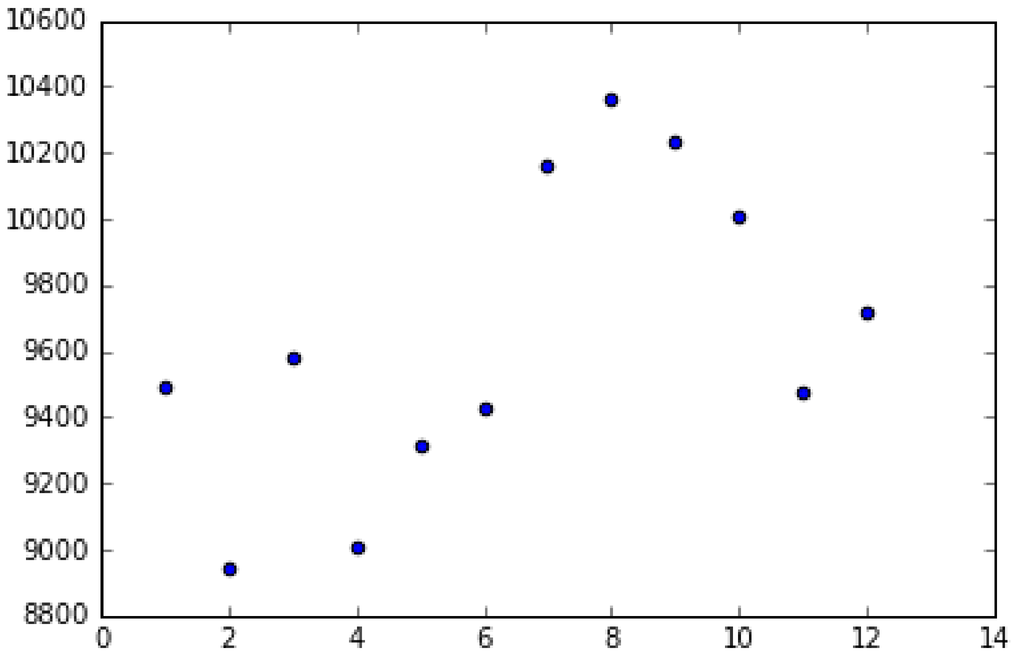
```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x119ad1910>
```




```
In [18]: df_month['num_births'].plot(kind = 'bar')

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x119b01390>
```



```
In [19]: ax = plt.scatter(x = df_month.index, y =df_month.num_births)
```

