Appendix B

June 21, 2018

This jupyter notebook contains analysis of the counts of 'ED four-hour target breaches' and 'Delayed Transfers Of Care' at English Trusts August 2010-March 2017. It contains all the complete analysis steps used in the paper.

import useful libraries

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

        import matplotlib.pyplot as plt
        import seaborn as sns

        sns.set()
        %matplotlib inline
```

1 Load data

```
In [2]: df = pd.read_csv('NHSE_data.csv')
        df.shape

Out[2]: (80, 10)

In [3]: df.head()

Out[3]:       year      month  total_attendances  total_attendances_t1  \
        0  2010-11     August        1719197.000           1138652.000
        1  2010-11  September        1715117.000           1150728.000
        2  2010-11    October        1753934.000           1163143.000
        3  2010-11   November        1604591.000           1111294.571
        4  2010-11   December        1647823.857           1159203.857

           total_breaches  95%_targ  total_admissions  dtoc_a  dtoc_na  total_dtocs
        0     33184.00000  0.980698       425702.0000    2559     2381         4940
        1     41151.00000  0.976007       424900.0000    2647     2357         5004
```

```
2    47414.00000  0.972967    436215.0000   2513    2075        4588
3    46436.42857  0.971060    429099.0000   2352    2057        4409
4    89917.28571  0.945433    452728.7143   1995    1866        3861
```

make flag for data used in previous analysis

```
In [4]: df['flag_previous'] = 0

        df.loc[0:68,'flag_previous'] = 1
```

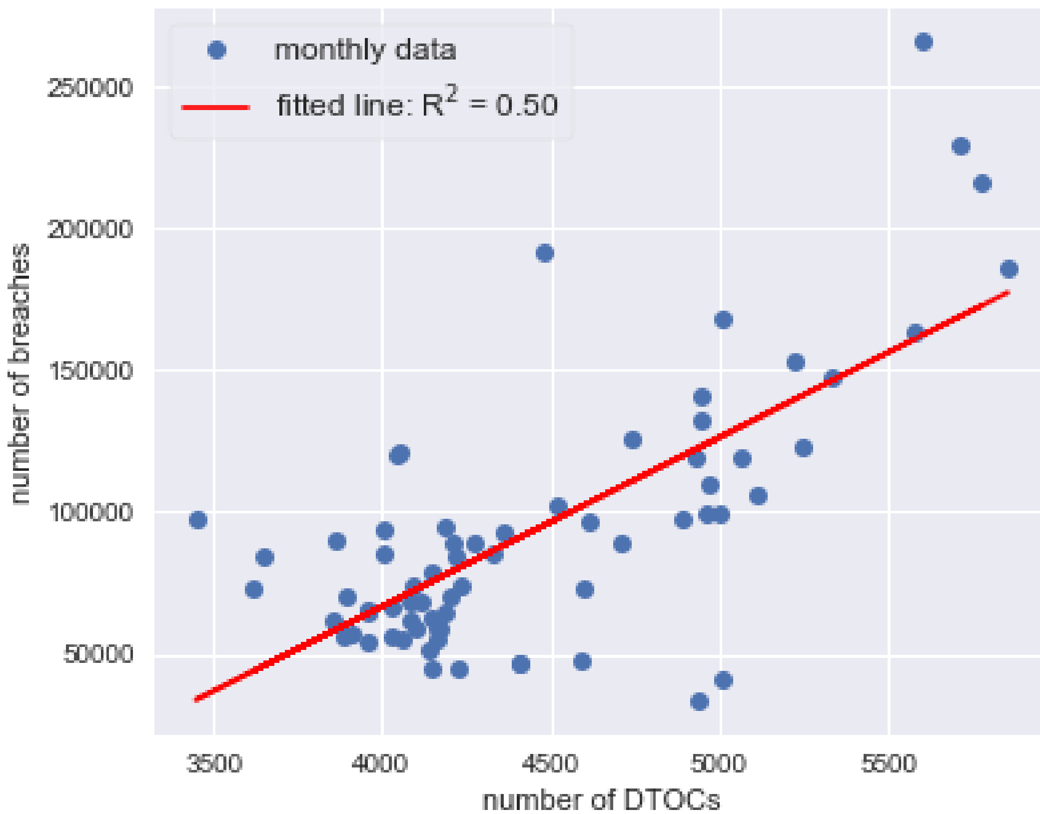
remove most recent data to reproduce previous analysis.

