# **Understanding the effect of Public**

# transportation on Crime

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# **Introduction**

Public transit system, the system built for the general public to move from here to there. In today's world it is one of the most necessary components to run a city. Transit system helps commuters in many ways including affordable pricing, time saving and safety. It also helps in reducing congestion and air pollution. But does it also increase the rate of crime? Or instigates crime? Research suggests that most people belonging to the lower economic group live in the center of the city, as most of the major transport systems start from there and ends there. These systems help lower crime rates, as people engage more into jobs because of convenient transport. While other researchers suggest there can be another angle to it. It has often been seen that criminals target crowded places such as transit stations, transit interchange connection stations, and the area around transit stations.

Another way of looking at this scenario can be the easy route of escape. If a criminal commits a crime like robbing a house and then goes to a crowded bus stop or subway station it will be a very difficult job to catch hold of him. The question which arises here is why crime is generating around public transportation. Most researchers have found that Public transit stops are generally hotspots for crime, generally there are specific features that appears around these areas including vacant buildings, graffiti, liquor stores, abandoned areas. As the Broken Windows theory proposes that public disorder like this in an area, leads to an increase in some more crimes like robbery, drug sales and much more violent offences. This happens as the offender mostly assumes from the above-mentioned visual science of disorders that neighbors are either too afraid or too indifferent about giving attention to what is happening in the neighborhood. This scary perception thus encourages more crimes. This theory can easily be applied to a transit stop or neighborhood areas

near transit stops which has been experiencing an increase in crime rates. An extensive body of literature exists on how different design features of transit locations are correlated with the variation in crime. Various experiments have also been done that examine crime before and after the opening of transit compared to other locations which provide proofs of transit bringing an increase in crime

A research on the status of public security around Bay Area Rapid Transit (BART) in San Francisco has suggested that at the macro level, the mean center of crime is around BART transit lines. On the micro level, crimes cluster significantly around BART stations. (Wang, Di. (2016). "The Impact of Mass Transit on Public Security - *A Study of Bay Area Rapid Transit in San Francisco." Transportation Research Procedia* 25 (2017) 3233–3252)

Another research on analysis of city connector train at Durham suggested that expansion of public transportation which results in a decrease of transportation costs also result in the shift of crime from neighborhoods which are away from the city to other especially populated neighborhoods in the center of the city. (Willoughby, Jack. (2014)." An Analysis of Durham's Bull City Connector." *The Urban Economics*)

# **Research Question**

- What is the effect of public transportation (like Bus stops and T stops) on crime?
- Does the presence of bus stop on a street segment effect crime?
- Do bus stops in different neighborhoods have impact on crime?

# **Datasets Used:**

I have obtained the datasets from the website of Analyze Boston (https://data.boston.gov/),

Massachusetts GIS data website ( https://www.mass.gov/) and the website of Boston Area

Research map (http://worldmap.harvard.edu/boston/)

Data Name	Description	Data type	
Boston Neighborhood data	The data comprises of the neighborhoods in Boston, along with the total acre of area they spread too	Shapefile	
Boston MBTA bus stops	The data comprises of all bus stops in Boston	Shapefile	
Boston MBTA train lines	The data comprises of all transit lines of MBTA bus train spread across the city of Boston	Shapefile	
Boston MBTA Train stops	The data comprises of all train stops of MBTA train spread across the city of Boston	Shapefile	
Boston Roads and road segments MBTA	The data comprises of all roads and road segments in the city of Boston	Shapefile	
Crime Incidents in Boston 2015 -19	The dataset comprises of crime incidents in and across Boston from the year 2015- 19	CSV file	
American Community Survey data (Boston)	Survey data of demographics in Boston	CSV File	

### **Data scale and accuracy**

*Scale:* All the data had different projections from each other, I projected the datasets into required projections. There were few Null values in the data which I cleaned and sorted. The crime incident data was extracted from a csv file and then converted to use in ArcGIS Pro. There were some latitude and longitude coordinates which were missing in the data and they were cleaned to use for ArcMap.

Accuracy: There could have been accuracy issues while cleaning the data. Especially while deleting the null values and adjusting the coordinate values. The datasets from crimes incidents were also too big and ArcMap stopped responding multiple times while the dataset was loading.