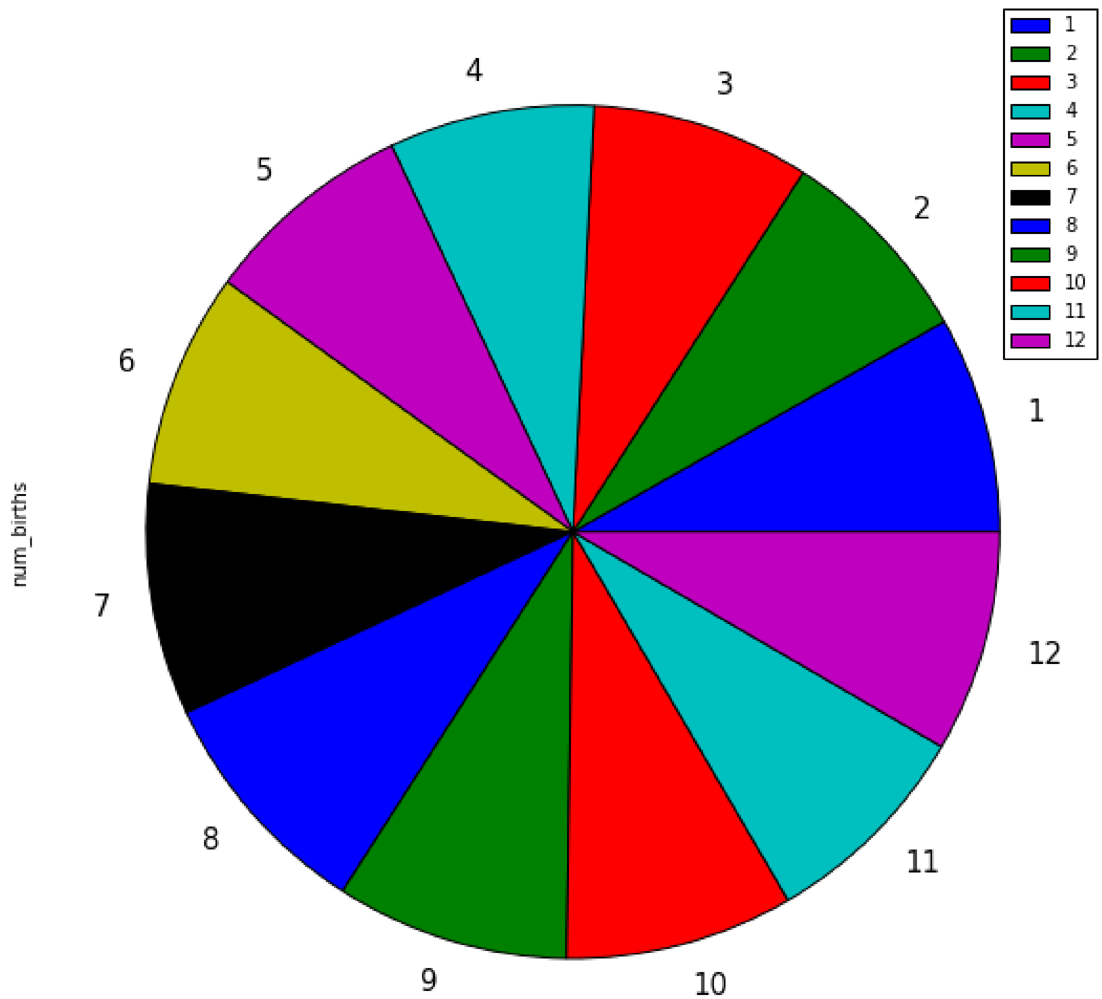



```
In [20]: df_month
```

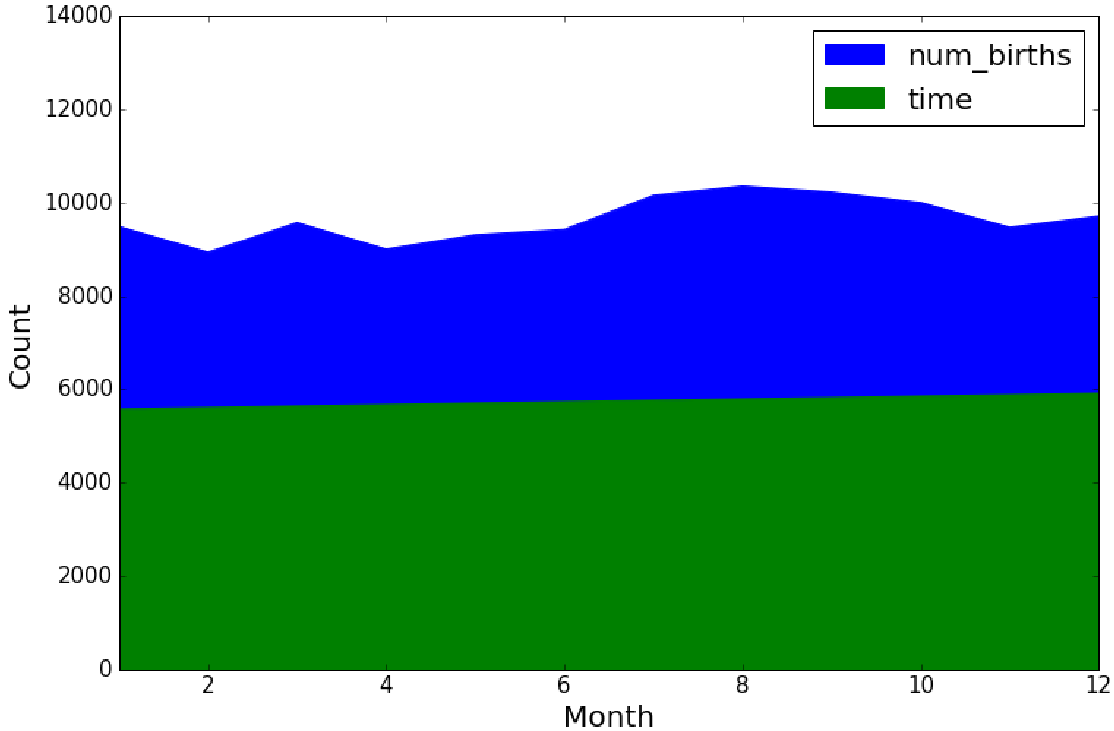
Out[20]:

month	num_births	time	year	quarters
1	9493	5580	61845	31
2	8942	5611	61845	31
3	9577	5642	61845	31
4	9008	5673	61845	62
5	9315	5704	61845	62
6	9428	5735	61845	62
7	10164	5766	61845	93
8	10359	5797	61845	93
9	10231	5828	61845	93
10	10008	5859	61845	124
11	9475	5890	61845	124
12	9719	5921	61845	124

```
In [21]: ax = df_month['num_births'].plot('pie', figsize=(10,10),fontsize = 15)
         ax.legend(fontsize = 10)
         plt.show()
```




```
In [22]: ax = df_month['num_births'].plot('area', figsize=(20,10),fontsize = 15)
         ax = df_month['time'].plot('area', figsize=(12,8),fontsize = 15)
         ax.set_xlabel('Month', fontsize = 20)
         ax.set_ylabel('Count',fontsize = 20)
         ax.set_ylim(0,14000)
         ax.legend(fontsize = 20)
         plt.show()
```




```
In [23]: df_month
```

Out[23]:

month	num_births	time	year	quarters
1	9493	5580	61845	31
2	8942	5611	61845	31
3	9577	5642	61845	31
4	9008	5673	61845	62
5	9315	5704	61845	62
6	9428	5735	61845	62
7	10164	5766	61845	93
8	10359	5797	61845	93
9	10231	5828	61845	93
10	10008	5859	61845	124
11	9475	5890	61845	124
12	9719	5921	61845	124

```
In [24]: idx = np.argmax(df_month.num_births)
         print idx,df_month.num_births[idx]
         df_month.loc[idx].num_births
```

```
8 10359
```

```
Out[24]: 10359
```

```
In [25]: df_month.idxmax()
```

```
Out[25]: num_births     8
         time          12
```

```
year           1
quarters      10
dtype: int64
```

In [26]:
```
df_month.num_births.idxmax()
```

Out[26]:
```
8
```

In [27]:
```
df_month.num_births[idx]
```

Out[27]:
```
10359
```

In [28]:
```
df_year = df.groupby('year').sum()['num_births']
indx = np.argmax(df_year)
indx
```

Out[28]:
```
1993
```

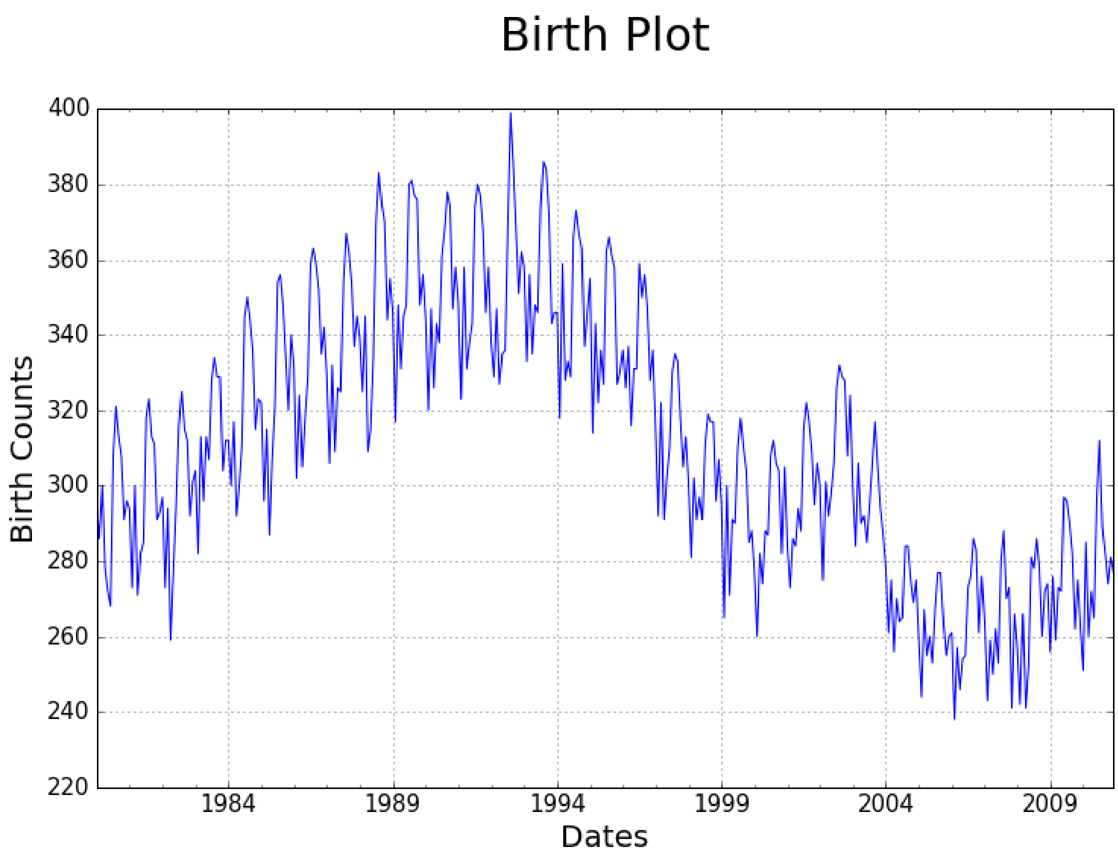
In [29]:
```
df.groupby('year').mean()['num_births'].idxmax()
```