```
In [5]: df = df[df.flag_previous == 1]

In [6]: df = df[['total_breaches','total_dtocs']] # select only variables of interest
```

2 Data briefing reproduction

A reproduction of the analysis in BMJ data briefing by Appleby: https://www.bmj.com/content/353/bmj.i3585

```
In [7]: # get coeffs of linear fit
        slope, intercept, r_value, p_value, std_err = stats.linregress(df['total_dtocs'],df['tot

In [8]: fig, ax = plt.subplots(figsize=(6,5))
        y = df['total_breaches']
        x = df['total_dtocs']
        plt.plot(x,y,'o', label='monthly data')
        plt.plot(df['total_dtocs'], intercept + slope*x, 'r', label='fitted line: R$^2$ = {0:.2f
        plt.legend(frameon=True,fontsize='large')
        ax.set_xlabel('number of DTOCs')
        ax.set_ylabel('number of breaches')
        #plt.
        plt.show()
```



In [9]: fig.savefig('original.png',dpi=600) # save fig for paper

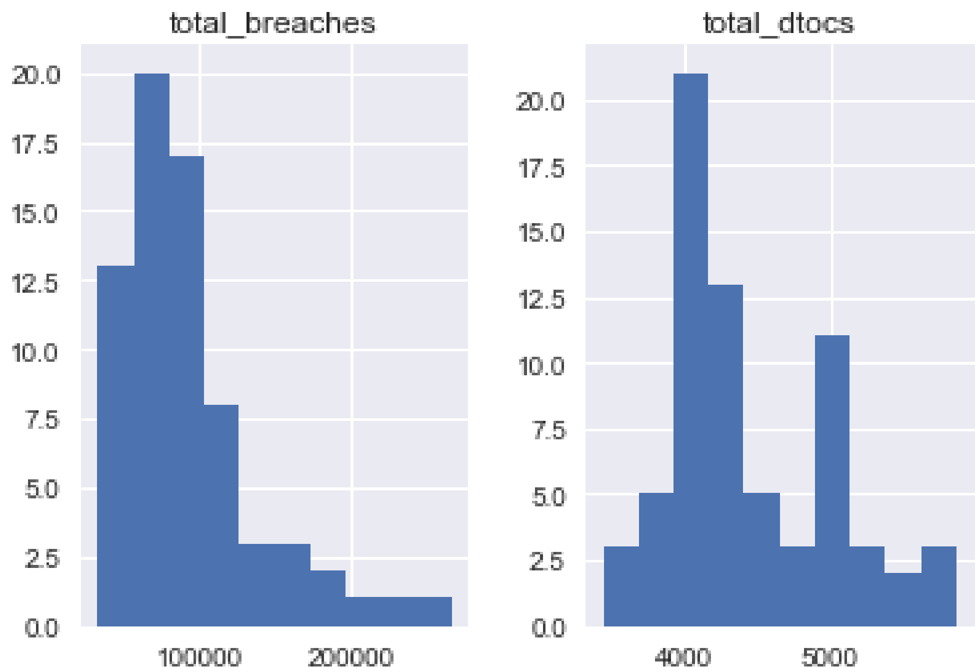
We find similar R2 value that was found in the previous analysis:

In [10]: (r_value**2).round(3)

Out[10]: 0.504

distribution of data Check distribution of each variable.

In [11]: df.hist();



correlation coefficient Data appears to not be normally distributed. Hence, we should avoid using Pearson correlation coefficient. Calculate correlation values:

```
In [12]: from scipy.stats.stats import pearsonr
```

```
In [13]: corr, p = pearsonr(df['total_dtocs'],df['total_breaches'])
```

```
In [14]: print('Pearson')
         print('Coeficient: ', corr)
         print('P-value' , p)
```

```
Pearson
Coeficient:  0.710060292485
P-value 8.37892018508e-12
```

```
In [15]: from scipy.stats.stats import spearmanr
```

```
In [16]: corr, p = spearmanr(df['total_dtocs'],df['total_breaches'])
```

```
In [17]: print('Spearman')
         print('Coeficient: ', corr)
         print('P-value' , p)
```

```
Spearman
Coeficient:  0.541634696551
P-value 1.53991353597e-06
```

3 Investigate timeseries properties

Stationarity One method to asses if timeseries is stationary is to use a dickey-fuller test. This tests to see if a unit root is present within the data - which would indicate non-stationarity.