### **Data Limitation:**

Data was only available for Boston, I wished data was also available for the satellite cities so that I could do an overall analysis for them.

# Methodology

- a) Crime data preparation
- The crime data was divided under the following categories for the year 2018
- Social Disorder- This includes crimes like Larceny, Vandalism, Intoxication and Lewd
   Behavior
- **Public Violence** This includes crimes like Burglary, Assault, Auto theft, Homicide
- Private Conflict This includes crimes like Domestic Violence, Violation of orders,
   Trespassing
- Gun Violence- This includes crimes like Shots fired, Armed Robbery, Assault with Gun

### b) Dependent and independent variables

### • The dependent variables were the four types of crimes

- (i)- Counts of Social Disorder
- (ii)- Counts of Private Conflict
- (iii)-Count of Violence
- (iv)- Count of Guns

### • The independent variables were as follows

- 1. Count of Bus stops and T stops
- 2. The number of properties, parking spaces, supermarkets, schools and police stations

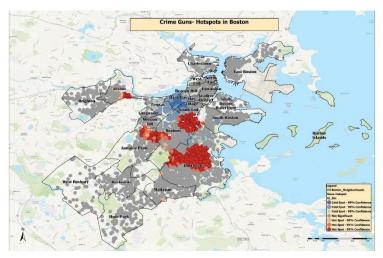
### c) Steps of analysis

- 1. Hotspot analysis to understand the clusters of the 4 divided categories of crime
- OLS regression analysis to understand the effects of independent variables on the 4 dependent variables
- Geographical Weighted Regression analysis to understand the effect over on local geographical levels

# **Analysis and Results**

### 1. Hotspot analysis

The first analysis was hotspot analysis of the 4 types of crime aggregated at the street segment level. The analysis was done to understand where the hotspot of each of the type of crime in the city are. Hotspots (red dots) are created when increased numbers of crime happen at a place and forms a cluster. The analysis would also indicate the cold spots (blue dots) of the crime, meaning where there have been no significant number of crimes happening over a long period. The results from the hotspot analysis are below:



Crime Private Conflict - Hotspots in Boston

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Figure 4- Crime Guns Hotspot

Figure 3- Crime Private Conflict Hotspot

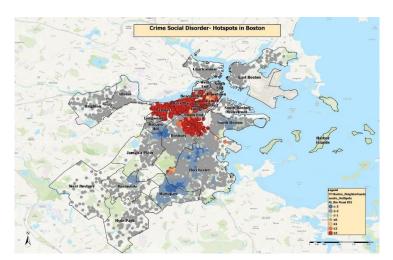




Figure 2- Crime Social Disorder Hotspots

Figure 1- Crime Violence Hotspots

### **Results from Hotspot Analysis**

- Crimes under Social Disorder are mostly clustered around Central Boston Area like-Fenway, Back Bay, Downtown and South End
- Crimes under Public Violence are mostly clustered around Roxbury, Dorchester and some parts of Fenway
- Crimes under Guns and Private Conflict are mostly clustered around Dorchester,
   Roxbury, some parts of Beacon Hill and South End

### 2. OLS Regression Analysis

Regression analysis was done next to understand the effect of all the independent variables/predictors on the dependent variables.

### • The dependent variables were the four types of crimes

- (a)- Counts of Social Disorder
- (b)- Counts of Private Conflict
- (c)-Count of Violence
- (d)- Count of Guns

### • The independent variables were as follows

- 1. Count of Bus stops and T stops
- 2. The number of properties, parking spaces, supermarkets, schools and police stations

### The results of the regression are as follows:

### 2.1 Violence

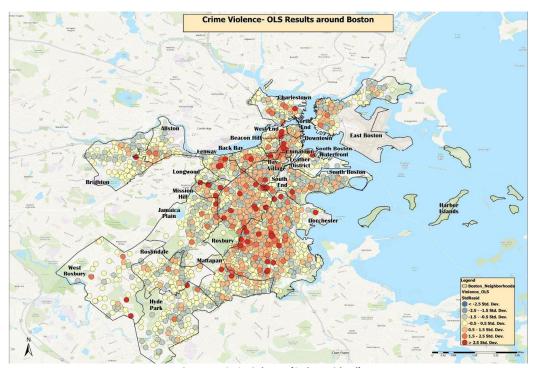


Figure 5- OLS Violence (Std. Residual)

The regression results mapped over Boston shows the number of crimes happening all over the city. The red dots on the map (where standard residual is more than 2.5) represents areas where a greater number of crime violence have happened compared to the average number of crimes all over Boston.