Out[29]:
```
1993
```

In [30]:
```
birthSeries = pd.Series(df['num_births'])
bs = pd.Series(df['num_births'])
birthSeries.head(2)
```

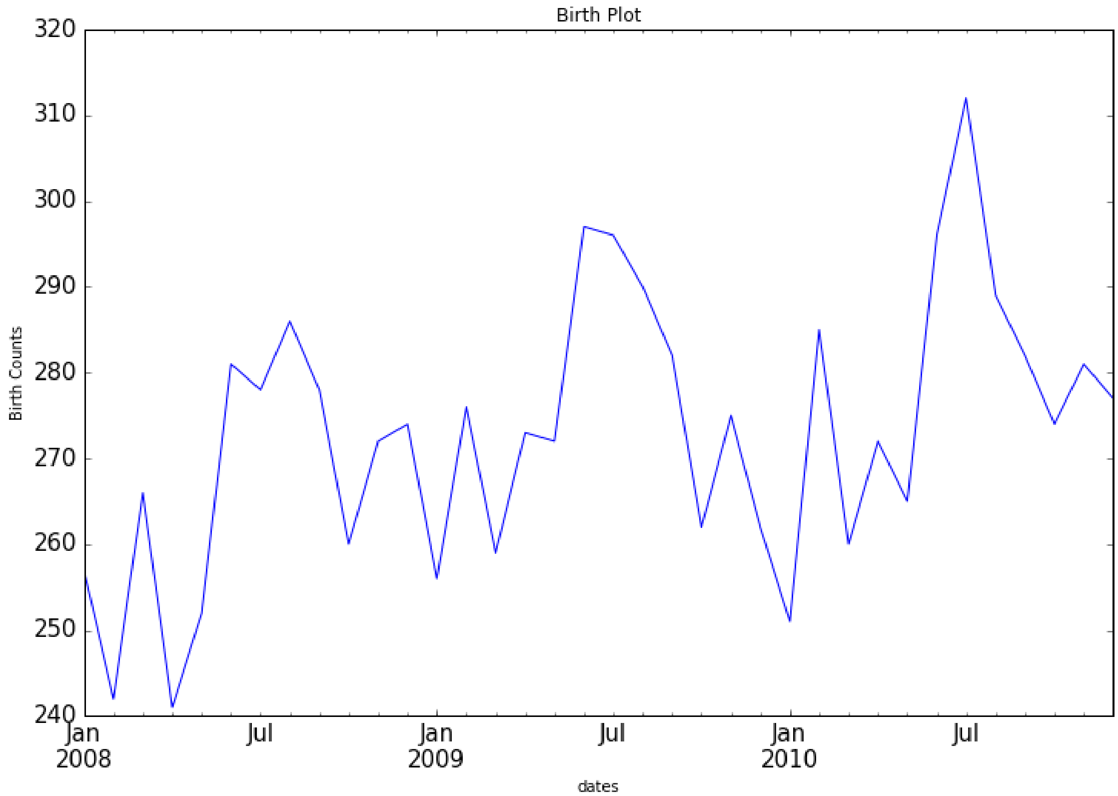
Out[30]:
```
dates
1980-01-31    295
1980-02-29    286
Name: num_births, dtype: int64
```

In [31]:
```
ax = birthSeries.plot(figsize=(12,8), fontsize = 15,kind='line',grid=True)
ax.set_xlabel('Dates',fontsize = 20)
ax.set_ylabel('Birth Counts', fontsize = 20)
ax.set_title('Birth Plot\n', fontsize = 30)
plt.show()
```



Plot the data for 2006-2010, is the seasonal pattern more apparent?

In [32]:
```
#birthSeries = pd.Series(df['num_births'])
ax = birthSeries['2008':'2010'].plot(fontsize = 15, title='Birth Plot',figsize=(12,8))
ax.set_xlabel('dates')
ax.set_ylabel('Birth Counts')
plt.show()
```