```
In [18]: from statsmodels.tsa.stattools import adfuller
```

```
In [19]: def check_stationarity(series):
             result = adfuller(series)
             print('ADF Statistic: %f' % result[0])
             print('p-value: %f' % result[1])
             for key, value in result[4].items():
                 print('\t%s: %.3f' % (key, value))
```

```
In [20]: check_stationarity(df['total_breaches'])
```

```
ADF Statistic: -1.555714
p-value: 0.505793
        1%: -3.530
        5%: -2.905
        10%: -2.590
```

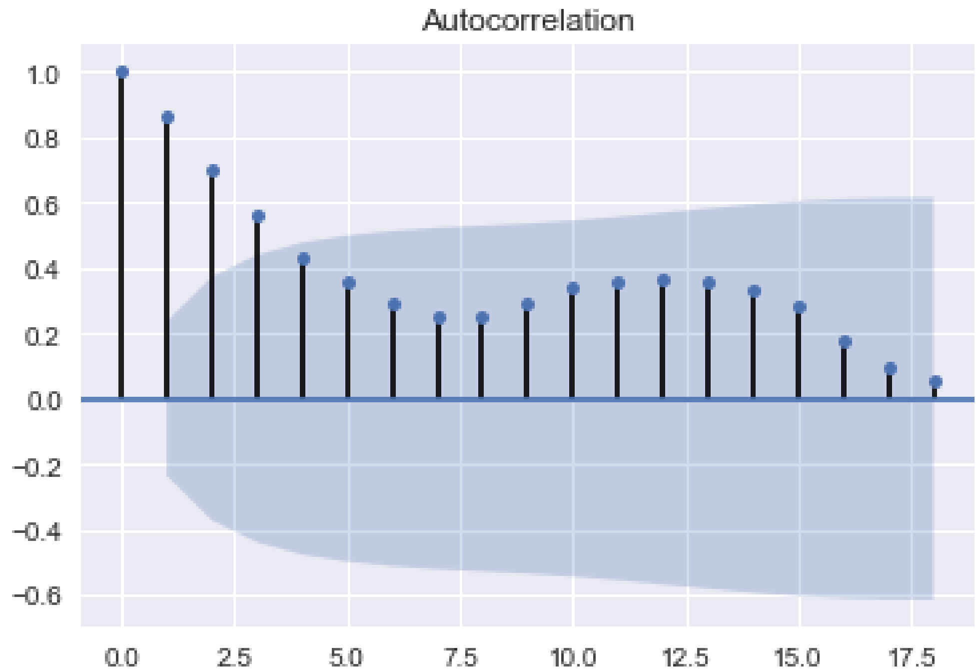
```
In [21]: check_stationarity(df['total_dtocs'])
```

```
ADF Statistic: 1.641969
p-value: 0.997978
        1%: -3.551
        5%: -2.914
        10%: -2.595
```

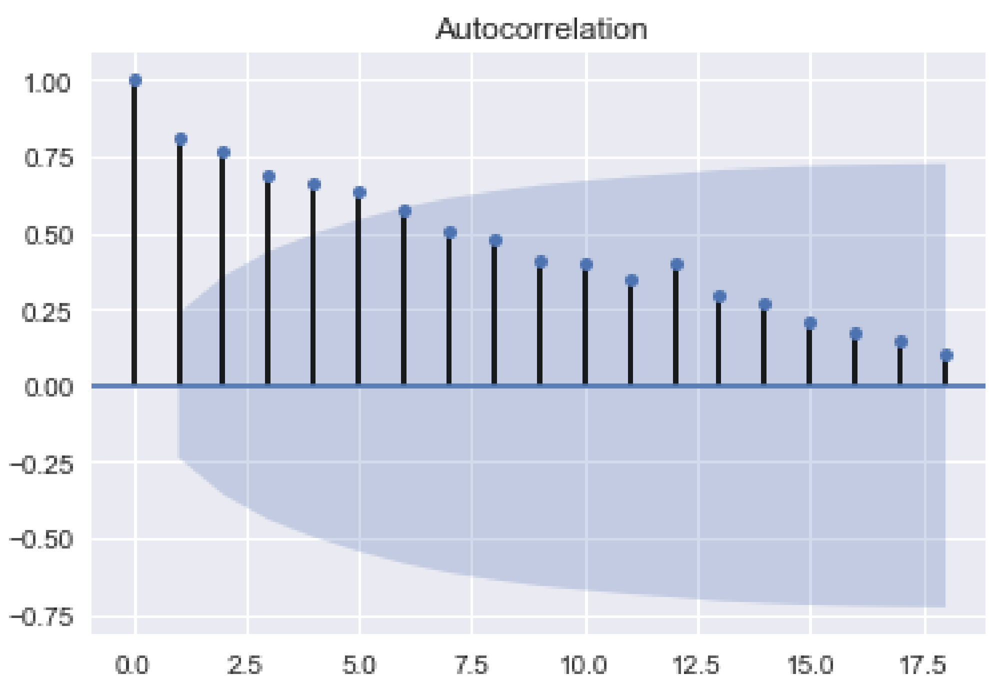
The p-value >> 0.05 indicates that there is a unit root present in both of the timeseries. This implies each variable is non-stationary.

Assess level of autocorrelation using ACF