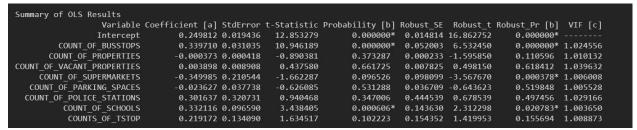


Figure 6- Regression summary, crime Violence

The summary of OLS results gives us the significant independent variables and their coefficients. The variable is called as significant when the Probability of the variable or in statistical terms the p value of the variable is less than 0.05, meaning it has significant effect on the dependent variable. The coefficient of the variable predicts the extent of unit values by which the variable effects the dependent variable.

We can see from the summary that Count of Bus stops and Count of schools are significant variables and both have positive coefficient effecting the increase of the crime of Violence by 0.34 and 0.33 units respectively.

# 

### 2.2 Social Disorder

Figure 7- OLS Social Disorder (Std. Residual)

The regression results mapped over Boston shows the number of crimes happening all over the city. The red dots on the map (where standard residual is more than 2.5) represents areas where a greater number of crime Social Disorder have happened compared to the average number of crimes all over Boston.

```
Summary of OLS Results
                  Variable Coefficient [a] StdError
                                                       -Statistic Probability [b] Robust_SE
                                                                                              Robust_t Robust_Pr [b]
                                                                                                                       VIF [c]
                 Intercept
                                   0.070135 0.007383
                                                        9.499580
                                                                        0.0000003
                                                                                   0.007219
                                                                                              9.715472
                                                                                                            0.000000
         COUNT OF BUSSTOPS
                                                                        0.000000*
                                   0.096546 0.011789
                                                                                              6.882407
                                                                                                            0.000000*
                                                                                                                      1.024556
                                                        8.189528
                                                                                   0.014028
      COUNT OF PROPERTIES
                                   0.000117 0.000159
                                                                        0.460363
                                                                                                            0.525070
                                                        0.738289
                                                                                   0.000185
                                                                                              0.635593
                                                                                                                      1.010132
                                  -0.010166 0.003384
COUNT OF VACANT PROPERTIES
                                                        3.004149
                                                                                                            0.000240*
                                                                                    0.002755
                                                                                              3.690066
                                                                                                                      1.039632
    COUNT_OF_SUPERMARKETS
                                  -0.088553 0.079979
                                                        1.107208
                                                                        0.268248
                                                                                    0.040698
                                                                                                            0.029594*
                                                                                              2.175866
   COUNT_OF_PARKING_SPACES
                                   0.032021 0.014335
                                                        2.233744
                                                                                    0.009281
 COUNT_OF_POLICE_STATIONS
                                   0.016071 0.121835
                                                        0.131909
                                                                        0.895047
                                                                                    0.082956
                                                                                                            0.846389
                                                                                              0.193731
                                                                                                                      1.029166
                                                                                                            0.000406*
                                                                                              3.548675
          COUNT_OF_SCHOOLS
                                   0.061847 0.036691
                                                                        0.091942
                                                                                    0.017428
                                                                                                                      1.003650
           COUNTS_OF_TSTOP
                                   0.152294 0.050936
                                                         2.989883
                                                                        0.002815*
                                                                                    0.155354
                                                                                              0.980299
                                                                                                            0.326970 1.008873
```

Figure 8- Regression summary, crime Social Disorder

We can see from the summary that Count of Bus stops, Count of Properties, Count of Parking spaces and Count of T stops are significant variables. Count of Bus and T stops have positive coefficients and helps in increasing the crime of Social Disorder while Count of Properties and parking spaces with negative coefficients helps in decreasing the crime of Social Disorder.