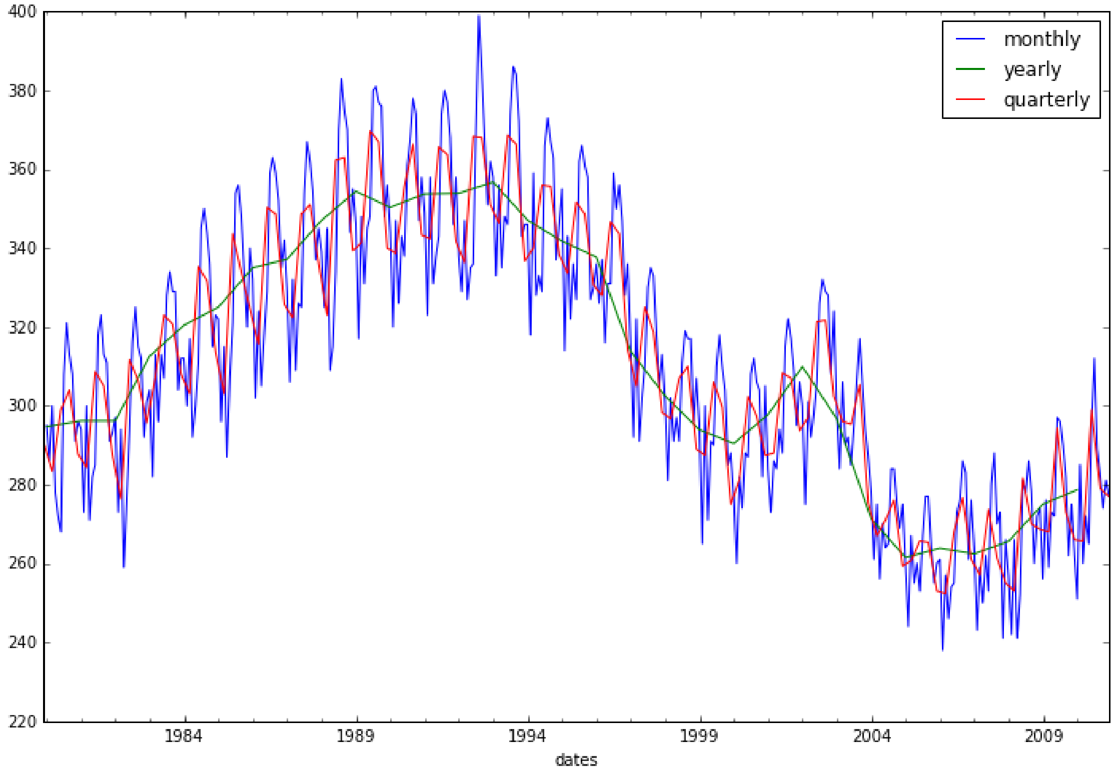


Use df.resample('Q-NOV') to get quarterly means that follow the seasons of the year (spring, summer, fall, winter).

```
In [33]: df['num_births'].head()

Out[33]: dates
         1980-01-31    295
         1980-02-29    286
         1980-03-31    300
         1980-04-30    278
         1980-05-31    272
         Name: num_births, dtype: int64

In [34]: bs.resample('A').mean().head() #year end

Out[34]: dates
         1980-12-31    294.666667
         1981-12-31    296.166667
         1982-12-31    296.166667
         1983-12-31    312.583333
         1984-12-31    320.416667
         Freq: A-DEC, Name: num_births, dtype: float64

In [35]: bs.resample('Q').mean().head()

Out[35]: dates
         1980-03-31    293.666667
```

```
1980-06-30    272.666667
1980-09-30    314.000000
1980-12-31    298.333333
1981-03-31    289.000000
Freq: Q-DEC, Name: num_births, dtype: float64
```

In [36]:
```
bs.plot(figsize=(12,8), label = 'monthly')
bs.resample('A').mean().plot(label = 'yearly')
bs.resample('Q-NOV').mean().plot(label = 'quarterly')
plt.legend();
```



In [37]:
```
df['time^2'] = df['time']**2
df['time^3'] = df['time']**3
df['time^4'] = df['time']**4
df['time^5'] = df['time']**5
df.head()
```

Out[37]:

dates	num_births	time	month	year	quarters	time^2	time^3	time^4 \
1980-01-31	295	0	1	1980	1	0	0	0
1980-02-29	286	1	2	1980	1	1	1	1
1980-03-31	300	2	3	1980	1	4	8	16
1980-04-30	278	3	4	1980	2	9	27	81
1980-05-31	272	4	5	1980	2	16	64	256

```
            time^5
```

```
dates
1980-01-31       0
1980-02-29       1
1980-03-31      32
1980-04-30     243
1980-05-31    1024
```

```
In [38]: type(df['num_births'])
```

```
Out[38]: pandas.core.series.Series
```

```
In [39]: type(df['num_births'].values)
```

```
Out[39]: numpy.ndarray
```

```
In [40]: y = df['num_births'].values
         X = df['time'].values
```

```
In [41]: model = sm.OLS(y, sm.add_constant(X)).fit()
```

```
In [42]: model.params
```

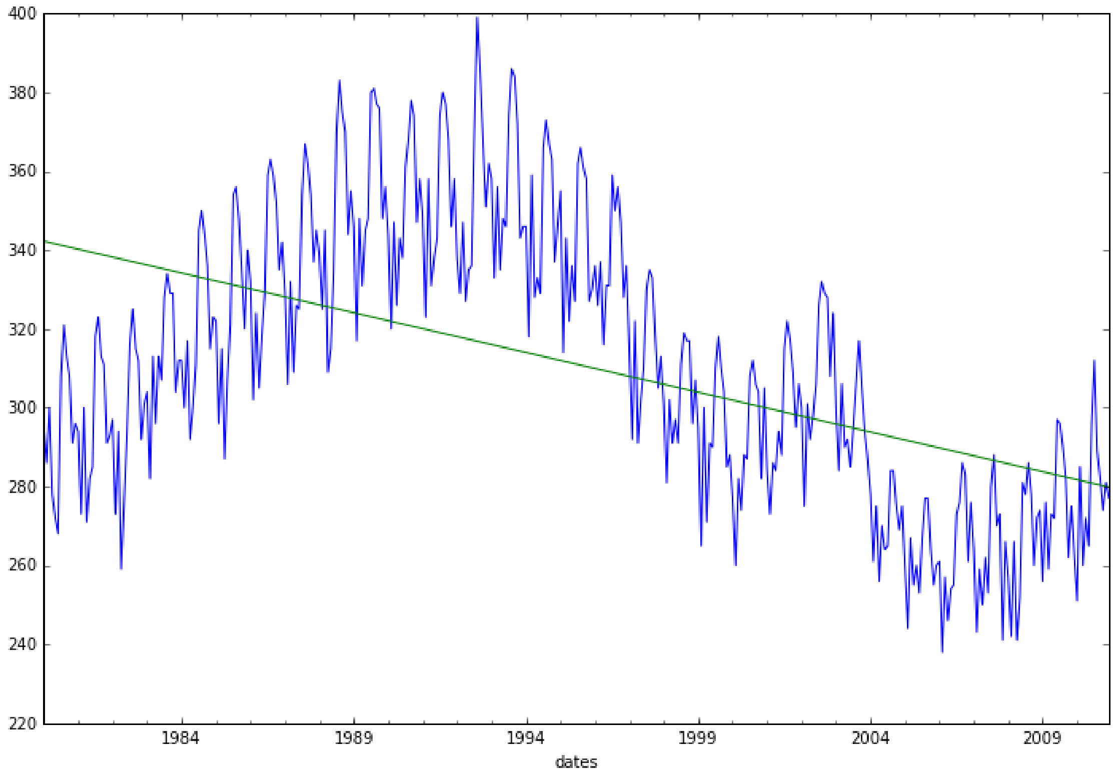
```
Out[42]: array([  3.42255081e+02,  -1.68099732e-01])
```

```
In [43]: model.fittedvalues[:10]
```