```
In [22]: fig = sm.graphics.tsa.plot_acf(df['total_breaches'],lags=18)
```

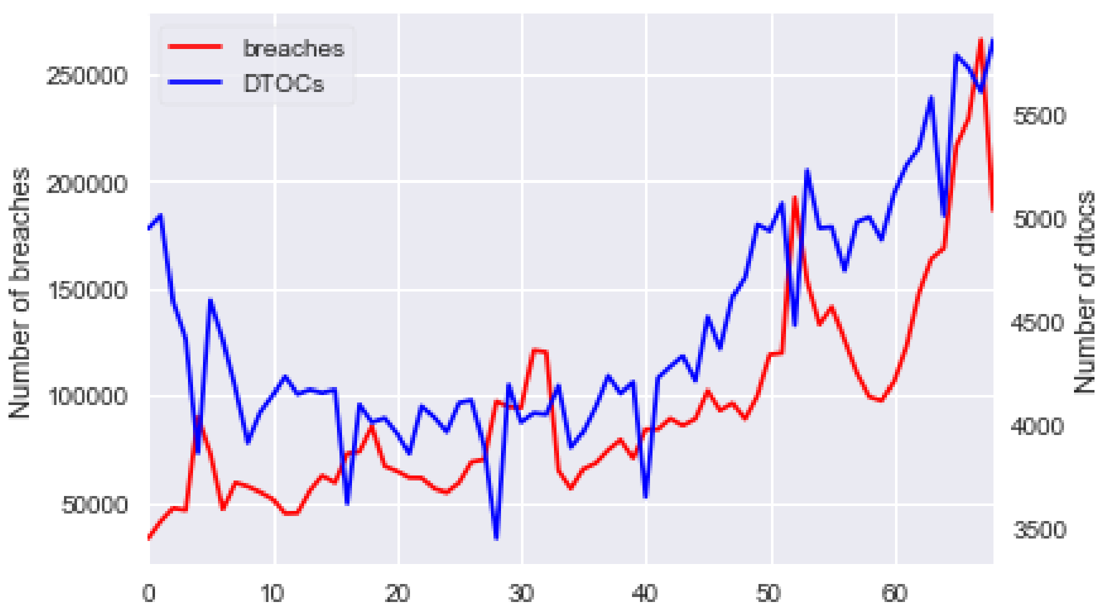



```
In [23]: fig = sm.graphics.tsa.plot_acf(df['total_dtocs'],lags=18)
```



High autocorrelation values for many lags in both timeseries demontrate that each time point is highly dependent on the previous ones. This may indicate an increasing growth over time; one cause of a timeseries being non-stationary. This is very clear upon plotting the time-series below.

```
In [24]: fig = plt.figure() # Create matplotlib figure

         ax = fig.add_subplot(111) # Create matplotlib axes
         ax2 = ax.twinx() # Create another axes that shares the same x-axis as ax.

         df.total_breaches.plot(color='red', ax=ax)#, width=width)#, position=1)
         df.total_dtocs.plot(color='blue', ax=ax2)

         ax.set_ylabel('Number of breaches')
         ax2.set_ylabel('Number of dtocs')
         ax2.grid(b=False)