### 2.3 Private Conflict

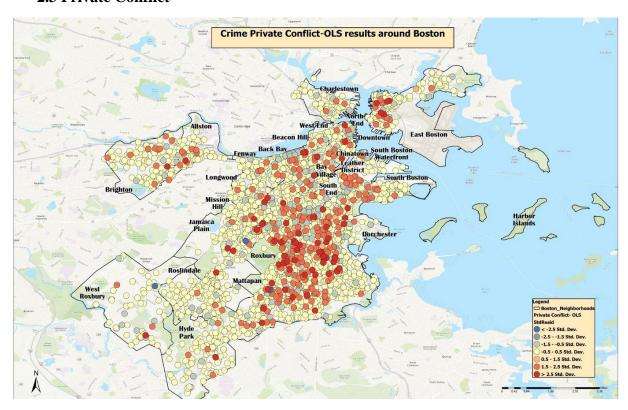


Figure 9- OLS Private Conflict (Std. Residual)

The regression results mapped over Boston shows the number of crimes happening all over the city. The red dots on the map (where standard residual is more than 2.5) represents areas where a

greater number of crime Private Conflict have happened compared to the average number of crimes all over Boston.

```
Variable Coefficient [a] StdError
Intercept 0.116626 0.008770
                                                          Statistic Probability [b] Robust_SE
                                                                                                           Robust_Pr [b]
                  Intercept
                                                          13.298568
                                                                           0.000000
                                                                                       0.008125
                                                                                                 14.354788
                                                                                                                0.000000
                                                                           0.871361
         COUNT_OF_BUSSTOPS
                                    0.002268 0.014003
                                                                                                 -0.178770
                                                                                                                0.858117
                                                                                                                           1.024556
       COUNT_OF_PROPERTIES
                                    0.000678 0.000189
                                                                           0.000349*
                                                                                       0.000175
                                                                                                                0.000117*
COUNT_OF_VACANT_PROPERTIES
                                    0.025583 0.004020
                                                                           0.000000*
                                                                                       0.004757
                                                                                                                0.000000*
                                                                                                                             .039632
     COUNT_OF_SUPERMARKETS
                                    0.073492 0.095002
                                                           0.773585
                                                                           0.439200
                                                                                       0.040241
                                                                                                  1.826303
                                                                                                                0.067863
                                                                                                                           1.006008
   COUNT OF PARKING SPACES
                                                           -1.428333
                                    0.024322 0.017028
                                                                           0.153270
                                                                                       0.014810
                                                                                                  1.642285
                                                                                                                0.100603
                                                                                                                           1.005528
  COUNT_OF_POLICE_STATIONS
                                     1.613063 0.144721
                                                          11.146032
                                                                           0.000000*
                                                                                       0.404089
                                                                                                  3.991846
                                                                                                                0.000075*
                                                                                                                          1.029166
          COUNT OF SCHOOLS
                                    0.130039 0.043584
                                                                                                                0.023408*
                                                           2.983660
                                                                           0.002872*
                                                                                       0.057359
                                                                                                  2.267092
                                                                                                                           1.003650
           COUNTS OF TSTOP
                                     0.001228 0.060504
                                                                                                                0.980144
                                                           0.020296
```

Figure 10- Regression summary, crime Private Conflict

We can see from the summary that Count of Properties, Count of Vacant Properties, Count of Police stations and Schools are significant variables. All the variables have positive estimates and helps in increasing the crime of Private Conflict by their respective units.

### **2.2 Guns**

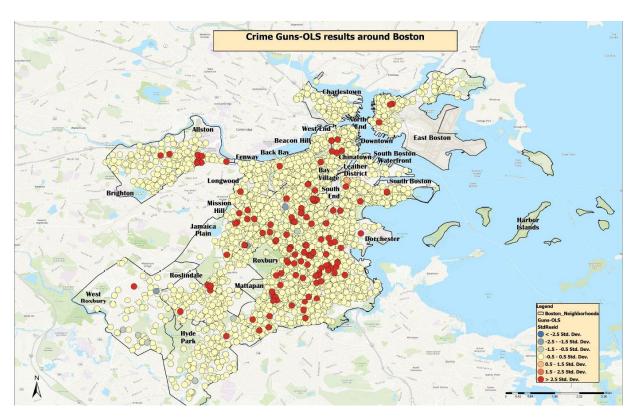


Figure 11- OLS Guns (Std. Residual)

The regression results mapped over Boston shows the number of crimes happening all over the city. The red dots on the map (where standard residual is more than 2.5) represents areas where a greater number of crime Guns have happened compared to the average number of crimes all over Boston. We can also note that compared to all the other categories of crime, Gun crime's count is lower.