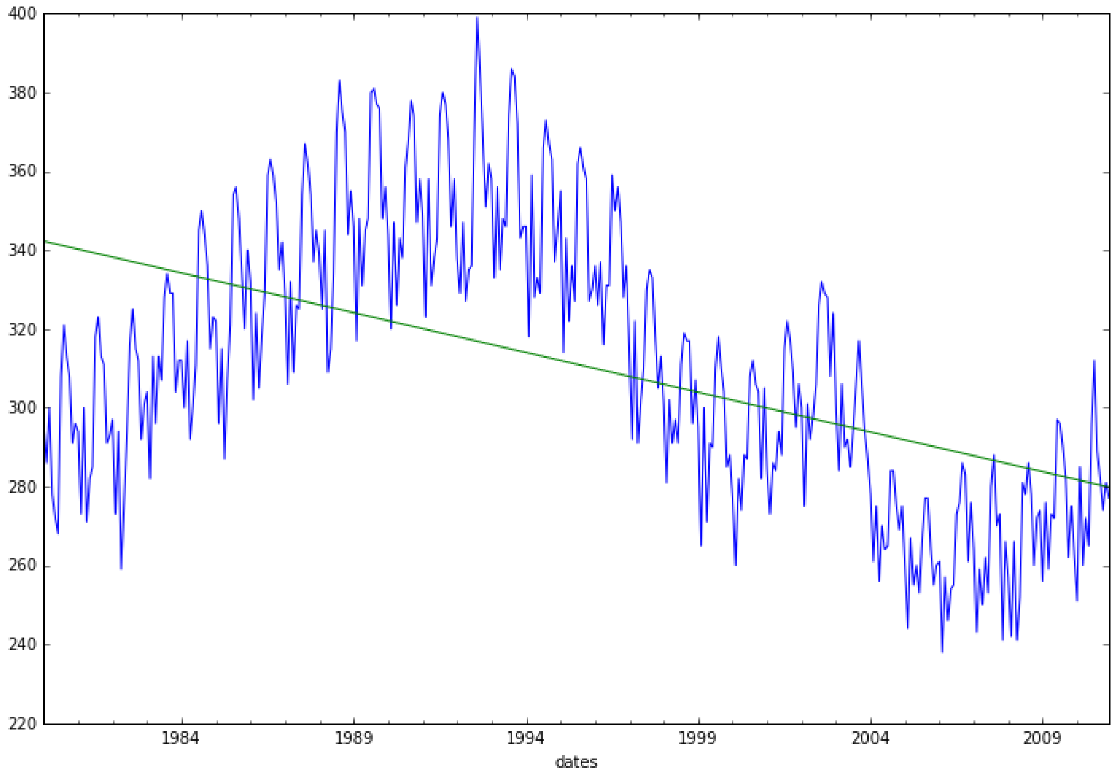
```
Out[43]: array([ 342.25508086,  342.08698113,  341.9188814 ,  341.75078167,
                 341.58268193,  341.4145822 ,  341.24648247,  341.07838274,
                 340.91028301,  340.74218328])
```

0.0.1 If use X = df['time] instead of df['time'].values, then no need to add index = df.index since it's already indexed.

```
In [44]: bs.plot(figsize=(12,8))
         pd.Series(model.fittedvalues, index = df.index).plot();
         # df['time'].plot();
```




```
In [45]: y = df['num_births'].values #no index
         X = df['time'] #keep the index
         model = sm.OLS(y, sm.add_constant(X)).fit()
         bs.plot(figsize=(12,8))
         model.fittedvalues.plot(); # still indexed, same as bs
```



In [46]: model.fittedvalues[:10] #show the index

Out[46]:
```
dates
1980-01-31    342.255081
1980-02-29    342.086981
1980-03-31    341.918881
1980-04-30    341.750782
1980-05-31    341.582682
1980-06-30    341.414582
1980-07-31    341.246482
1980-08-31    341.078383
1980-09-30    340.910283
1980-10-31    340.742183
dtype: float64
```

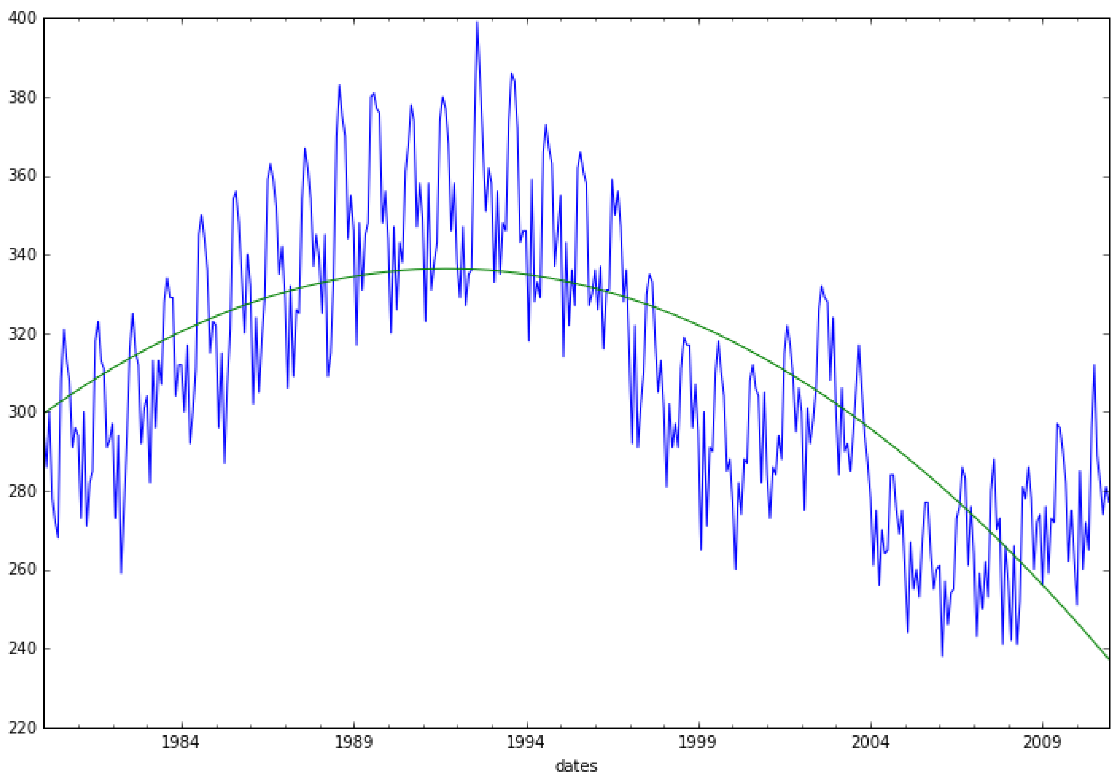
In [47]: model.summary()