         #sort legend
         lns = ax.get_lines()+ax2.get_lines()
         ax.legend(lns,['breaches','DTOCs'],frameon=True)

         plt.show()
```



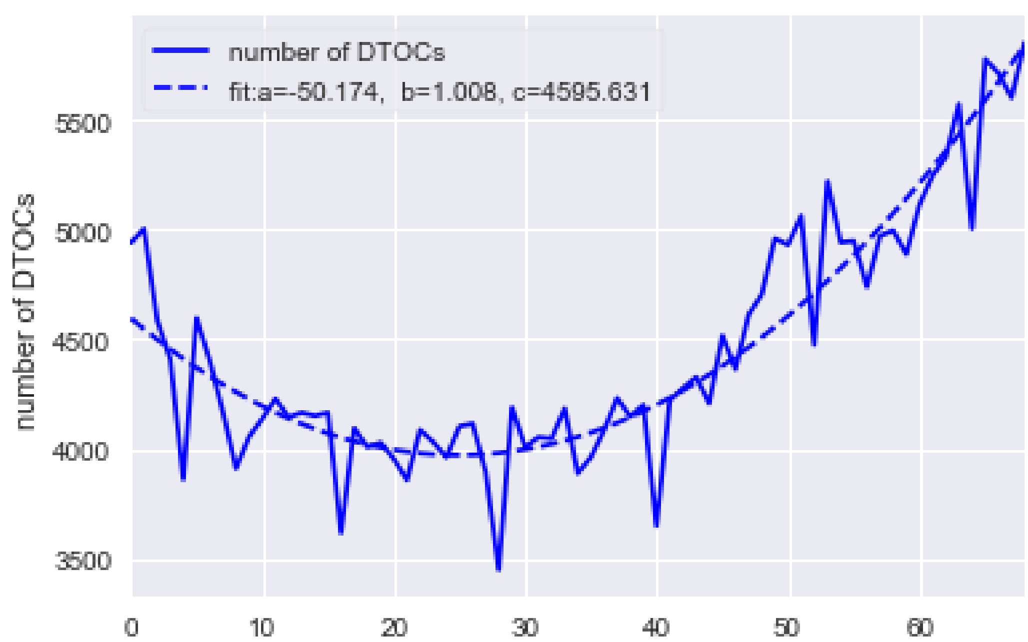
4 Detrend using fitted polynomial

One method to detrend the time-series is by fitting polynomial equations and subtracting these from the time-series.

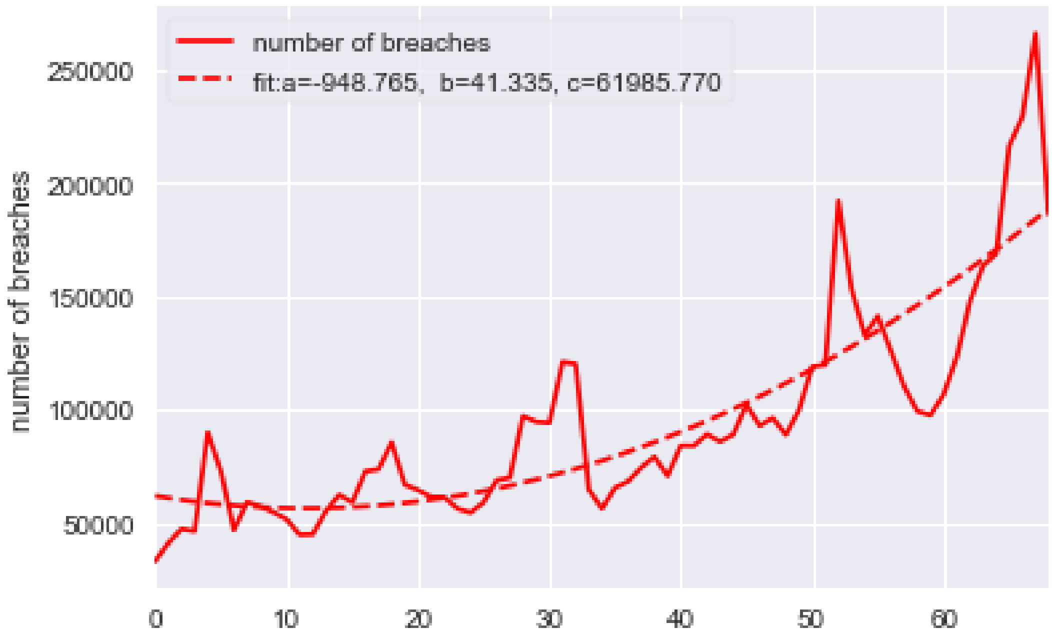
In [25]:
```
def func_dtoc(x, a, b, c):
    return (a * x) + (b * x**2) + c
```

In [26]:
```
def detrend_using_func(dta,column,func,ylabel,color='b'):