Summary of OLS Results								
Variable	Coefficient [a] StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]	
Intercept	0.045905 0.005793	7.924876	0.000000*	0.004402	10.427832	0.000000*		
COUNT_OF_BUSSTOPS	0.027092 0.009249	2.929082	0.003423*	0.009187	2.948983	0.003212*	1.024556	
COUNT OF PROPERTIES	-0.000048 0.000125	-0.388445	0.697718	0.000090	-0.539015	0.589909	1.010132	
COUNT_OF_VACANT_PROPERTIES	0.007649 0.002655	2.880833	0.003989*	0.002861	2.672946	0.007539*	1.039632	
COUNT OF SUPERMARKETS	-0.060535 0.062750	-0.964706	0.334723	0.007289	-8.304714	0.000000*	1.006008	
COUNT_OF_PARKING_SPACES	-0.022586 0.011247	-2.008138	0.044670*	0.005026	-4.493883	0.000010*	1.005528	
COUNT_OF_POLICE_STATIONS	0.429893 0.095590	4.497275	0.000009*	0.136271	3.154690	0.001631*	1.029166	
COUNT OF SCHOOLS	-0.025235 0.028787	-0.876582	0.380739	0.014584	-1.730332	0.083638	1.003650	
COUNTS OF TSTOP	-0.034034 0.039964	-0.851620	0.394449	0.016404	-2.074672	0.038053*	1.008873	

Figure 12- Regression summary, Crime Guns

We can see from the summary that Count of Bus stops, count of vacant properties, count of parking spaces, count of police stations are significant variables. Bus stops, vacant properties and police stations have positive coefficients which are expected to increase the occurrence of crime involving Guns. While count of parking spaces with negative estimate decreases the occurrence of crime involving Guns.

### 3 Geographical Weighted Regression (GWR)

As bus stop is a significant variable which effects the occurrence of all 4 types of crime. GWR was run with bus stop as the predictor variable on the 4 dependent variables to understand the effect on local level. The results are as follows:

### 3.1 Violence

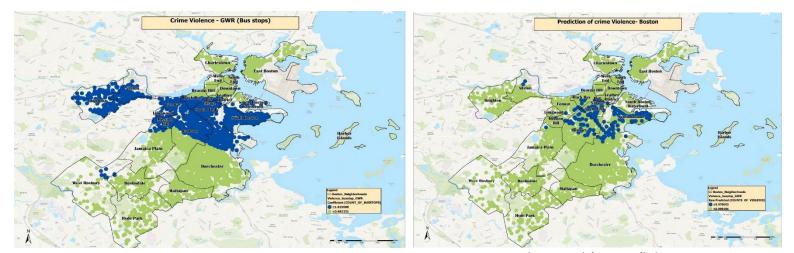


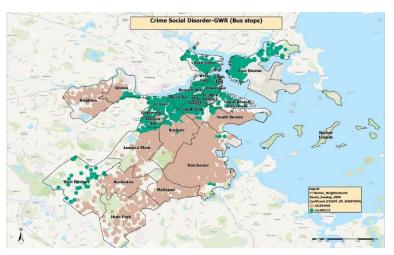
Figure 13- GWR - Crime Violence

Figure 14- Violence Predictions

The results of GWR for crime violence suggests that the dark blue areas in the map have the highest effect of presence of bus stops on crime violence, as compared to other areas in the city. GWR also predicts the number of crimes which can happen in the future which we can see from figure 14. The figure indicates that the predictions are mostly from the areas where bus stops have maximum effect on crime in the city. This gives us an idea that violence is different in different neighborhoods of Boston depending on the number of bus stops there.

Further the GWR model explains 11% deviance at the local level.

### 3.2 Social Disorder



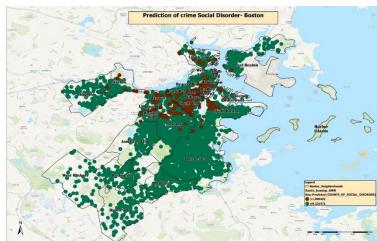
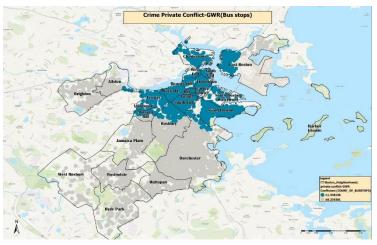


Figure 15- GWR Crime Social Disorder

Figure 16- Social Disorder Prediction

The results of GWR for crime Social Disorder suggests that the dark green areas in the map (Figure 15) have the highest effect of presence of bus stops on crime Social Disorder, as compared to other areas in the city. GWR also predicts the number of crimes which can happen in the future which we can see from figure 16. The figure indicates that the predictions are mostly from the areas where bus stops have maximum effect on crime in the city. This gives us an idea that violence is different in different neighborhoods of Boston depending on the number of bus stops there. Further the GWR model explains 14% deviance at the local level.