Out[47]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.264
Model:                            OLS   Adj. R-squared:                  0.262
Method:                 Least Squares   F-statistic:                     133.0
Date:                Mon, 23 Jan 2017   Prob (F-statistic):           1.72e-26
Time:                        22:10:59   Log-Likelihood:                -1794.5
No. Observations:                 372   AIC:                             3593.
```

```
Df Residuals:                     370   BIC:                             3601.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const        342.2551      3.125    109.535      0.000       336.111   348.399
time          -0.1681      0.015    -11.531      0.000        -0.197    -0.139
==============================================================================
Omnibus:                        3.968   Durbin-Watson:                   0.316
Prob(Omnibus):                  0.138   Jarque-Bera (JB):                3.093
Skew:                           0.099   Prob(JB):                        0.213
Kurtosis:                       2.600   Cond. No.                         428.
==============================================================================

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

In [48]:
```python
y = df['num_births'].values
X = df[['time', 'time^2']]
model = sm.OLS(y, sm.add_constant(X)).fit()
bs.plot(figsize=(12,8))
model.fittedvalues.plot()
```

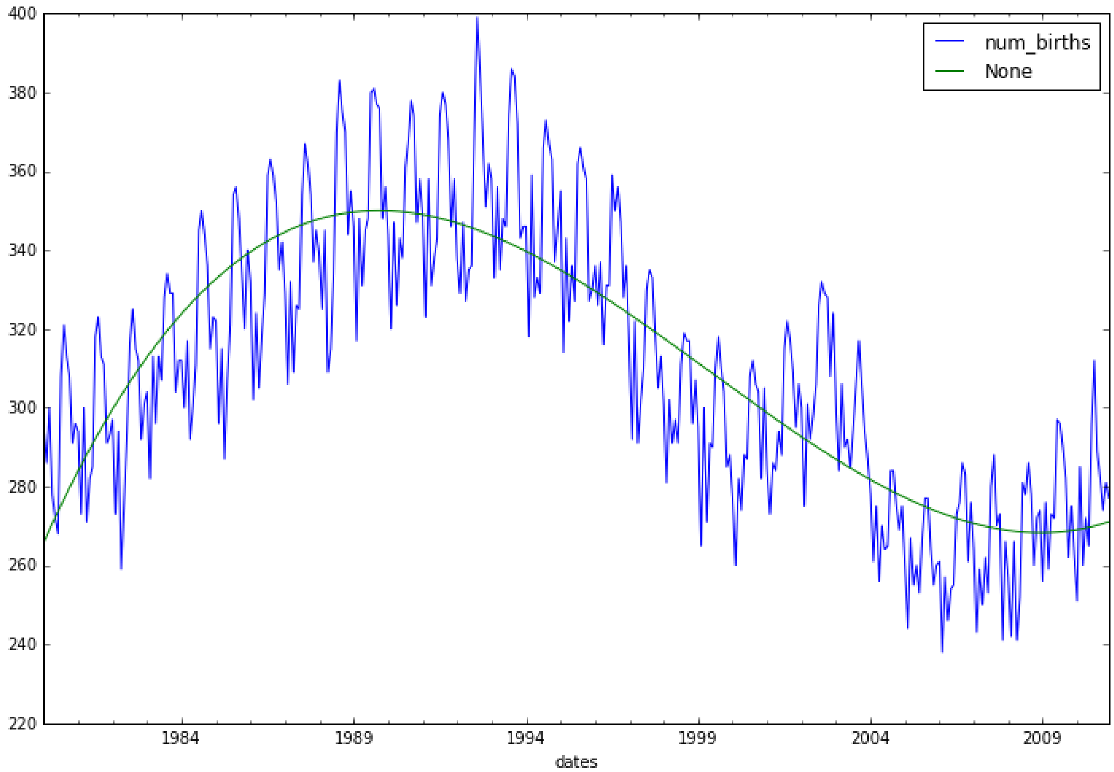
Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x11b96fd10>



In [49]:
```
model.summary()
```

Out[49]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.564
Model:                            OLS   Adj. R-squared:                  0.562
Method:                 Least Squares   F-statistic:                     239.0
Date:                Mon, 23 Jan 2017   Prob (F-statistic):           2.62e-67
Time:                        22:10:59   Log-Likelihood:                -1697.0
No. Observations:                 372   AIC:                             3400.
Df Residuals:                     369   BIC:                             3412.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const        299.6021      3.600     83.232      0.000       292.524   306.680
time           0.5236      0.045     11.681      0.000         0.435     0.612
time^2        -0.0019      0.000    -15.941      0.000        -0.002    -0.002
==============================================================================
Omnibus:                        5.782   Durbin-Watson:                   0.534
Prob(Omnibus):                  0.056   Jarque-Bera (JB):                5.168
Skew:                           0.222   Prob(JB):                       0.0755
Kurtosis:                       2.630   Cond. No.                     1.84e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.84e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