    #### fit func
    xdata = dta.index
    ydata = dta[column]
    popt, pcov = scipy.optimize.curve_fit(func, xdata, ydata)

    #### plot fig
    fig = plt.figure() # Create matplotlib figure

    ax = fig.add_subplot(111) # Create matplotlib axes
    df[column].plot(color=color, ax=ax, label=ylabel)#, width=width)#, position=0)
    plt.plot(xdata, func(xdata, *popt), color+ '--',
             label='fit:a=%5.3f,  b=%5.3f, c=%5.3f' % tuple(popt)) #

    ax.set_ylabel(ylabel)
    ax.legend(frameon=True)
    plt.show()

    #### make new column with detrended data
    dta.loc[dta.index,column+'_detrend'] = dta[column] - func(dta[column].index,popt[0]

    return dta
```

In [27]:
```
df = detrend_using_func(df,'total_dtocs',func_dtoc,'number of DTOCs')
```



```
In [28]: df = detrend_using_func(df,'total_breaches',func_dtoc,'number of breaches','r')
```



Plotting the detrended time-series (below) we see there is now no increasing trend over time.

```
In [29]: fig = plt.figure() # Create matplotlib figure

         ax = fig.add_subplot(111) # Create matplotlib axes
         ax2 = ax.twinx() # Create another axes that shares the same x-axis as ax.

         df.total_breaches_detrend.plot(color='red', ax=ax)#, width=width)#, position=1)
         df.total_dtocs_detrend.plot(color='blue', ax=ax2)

         ax.set_ylabel('Number of breaches')
         ax2.set_ylabel('Number of dtocs')
         ax2.grid(b=False)

         #sort legend
         lns = ax.get_lines()+ax2.get_lines()
         ax2.legend(lns,['breaches','DTOCs'],frameon=True)

         plt.show()
```

Is the data now stationary? Again using a dickey-fuller test to ascertain if detrended data is stationarity.

```
In [30]: check_stationarity(df['total_breaches_detrend'])
```

```
ADF Statistic: -3.952409
p-value: 0.001681
        1%: -3.530
        5%: -2.905
        10%: -2.590
```

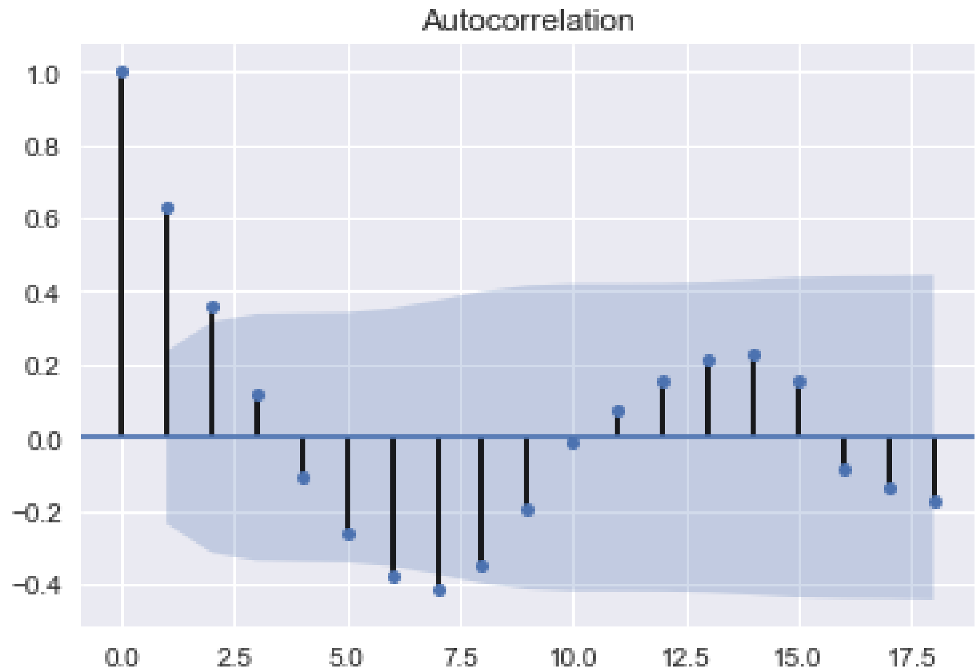
```
In [31]: check_stationarity(df['total_dtocs_detrend'])
```