### 3.3 Private Conflict





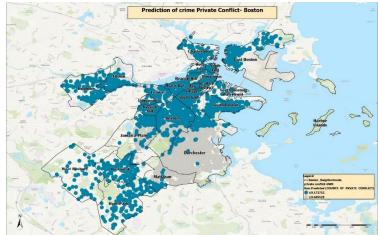


Figure 18- Prediction GWR

The results of GWR for crime Private Conflict suggests that the dark blue areas in the map (Figure 17) have the highest effect of presence of bus stops on crime Private Conflict, as compared to other areas in the city. GWR also predicts the number of crimes which can happen in the future which we can see from figure 18. Interestingly, the figure indicates that the predictions are a lot in number and allover Boston. This gives us an idea that Private Conflict is not really affected by the presence of bus stops, as it is something which is a more private matter of neighborhood. We also saw this previously from the OLS results of Private Conflict that count of bus stops was not a significant variable.

### **3.4 Guns**

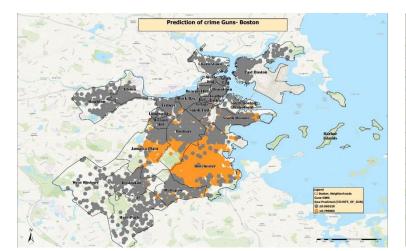




Figure 19- GWR Crime Guns

Figure 20- Prediction of Guns

The results of GWR for crime Guns suggests that the dark grey areas in the map (Figure 19) have the highest effect of presence of bus stops on crime Guns, as compared to other areas in the city. GWR also predicts the number of crimes which can happen in the future which we can see from figure 20. The figure indicates that the predictions are little different, the GWR predicts more areas for crime Guns in the areas of Dorchester.

# **Discussion**

- The occurrence of crime is affected by the presence of transit
- Presence of Bus stops on streets increases the occurrence of all crimes except crime group of Private Conflict
- Bus stops have maximum effect on crime Violence followed by Social Disorder
- Presence of Parking spaces, Schools and Police stations also increases occurrence of crime
- Crime differs by neighborhoods
- Crime varies also by place and time

# **Conclusion**

Crime has always been a very skeptical topic, it can have many occurrences and causes. Though this proposed study may in a way show there has been a significant effect of bus stops on the rate of crime, it can have much more hidden factors to it. This is a very important issue for cities, if adding a new way of transport to connect cities and encourage more business and jobs for people helps enhances economy, at the same time it can also bring increasing rate of crime to it. It is always advisable to rather have safety measures like a greater number of crime helpline, more policing and safety features to be added while expanding transport to make it more effective. Also, usage of methods like Predictive Policing can help identify and Combat crime to a great extent.

# **Recommendations**

• Crime Mapping, Analytics and Predictive System (CMAPS)

This is one innovative crime mapping technique which is used to gather real time data for crime. This GIS based crime mapping system gives detailed information about time, place and

type of crime. This data can be used to predict the spatial and temporal patterns of crime. This data can be further used for predictive analysis of time of crime, place of crime and to predict social network of the crime gang.

## • Predictive Analysis

This analysis can be done to predict the location and time of crime using the data from trend analysis of crime. This real time data software can be used to predict crime and take necessary measures to prevent it.

# **References**

Brantingham Patricia and Paul Brantingham. (1991). "How Public Transit Feeds Private Crime: Notes on the Vancouver 'Skytrain' Experience."

Wang, Di. (2016). "The Impact of Mass Transit on Public Security - A Study of Bay Area Rapid Transit in San Francisco." Transportation Research Procedia 25 (2017) 3233–3252

Willoughby, Jack. (2014)." An Analysis of Durham's Bull City Connector." *The Urban Economics*