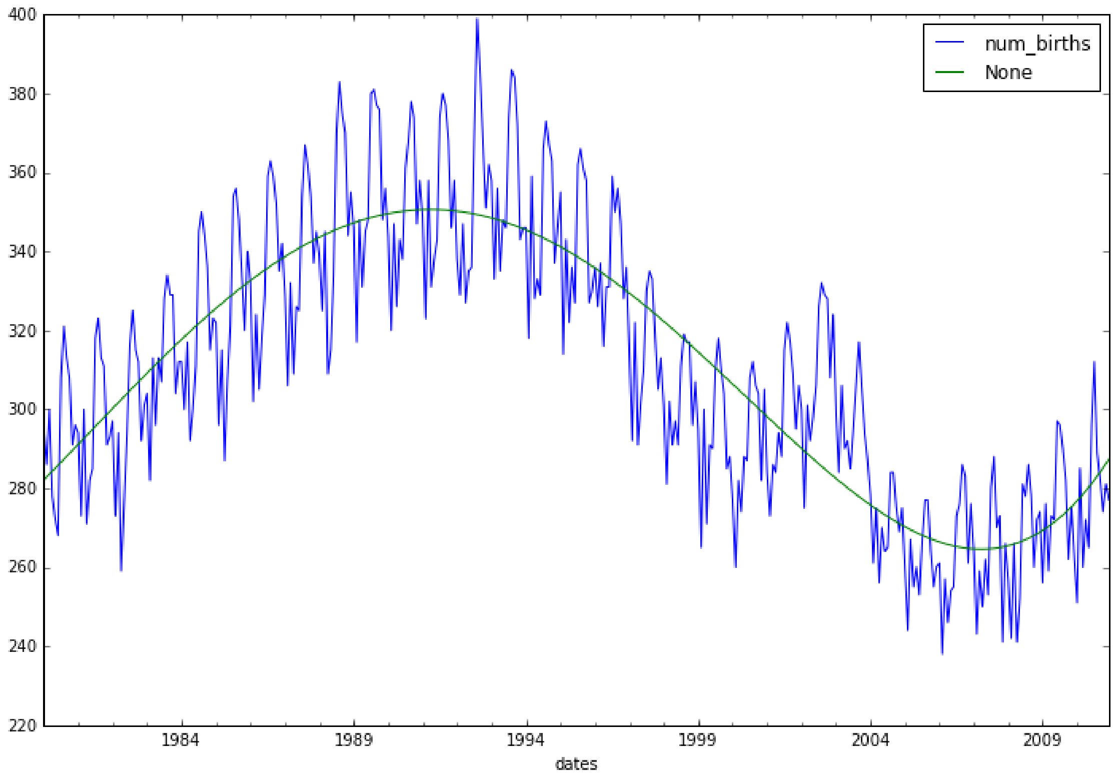
In [50]:
```
X = df[['time', 'time^2', 'time^3']]
model3 = sm.OLS(y, sm.add_constant(X)).fit()
bs.plot(figsize=(12,8))
model3.fittedvalues.plot()
plt.legend();
```




```
In [51]: model3.summary()

Out[51]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.701
Model:                            OLS   Adj. R-squared:                  0.699
Method:                 Least Squares   F-statistic:                     287.6
Date:                Mon, 23 Jan 2017   Prob (F-statistic):           4.31e-96
Time:                        22:11:00   Log-Likelihood:                -1627.0
No. Observations:                 372   AIC:                             3262.
Df Residuals:                     368   BIC:                             3278.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const        265.8165      3.963     67.074      0.000       258.023   273.609
time           1.6238      0.093     17.529      0.000         1.442     1.806
time^2        -0.0093      0.001    -15.996      0.000        -0.010    -0.008
time^3      1.334e-05   1.03e-06     12.968      0.000      1.13e-05  1.54e-05
==============================================================================
Omnibus:                        3.849   Durbin-Watson:                   0.778
Prob(Omnibus):                  0.146   Jarque-Bera (JB):                3.070
Skew:                           0.106   Prob(JB):                        0.215
```

```
Kurtosis:                       2.609   Cond. No.                     7.67e+07
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.67e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

In [52]:
```
X = df[['time', 'time^2', 'time^3', 'time^4']]
bs.plot(figsize = (12,8))
model4 = sm.OLS(y, sm.add_constant(X)).fit()
model4.fittedvalues.plot()
plt.legend();
```



In [53]:
```
model4.summary()
```

Out[53]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.726
Model:                            OLS   Adj. R-squared:                  0.723
Method:                 Least Squares   F-statistic:                     243.3
Date:                Mon, 23 Jan 2017   Prob (F-statistic):          8.01e-102
Time:                        22:11:00   Log-Likelihood:                -1610.7
```

```
No. Observations:                 372   AIC:                             3231.
Df Residuals:                     367   BIC:                             3251.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const        282.0876      4.719     59.782      0.000       272.809   291.367
time           0.7359      0.177      4.164      0.000         0.388     1.083
time^2         0.0015      0.002      0.781      0.435        -0.002     0.005
time^3       -3.2e-05   7.87e-06     -4.068      0.000     -4.75e-05 -1.65e-05
time^4       6.11e-08   1.05e-08      5.810      0.000      4.04e-08  8.18e-08
==============================================================================
Omnibus:                        3.293   Durbin-Watson:                   0.850
Prob(Omnibus):                  0.193   Jarque-Bera (JB):                2.683
Skew:                           0.092   Prob(JB):                        0.261
Kurtosis:                       2.627   Cond. No.                     3.12e+10
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.12e+10. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

In [54]:
```
df.head()
```

Out[54]:
```
            num_births  time  month  year  quarters  time^2  time^3  time^4  \
dates
1980-01-31         295     0      1  1980         1       0       0       0
1980-02-29         286     1      2  1980         1       1       1       1
1980-03-31         300     2      3  1980         1       4       8      16
1980-04-30         278     3      4  1980         2       9      27      81
1980-05-31         272     4      5  1980         2      16      64     256

            time^5
dates
1980-01-31       0
1980-02-29       1
1980-03-31      32
1980-04-30     243
1980-05-31    1024
```

Now that you have fit trend, add in the monthly component via dummy variables to capture seasonality. You could also try to create a 'seasons of the year' variable and fit the quarterly time series instead of the original monthly time you plotted earlier... opportunity to play around.

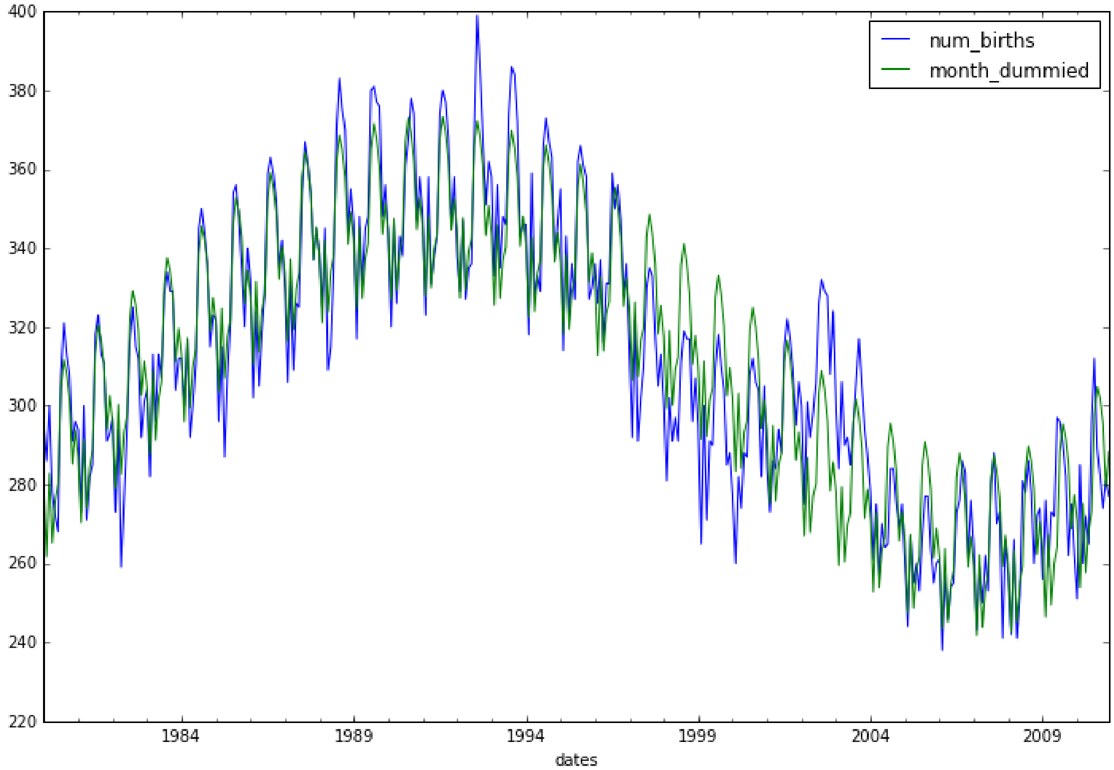
In [55]:
```
X = pd.get_dummies(df[['time','time^2','time^3','time^4','month']],
                   columns=['month']).drop('month_1',axis = 1)
```

In [56]:
```
X.shape
```

Out[56]:
```
(372, 15)
```

In [57]:
```
model_m = sm.OLS(y, sm.add_constant(X)).fit()
bs.plot(figsize=(12,8))
```