```
ADF Statistic: -1.586171
p-value: 0.490537
        1%: -3.551
        5%: -2.914
        10%: -2.595
```

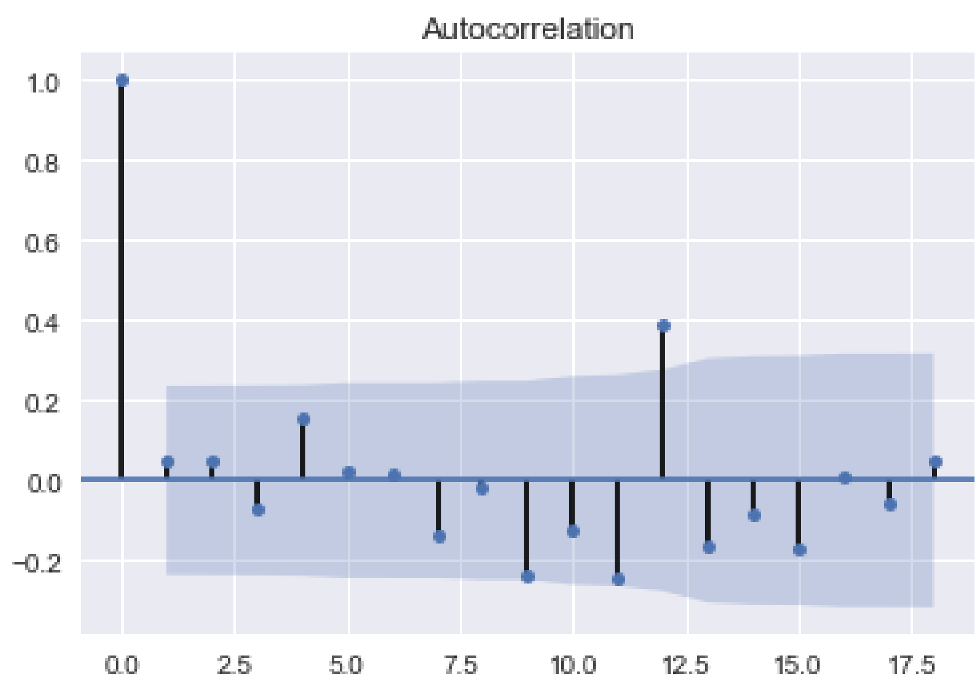
Although we have removed the long-term trend, and breaches now appears to be stationary, it appears that the DTOCs timeseries may still not be stationary (p-value = 0.490).

Re-assesing the level of autocorrelation using the ACF we see that the seasonal variation is still present in the timeseries, but the high and persistent levels of autocorrelation over many lags has been removed.

```
In [32]: fig = sm.graphics.tsa.plot_acf(df['total_breaches_detrend'],lags=18)
```




```
In [33]: fig = sm.graphics.tsa.plot_acf(df['total_dtocs_detrend'],lags=18)
```

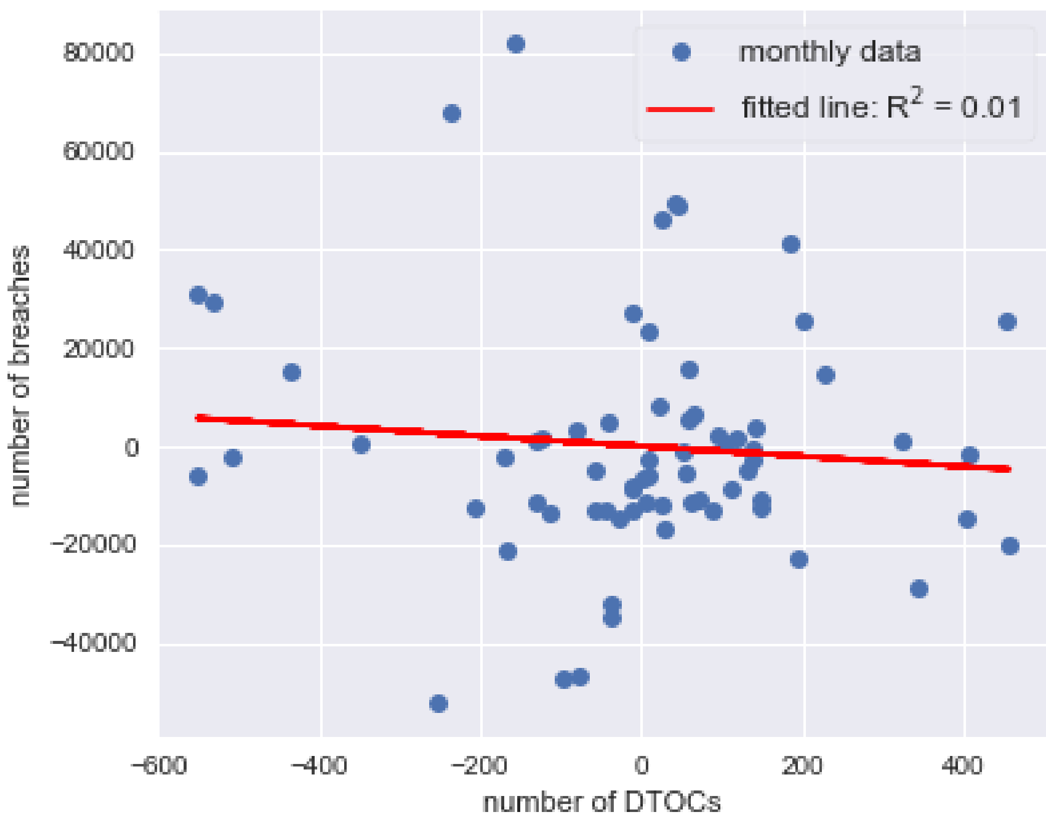


5 Analysis on detrended data

Completing the same linear regression analysis on the detrended data as before we find there are much smaller correlation coeficients.

In [34]:
```
# get coeffs of linear fit
slope, intercept, r_value, p_value, std_err = stats.linregress(df['total_dtocs_detrend'
```

In [35]:
```
fig, ax = plt.subplots(figsize=(6,5))
y = df['total_breaches_detrend']
x = df['total_dtocs_detrend']
plt.plot(x,y,'o', label='monthly data')
plt.plot(x, intercept + slope*x, 'r', label='fitted line: R$^2$ = {0:.2f}'.format(r_val
plt.legend(frameon=True,fontsize='large')
ax.set_xlabel('number of DTOCs')
ax.set_ylabel('number of breaches')
plt.show()
```



In [36]:
```
fig.savefig('detrended.png',dpi=600) # save plot for paper
```

In [37]:
```
df[['total_breaches_detrend','total_dtocs_detrend']].hist();
```


```
In [38]: xdata=df['total_breaches']
         ydata=df['total_dtocs']

         from scipy.stats.stats import spearmanr
         from scipy.stats.stats import pearsonr

         def test_corrs(xdata,ydata,test):
             result = test(xdata,ydata)
             return(result)

         def create_test_df(df):
             index =[]
             corrs = []
             ps = []

             corr,p = test_corrs(df['total_breaches'],df['total_dtocs'],pearsonr)
             index.append('original (pearson)')
             corrs.append(corr)
             ps.append(p)


             corr,p = test_corrs(df['total_breaches'],df['total_dtocs'],spearmanr)
             index.append('original (spearman)')
             corrs.append(corr)
             ps.append(p)
```

```
    corr,p = test_corrs(df['total_breaches_detrend'],df['total_dtocs_detrend'],pearsonr
    index.append('detrended (pearson)')
    corrs.append(corr)
    ps.append(p)



    corr,p = test_corrs(df['total_breaches_detrend'],df['total_dtocs_detrend'],spearman
    index.append('detrended (spearman)')
    corrs.append(corr)
    ps.append(p)


    result = pd.DataFrame(data={'correlations':corrs,'p_values':ps},index=index)
    return(result)

corrs = create_test_df(df)
```

In [39]:
```
corrs.round(4) # produce table for paper
```

Out[39]:

	correlations	p_values
original (pearson)	0.7101	0.0000
original (spearman)	0.5416	0.0000
detrended (pearson)	-0.0915	0.4544
detrended (spearman)	0.0178	0.8844

The p-value roughly indicates the probability of an uncorrelated system producing datasets that have a correlation at least as extreme as the one computed from these datasets. The high p-values for the detrended data indicate that there is a high probability that breaches and DTOCs have little correlation to one another.