```python
model_m.fittedvalues.plot(label = 'month_dummied')
plt.legend();
```



In [58]:
```python
model_m.summary()
```

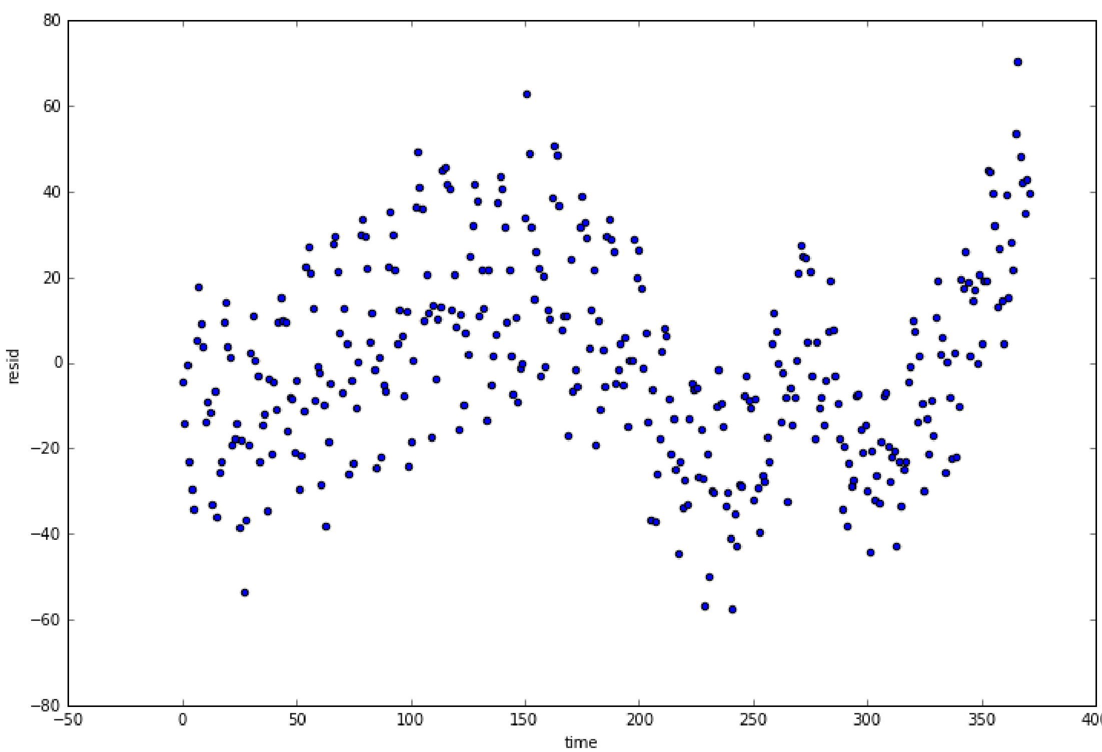
Out[58]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.893
Model:                            OLS   Adj. R-squared:                  0.888
Method:                 Least Squares   F-statistic:                     197.2
Date:                Mon, 23 Jan 2017   Prob (F-statistic):         4.32e-162
Time:                        22:11:01   Log-Likelihood:                -1436.6
No. Observations:                 372   AIC:                             2905.
Df Residuals:                     356   BIC:                             2968.
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const        278.7809      3.588     77.695      0.000       271.724   285.838
time           0.6978      0.112      6.206      0.000         0.477     0.919
time^2         0.0018      0.001      1.435      0.152        -0.001     0.004
time^3     -3.254e-05      5e-06     -6.505      0.000     -4.24e-05 -2.27e-05
time^4       6.13e-08   6.69e-09      9.165      0.000      4.81e-08  7.45e-08
```

```
month_2      -17.7778      2.988     -5.950      0.000       -23.654   -11.902
month_3        2.7017      2.988      0.904      0.366        -3.174     8.578
month_4      -15.6583      2.988     -5.240      0.000       -21.535    -9.782
month_5       -5.7612      2.988     -1.928      0.055       -11.638     0.115
month_6       -2.1232      2.988     -0.711      0.478        -8.000     3.754
month_7       21.6105      2.988      7.231      0.000        15.733    27.488
month_8       27.8915      2.989      9.332      0.000        22.014    33.769
month_9       23.7519      2.989      7.946      0.000        17.874    29.630
month_10      16.5464      2.989      5.535      0.000        10.668    22.425
month_11      -0.6604      2.990     -0.221      0.825        -6.540     5.219
month_12       7.1958      2.990      2.407      0.017         1.315    13.076
==============================================================================
Omnibus:                        8.418   Durbin-Watson:                   0.733
Prob(Omnibus):                  0.015   Jarque-Bera (JB):                8.343
Skew:                           0.334   Prob(JB):                       0.0154
Kurtosis:                       3.303   Cond. No.                     7.93e+10
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.93e+10. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Plot the dates variable (x) against the residuals (y) of the final model (including the seasonality term). Is there an obvious pattern of the residuals with respect to time? If there is any autocorrelation left in the model, there will be some pattern in your residual and we'll learn to address that in the afternoon.

```
In [59]: df['resid'] = model.resid
```

```
In [60]: df.plot(x = 'time', y = 'resid',figsize = (12,8), kind = 'scatter');
```



```
In [61]: pd.__version__

Out[61]: u'0.19.1'
```